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Study on Optimization of Sea Ice Concentration with Adjoint Method

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ABSTRACT

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Obtaining initial sea ice concentration (SIC) values with high accuracy that are consistent with other models have been a hot topic in both sea ice prediction and sea ice modeling studies. Here, an ocean-sea ice coupled numerical model and its adjoint code have been utilized to carry out numerical experiments to optimize the initial SIC values. In the experiments, the cost function was defined as the difference between the SIC values from the reanalysis dataset and the modeled results. The gradient of cost function, relative to SIC and other model variables, was computed by the adjoint model, and a linear search algorithm was employed to optimize the SIC values by minimizing the cost function. The influences of the weight coefficients of the cost function, the extent of the geographical region, and the seawater temperature and sea ice thickness initial values on the optimization results have been analyzed. The weight coefficients of the cost function had little effect on the SIC distribution pattern but substantial influence on the SIC values. The optimized SIC in the Greenland Sea, Okhotsk Sea, and the Arctic Ocean, with a constant weight coefficient, is better than that with variable weight coefficients. The errors in the initial model fields, other than SIC, may deteriorate the overall result, implying that optimizing multiple model fields simultaneously may improve the optimization effect. Decreasing the size of the geographical region for optimization does not improve the SIC optimization results substantially. Compared to the results from a global cost function, the Barents Sea SIC values from a northern hemispheric cost function are poorly optimized.

ADDITIONAL INDEX WORDS: *Numerical prediction, initial values, cost function, coupled model.*

INTRODUCTION

Global climate and environmental change has been a hot topic in current earth science research, encompassing the complex interactions between the different earth spheres. To obtain an accurate understanding of the overall behavior of such a complicated system, it is necessary to have a solid grasp on the key mechanisms of each individual sphere. As an important component of the cryosphere, sea ice has been receiving increasing attention in the scientific community. Sea ice has a much higher albedo than other earth surfaces, such as the surrounding ocean. The high albedo of the sea ice serves a role in maintaining cooler polar temperatures by reflecting much of the received sunlight away from the surface. The sea ice cover hinders the heat and mass exchanges between the atmosphere and ocean. When sea ice forms, much of the salt in the seawater is squeezed out of the frozen crystalline matrix of the sea ice, with the salty, dense water beneath the sea ice cover potentially leading to a convection instability. These effects contribute to the evolution of the climate system. On a seasonal scale, seawater freezes to form sea ice in the winter, releasing heat into the seawater, and the sea ice then melts in the summer, absorbing heat from the seawater. The seasonal seawater temperature extremes are reduced by the effect of the sea ice acting as an insulating barrier between the air and seawater. At longer time scales, the sea ice not only affects the local climate through ocean-atmosphere interactions, but it also effects broader regions through internal atmospheric and oceanic processes. Since sea ice has such an important role in ocean-atmosphere interactions, accurately depicting the evolution of sea ice has become important research direction in the numerical simulation of the climate system (Liu *et al.*, 2008). In addition, since sea ice has impacts on navigational activities, it is important to accurately predict sea ice distribution and thickness changes. The performance of sea ice numerical simulations and forecasting is related to the sea ice model, ocean model, atmospheric forcing, and initial model values. Among these, the quality of the initial values of the sea ice model is an important influencing factor.

Initial value processing techniques have been widely used in atmospheric and oceanic numerical simulation and prediction studies (Pohlmann *et al.*, 2009; Smith *et al.*, 2007). Studies have shown that these slower surface processes may provide an important contribution that is needed in models to improve climate predictability (Hurrell *et al.*, 2009; Liu *et al.*, 2005; Shepherd *et al.*, 2011), thus requiring better simulation and prediction methods to capture these slow changes. High-quality

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initial sea ice values are necessary to improve sea ice model simulations and predictions. This is primarily achieved through the assimilation of sea ice observations. There have been many works on sea ice data assimilation, but most are confined to either the statistical optimization method (Meier, Maslanik, and Fowler, 2000; Zhang *et al.*, 2003) or the relaxation technique (Tietsche *et al.*, 2013). Toyoda *et al.* (2016) assimilated sea ice concentrations into a global ocean-sea ice model with a three-dimensional variational method. Dynamic optimization using the model equations as a constraint (*e.g.*, the adjoint method) possesses several unique advantages, including a clear physical meaning and greater consistency among the model variables, but this kind of approach on sea ice is still rare at present.

The adjoint method is a kind of dynamic analysis method based on the dynamic prediction problem (forward problem) to obtain the inverse deduction (inverse problem). It is a powerful tool for studying the sensitivity of the outputs to the inputs, and it has been used in many studies, such as optimization problems, stability analyses, and parameter estimations (Errico, 1997). Over the past few decades, the adjoint method has been applied to many fields, including atmospheric science, computational fluid dynamics, ice sheet modeling, and engineering design optimization (Giannakoglou and Papadimitriou, 2008; Giles and Pierce, 2000; Goldberg and Heimbach, 2013; Heimbach and Bugnion, 2009; Homescu and Navon, 2003; Ngodock *et al.*, 2017). Adjoint approaches have been proven to outperform other relevant methods, such as direct sensitivity analyses, finite differences, and the complex variable approach (Giannakoglou and Papadimitriou, 2008). For example, the adjoint method has been employed to determine the sensitivity of the typhoon intensity to the initial model value, and the terrain in the whole computation zone can be obtained in one numerical experiment without the need to design different tests for different regions within the zone (Liu, 2014).

For climate studies, the most important sea ice parameters are sea ice concentration (SIC) and sea ice thickness. While the SIC observational record is dense in both space and time, ice thickness observations are sparse. Therefore, the assimilation of sea ice thickness data cannot avoid the problem of large uncertainties associated with the true ice thickness. Initial conditions derived from the assimilation result inherit this uncertainty, which in turn severely limits the reliability of sea ice predictions (Tietsche *et al.*, 2013). Here a coupled ocean-sea ice model, as well as its adjoint model, will be used to study Arctic SIC optimization, and then analyze the effects of the cost function and the initial values of the key seawater and sea ice parameters on SIC optimization. Although the adjoint method has been widely used for sensitivity analysis and data assimilation studies in the atmospheric and oceanic sciences, its use in sea ice simulations and research is rare.

METHODS

An ocean-sea ice coupled model and its adjoint code have been utilized to carry out numerical experiments to optimize the initial SIC values.

Numerical Model

The Massachusetts Institute of Technology general circulation model (MITgcm) (Marshall *et al.*, 1997) is used to carry out this research. MITgcm is a numerical model that simulates the atmosphere and oceans. Compared to other numerical models, it merits some outstanding features, including: the atmospheric oceanic components are constructed based on the same dynamic framework, such that it can be used to study both atmospheric and oceanic phenomena; the atmospheric and oceanic components can be coupled to study the ocean-atmosphere interaction problem; the model can adopt a non-static equilibrium form for the momentum equation to study both large-scale and small-scale processes; the dynamic framework adopts a curvilinear coordinate system, and an alternative cubed sphere grid can be used to solve the "pole problem" effectively; the model uses the finite volume method to represent the terrain, which can depict the complex terrain more accurately; and it can be used to study sensitivity and optimization problems since the tangent linear and adjoint codes can be readily obtained from the model (Heimbach, Hill, and Giering, 2005). For more information on the MITgcm, see the latest online documentation at the MITgcm website (http://mitgcm.org/public/r2_manual/latest/online_documents/manual.html).

Two sea ice configurations are provided in the MITgcm (Checkpoint 621). One is a thermodynamic sea ice configuration (the Semtner three-layer thermodynamics (Semtner, 1976)), and the other is an alternative that includes both the thermodynamic (the Semtner zero-layer scheme (Semtner, 1976)) and dynamic processes. For the dynamic processes, either the elastic-viscous-plastic (EVP) rheology (Hunke and Dukowicz, 1997) or the viscous-plastic rheology (Hibler, 1979) can be used.

Dataset

The atmospheric forcing fields and SIC were taken from the reanalysis dataset ERA-Interim, which was provided by the European Center for Medium-range Weather Forecasts (ECMWF) (Simmons *et al.*, 2007). The atmospheric forcing fields included wind (speed and direction) at 10 m, air temperature at 2 m, specific humidity at 2 m (converted from the dew point temperature at 2 m), surface downward short wave radiation flux, and surface downward long wave radiation flux. Each of these fields was calculated four times a day.

Experiment Design

The Semtner zero-layer scheme and EVP rheology were used in each of the experiments. The initial SIC values of the experiments were the simulation outputs from 0:00 UTC on March 1, 2012, taken from a simulation the evolution of the ocean and sea ice under atmospheric forcing from 1989 to 2012 (Liu and Liu, 2012). The parameters used in the forward-integration model were identical to those in Liu and Liu (2012), employing a cubed sphere, a horizontal grid spacing of 150 km, and 30 layers in the vertical. The global ocean and sea ice were simulated with the forward-integration model. The automatic difference transformation of algorithms in Fortran (TAF) tool (Giering and Kaminski, 2003; Heimbach, Hill, and Giering, 2005) was used to generate the adjoint code of the forward-integration model.

To determine the SIC constraint imposed by the ERA-Interim dataset, the cost function J is defined as:

$$J = \sum_{i=1}^{N} w_i[\bar{c}_i - \mathrm{I}_i(\bar{c}^o)]^2 \tag{1}$$

where, $\bar{c}_i$ is the simulated daily mean SIC of grid point i, $\bar{c}^o$ is the daily mean SIC of ERA-Interim dataset, I_i is an bilinear interpolation operator that transforms the field from the ERA-Interim dataset grids to the model grid, w_i is the weight coefficient, and N is the total model grid points covered by sea ice. The definition of the cost function here is different from that in data assimilation, since the emphasis is different in the two kinds of research.

A linear search algorithm was employed to minimize the cost function by optimizing the SIC values. The linear search algorithm is based on a quasi-Newton variable storage method that was implemented by Gilbert and Lemaréchal (1989). The cost function gradients of the model variables were calculated and the initial SIC values were adjusted with the linear search algorithm using the adjoint code. The process was iterated until the descent direction of the cost function changed. The updated control was then used as the input for these simulations, employing the same descent direction, but with different step sizes.

The weight coefficient values will influence the cost function and thus influence the results of the SIC optimization. To study the influence of the weight coefficients on the optimization, two kinds of weights were employed to carry out the numerical simulations. It should be noted that the initial ocean and sea ice values will also influence the SIC optimization results. Thus, numerical experiments on the influences of these initial values with seawater temperature and uniform sea ice thickness were performed. In addition, to study the effects of the spatial extent of the cost function calculations on the SIC optimization results, one numerical SIC experiment was also performed that included the southern hemisphere and was not optimized. The numerical experiments performed in this study are listed in Table 1.

Table 1. *Description of the numerical experiments.*

Name	Description
EXP_WC1	$w_i = 1/d_i^2$, $d_i = 0.5$.
EXP_WC2	$w_i = 1/d_i^2$, $d_i = \sigma_i^o$, σ_i^o is the standard deviation of the SIC daily mean in March 2012.
EXP_TEM	Identical to EXP_WC2, with the exception that the climate seawater temperature is used as the initial value of the seawater temperature.
EXP_ITH	Identical to EXP_WC2, with the exception that the initial sea ice thickness value is assumed to be 2 m.
EXP_NOR	Identical to EXP_WC2, with the exception that $w_i = 0$ in the southern hemisphere.

RESULTS

The variations in the cost function were different for each of the experiments, but they all decreased gradually. After fourteen iterations, the cost function change in all experiments was < 0.1%. However, the speed of the cost function decrease in EXP_WC1 was faster than in the other experiments (figures not shown). Thus, the faster convergence speed of EXP_WC1 highlighted its better performance. In a later analysis of the numerical experiment results, the output data from the fifteenth iteration of each experiment would be used. From the ERA-Interim reanalysis dataset (Figure 1b), the impact of the North Atlantic Warm Current clearly influences the ice-free conditions in both the Greenland Sea (south of Svalbard) and Norway Sea, with the southern Barents Sea also being ice-free. The sea ice extent in the Labrador Sea along the coast of North America extends southward to Newfoundland, with sea ice cover across both the Bering Sea and Okhotsk Sea. The initial SIC values of the numerical experiments (Figure 1a) come from the numerical simulation results for 0:00 UTC on March 1, 2012, with no optimization. Compared to the reanalysis dataset results, there is more sea ice in the Greenland Sea, Barents Sea, Labrador Sea, Okhotsk Sea, and in the northern Davies Strait, but less sea ice in the Bering Sea for the initial SIC results (Figure 1).

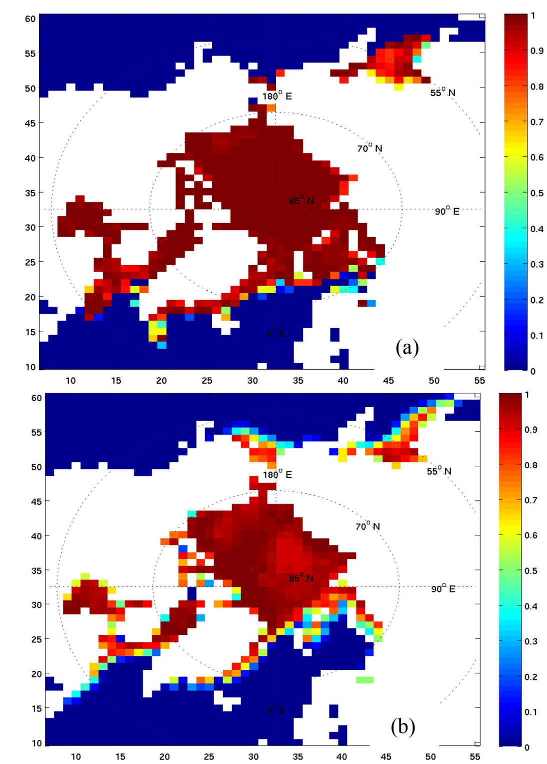
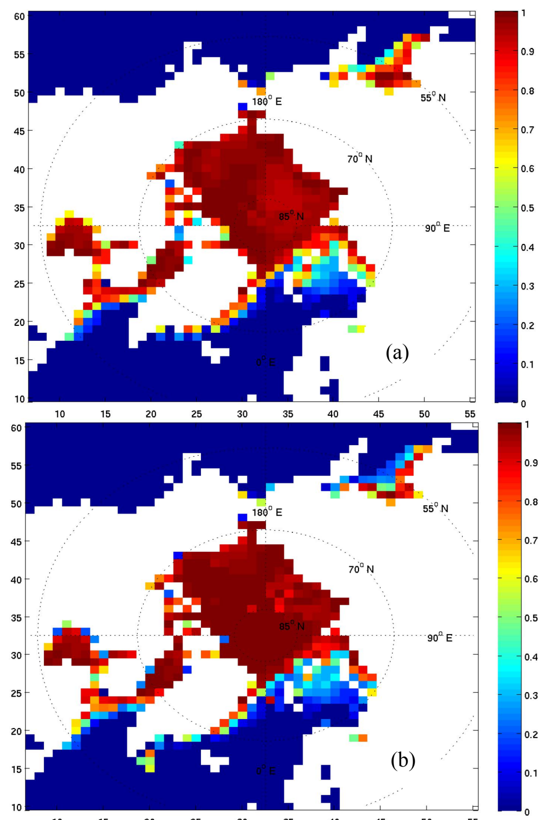


Figure 1. SIC distribution at the start of the model integration. (a) Initial SIC values; (b) SIC results from the ERA-Interim reanalysis dataset. The numbers along the coordinate axes denote the position of model grids. The SIC distributions are represented by color-filled grid cells, with the legend on the right side of each panel providing the SIC values.

Here the adjoint model is used to optimize the initial SIC values. The SIC values from the reanalysis dataset and numerical model are employed together to adjust the initial SIC values to reach the state where its difference from the reanalysis dataset is minimized (*e.g.*, the cost function was minimized). Consequently, the adjusted SIC values are influenced by both the reanalysis data and the numerical model performance. For each of the five experiments, the adjusted SIC distribution (Figure 2) is improved compared to its counterpart without optimization (Figure 1). There are, however, substantial differences between the results of different numerical experiments (Figures 2a–e). The weight coefficients in the cost function have little effect on the SIC distribution pattern but substantial influence on the SIC values (Figures 2a and 2b). Comparing the simulation results between EXP_WC1 and EXP_WC2, the optimized SIC extent in the Greenland Sea, Okhotsk Sea, and the Arctic Ocean from EXP_WC1 is in better agreement with the reanalysis results. Generally speaking, the experiment results that employ a constant weight coefficient (EXP_WC1) are better than those that employ variable weight coefficients (EXP_WC2) (compare Figures 2a and 2b to Figure 1b).



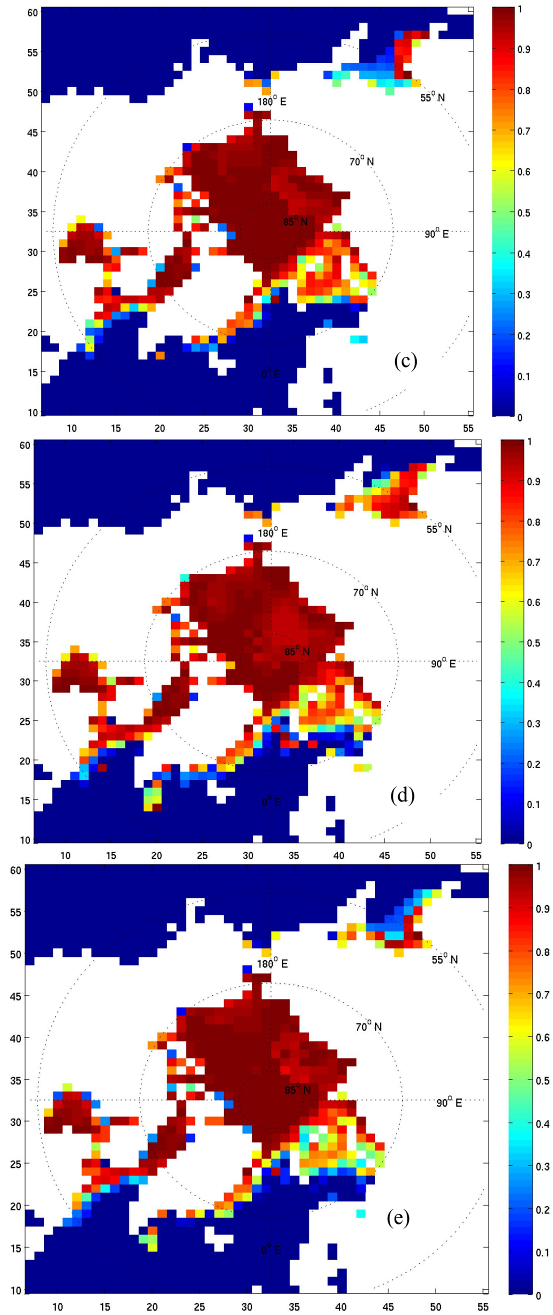


Figure 2. Optimized SIC from the different experiments: (a) EXP_WC1; (b) EXP_WC2; (c) EXP_TEM; (d) EXP_ITH; and (e) EXP_NOR. The numbers along the coordinate axes denote position of model grids. The SIC distributions are represented by color-filled grid cells, with the legend on the right side of each panel providing the SIC values.

The results of the initial seawater temperature (EXP_TEM) and sea ice thickness (EXP_ITH) numerical experiments (Figures 2c and 2d) highlight that errors in the initial values of the model variables, other than SIC, have significant effects on the SIC optimization. The EXP_TEM and EXP_ITH results reveal that the optimized SIC values in the Barents Sea and Okhotsk Sea are worse than the optimized EXP_WC1 and EXP_WC2 SIC values. This implies that the SIC optimization is improved when more initial values of the model variables are optimized simultaneously.

The EXP_NOR experiment was carried out to investigate the influence of changing the spatial area of optimization on the SIC optimization. Compared to the results from the experiment with a global sea ice cover adjustment (EXP_WC2), reducing the spatial area of optimization does not improve the SIC optimization results, and the SIC results in the Barents Sea worsen (Figures 2b–e).

The advantage of optimization with the adjoint method is that when a particular field is optimized, the other quantities will be adjusted at the same time to ensure that all the model fields are consistent under the constraint of the model equations. After the initial SIC values have been optimized, the sea ice in the Greenland Sea, Barents Sea, Davies Strait, northern Labrador Sea, and northern Okhotsk Sea are all reduced and yield better agreement with the reanalysis results (Compare Figure 2 with Figure 1). The reduction in sea ice cover across those regions leads to increased losses in both the sensible and latent heat fluxes from the sea surface, which favors the decrease in sea surface temperature (See Figure 3; The results from EXP_WC1 is used here as an illustration, although the results from the other experiments are similar.), which goes against the reduction of sea ice there. However, the surface ocean currents also change, with the East Greenland Current weakening and the North Atlantic Ocean Warm Current strengthening, both of which favor the reduction in sea ice cover across the Greenland Sea and Barents Sea.

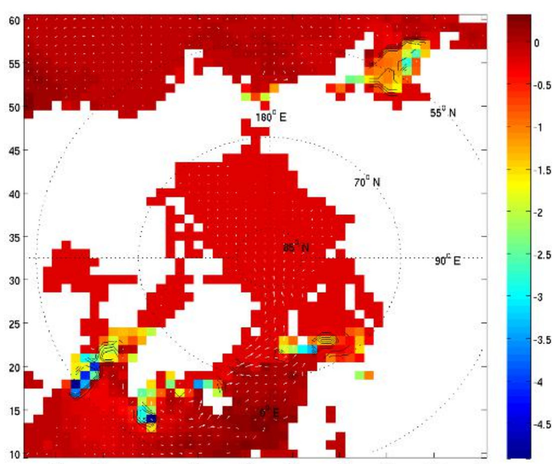


Figure 3. Differences of sea surface temperature (color shaded), SIC (contour), and sea surface current (vector) between EXP_WC1 and the initial values. The SIC contour levels are –0.7, –0.5, –0.3, and –0.1, respectively. The numbers along the coordinate axes denote the position of the model grids. The maximum length of arrow denotes 0.5 m/s, and the legend for sea surface temperature is on the right side.

None of the numerical experiments produce sea ice in the southern Bering Sea due to the simulated sea surface temperature being higher than the real case there. Since the sea surface temperature is well above the freezing point of seawater in the model, any increased sea ice from the adjustment process will still be quickly melted away by the model. Meanwhile, the seawater temperature will decrease due to the sea ice melt in the model. This sea ice bias in the Bering Sea is the result of a heat flux imbalance between the ocean and atmosphere, implying that there are errors in the atmospheric forcing and/or ocean processes. These errors lead to a warm bias of the sea surface temperature in this region, such that the thermodynamic condition of sea ice formation cannot be met. During the optimization process, the Bering Sea SIC values are adjusted (made to increase) in each iteration, but the increased sea ice will still be melted away immediately. This shows that the performance of the numerical model has substantial influence on the optimization results. If the performance of a numerical model is bad, it will then be difficult to obtain good optimization results.

DISCUSSION

Adjoint models are widely used in geophysical fluid modeling, but few models are freely accessible to the scientific community. The numerical code of the MITgcm is designed to enable computer generation of its adjoint model using the automatic differentiation TAF tool, which is freely accessible and has been applied to many studies. For example, the sensitivity analysis of ocean circulation to topography (Losch and Heimbach, 2007), the evaluation of carbon sequestration efficiency (Hill *et al.*, 2004), the parameter and state estimation in ice sheet modeling (Goldberg and Heimbach, 2013), and sensitivity studies of loop current and eddy shedding in the Gulf of Mexico (Gopalakrishnan, Cornuelle, and Hoteit, 2013) have all employed the MITgcm adjoint model. These works have thus verified the feasibility and robustness of the adjoint code, which prompted the choice of the MITgcm adjoint model for this SIC study.

Only the daily mean SIC from the reanalysis dataset was used to carry out the experiments. Further research on SIC optimization with the observed SIC values over longer periods needs to be undertaken. In addition, since sea ice thickness is also an important factor in sea ice modeling, especially in climate research, the sparse sea ice thickness datasets should be more thoroughly analyzed. Future research should consider employing the adjoint method in sea ice thickness optimization studies.

It should be noted that the TAF, which is employed in the adjoint code, is a commercial software. The MITgcm also enabled computer generation of its adjoint model using OpenAD (Utke *et al.*, 2008), which is a flexible, modular, open source tool. However, the configuration has not been tested with it yet.

CONCLUSIONS

Five numerical experiments were performed with the MITgcm adjoint model to study SIC optimization. The influences of the cost function weight coefficients, the seawater and sea ice initial values, and the extent of the geographical region were evaluated to determine the optimization of the initial SIC values. The cost function weight coefficients have little effect on the SIC distribution pattern but a substantial influence on the SIC values. The optimized SIC in the Greenland Sea, Okhotsk Sea, and the Arctic Ocean with a constant weight coefficient is better than that with variable weight coefficients. The impacts of the initial seawater and sea ice values on the optimization results of the initial SIC values are significant. When seawater temperature and sea ice thickness values with larger bias are used as the initial values, the optimized SIC values in the Barents Sea and Okhotsk Sea get worse. Decreasing the extent of the geographical region for optimization does not improve the results of the SIC optimization substantially. Compared to the result from the global optimization scheme, the SIC results in the Barents Sea from the northern hemispheric scheme worsen.

It can be deduced that a better result would be achieved if more initial seawater and sea ice values are optimized simultaneously. The negative bias of sea ice in the Bering Sea in the numerical experiments would be reduced if the sea surface temperature is also optimized.

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