Optimizing the key parameter to accelerate the recovery of AMOC under a rapid increase in greenhouse gas forcing

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Abstract

The Atlantic Meridional Overturning Circulation (AMOC) plays a central role in long-term climate variations through its heat and freshwater transports, which can collapse under a rapid increase in greenhouse gas forcing in climate models. Previous studies have suggested that the deviation of model parameters is one of the major factors inducing inaccurate AMOC simulations. In this work, with a low-resolution Earth system model, we try to explore whether reasonably adjusting the key model parameter can help to re-establish the AMOC after its collapse. Through a new optimization strategy, the freshwater flux (FWF) parameter is determined to be the dominant one on affecting the AMOC's variability.

Traditional ensemble optimal interpolation (EnOI) data assimilation and new machine learning methods are adopted to optimize the FWF parameter in an abrupted 4×CO$_2$ forcing experiment to improve the adaptability of model parameters and accelerate the recovery of AMOC. The results show that under an abrupted 4×CO$_2$ forcing in millennial simulations, the AMOC will first collapse and then be slowly re-established by the default FWF parameter. However, during the parameter adjustment process, the saltier and colder sea water over the North Atlantic region are the dominant factors in usefully improving the adaptability of the FWF parameter and accelerating the recovery of AMOC, according to their physical relationship with FWF on the interdecadal timescale.

1 Introduction

In coupled climate models or earth system models, for physical processes and dynamical motions whose spatial scales are smaller than the model resolution cannot be fully resolved by the model equations, contributions from them are usually represented through subgrid-scale schemes or parametrizations in numerical models (Shen et al., 2022). Theoretically, model parameters can be adjusted or optimized using observations; this process is called parameter estimation (PE). PE uses the covariance between model states and parameters, similar to state estimation. Therefore, any parameter related to the observable state variables can be optimized using the data assimilation method. In practice, PE is more difficult than state estimation due to the difficulties in estimating the state-parameter covariance, which is influenced by multiple factors, such as model errors, sampling errors, and observational errors, as well as low model sensitivity (Ruiz et al., 2013a). In a coupled model, coupled parameter estimation is even more difficult than single-component model parameter estimation due to the complex model sensitivities associated with the variability of different spatial and temporal time scales in different model components and the misfitting of air–sea interaction processes (Zhang et al., 2020); thus, PE is still a challenging question.

In PE, the accuracy of the estimated parameters depends on the amount of data that contains information about the parameter value and on the accuracy of the estimated covariances (Ruiz et al., 2013b). When the ensemble size is relatively small, sampling errors in the estimation of the covariances are significant (Tong and Xue, 2008). The computational cost of the state-of-the-art numerical models is expensive, and it is unrealistic to use a large ensemble size in such models. However, we can use the simplified model to explore the relationship between model states and parameters through large samples. The reduced physics coupled model used in this work has been used in parameter estimation
experiments in previous studies (e.g., Hargreaves et al., 2004; Edwards et al., 2005; Annan et al., 2005). Most parameters cannot be directly measured; hence, they might be estimated through covariances between parameters and state variables; however, if the observed variables are weakly correlated with the parameter value, the parameter cannot be estimated well (Ruiz et al., 2013a). Therefore, in this work, we use the traditional data assimilation method to explore efficient and reasonable model states to estimate the parameter through large samples, and we also compare the traditional data assimilation method with the machine learning method, which has received much attention in atmospheric science (e.g., Barnes et al., 2019; Ham et al., 2019; Hwang et al., 2019; Gao et al., 2021), including parameterization with numerical models (e.g., Rasp et al, 2018; Bolton et al., 2019; Brenowitz et al., 2019), to adjust the model parameters.

AMOC is defined as the stream function for the zonally integrated meridional volume transport in depth coordinates and plays a central role in climate through its heat and freshwater transports (Buckley et al., 2016). The AMOC and its variability influence the climate over the North Atlantic and surrounding regions as well as heat and freshwater transports around the world (e.g., Drijfhout et al., 2012; Winton et al., 2013; Liu et al., 2017). From previous studies, the AMOC will mostly decline under greenhouse gas forcing in climate models (e.g., Cheng et al., 2016; MacMartin et al., 2016; Armstrong et al., 2017; Ma et al., 2021). Climate models tend to have difficulty representing the mean AMOC; the strength and depth of the AMOC appear to be sensitive to model details (Buckley et al., 2016), such as resolution and parameterizations (e.g., Zhang and Wang, 2013; Kostov et al., 2014). Many studies also find that the freshwater flux over the Atlantic Basin is a key factor for bistable AMOC behavior; if the AMOC exports freshwater from the Atlantic Basin, then the AMOC is in the bistable regime (e.g., Drijfhout et al., 2011; Weaver et al., 2012; Deshayes et al., 2013), which demonstrates that the AMOC is very sensitive to freshwater transport, whether through the atmosphere or ocean circulation. Although many studies have focused on the variations in AMOC under greenhouse gas forcing, the potential for the evolution of AMOC due to greenhouse gas forcing remains controversial (e.g., Rugenstein et al., 2013; Ding et al., 2014). In this work, our purpose is not to study the specific evolution of AMOC under 4×CO₂ forcing but to improve the adaptability of the key parameter through PE by large samples so that the AMOC can adjust faster under a rapid increase in greenhouse gas forcing, and in this way, we can further understand the physical relationship between model state variables and parameters. The paper is organized as follows. In Section 2, we describe the climate model and the methods used in this work, as well as the experiment design. In Section 3, we present the implementation and the results of improving the adaptability of the key parameter under an abrupted 4×CO₂ forcing. A conclusion and discussion are presented in Section 4.

2 Model and Experiments

2.1 Model description

The low-resolution coupled atmosphere-ocean Earth System Model, C-GOLDSTEIN, was outlined in Annan et al. (2004) and is described more comprehensively in Edwards and Marsh (2005). The version used in
The numerical model can be formally written as:

\[ X(t) = M_t(P)(X_0) \]  \# (1)

where \( X(t) \) is the state vector of the model at time \( t \), \( M_t(P) \) denotes a nonlinear model with a parameter vector \( P = (P_1, P_2, \ldots, P_m) \), and \( X_0 \) is the initial state vector. If we suppose that there exist no uncertainties in the initial conditions, the amplitude of state perturbations in the model output at final time \( t \) caused by the perturbations of all parameters \( P = (p_1, p_2, \ldots, p_m) \) can be denoted as:

\[ J_{total}(P_1, P_2, \ldots, P_m) = \| M_t(P_1 + p_1, P_2 + p_2, \ldots, P_m + p_m)(X_0) \| # (2) \]

Similarly, the amplitude of the state perturbations induced by all the parameter perturbations except the \( i \)th perturbation \( p_i \) can be written as:

\[ J_{-i}(P_1, P_2, \ldots, P_{i-1}, P_{i+1}, \ldots, P_m) = \| M_t(P_1 + p_1, P_2 + p_2, \ldots, P_{i-1} + p_{i-1}, P_i, P_{i+1} + p_{i+1}, \ldots, P_m + p_m)(X_0) \| # (3) \]

Then, the magnitude of the state perturbations yielded by the parameter perturbation \( p_i \) itself and its interaction roles with perturbations of other parameters is defined as

\[ J_i(P_1, P_2, \ldots, P_m) = J_{total}(P_1, P_2, \ldots, P_m) - J_{-i}(P_1, P_2, \ldots, P_{i-1}, P_{i+1}, \ldots, P_m) \]  \# (4)
Based on the state vector augmentation technique, the EnOI method (Evensen, 2003) is used to estimate the covariance between the model state and parameter. The EnOI method no longer uses the ensemble prediction of the model but uses a set of finite static model state samples to estimate the covariance. It can also depict the flow-dependent characteristics of the background error, but only one model sample needs to be integrated forward, which greatly reduces the calculation amount.

2.3 Experiment design

From previous studies (e.g., Stouffer et al., 2003; Armstrong et al., 2017), in millennial simulations of the climate models, the AMOC will first collapse and then slowly recover under 4×CO$_2$ forcing experiments. This phenomenon also occurred in this reduced physical climate model, as shown in Fig. 2d. In this work, we want to improve the adaptability of the key parameter under an abrupt 4×CO$_2$ forcing through parameter estimation and accelerate the adjustment of the AMOC compared with the default parameter set. Through an optimization strategy, we first identify the sensitivity of the AMOC to all model parameters and determine the key parameter to the AMOC. Then, we draw 1,000 Gaussian random numbers of the key parameter starting from the same initial conditions (which are integrated to equilibrium from a cold start, and all the parameters remain in the default set, hereafter called $Z_0$) to integrate to the equilibrium to examine the model state variable’s relationship with the key parameter. Then, the EnOI method is used to estimate the determined key parameter in the following “twin” 4×CO$_2$ forcing experiments. The EnOI method can be written as:

$$
\text{varvec}A^a_t = \text{varvec}A^f_{t-1} + K \left( \text{varvec}Y - \text{varvec}H \text{varvec}A^f_{t-1} \right) \tag{5}
$$

\text{varvec}A^a_t = \begin{pmatrix} V_{1:t} \\ \vdots \\ P_t \end{pmatrix} \text{ and } \text{varvec}A^f_{t-1} = \begin{pmatrix} V_{1:t-1} \\ \vdots \\ P_{t-1} \end{pmatrix}

represent the $t$ step and the $t - 1$ step state vectors, respectively, which contain the determined key parameter. $\text{varvec}H$ represents the linear observation operator, simplified as $\text{varvec}H = \begin{pmatrix} 1 & \ldots & 0 \end{pmatrix}$, and $\text{varvec}Y$ denotes the model output at the $t$ step. We assume that this represents the observation at the $t$ step. $\text{varvec}K$ represents the gain, or weight matrix, which can be written as:

$$
K = B \text{varvec}H^T \left( \text{varvec}H \text{varvec}B \text{varvec}H^T + \text{varvec}R \right)^{-1} \tag{6}
$$

For simplification, we assume the observation error $\text{varvec}R = 0$. $\text{varvec}B$ in Eq. (6) represents the statistical background error covariance between the model state variables and the key parameter, which is calculated from 1,000 Gaussian random number runs. Thus, we can use Eq. (5) through the increment of the model state variables to optimize the key parameter in the “twin” 4×CO$_2$ forcing experiments, one with a default parameter (hereafter called Default_Param. scheme), another with an updated key parameter (hereafter called EnOI_Param. scheme), both experiments started from $Z_0$ under an abrupt 4×CO$_2$ forcing, as shown in Table 1. Because the Atlantic Multidecadal Variability time series has
significant low-frequency variability and its peak variability is approximately 40–70 years according to previous studies (Frankcombe et al., 2010; Buckley et al., 2016), the EnOI_Param. scheme update the key parameter every 50 model years under the 4×CO$_2$ forcing.

Table 1

<table>
<thead>
<tr>
<th>Experiment ID</th>
<th>Parameter</th>
<th>External Forcing</th>
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<tbody>
<tr>
<td>Default_Param. scheme</td>
<td>Default parameter</td>
<td>Abrupt 4×CO$_2$</td>
</tr>
<tr>
<td>EnOI_Param. scheme</td>
<td>Updated key parameter</td>
<td>Abrupt 4×CO$_2$</td>
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</table>

3 The implementation of parameter estimation

3.1 Model sensitivity examination

Through the optimization strategy proposed by Wang et al. (2017), we identify the sensitivity of the AMOC to the 12 adjustable parameters and determine that the FWF parameter is the key parameter to the AMOC (Fig. 1a). Then, we investigate the model state sensitivities with respect to the FWF parameter. The ensemble spread of a model prognostic variable when a perturbation is added to a parameter is used to evaluate the relevant sensitivities quantitatively (Wu et al., 2012). As described above, for the FWF parameter, we draw 1,000 Gaussian random numbers with a standard deviation of 0.05 and a mean value of 0.75 to produce perturbations, as shown in Fig. 1c, while the other parameters remain unperturbed, starting from $Z_0$ to integrate to equilibrium. As shown in Fig. 1b, the leftmost is the standard deviation of the FWF parameter (black box), and the rest of them are the sensitivity of different variables to the parameter. The most sensitive is the strength of the AMOC, called the AMOC index (blue box), and a small change in the parameter will cause a large difference in the strength of the AMOC. The next two sensitive variables shown in Fig. 1b are sea surface temperature in the North Atlantic (called SST_NA, calculated from the mean SST north of the 15°N Atlantic Ocean) and sea surface salinity in the North Atlantic (called SSS_NA, same as SST_NA but for SSS); the remaining variables from left to right are the sensitivities of global mean SSS, SST, air temperature, precipitation, evaporation, and Atlantic Ocean heat transport to the FWF parameter. Figure 1d-f shows the specific distributions for the AMOC index, SST_NA, and SSS_NA reaching equilibrium. Through large sample statistics, the two most sensitive model state variables to the parameter are SST_NA and SSS_NA; thus, we try to use these two variables to adjust the FWF parameter under an abrupt 4×CO$_2$ forcing to improve the adaptability of the FWF parameter, in other words, to accelerate the convergence of the AMOC under 4×CO$_2$ forcing.

3.2 Parameter estimation and adjustment process
We first use the EnOI method to adjust the FWF parameter. The 5000-year simulation was performed by the default parameter sets starting from $Z_0$ under an abrupt 4×$CO_2$ forcing. The variations in SST_NA, SSS_NA, and the AMOC index under 4×$CO_2$ forcing are shown in Fig. 2a-c. Then, we use the increments in SST_NA and SSS_NA every 50 years to adjust the FWF parameter through Eq. (5); eventually, we obtain the new 100 FWF parameter values. After that, we performed the 4×$CO_2$ experiment again, but with the new 100 FWF parameter values, and each parameter value was run for 50 years; the new results (blue line) are shown in Fig. 2d. Compared with the Default_Param. scheme, the EnOI_Param. scheme can accelerate the convergence of the AMOC. This demonstrates the feasibility of using SST_NA and SSS_NA to adjust the FWF parameter, and the adjustment can improve its adaptability under 4×$CO_2$ forcing. The green line in Fig. 2e is the result of using machine learning to adjust the FWF parameter, the input layers are SST_NA and SSS_NA, and the output layer is the corresponding FWF parameter. The 1000 pairs of variables were preprocessed by subtracting the mean and shuffled before training. One-tenth of the total was set as test data, and the rest was set as training data. The optimal parameters of the network, such as the number of middle layer neurons, activation function, and optimizer, were obtained based on Bayesian optimization. To avoid overfitting, the early stopping method was also used, and the results were almost the same as those of the EnOI method. We also show the simulation of AMOC by a state-of-the-art climate model under an abrupt 4×$CO_2$ forcing (Danabasoglu and Gokhan, 2019) in Fig. 2e with the black dotted line. It can be seen from Fig. 2e that whether the reduced physics model or the state-of-the-art model is used for the simulations of AMOC under 4×$CO_2$ forcing on millennial timescales, the AMOC will first collapse and then recover. The recovery of the AMOC intensity in the greenhouse gas forcing integration is attributable to the increase in the density contrast between the narrow sinking regions near Greenland and broad rising regions in low and southern latitudes in the subsurface layer of the North Atlantic Ocean, as discussed by Manabe and Stouffer (1993, 1994); however, in the 4×$CO_2$ integration, the recovery of the AMOC intensity is slow, as shown in Fig. 2e by the black dotted line, which is aided by the slow decrease in the static stability of the Atlantic Ocean due to the gradual warming of the bottom water (Stouffer et al., 2003). In our simplified model, due to the reduced physical process, the AMOC is sensitive to $CO_2$ forcing compared with the state-of-the-art climate model.

In our experiments, the EnOI_Param. scheme accelerates the convergence of the AMOC, here we try to explain the physical process during the adjustment. The relative importance of temperature and salinity in the modes of AMOC variability depends on the timescale (Buckley et al., 2016); on longer timescales, salinity anomalies likely play a more significant role in AMOC variability because of less vigorous damping (Deshayes et al., 2014). Figure 3a-c show the differences in SSS between Default_Param. scheme and the model climatology, whether at the 12th year of integration (the minimal of the AMOC) or at the 50th year of integration, the differences are not obvious. It is notable that due to the reduced physical process, the SSS in the Mediterranean Sea is cumulative over time. However, in the EnOI_Param. scheme, the updated FWF parameter led to a large SSS compared to the model climatology, which increases the density of the sea water. In addition, the SSS in EnOI_Param. scheme is also saltier than that in the Default_Param. scheme, as shown in Fig. 4a, this saltier sea water led to denser sea water both at the sea surface and mid-water (Fig. 4b and 4c), thus maintaining a stronger AMOC (Fig. 5b), and it is
also documented that salinity plays an essential role in the AMOC in other studies (Ferreira et al., 2010). We also display the minimum AMOC in EnOI_Param. scheme, the AMOC maintains its shape and strength in the North Atlantic Ocean through parameter adjustment, as shown in Fig. 5a, and compared with Default_Param. scheme that the AMOC has overall enhancements in the entire interior of the North Atlantic Ocean (Fig. 5b), and the dotted line on the right side is the climatology of the AMOC index at each layer of the model. The differences in SST between EnOI_Param. scheme and Default_Param. scheme are shown in Fig. 5c due to the stronger overturning in EnOI_Param. scheme the warm surface water sink more easily, keeping the surface water colder than that in the Default_Param. scheme, and the colder surface water further increases the density of the sea surface, enhancing the AMOC in turn.

4 Conclusion and Discussion

From previous studies (e.g., Wu et al., 2013; Zhang et al., 2020), PE has shown great potential to reduce model biases and improve model simulation and prediction. The state augmentation technique, where the state vectors are augmented with poorly known parameters, provides a general framework to handle the parameter estimation problem using data assimilation methods (Shen et al., 2022). However, it is difficult to accurately estimate the covariance between model states and parameters in state-of-the-art climate models due to the expensive calculation costs, and many new techniques have been developed to solve this issue (e.g., Zhang et al., 2012; Liu et al., 2014a, b).

In this work, we use a reduced physical model and estimate the state-parameter covariance through large samples to demonstrate the feasibility of using SST_NA and SSS_NA to adjust the FWF parameter. We first identify the sensitivity of the AMOC to the 12 adjustable parameters and find that the FWF parameter is the key parameter to the AMOC. Then, we evaluate the sensitivities of different variables to the FWF parameter and confirm the most two relative variables SST_NA and SSS_NA. Then, we use the increment of SST_NA and SSS_NA under an abrupted 4×CO2 forcing to adjust the FWF parameter to improve the adaptability of the parameter, which results in accelerating the convergence of the AMOC under greenhouse gas forcing. After that, we explain the saltier and colder sea water in EnOI_Param. scheme is the dominant reason to accelerate the adjustment of the AMOC.

Although the parameter estimation techniques are very promising, there are still some issues that need more attention before this method can be used operationally for tuning complex numerical models (Ruiz et al., 2013a). One of the major problems is how the covariance between model states and parameters can be strengthened to update parameter values with observations. There are many error sources in the estimation of the relationship between model states and parameters, for example, model errors, sampling errors, and observational errors, as well as low model sensitivity (Zhang et al., 2020). Different climate models have different adjustable parameters, and the situation in the state-of-the-art climate model can be more sophisticated. This work just give the theoretical foundation for the application of PE. How to adjust other parameters, such as the vertical mixing parameter in the ocean, more effectively and whether it is more reasonable to adjust multiple parameters simultaneously than only adjust one single parameter remain to be further discussed. Overall, PE has been shown to be successful in coupled models of
varying complexity; however, it has only been performed in the perfect model scenario (e.g., Wu et al., 2016; Li et al., 2018; Zhao et al., 2019). The application of PE in state-of-the-art climate models to improve coupled model reanalysis and prediction with real observations still has a long way to go.

**Abbreviations**

<table>
<thead>
<tr>
<th>Abbreviations</th>
<th>Full name</th>
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<tbody>
<tr>
<td>AMOC</td>
<td>Atlantic Meridional Overturning Circulation</td>
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<tr>
<td>FWF</td>
<td>Freshwater flux</td>
</tr>
<tr>
<td>EnOI</td>
<td>Ensemble optimal interpolation</td>
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<tr>
<td>PE</td>
<td>Parameter estimation</td>
</tr>
<tr>
<td>SST</td>
<td>Sea surface temperature</td>
</tr>
<tr>
<td>SSS</td>
<td>Sea surface salinity</td>
</tr>
<tr>
<td>SST_NA</td>
<td>The mean SST north of the 15°N Atlantic Ocean</td>
</tr>
<tr>
<td>SSS_NA</td>
<td>The mean SSS north of the 15°N Atlantic Ocean</td>
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**Declarations**

**Availability of data and materials**

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

**Competing interests**

The authors declare that they have no competing interests.

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**Authors' contributions**

REN Haolan, design the work and the acquisition, analysis, and interpretation of data.  
ZHENG Fei, design the work and substantively revised the work.  
CAO Tingwei, analysis of data.
WANG Qiang, provide analytical methods.

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Not applicable.

Authors' information

Not applicable.

References


**Figures**
Figure 1

(a) The sensitivity of the AMOC to the 12 adjustable parameters of the model. From left to right are ocean isopycnal diffusion, diapycnal diffusion, friction, wind-scale, air temperature diffusion amplitude, air temperature diffusion width, air temperature diffusion slope, air humidity diffusion, air temperature advection coefficient, air humidity advection coefficient, FWF parameter and sea-ice diffusion. (b) The sensitivities of the variables to the FWF parameter; the leftmost is the standard deviation of the FWF
parameter (black box), and the rest of them are the sensitivities of different variables to the parameter. (c) Specific distributions of the FWF parameter. (d) Same as (c) but for the AMOC index after equilibrium. (e) Same as (c) but for SST_NA. (f) Same as (c) but for SSS_NA.

Figure 2
Variations in different variables under an abrupt 4×CO₂ forcing. (a) The variation in SST_NA by the default FWF parameter under an abrupt 4×CO₂ forcing. (b) Same as (a) but for the SSS_NA. (c) Same as (a) but for the AMOC index. (d) The variation in the AMOC index by the default FWF parameter (red line) and the updated FWF parameter (blue line) under an abrupt 4×CO₂ forcing. (e) Same as (d), but for the first 1000 years, the green line is the result of adjusting the FWF parameter using machine learning, and the black dotted line is the result of CESM2 under an abrupt 4×CO₂ forcing.

Figure 3

(a)-(c) are the differences in SSS between Default_Param. scheme and model climatology at different integral times. (d)-(f) are the differences in SSS between EnOL_Param. scheme and model climatology at different integral times.
Figure 4

The differences between EnOL_Param. scheme and Default_Param. scheme at the weakest point of the AMOC. (a) Differences in SSS. (b) Differences in density. (c) Same as (b) but for the profile.
Figure 5

(a) The minimum AMOC in EnOl_Param. scheme. (b) The differences in AMOC between EnOl_Param. scheme and Default_Param. scheme at the weakest point, the dotted line on the right side is the climatology of the AMOC index at each layer of the model. (c) Same as (b) but for the SST.