Ensemble-Based Parameter Estimation in a Coupled General Circulation Model

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ABSTRACT

Parameter estimation provides a potentially powerful approach to reduce model bias for complex climate models. Here, in a twin experiment framework, the authors perform the first parameter estimation in a fully coupled ocean–atmosphere general circulation model using an ensemble coupled data assimilation system facilitated with parameter estimation. The authors first perform single-parameter estimation and then multiple-parameter estimation. In the case of the single-parameter estimation, the error of the parameter [solar penetration depth (SPD)] is reduced by over 90% after ~40 years of assimilation of the conventional observations of monthly sea surface temperature (SST) and salinity (SSS). The results of multiple-parameter estimation are less reliable than those of single-parameter estimation when only the monthly SST and SSS are assimilated. Assimilating additional observations of atmospheric data of temperature and wind improves the reliability of multiple-parameter estimation. The errors of the parameters are reduced by 90% in ~8 years of assimilation. Finally, the improved parameters also improve the model climatology. With the optimized parameters, the bias of the climatology of SST is reduced by ~90%. Overall, this study suggests the feasibility of ensemble-based parameter estimation in a fully coupled general circulation model.

1. Introduction

In spite of the efforts of the climate modeling community over recent decades, current climate models still suffer from significant climate biases (e.g., Lin 2007). One important source of bias is the model parameters. The tuning of the model parameters, however, has remained a challenging task, especially in a complex climate model, such as a coupled general circulation model (CGCM), which consists of nonlinear dynamical processes on a wide range of time scales and requires substantial computational resources. Early research suggests that data assimilation can provide a potentially powerful approach to optimizing model parameters using observations (Zou et al. 1992; Navon 1998). However, there

has been no published result of parameter estimation in a CGCM. Here, we present the first study of successful ensemble-based parameter estimation in a CGCM using an idealized observation network, demonstrating the feasibility of parameter estimation in a CGCM.

The advent of the ensemble Kalman filter scheme (EnKF) for parameter estimation (Anderson 2001) provides a practical means for an automatic optimization of the model parameters in a complex model. Previous studies of parameter estimation using EnKF have led to encouraging results. One approach focused on the improvement of model state climatology, using an iteration method with the assimilation of the long-term observation of climatology (Annan and Hargreaves 2004; Hacker and Snyder 2005; Annan et al. 2005a,b; Ridgwell et al. 2007). The other approach performed simultaneous estimation of model state variables and parameters with the assimilation of the temporally varying observations (Hacker and Snyder 2005; Aksoy et al. 2006a,b; Nielsen-Gammon et al. 2010; Hu et al. 2010; Tong and Xue 2008a,b;

Zhang 2011a,b; Zhang et al. 2012; Wu et al. 2012, 2013). Zhang et al. (2012) further proposed to include a spinup period of pure state estimation before activating the parameter estimation in a so-called data assimilation with enhance parameter correction (DAEPC), which further reduces the model bias and improves model forecast more effectively. DAEPC has been applied successfully to conceptual coupled climate models (Zhang 2011a,b; Zhang et al. 2012) and an intermediate coupled atmosphere–ocean–land model (Wu et al. 2012, 2013).

Here, we will investigate parameter estimation in a CGCM using an ensemble coupled data assimilation (ECDA) scheme of DAEPC (Zhang et al. 2012) in a twin experiment framework where the parameter errors are the only source of model error. We will show successful estimations in both cases of single parameter and multiple parameters after the parameters are carefully selected. The paper is organized as follows: Section 2 briefly describes the assimilation scheme and the CGCM we used in this paper. Sections 3 and 4 show the results of parameter estimation for single and multiple parameters, respectively. A summary is given in section 5.

2. Model and methodology

a. The Fast Ocean Atmosphere Model

The model used in this study is the Fast Ocean Atmosphere Model (FOAM), which is a CGCM with a fully parallel implementation (Jacob 1997). The atmospheric component is a R15 spectral model with an equivalent resolution of 4° latitude, 7.5° longitude, and 18 vertical levels. The ocean component is a z-coordinate model similar to the Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model (MOM) version 1.0 with a resolution of 1.4° latitude, 2.8° longitude, and 24 vertical levels. A simple thermodynamic sea ice model is incorporated. Without flux adjustment, the fully coupled model has been run for over 6000 model years with no apparent drift in tropical climate (Liu et al. 2007a). In spite of its low resolution, FOAM has a reasonable tropical climatology (Liu et al. 2003), ENSO variability (Liu et al. 2000), and Pacific decadal variability (Wu et al. 2003; Liu et al. 2007b) largely comparable with current CGCMs.

b. Coupled data assimilation with enhance parameter correction

In data assimilation, parameters can be estimated by augmenting state variables with model parameters (e.g., Banks 1992a,b; Anderson 2001). Here we will use the data assimilation with enhance parameter correction (Zhang et al. 2012). The DAEPC uses one particular EnKF scheme, the ensemble adjustment Kalman filter (EAKF) (Anderson 2001, 2003), to estimate state variable and parameter simultaneously in the coupled system. One key factor for successful parameter estimation is to extract signal-dominant state–parameter covariance. The covariance is calculated by using the parameter uncertainty and the forecast uncertainty in the observation space. The signal is the model response to the parameter uncertainty. The noise is introduced by the limited ensemble size and is proportional to the total forecast uncertainty. Before the parameter estimation is activated, the DAEPC performs a spinup process for the state estimation to reach a quasi-equilibrium state such that the uncertainty of the model state is sufficiently constrained by observations (see Zhang et al. 2012 for details).

c. The adaptive spatial average scheme

The parameters in this study are assumed to be globally uniform. If a globally uniform parameter is treated as a single-value parameter, there will be a large number of observations available for updating. This will lead to the accumulation of all of the sampling errors, therefore contaminating the estimation (Aksoy et al. 2006a). To address this issue, Aksoy et al. used an updating method that transforms a globally uniform parameter into a two-dimensional field and updates the field spatially using localization. They also used a spatial average method (SA) to retain global uniformity of the estimated parameter after spatial updating. For a complex system such as a CGCM, the sensitivity and response of a model variable to a model parameter may vary spatially and temporally. Recently, the SA was further refined to an adaptive spatial average (ASA) scheme by Liu et al. (2014), which increases the convergence rate of parameter estimation in a CGCM.

Briefly, the ASA uses the ensemble spread as the criterion for selecting "good" values from the spatially varying posterior parameter field, and those good values are then averaged to give the final analysis of the globally uniform posterior parameter. A posterior value is called good if its ensemble spread decreases substantially from that in the prior. The ASA calculates the uncertainty ratios between the posterior and prior. If the ratio is below a threshold, the ASA defines the posterior value as a good posterior value. The speed of the decrease of the parameter uncertainty depends greatly on the magnitude of the signal. Initially, the ASA can use a small value as the threshold because the initial parameter uncertainty is large and the response magnitude (signal) is large. The threshold will be increased during the simulation with the decrease of parameter uncertainty. The initial threshold in our experiments is 0.68. If the total number of good posterior values is less than

400, the threshold increases by 0.1 until it reaches 0.98. The ASA is applied every few EnKF analysis cycles (in our case, every six analysis cycles) to obtain a sufficient number of good parameter posterior values. A more detailed description of ASA is beyond the scope of this study and is reported in Liu et al. (2014).

3. Observations and ensemble configuration

An ensemble size of 30 is used in our experiments. A 30-yr simulation from the control "truth" run is used for the initialization of the ensemble with the model state valid at 1 January of each year. The observations in ocean are monthly sea surface temperature (SST) and salinity (SSS), which cover the global ocean basin. The observations are generated by adding Gaussian white noise on the corresponding truth states at each grid point with the observational error scales (standard deviation) of 1 K and 1 psu (practical salinity units) for SST and SSS. The ocean surface observations are used to update the upper eight layers of ocean temperature (T) and salinity (S) ($0 \sim 235$ m). Here the cross-covariances between SST and SSS are used to update each other. The Gaspari and Cohn (1999) covariance localization is applied with the influence radius of three grid points horizontally for the state variables. The observations in the atmosphere include winds and temperatures (U, V, and T) for all the atmospheric grids (3D) with the error scales of $1.0 \, \mathrm{m \, s^{-1}}$, $1.0 \, \mathrm{m \, s^{-1}}$, and $1.0 \, \mathrm{K}$, respectively, and a time interval of 12 h. This gridded reanalysis format setting of atmospheric observations was applied in the Geophysical Fluid Dynamics Laboratory's ECDA system (Zhang et al. 2007). An observation is used only to update the state variables (U, V, and T) at its own location.

We first perform single-parameter estimation and then multiple-parameter estimation. In the single-parameter estimation experiment, we only assimilate the oceanic observations and the biased parameter convergences to the truth values after the assimilation. We have tested two different experimental settings for multiple-parameter estimation. One experiment (EXP-M1) only uses the oceanic observations as the single-parameter estimation experiment. The other experiment (EXP-M2) assimilates both oceanic observations and atmospheric observations.

In parameter estimation, an observation can constrain a parameter directly and indirectly. An observation constrains a parameter directly by updating the parameter using the state–parameter covariance between the forecast of the observational variable and the parameter. An observation can constrain a parameter indirectly by constraining the state variables and thus improving the analysis and forecast of state variables

and the state–parameter covariance. The state–parameter covariance is the key for parameter estimation and is expected to be signal dominant. The signal, generated by the parameter uncertainty, is only part of the model total forecast uncertainty. The noise, introduced by the limited ensemble size, is proportional to the model total forecast uncertainty. The weights of the signals on the total forecast uncertainty, to some extent, indicate the signal/noise ratio of state–parameter covariance(s). The weights, which are different for different state variables, can be quantified from model forward sensitive experiments (Aksoy et al. 2006a; Tong and Xue 2008a; Nielsen-Gammon et al. 2010; Liu et al. 2014). One can choose the state variable with the biggest weight to directly update a parameter to enhance the signal/noise ratio of state–parameter covariance.

Here, the SST is the chosen variable to directly update parameters for both single-parameter and multiple-parameter estimation. Other observations constrain the parameters indirectly through constraining the model state, which improves the forecast of SST and the state–parameter covariance. The parameter updating is activated two years after a spinup period, in which only the state variables are updated by the observations. As for the updating of state variables, the direct updating of parameters also uses covariance localization (Gaspari and Cohn 1999) with an influence radius of three grid points horizontally. A conditional covariance inflation (CCI) technique, as in Aksoy et al. (2006b), is also employed here on parameter ensembles after each ASA step to avoid filter divergence for parameter estimation. The CCI inflates the parameter ensemble spread back to a predefined minimum value when necessary. The predefined minimum value is also the final uncertainty target for the estimated parameter.

4. Single-parameter estimation

We first use the solar penetration depth (SPD) as the parameter for estimation. Solar attenuation in the ocean is a function of the amount of biomass in the upper layers of the ocean (Smith and Baker 1978, Ohlmann et al. 2000). Following Murtugudde et al. (2002), the downward solar radiation $I(z)$ at a depth of z in FOAM is calculated as

$$I(z) = I(0)re^{-z/h}, \tag{1}$$

where $I(0)$ is the total incident solar radiation at the sea surface and $r = 0.47$ (Frouin et al. 1989) represents the fraction of total solar radiation in the photosynthetically available radiation band (wavelengths from 380 to 700 nm). The remaining fraction of solar radiance
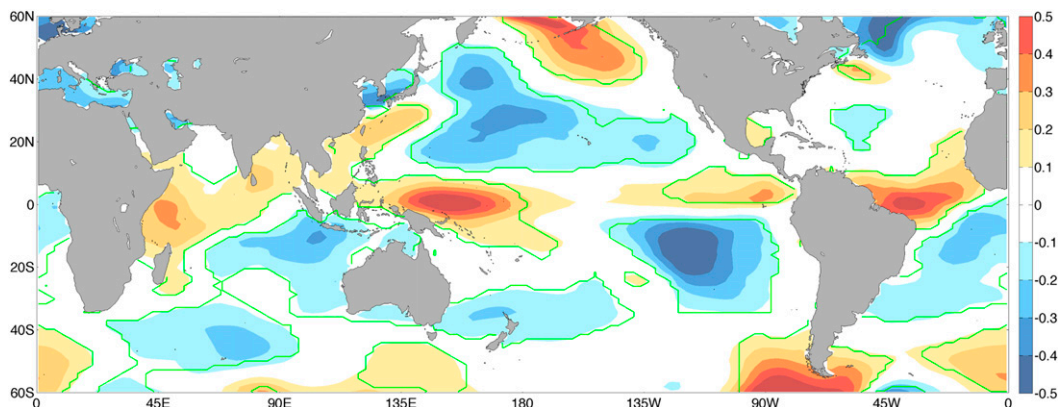
Fig. 1. The climatological annual mean SST difference between two simulations with the same initial conditions but different SPD (20–17 m). The climatological mean SST(s) are calculated from the 80-yr average after 20 years of spinup. The green contours represent the 95% confidence level.

is fully absorbed in the top model layer of 20 m. The h is the SPD that will be estimated in our experiments. In the real world, the SPD can be treated as a state variable too, because it can be calibrated using the remote sensing observation of ocean color. Here, however, it is treated as a globally uniform model parameter in FOAM that will be estimated using DAEPC.

Previous studies suggest the SPD is a parameter that has a significant impact on the surface climate (Schneider and Zhu 1998; Nakamoto et al. 2001; Murtugudde et al. 2002; Ballabrera-Poy et al. 2007; Anderson et al. 2007). This impact can also be seen in FOAM in the difference of the climatology of SST between two simulations with different SPDs (the one with a 20-m SPD minus the one with a 17-m SPD) (Fig. 1). A larger SPD induces significant surface warming over the tropical Pacific, consistent with previous studies (Murtugudde et al. 2002; Ballabrera-Poy et al. 2007; Anderson et al. 2007; Hokanson 2006). Physically, a deeper SPD allows more solar radiation to penetrate below the surface layer, leaving less short-wave radiation to heat the surface layer. This direct effect tends to generate surface cooling, opposing the surface warming in the tropical Pacific. Instead, the surface warming in the tropical Pacific is caused by an indirect effect of solar penetration, which involves momentum redistribution in the oceanic mixed layer (Murtugudde et al. 2002). Figure 1 shows that deeper SPD also leads to significant surface cooling in subtropical oceans and significant warming in the Southern Ocean at high latitudes. The indirect and direct effects discussed above combine to contribute to the locations of warming and cooling. Overall, this sensitivity experiment suggests that the model climate will vary with the SPD parameter.

The DAEPC combined with the adaptive spatial average leads to a successful estimation of the SPD with

the first guess of SPD of 20 m with an uncertainty of 3 m (standard deviation) and the truth SPD of 17 m (Fig. 2). The SPD is not a dynamical variable. Therefore, its variance (ensemble spread) does not increase during the model integration; yet, its variance is reduced at each analysis step. As a result, the ensemble spread of SPD initially decreases much faster than its rms error (RMSE) (Fig. 2). The CCI prevents parameter variance from decreasing indefinitely by adopting a minimum parameter ensemble spread of 0.3 m (1/10 of the initial standard deviation) in the first 30 years of simulation. The minimum parameter ensemble spread is decreased
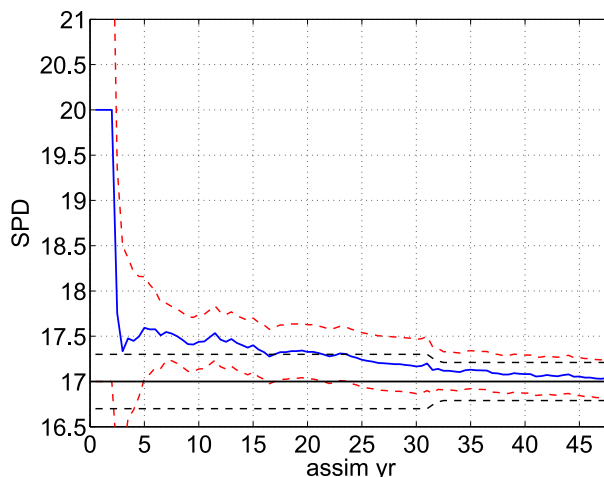

Fig. 2. Single-parameter estimation (SPD) uses DAEPC with the adaptive spatial average (ASA) method. The ensemble size is 30. The observations are the monthly SST and SSS. The blue line is for the temporal evolution of the ensemble mean of SPD, and the red dashed lines are the 1 standard deviation of its ensemble spread. The black solid line is the truth, and the black dashed lines are the minimum parameter ensemble spreads (uncertainty goals) of CCI in the experiment.
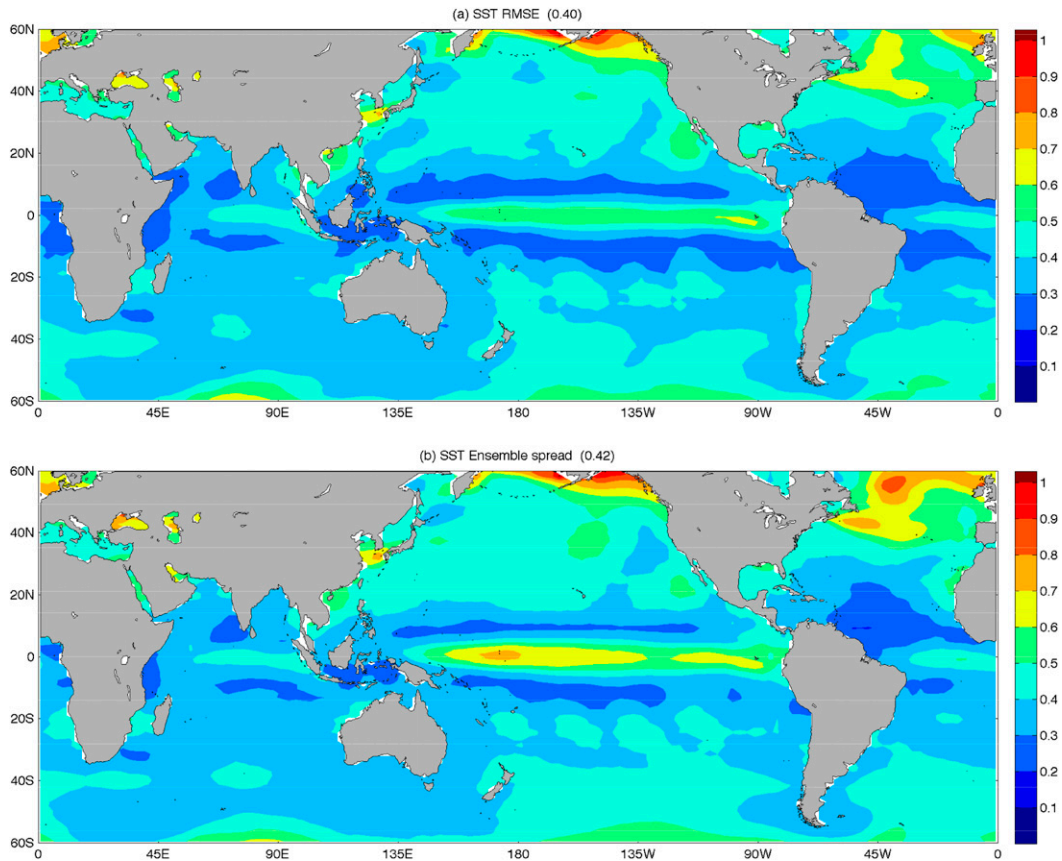
FIG. 3. The spatial patterns of the (a) RMSE and (b) ensemble spread of the forecast monthly SST (first month) averaging 332 cases, which initiate from each month of the simulation years 21–48 in the single-parameter estimation experiment using DAEPC with the ASA method.

to 0.2 m for the simulation afterward (year 31 ∼ 47), when we believe the estimated SPD has converged close to the truth value. The error of the parameter SPD decreased from 3 to 0.2 m after 47 years of assimilation.

The consistency between the ensemble spread and its represented forecast error is a very important factor for EnKF to succeed. The spatial pattern of the monthly average SST error (RMSE) shows maximums at both the high latitudes and equatorial region and a minimum in the off-equatorial regions (Fig. 3a). This pattern resembles that of the SST variance (figure not shown) because the regions of higher variance usually have larger forecast errors. The larger SST RMSE and variance located in the Pacific equatorial region are related to the model ENSO variability. The spatial pattern and amplitude of the ensemble spread of SST resemble closely those of the forecast RMSE of SST (Fig. 3b), suggesting a good quality of the ensemble-based filter.

The improvement of the parameter also improves the model climate and, in turn, the forecast errors of state variables. The experiment after parameter estimation produces a better forecast of monthly SST (the first month) in comparison with a pure data assimilation experiment, which uses the same experiment design but with the biased SPD parameter (20 m) and no parameter correction. The spatial patterns of the RMSE of the first month SST forecast resembles closely that in the experiments of pure data, but the amplitude is reduced by 12% in the former relative to the latter (0.40 vs 0.45 K) for the SST RMSE averaged between 60°S and 60°N. In the pure data assimilation experiment, the average RMSE of 500-mb geopotential height (GPH) is ∼21 m, which is ∼²⁄₃ of that in a model ensemble simulation that does not assimilate any observations. The addition of parameter estimation in the ocean does not further improve the quality of atmosphere analysis and forecast.

The robustness of our parameter estimation is confirmed with another experiment that uses the SA method of Aksoy et al. (2006a). The SA experiment also estimates the parameter successfully but with a slower convergence rate (see Liu et al. 2013 for details).

5. Multiple-parameter estimation

In this section, we extend the parameter estimation from a single parameter (SPD) to three biased parameters: One is in the ocean component, and the other two are related to air–sea coupling (Table 1). The imperfect ocean parameter is still the SPD that has been discussed in the previous section. The imperfect parameters for air–sea coupling are two artificial parameters, m_d and m_q, which are the multipliers to the momentum and latent heat fluxes, respectively, between the ocean and atmosphere (calculated in the coupler component of the model). Thus, $m_d = 1.0$ and $m_q = 1.0$ recover the default setting of air–sea coupling. The specific value and the minimum ensemble spread for each imperfect parameter are shown in Table 1.

The model climatology of SST shows significant sensitivity to the two coupling parameters, m_d and m_q (Fig. 4). The parameter m_d directly influences the momentum flux between the ocean and the atmosphere. When m_d is increased from 1 to 1.2, the SST shows a significant warming in the subtropical oceans and cooling at higher latitudes (Fig. 4a). The warming in the subtropics seems to be induced, partly, by the slower surface wind (in

TABLE 1. Multiple-parameter estimation experiment (the estimated values are from EXP-M2).

Parameter (unit)	Initial guess value	Estimated value	Truth value	CCI threshold
SPD (m)	20.0	17.1	17.0	0.3
m_d	1.20	0.99	1.0	0.02
m_q	1.20	1.00	1.0	0.02

response to a larger drag coefficient) and, in turn, reduced evaporative cooling, while the cooling in the midlatitude and subpolar regions may be contributed by a stronger mixing of the colder water from the bottom of the mixed layer and a stronger Ekman upwelling. The parameter m_q influences the latent heat flux between the atmosphere and ocean and therefore impacts SST directly. An increase in m_q (from 1 to 1.2) enhances latent heat flux cooling and therefore leads to a significant surface cooling over the global ocean, except for high latitudes where the latent heat flux is small (Fig. 4b).

The results of multiple-parameter estimation are not as good as the single-parameter estimation when the same experimental setting is used, because the nonlinearity between parameters and state variables weakens
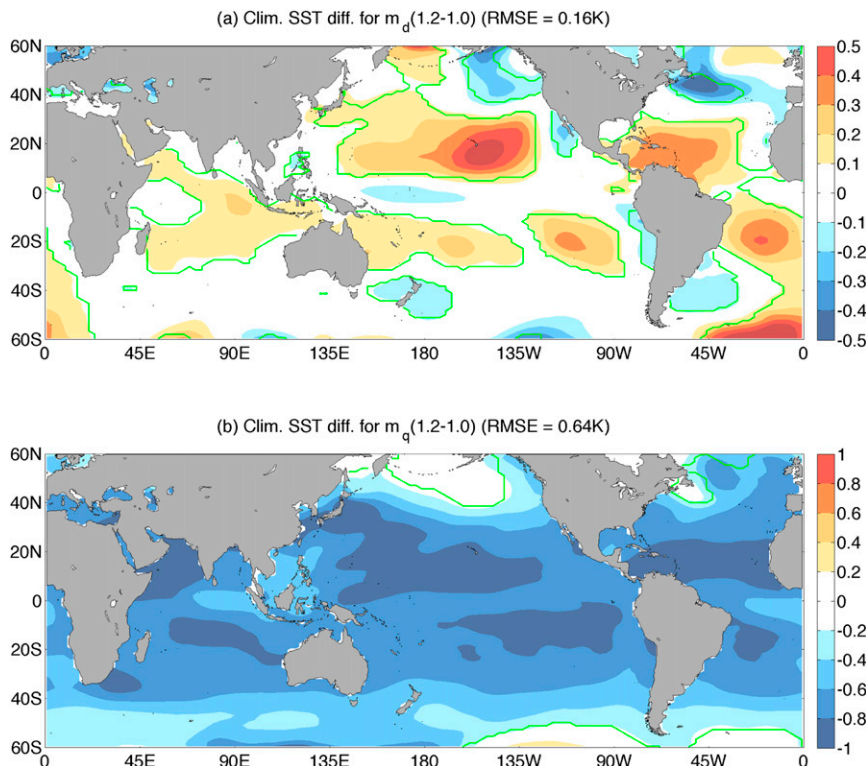

FIG. 4. The climatological annual mean SST difference between two simulations with the same initial conditions but different parameters: (a) the different m_d (1.2–1.0); (b) the different m_q (1.2–1.0). The climatological mean SST(s) are calculated from the 80-yr average after 20 years of spinup. The green contours represent the 95% confidence level.

the correlation between forecast error and individual parameter uncertainty. For the EXP-M1, some parameters do not converge when we only assimilate the oceanic observations (monthly SST and SSS) (Fig. 5). Only the SPD successfully converges to the truth in 50 years of assimilation (Fig. 5a). The evolution of estimation SPD has slower convergence speed and less parameter stability compared with the estimation SPD in single-parameter estimation (Fig. 2). The error of the m_q is only reduced by ~50% in 50 years of assimilation (Fig. 5c), and the error of the m_d shows a slight increase after the assimilation (Fig. 5b). However, the m_d and m_q converge successfully in the single-parameter estimation with the same observational setting (see Fig. 5 in Liu et al. 2014). The lower estimation performance of multiple-parameter estimation compared with single-parameter estimation is consistent with previous works (Aksoy et al. 2006b; Tong and Xue 2008b; Hu et al. 2010).

The smaller reliability of multiple-parameter estimation can, in theory, be improved by decreasing the forecast errors of model variables that are used to constrain parameters directly. The assimilation of additional atmospheric observations into the model in EXP-M2 generates more accurate analysis and forecast of SST. The smaller forecast uncertainty of SST, with the reduced sampling error, enhances the signal/noise ratio of state–parameter covariance, which then accelerates the convergence of the parameter estimation (Fig. 6). The parameters in EXP-M2 almost all converge to the truth values after a 16-yr assimilation, and the convergence speed is much faster than the speed of those in EXP-M1 (Fig. 5). The estimated m_d and m_q monotonically converge to the truth in 8 model years (Figs. 6b,c). The estimated SPD initially exhibits a small overshoot; that is, the parameter error decreases from positive (3.0 m) to negative (~−0.5 m) and then converges back to the truth. The estimated SPD relaxes back to the truth in eight model years (Fig. 6a). Our other experiments show that this type of overshooting sometimes occurs yet appears to have little impact on the final convergence. Similar to the single-parameter estimation that has been discussed in section 3, parameter ensemble spreads initially all suffer a negative bias compared with their RMSEs, which confirms the necessity of applying CCI on the parameter ensemble spreads.

The parameter estimation also helps to improve the analysis of the state variables. Here we use the short forecast to indicate the decrease of analysis error of state variables (because the analyses are not saved in our experiment). Figure 6d shows the evolution of the forecast RMSEs of monthly SST and 500-hPa geopotential height (GPH) during the assimilation. During the spinup period of DAECP (first two years), the forecast errors for SST
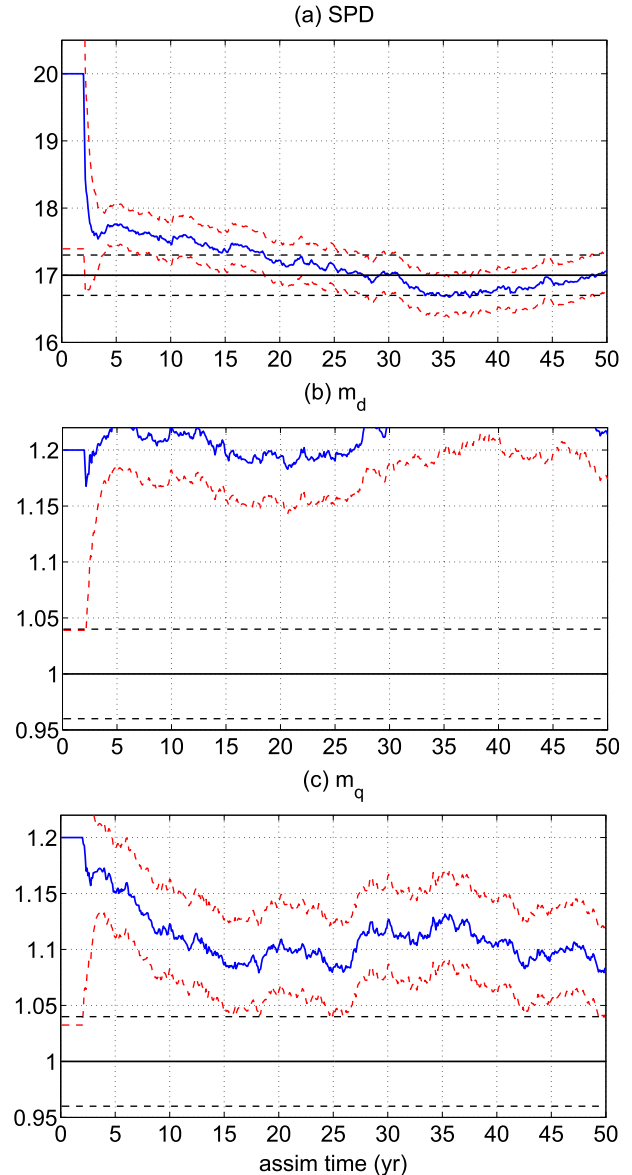

FIG. 5. The temporal evolution of estimated parameters for the multiple-parameter estimation experiment of EXP-M1, which only assimilates the oceanic observations of monthly SST and SSS: (a) the SPD, (b) m_d, and (c) m_q. The solid blue lines are the parameter ensemble means, the red dashed lines are the 1 standard deviation of ensemble spreads, the black solid lines are the truth, and the black dashed lines are the minimum parameter ensemble spreads of CCI in the experiment.

decrease very rapidly and reach quasiequilibrium in a few months, with the average RMSE reduced from ~1 to ~0.2 K. The RMSE further decreases to ~0.1 K when the parameter updating is activated and the uncertainties of parameters are reduced. During the period of parameter estimation (after year 2), the ensemble spread of forecast SST becomes smaller than the SST RMSE (Fig. 6d), but
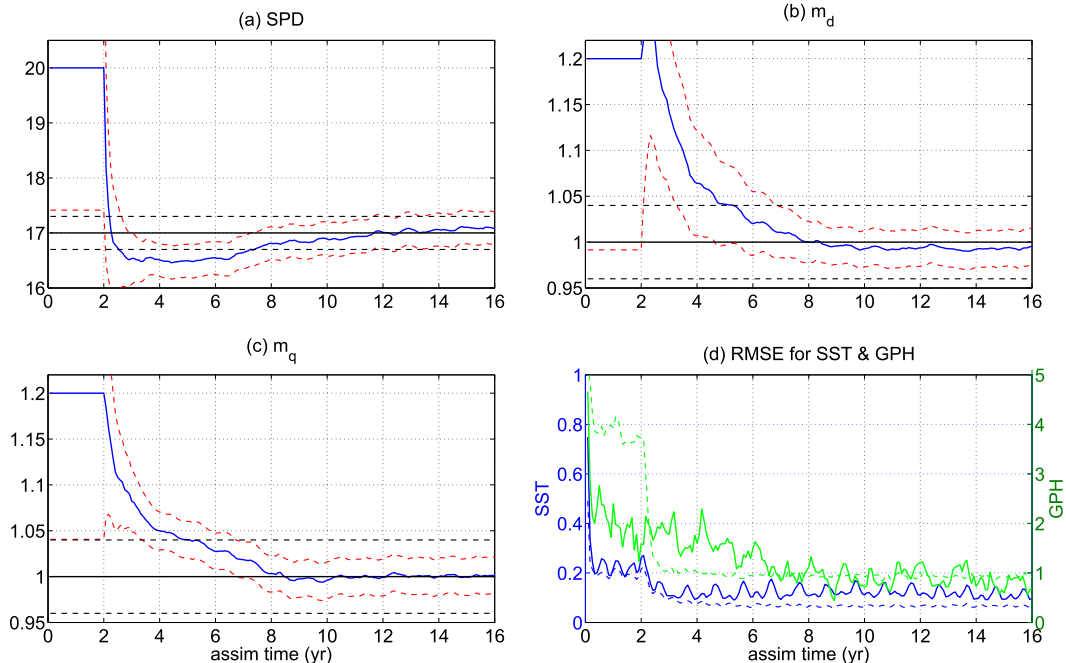
FIG. 6. The temporal evolution of estimated parameters and forecast RMSE of SST and GPH for the multiple-parameter estimation experiment of EXP-M2, which assimilates both the oceanic observations and the atmospheric observations: (a) the SPD, (b) m_d, and (c) m_q, as well as (d) the SST RMSE. The solid blue lines in (a),(b), and (c) are the parameter ensemble means, and the red dashed lines are the 1 standard deviation of ensemble spreads. The black solid lines are the truth, and the black dashed lines are the minimum parameter ensemble spreads of CCI in the experiment. The solid line and the dashed line in (d) are the 1-monthly forecast RMSE and ensemble spread of SST (blue lines) and GPH (green lines), respectively. The RMSE and ensemble spread are first calculated in each grid and then averaged from 60°S to 60°N.

the smaller ensemble spread of state variables does not seem to affect the parameter estimation. All of the three biased parameters converge to the truth values quickly. It should be pointed out that, for simplicity, we have not used covariance inflation on state variables to enhance their ensemble spreads. It is conceivable that, with an inflation scheme, the estimation of the parameter and state variables will be further improved.

Similar to SST, the forecast error of GPH decreases dramatically with the assimilation of atmospheric observations of U, V, and T. The forecast error reaches quasiequilibrium during the spinup period of DAECP with an average RMSE of ~2.0 m. The RMSE further decreases to ~1.0 m when the parameter updating is activated and the uncertainties of parameters are reduced. The ensemble spread of GPH is sensitive to the parameter ensemble spread. The ensemble spread is greater than its RMSE during the spinup period of DAECP and becomes smaller than its RMSE when the parameter updating is activated and the parameter ensembles suffer the negative bias. The ensemble spread of GPH and its RMSE become consistent when the analyses reach equilibrium and the negative bias of parameter

ensemble disappears. In addition, to decrease the computational cost, the atmospheric observations are only used to update the state variables locally in EXP-M2. It is expected that the state variables will be further improved when the observations are also used to update the nearby regions with a covariance localization scheme.

As expected, the improved parameters also improve the model climate. The bias of the SST climatology, generated by the initial parameter errors (see Table 1), shows significant cooling with an average RMSE of ~0.61 K (Fig. 7a). The spatial pattern is very similar to Fig. 3b, because the effect of m_q is the strongest among the three biased parameters. The weak bias along the equatorial region is due to the warming produced by the positive biases of SPD and m_d, which counteracts the cooling generated by the biased m_q. The significant cooling of SST accompanies a cold bias in the atmosphere in FOAM, which lowers the GPH (Fig. 8a). The GPH climatology at 500 hPa shows a significant negative bias with an average RMSE of ~12.5 m. The spatial pattern of GPH bias (Fig. 8a) matches the spatial pattern of SST climatology bias (Fig. 7a). When the updated parameters (Table 1) are used, the biases in SST and
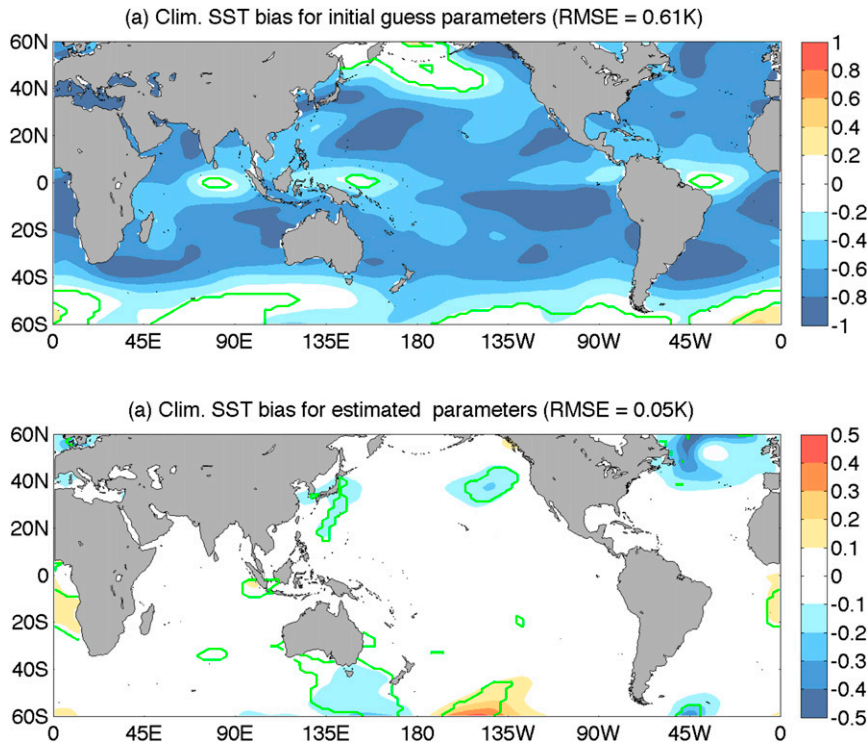
FIG. 7. The SST climatology difference between two simulations with the same initial conditions but different parameters: (a) the initial parameters (Table 1) minus the truth parameters; (b) the estimated parameters (Table 1) minus the truth parameters. The climatological mean SST(s) are calculated from the 80-yr average after 20 years of spinup. The green contours represent the 95% confidence level.

GPH climatology decrease dramatically, with the RMSE of SST and GPH reduced to ~0.05 K and ~1.4 m (Figs. 7b and 8b). Overall, like the single-parameter experiment, the multiparameter estimation also improves the model climate and forecast significantly.

6. Summary

In this study, we explored the parameter estimation in a CGCM using an ensemble-based assimilation scheme in a twin experiment framework. Here, our DAEPC successfully optimized the single imperfect parameter SPD using the conventional observations of monthly SST and SSS. The SPD error was reduced from 3 to 0.2 m after ~40 yr of assimilation. The DAEPC also performed well in the experiments of multiple-parameter estimation by using the 12-hourly atmospheric winds and temperature observations and the monthly SST and SSS observations in the ocean. The three imperfect parameters all converged on the truth values after a 16-yr assimilation.

The improved model parameter also improved the model climatology and model forecast. The RMSE of the SST climatology was reduced from ~0.6 to ~0.05 K, from the model of initial biased parameters to the optimized

parameters (Table 1). The RMSE of the forecast monthly SST (first month) was reduced by 12% with the parameter correction in the experiment of single-parameter estimation. The forecast RMSE of monthly SST and GPH decreased from ~0.12 to ~0.07 K and from ~2.0 to ~1.0 m, respectively, by correcting biased parameters in the experiments of multiple-parameter estimation.

It is important for ensemble-based parameter estimation to choose the right observations to update parameters directly. Parameters are not dynamical variables; they cannot be modified by model dynamics but only by the observations directly through the state–parameter covariance. The error of a parameter decreases when the parameter is directly updated by observations with signal-dominated state–parameter covariance(s). The error of a parameter could increase when the parameter is directly updated by the observations with a noise-dominated state–parameter covariance(s). The signal/noise ratios of state–parameter covariance(s) are different for different observational variables. To retain successful parameter estimation, we have to choose the observational variables with robust state–parameter covariance(s) to directly update the parameters. The other observations can still improve parameter estimation by improving the
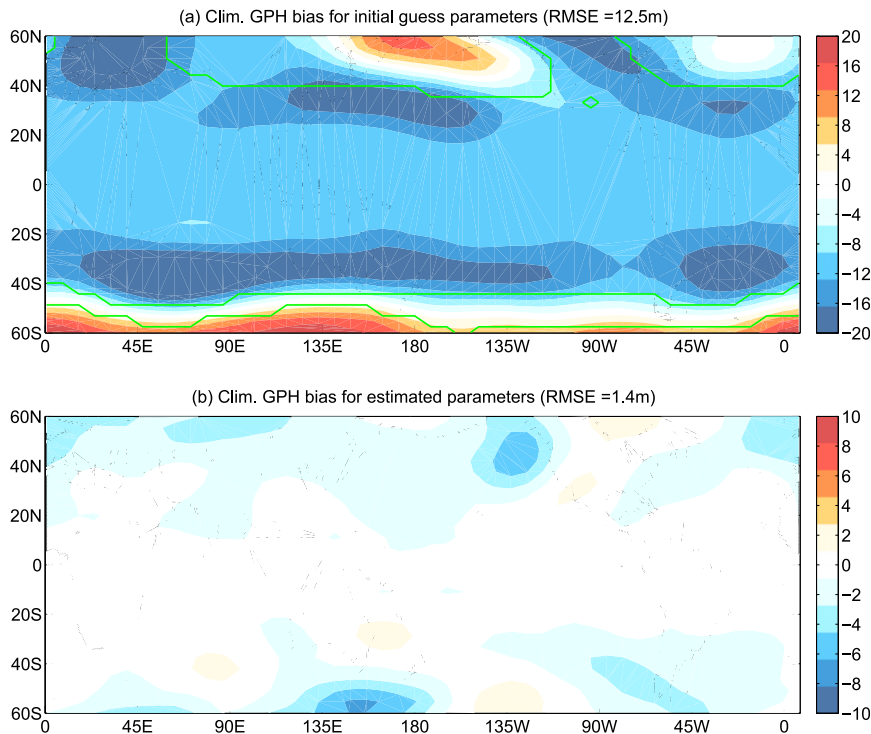
FIG. 8. As in Fig. 7, but for GPH climatology difference at 500 hPa.

model forecast and enhancing the state–parameter covariance used for parameter updating. In this study, SST was chosen as the observational variable to directly update parameters, which leads to the parameter estimation success in single-parameter estimation. When multiple parameters are biased in EXP-M1, the state–parameter covariance(s) of SST become less robust, which results in a failure to estimate the parameters of m_d and m_q. Decreasing the forecast error of SST can enhance the state–parameter covariance and improve the parameter estimation. Indeed, the assimilation of additional atmospheric observations into the model in EXP-M2 narrows the SST uncertainty and produces successful estimation for all three biased parameters. However, when we replaced SST with SSS to directly update parameters, the parameter estimation failed even for single-parameter estimation because the response of SSS to parameters is much weaker than that of SST.

To our knowledge, this is the first demonstration of successful ensemble-based parameter estimation in a general circulation model with a fully coupled ocean–atmosphere dynamic. It demonstrates the feasibility of parameter optimization in a complex CGCM using an ensemble-based filter for parameter optimization and therefore suggests the potential of parameter optimization to reduce model bias and improve CGCMs in the future. The idealized observation network used in this study is very different than the realistic observation network. The atmospheric observations applied in this study are using the gridded reanalysis format setting. Previous works show that, by assimilating the reanalysis data, ensemble coupled data assimilation (ECDA) significantly improves the forecast and analysis in Geophysical Fluid Dynamics Laboratory Climate Models (Zhang et al. 2007; Yang et al. 2013; Chang et al. 2013; Zhang et al. 2014). The ensemble-based parameter estimation in the CGCM using realistic reanalysis products as observations remains to be further studied.

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