ADVANCES IN ATMOSPHERIC SCIENCES, VOL. 34, NOVEMBER 2017, 1346–??

• Original Paper •

Impact of the Time Scale of Model Sensitivity Response on Coupled Model Parameter Estimation

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(Received 21 December 2016; revised 19 May 2017; accepted 26 May 2017)

ABSTRACT

That a model has sensitivity responses to parameter uncertainties is a key concept in implementing model parameter estimation using filtering theory and methodology. Depending on the nature of associated physics and characteristic variability of the fluid in a coupled system, the response time scales of a model to parameters can be different, from hourly to decadal. Unlike state estimation, where the update frequency is usually linked with observational frequency, the update frequency for parameter estimation must be associated with the time scale of the model sensitivity response to the parameter being estimated. Here, with a simple coupled model, the impact of model sensitivity response time scales on coupled model parameter estimation is studied. The model includes characteristic synoptic to decadal scales by coupling a long-term varying deep ocean with a slow-varying upper ocean forced by a chaotic atmosphere. Results show that, using the update frequency determined by the model sensitivity response time scale, both the reliability and quality of parameter estimation can be improved significantly, and thus the estimated parameters make the model more consistent with the observation. These simple model results provide a guideline for when real observations are used to optimize the parameters in a coupled general circulation model for improving climate analysis and prediction initialization.

Key words: coupled model, parameter estimation, time scale of model sensitivity

Citation: Liu, C., S. Q. Zhang, S. Li, and Z. Y. Liu, 2017: Impact of the time scale of model sensitivity response on coupled model parameter estimation. *Adv. Atmos. Sci.*, **34**(11), 1346–1357, https://doi.org/10.1007/s00376-017-6272-6.

1. Introduction

While a coupled climate model reasonably simulates the interaction of major components (atmosphere, ocean, sea ice, land process etc.) of the earth climate system, and gives an assessment of climate changes (Randall et al., 2007), the simulated climate tends to drift away from the real world due to model errors, or model biases (e.g., Collins et al., 2006; Delworth et al., 2006; Smith et al., 2007). There are two types of major sources for model errors (e.g., Zhang et al., 2012). The first type is associated with the imperfect model structure, including an imperfect dynamical core, approximate parameterizations etc., which can be referred to as structural errors. The structural errors can be viewed as "built-in" model errors and are difficult to alleviate through a direct observation-correction process. The other type of model errors is induced by the errors in model parameters. Model parameters are introduced mostly in model physical parameterizations. Physical parameterization is an approximate expression of a certain physical process in the atmosphere and ocean. However, the values for most of the parameters are set empirically and are usually not optimal in the coupled system, despite tuning by a trail-and-error procedure in terms of better climatological fitting. For constraining model bias and quantifying forecast uncertainties, the problem of observation-based parameter es-

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timation in climate modeling has attracted a great deal of attention (e.g., Forest et al., 2000; Andronova and Schlesinger, 2001; Knutti et al., 2002; Gregory et al., 2002).

Derived from data assimilation theory and methodology, parameter estimation (also referred to as parameter optimization in the literature) with observations has become a promising approach to mitigate model bias (e.g., Banks, 1992a, 1992b; Borkar and Mundra, 1999; Aksoy et al., 2006a, 2006b; Zhang, 2011), so as to constrain model climate drift with a particular variant for coupled models (Zhang et al., 2012). Customized from state estimation, the estimated parameters are traditionally updated with the frequency of observations available. This may work well in estimating atmospheric parameters because the quickly-varying atmospheric states may instantaneously respond to perturbations of such parameters (Zhang et al., 2012). However, for the parameters in the slow-varying media of a coupled system, such as the ocean, the model may take a long time to transfer the parameter uncertainties into the model states. The covariance used in traditional parameter estimation may be unreliable because, if the update cycle is too short, a signal-dominant covariance may not yet have established. But how does the time scale of the model sensitivity response impact on coupled model parameter estimation? Here, with a simple coupled model, we address this question.

The paper is organized as follows: After this introduction, section 2 presents the methodology, including a description of the model, the "twin" experiment and ensemble filter. The problem of traditional parameter estimation is examined in section 3. The dependence of robust state-parameter covariance on model sensitivity response time scales is also examined in this section. Section 4 presents the results of the impact of the model sensitivity response time scales on parameter estimation. Finally, a summary and discussion are given in section 5.

2. Methodology

2.1. *The model*

The impact of the time scales of model sensitivity response on coupled model parameter estimation is a fundamental issue. Here, to address this issue, we employ a simple conceptual coupled "climate" model developed by Zhang (2011), which is quite simple compared with a coupled general circulation model (CGCM). The simplified model does not change the nature of the problem and it is therefore a good tool to detect the problem and find a potentially deliverable solution for CGCMs. The simple conceptual model takes the following form:

$$\begin{cases} \dot{x}_1 = -\sigma x_1 + \sigma x_2 \\ \dot{x}_2 = -x_1 x_3 + (1 + c_1 w) k x_1 - x_2 \\ \dot{x}_3 = x_1 x_2 - b x_3 \\ O_\mathrm{m} \dot{w} = c_2 x_2 + c_3 \eta + c_4 w \eta - O_\mathrm{d} w + S_\mathrm{m} + S_\mathrm{s} \cos(2\pi t / S_\mathrm{pd}) \\ \Gamma \dot{\eta} = c_5 w + c_6 w \eta - O_\mathrm{d} \eta \end{cases} . \quad (1)$$

Here, x_1, x_2 and x_3 are the high-frequency variables that represent the atmosphere, while w is a low-frequency variable that stands for the slab ocean, and η represents the slower-varying deep ocean pycnocline. A dot above a model variable denotes time tendency. The definition and standard values of the model parameters are shown in Table 1.

2.2. *Ensemble filtering parameter estimation*

In climate and ocean modeling, we can use parameterization to approximate many physical variables, with one or more parameters playing important roles in the parameterizations. However, usually, a trial-and-error tuning procedure is used to heuristically set the values of such parameters, which could be a reasonable guess for the particular parameterization rather than an optimal guess for the whole coupled model (Zhang et al., 2012). The errors in the values of parameters are an important source that leads to the climate drift of the model away from the real world.

In an ensemble-based filter, the error statistics evaluated from ensemble model integrations, such as the error covariance between model states and model parameters, is used to transform the observational information to optimize the parameters' values (Anderson, 2001; Yang and Delsole, 2009). Here, we choose the ensemble adjustment Kalman filter (EAKF) (Anderson, 2001) to conduct the state and parameter estimation. EAKF is a sequential implementation (Evensen, 1994) of the Kalman filter (Kalman, 1960; Kalman and Bucy, 1961) under an "adjustment" idea. While its sequential implementation is convenient for data assimilation, EAKF maintains the nonlinearity of background flows in the filtering process as much as possible (Anderson, 2001, 2003; Zhang and Anderson, 2003). There are two important steps

Table 1. Parameters of the simple conceptual model.

Parameters	Definition	Standard values
σ	Sustain the chaotic nature of the atmosphere	9.95
k	Sustain the chaotic nature of the atmosphere	28
b	Sustain the chaotic nature of the atmosphere	8/3
c_1	Represent the slab ocean forcing on the atmosphere	0.1
c_2	Represent the atmosphere forcing on the slab ocean	1
O_d	The damping coefficient of the slab ocean	1
O_m	The heat capacity	10
S_m	The magnitudes of the annual mean	10
S_s	Seasonal cycle of the external forcing	1
S_pd	The period of the external forcing is comparable with the slab ocean time scale, defining the time scale of the model seasonal cycle	10
Γ	A constant of proportionality	100
c_3	The linear forcing of the deep ocean	0.01
c_4	The nonlinear interaction of the slab and deep ocean	0.01
c_5	Denote the linear forcing of the slab ocean	1
c_6	The nonlinear interaction of the slab and deep ocean	0.001

in the implementation of EAKF parameter estimation. The first step is to calculate the ensemble observational increment, which is identical to state estimation. The second step projects the observational increment onto the relevant parameter. This step is key for us to understand the special perspective of parameter estimation. The default values of parameters can be viewed as the erroneously-set ones and the associated errors can be transferred into the model states through the model integration. Due to the high nonlinearity in a model, the errors of parameters can lead to the model errors. We can then apply the observational increments to the error covariance between the model states and prior parameter ensemble through a local least-squares filtering to perform the parameter estimation (optimization) (Anderson, 2001, 2003). This process can be formulated as

$$\Delta\beta_i = \sum_{k=1}^{K} \frac{c(\beta,\Delta y_k)}{\sigma_k^2} \Delta y_{k,i} \ . \quad (2)$$

Here, $\Delta\beta_i$ stands for the adjustment amount for the ith ensemble member; k stands for the observational location or observed variables (in this study, for instance); $\Delta y_{k,i}$ represents the observation increment of the ith ensemble member; $c(\beta,\Delta y_k)$ defines the error covariance between the prior ensemble of the parameter β and the model-estimated observation ensemble; and σ_k is the standard deviation for the model estimated ensemble. The detailed computational implementation is described in the Appendix.

2.3. *Twin experiment setup*

We use a biased twin experiment framework in this study. On the one hand, a "truth" model is the model described in section 2.1, with standard values for all parameters. The "truth" model is used to generate the "true" solution of the model states and produce the observations sampling the "truth", and its timeline is shown in Fig. 1a. The method for generating "observations" is the same as employed in Zhang et al. (2012). In order to simulate the feature of the real observing system, the observational intervals are set as 0.05 TU (The "TU" is non-dimensional time unit defined in Lorenz 1963. The physical sense is the time scale by which the "atmosphere" approximately goes through a lobe of the attractor. 1 TU = 100 steps) for x_1, x_2 and x_3, and 0.2 TU for w. The standard deviation of observational errors is 2 for x_1, x_2 and x_3, and 0.5 for w. There is no observation for deep ocean. The obtained "truth" solutions and observations are used in all the assimilation experiments described next. On the other hand, the "biased" model is a model that has one or more biased parameters. The estimated parameter $P_{\rm error}$ is erroneously guessed with a 50% overestimated error from

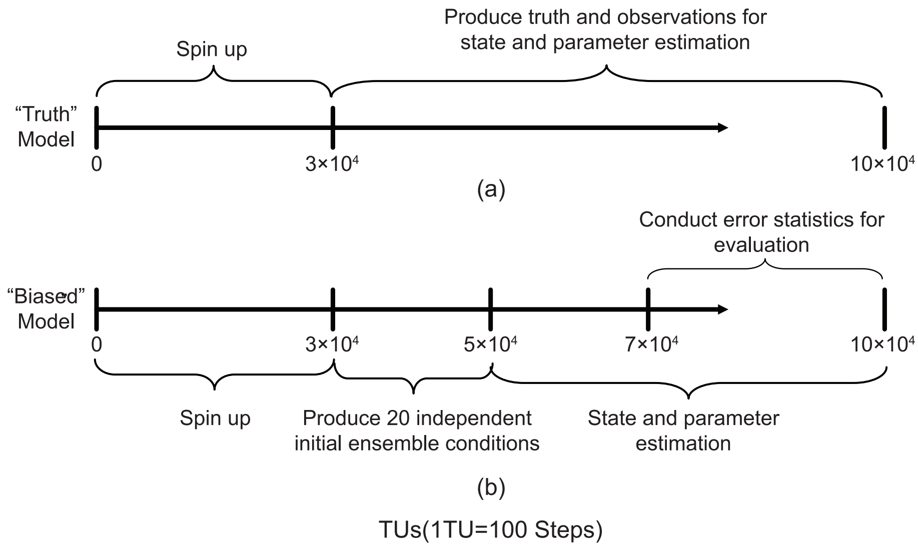

Fig. 1. Timelines for the "truth" model (a) and "biased" model (b). The "truth" model is first integrated for 3×10^4 TUs (1 TU = 100 steps) starting from the initiation condition (x_1, x_2, x_3, w, η) = (0, 1, 0, 0, 0) for sufficient spin-up and then integrated for another 7×10^4 TUs to generate the "truth" solution of the model states and produce the observations sampled from the "truth". As in the "truth" model, the "biased" model firstly runs for 3×10^4 TUs starting from the initiation condition for spin-up. Then, another 2×10^4 TUs are extended with the "biased" model to produce 20 independent initial ensemble conditions for each assimilation experiment. The independent initial ensemble conditions are produced by adding a white noise with the same standard deviation as observational errors on the model states apart each 1000 TUs during the second 2×10^4-TU biased model integration. Then, starting from these 20 independent initial ensemble conditions, each assimilation experiment using the "biased" model is integrated for 5×10^4 TUs, and the parameter estimation is activated after 20 TUs (2000 model integration steps). Finally, the data obtained in the last 3×10^4 TUs are used to calculate error statistics for evaluation.

its standard value —namely, $P_{\text{error}} = (1+0.5)P_{\text{true}}$—and then perturbed by the Gaussian random noise centered at P_{error} with a standard deviation σ_{est}, which is 10% of the truth ($\sigma_{\text{est}} = 10\% \times P_{\text{true}}$). The timeline of the "biased" model is shown in Fig. 1b. After sufficient spin-up, 20 independent initial ensemble conditions for each assimilation experiment are produced. Then, starting from these 20 independent initial ensemble conditions, each assimilation experiment with the biased model setting is integrated for 5×10^4 TUs. In this way, we minimize the dependence of the results on initial states. We analyze the mean value of 20 cases and the uncertainty evaluated from these cases.

In order to examine the impact of the time scales of model sensitivity response on coupled parameter estimation, the estimated parameter is updated with different frequencies of the observations, while model states are always updated with the same ones (0.05 TU for the "atmosphere" and 0.2 TU for the ocean) in all parameter estimation experiments (denoted as CDAPE). It should be emphasized that the atmospheric states are adjusted only by the observation of atmosphere (with an interval of 0.05 TU), while the oceanic states are updated only by the oceanic observations (with an interval of 0.2 TU). Here, we are concerned with parameter estimation for the parameters in slow-varying media, so we focus on the performance of oceanic parameters and the estimated parameter is adjusted only using the oceanic observations. According to Zhang et al. (2012), to allow coupled model states to be constrained by observations sufficiently, the parameter estimation is activated after 20 TUs (2000 steps of model integrations), and the error statistics for evaluation are conducted with the data in the last 3×10^4 TUs. In addition, using the same parameters and initial ensemble condition as CDAPE, a free assimilation model control (without observational constraint — denoted as CTL) and a state estimation only by coupled data assimilation (without parameter estimation—denoted as CDA) are conducted, serving as references for the evaluation of parameter estimation. The state estimation in CDA is same as that in CDAPE.

In order to analyze the results of parameter and model state estimation properly, the sum of the root-mean-square errors (RMSE_{sum}) for the model states (x_1, x_2, x_3, w, η), and the RMSE of the estimated parameter, are used to evaluate the result in each assimilation experiment (Pan et al., 2011, 2014). The RMSE_{sum} of model states is calculated as

$$\text{RMSE}_{\text{sum}} = \left(\frac{\text{RMSE}_{x_1,\text{PE}}}{\text{RMSE}_{x_1,\text{CTL}}}\right) + \left(\frac{\text{RMSE}_{x_2,\text{PE}}}{\text{RMSE}_{x_2,\text{CTL}}}\right) + \left(\frac{\text{RMSE}_{x_3,\text{PE}}}{\text{RMSE}_{x_3,\text{CTL}}}\right) + \left(\frac{\text{RMSE}_{w,\text{PE}}}{\text{RMSE}_{w,\text{CTL}}}\right) + \left(\frac{\text{RMSE}_{\eta,\text{PE}}}{\text{RMSE}_{\eta,\text{CTL}}}\right), \quad (3)$$

where $\text{RMSE}_{x_1,\text{PE}}$ means the RMSE of model state x_1 in the parameter estimation experiment, while $\text{RMSE}_{x_1,\text{CTL}}$ means that in CTL. The RMSE of the model state or parameter is computed from the data obtained in the last 3×10^4 TUs of each assimilation experiment by the following equation:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=T_{\text{start}}}^{T_{\text{end}}} (\overline{x_i} - x_{\text{true}})^2}{(T_{\text{end}} - T_{\text{start}})}}, \quad (4)$$

where x stands for one of the model states (x_1, x_2, x_3, w, η) or the estimated parameter; x_{true} is the corresponding true value of x; and $\overline{x_i}$ represents the ensemble mean of that obtained from each assimilation experiment (i is the index of time). T_{start} denotes the start time to calculate the RMSE and T_{end} is the end time.

Following Zhang and Anderson (2003), an ensemble size of 20 is used in all the assimilation experiments throughout this study.

3. The problem in traditional parameter estimation

In this section, we use a simple example to address the potentially unreliability of traditional parameter estimation, especially for slow-varying media of a coupled system. Then, we examine the model sensitivities, focusing on oceanic parameters, and investigate the reliability of state-parameter covariance within a short update interval.

3.1. *Unstable parameter estimation*

Customized from state estimation in data assimilation, traditionally, a parameter is updated based on the frequency of observations available. To examine the performance of traditional parameter estimation, we first show the results of two experiments —$\text{CDAPE}_{P_{c_2}(c_2),O_{\text{obs}}(w)}$ and $\text{CDAPE}_{P_{c_5}(c_5),O_{\text{obs}}(w)}$—in which the oceanic parameters c_2 and c_5 are estimated with the interval of observations (I_{obs}) of w (see Table 2 for detailed descriptions). Here, I_{obs} represents 0.2 TU (every 20 model steps) (in real oceanic observations, it is usually daily). The subscript $P_{c_2}(c_2)$ [$P_{c_5}(c_5)$] represents only parameter c_2 (c_5) being perturbed and estimated in each experiment and, similarly, $O_{\text{obs}}(w)$ represents only the observations of w being used in parameter estimation, in which "obs" means the update interval of the parameter is the same as the observation interval of w being sampled. The examined parameter is perturbed, as mentioned in section 2.3, while other parameters remain as standard values. At the same time, four experiments—CTL_{c_2}, CDA_{c_2}, CTL_{c_5}, CDA_{c_5}—are conducted, in which the subscript stands for the parameter being perturbed. The ensemble means of the estimated parameter varying with time in the first case of $\text{CDAPE}_{P_{c_2}(c_2),O_{\text{obs}}(w)}$ and $\text{CDAPE}_{P_{c_5}(c_5),O_{\text{obs}}(w)}$ are plotted as the red and blue lines in Fig. 2, while the black line represents the "truth" (both c_2 and c_5 take the value of 1).

From Fig. 2, we can see that, starting from a big error at the initial time, the estimated parameter c_2 (c_5) converges to the "truth" very quickly, but there are some big oscillations in the time series for each case. The biggest deviation for c_5 is about 0.1 (10% of the "truth" value), observed at around 1.17×10^4 TUs, while two bigger oscillations for c_2 occur at

Table 2. List of experiments.

Abbreviation	Description	Meanings of parameters
CTL_{c_2}	The free model ensemble CTL	Subscript c_2 represents only c_2 being perturbed
CTL_{c_5}	The free model ensemble CTL	Subscript c_5 represents only c_5 being perturbed
CDA_{c_2}	The single coupled data assimilation CDA	Subscript c_2 represents only c_2 being perturbed
CDA_{c_5}	The single coupled data assimilation CDA	Subscript c_5 represents only c_5 being perturbed
$\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$	Parameter estimation using the traditional method	Subscript $P_{c_2}(c_2)$ represents c_2 is perturbed and estimated while $O_{\mathrm{obs}}(w)$ represents only the observations of w being used in parameter estimation and the update interval of parameter is the same as observational interval of w being sampled
$\mathrm{CDAPE}_{P_{c_5}(c_5),O_{\mathrm{obs}}(w)}$	Parameter estimation using the traditional method	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ but for the case of parameter estimation of c_5
SensT_w	Sensitivity study of oceanic model state w responses to different parameters	
$\mathrm{CDAPE}_{P_{c_2}(c_2),O_V(w)}$	Parameter estimation experiment to determinate suitable update interval for c_2	$O_V(w)$ represents only the observations of w being used in parameter estimation while V means the update interval of parameter is varied
$\mathrm{CDAPE}_{P_{c_5}(c_5),O_V(w)}$	Parameter estimation experiment to determinate suitable update interval for c_5	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_V(w)}$ but for the case of parameter estimation of c_5
$\mathrm{CDAPE}_{P_{c_2}(c_2),O_{V,\mathrm{win}}(w)}$	Parameter estimation experiment using an observational time window to determinate suitable update interval for c_2	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_V(w)}$ but for the case of parameter estimation using an observational time window
$\mathrm{CDAPE}_{P_{c_5}(c_5),O_{V,\mathrm{win}}(w)}$	Parameter estimation experiment using an observational time window to determinate suitable update interval for c_5	Same as $\mathrm{CDAPE}_{P_{c_5}(c_5),O_V(w)}$ but for the case of parameter estimation with an observational time window
CTL_{c_2,c_5}	The free model ensemble CTL with both c_2 and c_5 being perturbed	Subscript represents c_2 and c_5 being perturbed
$\mathrm{CDAPE}_{P_{c_2,c_5}(c_2,c_5),O_{\mathrm{obs}}(w)}$	Parameter estimation using the traditional method with both c_2 and c_5 being perturbed and estimated	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ but for the case of c_2 and c_5 being perturbed and estimated
$\mathrm{CDAPE}_{P_{c_2,c_5}(c_2,c_5),O_{V,\mathrm{win}}(w)}$	Parameter estimation experiment using an observational time window with both c_2 and c_5 being perturbed to determinate suitable update interval for c_2 and c_5	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{V,\mathrm{win}}(w)}$ but for the case of c_2 and c_5 being perturbed and estimated
$\mathrm{CDAPE}_{P_{c_2,c_5}(c_2),O_{\mathrm{obs}}(w)}$	Parameter estimation using the traditional method with both c_2 and c_5 being perturbed while only c_2 being estimated	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ but for the case of c_2 and c_5 being perturbed and only c_2 being estimated
$\mathrm{CDAPE}_{P_{c_2,c_5}(c_2),O_{V,\mathrm{win}}(w)}$	Parameter estimation experiment using an observational time window with both c_2 and c_5 being perturbed to determinate suitable update interval for c_2	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{V,\mathrm{win}}(w)}$ but for the case of c_2 and c_5 being perturbed and only c_2 being estimated
$\mathrm{CDAPE}_{P_{c_2,c_5}(c_5),O_{\mathrm{obs}}(w)}$	Parameter estimation using the traditional method with both c_2 and c_5 being perturbed while only c_5 being estimated	Same as $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ but for the case of c_2 and c_5 being perturbed and only c_5 being estimated
$\mathrm{CDAPE}_{P_{c_2,c_5}(c_5),O_{V,\mathrm{win}}(w)}$	Parameter estimation experiment using an observational time window with both c_2 and c_5 being perturbed to determinate suitable update interval for c_5	Same as $\mathrm{CDAPE}_{P_{c_5}(c_5),O_{V,\mathrm{win}}(w)}$ but for the case of c_2 and c_5 being perturbed and only c_5 being estimated

about 7.4×10^3 TUs and 2.82×10^4 TUs, having the biggest deviation of more than 12% from the "truth".

The corresponding time series of model states x_2 and w around the first big oscillation in the estimation experiment $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ are shown in Fig. 3. Compared to the case of state estimation only by coupled data assimilation (without parameter estimation) CDA_{c_2}, which is quite stable (solid black lines in Fig. 3), the estimated model states x_2 and w in $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ deviate from the "truth" with a big amplitude (dashed lines in Fig. 3) around the times that the estimated parameter c_2 has computational oscillations. It is clear that the parameter estimation makes that problem. It is worth mentioning that such a deviating phenomenon can be frequently observed in other time periods and other cases starting from different initial conditions. Here, what is shown in Figs. 2 and 3 only serves as an example.

In fact, as the time scale of the "ocean" is relatively longer, the coupled model takes a longer time to respond to

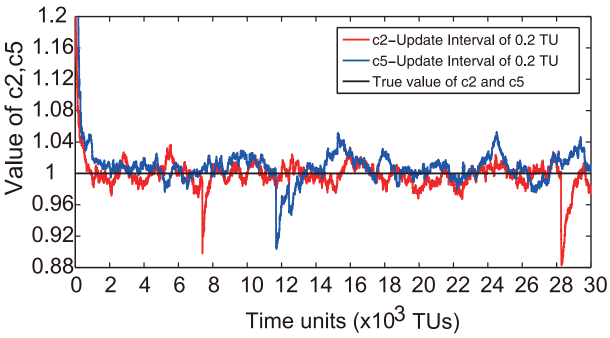

Fig. 2. Time series of the ensemble means for c_2 (red) and c_5 (blue) in the first case of 20 (described in section 2.3) parameter estimation experiments, $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ and $\mathrm{CDAPE}_{P_{c_5}(c_5),O_{\mathrm{obs}}(w)}$, with an update interval of 0.2 TU. The "truth" value (1 in this case) of both c_2 and c_5 is marked as the horizontal black line.

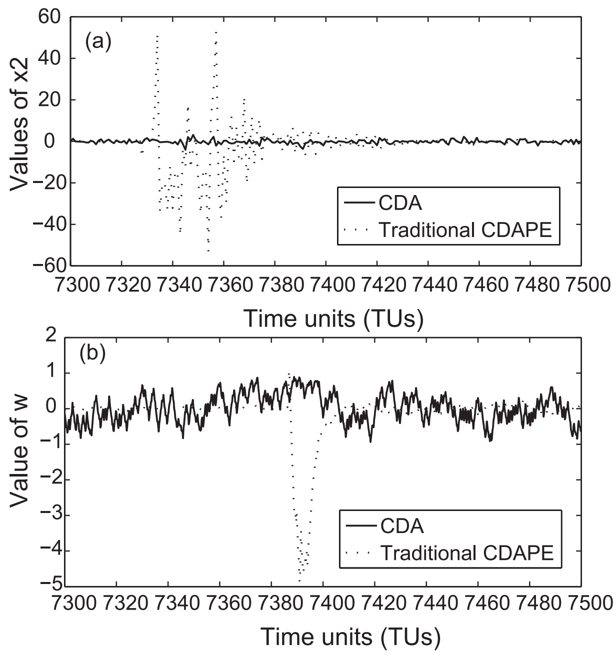

Fig. 3. An example of instability caused by insufficiently developed covariance in traditional parameter estimation. Shown is the time series of the errors of ensemble means of (a) x_2 and (b) w between 7300 and 7500 TUs in the first case of 20 experiments, $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{\mathrm{obs}}(w)}$ (dashed line) (traditional CDAPE, with 0.2-TU update interval as observational interval). The errors of state estimation by coupled data assimilation without parameter estimation (CDA) are plotted in black as reference.

the perturbed oceanic parameters (2–10 TUs) (Zhang et al., 2012). Next, we examine the relationship between the time scale of model sensitivity response and parameter estimation frequency in a coupled model.

3.2. *Different time scales of model sensitivity response to different parameters*

As our chief concern is the estimation of parameters in slow-varying media such as the ocean, the first step is to examine the sensitivity of the model to parameters related to the slab ocean (w). There are nine parameters ($O_{\mathrm{m}}, c_2, c_3, c_4, O_{\mathrm{d}}, S_{\mathrm{m}}, S_{\mathrm{s}}, c_5, c_6$) related to w in the simple model, and the sensitivity of w to each of them is examined in an experiment called SensT_w. To study the sensitivity, each examined parameter is perturbed by adding a white noise with 10% of the standard value as its standard deviation. Starting from the 20-member ensemble initial conditions described in section 2.3, the model ensemble for each parameter is integrated for another 10^4 TUs. The model sensitivity to each parameter is assessed by examining the 20-case mean temporal evolution of the ensemble spread of model state w. The ensemble spread is calculated as follows at each step:

$$w_{\mathrm{std}}(i) = \sqrt{\frac{\sum_{j=1}^{N}(w_{i,j} - \overline{w_i})^2}{N}}, \tag{5}$$

where $w_{\mathrm{std}}(i)$ denotes the ensemble standard deviation of model state w at the ith step, $w_{i,j}$ stands for the state of the ensemble member j, $\overline{w_i}$ is the ensemble mean of each experiment, and N denotes the ensemble size. The time series of the 20-case mean of the ensemble standard deviation of w over 0–30 TUs for each of O_{m}, c_2, c_3, c_4, O_{d}, S_{m}, S_{s}, c_5 and c_6 is plotted in Fig. 4.

From Fig. 4, it is apparent that w differs in its sensitivity to different oceanic parameters. Specifically, c_2 is the quickest parameter for the w sensitivity response. It reaches saturation (no longer systematically increasing with time) by about 5–6 TUs. Following c_2 are O_{d}, O_{m} and S_{m}. We refer to these parameters as fast oceanic parameters. In contrast, the slowest parameters for the w sensitivity response are c_5 and c_6. Both show a similar sensitivity response time scale of 10–12 TUs to reach saturation. Such parameters are referred to as slow oceanic parameters.

The sensitivity results show that, for slow-varying media like ocean, it takes a certain amount of time for the model to respond to the parameter perturbations (or errors). If the time within a parameter estimation cycle is too short for the model to transfer the uncertainty of the parameter to the model state, the signal-to-noise ratio of the state-parameter covariance is low. This will cause the parameter estimation to be unreliable. For example, if the model takes about 5–6 TUs for w to reach a sufficient sensitivity response, that is 30 times longer than the interval of observations of w (0.2 TU). Obviously, the covariance between the estimated parameter and the oceanic model state has not been established sufficiently within such a short observational interval. The parameter estimation with the covariance that has a low signal-to-noise ratio can cause computational oscillations of estimated parameter values, as shown in Figs. 2 and 3. But how does the time scale of model sensitivity response impact on the parameter estimation, and what is a suitable update frequency for these parameters being estimated? We answer these questions in the next section via a series of parameter estimation experiments with different update frequencies.

4. Parameter estimation update frequency depending on the model sensitivity response time scale

In this section, we examine one slow oceanic parameter (c_5) and one fast oceanic parameter (c_2) and compare their estimation performance to understand the relationship between the model sensitivity response time scale and the parameter estimation update frequency. We begin by examining the results of a single case, and then use the statistics of 20 cases to prove the robustness of the conclusion.

4.1. *Impact of longer update interval on parameter estimation in slow-varying media*

A series of experiments, $\mathrm{CDAPE}_{P_{c_2}(c_2),O_V(w)}$ and $\mathrm{CDAPE}_{P_{c_5}(c_5),O_V(w)}$, with different parameter update intervals that are longer than the 0.2 TU observational interval of w is conducted with the first set of ensemble initial conditions we created at 3×10^4 TUs, as described in section 2.3. The update intervals vary from 1 TU to 20 TUs, with an increment of 1 TU. The RMSE of the model states calculated by Eq. (4) in the c_2 and c_5 estimation cases is shown in Fig. 5.

From Fig. 5, we find that the model state errors decrease with the longer update intervals within 5 TUs in both cases, and then increase gradually as the update interval increases. This phenomenon is consistent with the one discovered in Pan et al. (2014). We observe that, in parameter estimation with a longer update cycle (2 TUs for c_2 and 5 TUs for c_5, for instance), the oscillations in estimation with I_{obs} (hereafter, I_{obs} denotes the traditional parameter estimation with the 0.2 TU update interval), as shown in Fig. 2, is eliminated (see Fig. 6), and model variability is recovered more accurately (compare Fig. 7 to Fig. 3). We also notice that, in the c_2 case, the $\mathrm{RMSE_{sum}}$ within 11 TUs of update intervals is less than

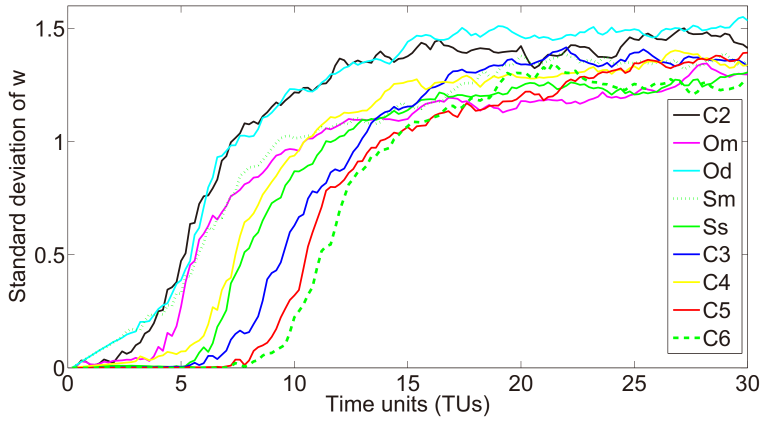

Fig. 4. Time series of ensemble spread of w when each parameter is perturbed by a Gaussian noise for the cases of c_2 (black), O_{m} (pink), c_3 (blue), c_4 (yellow), O_{d} (cyan), S_{m} (dotted green), S_{s} (solid green), c_5 (red), and c_6 (dashed green). Shown is the 20-case mean of ensemble spread in 20 experiments with independent initial conditions. The evolution of ensemble spread with model integration times starting from a randomly perturbed parameter is a measure of model sensitivity response with respect to the parameter being examined.

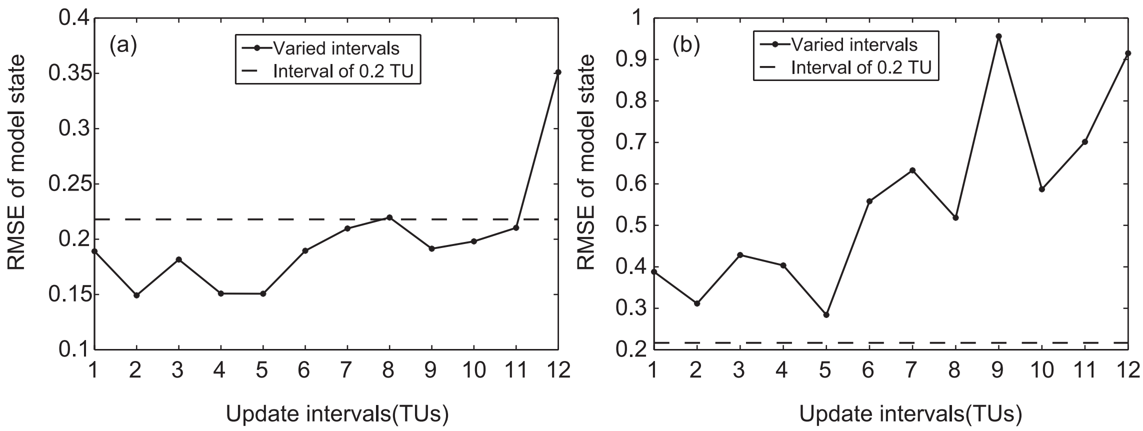

Fig. 5. The variation in RMSE of model states in the space of update intervals from the first case of 20 experiments: (a) $\mathrm{CDAPE}_{P_{c_2}(c_2),O_{V,\mathrm{win}}(w)}$; (b) $\mathrm{CDAPE}_{P_{c_5}(c_5),O_{V,\mathrm{win}}(w)}$. The black curve is the result with different update intervals (from 1 TU to 12 TUs, with an increment of 1 TU), and the dashed line is the result of traditional parameter estimation using the observational interval (0.2 TU) to update the parameter being estimated.

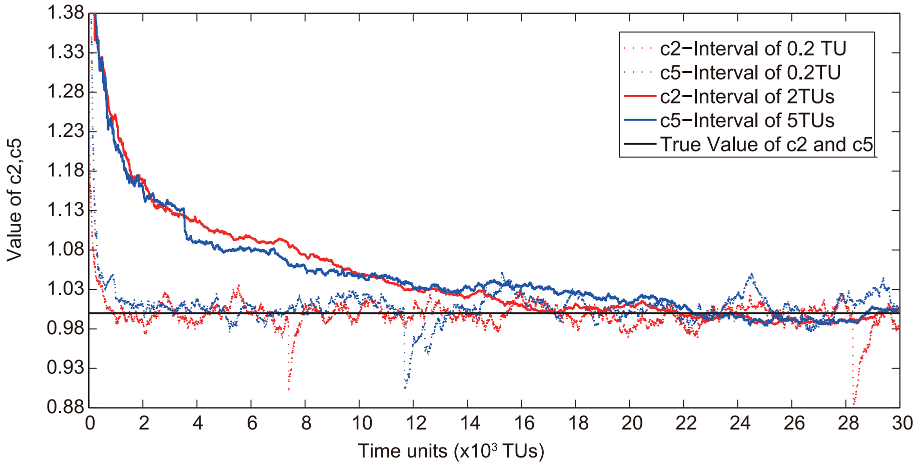

Fig. 6. Time series of the ensemble mean of parameters c_2 (blue) and c_5 (red) in the first case of 20 parameter estimation experiments, with update intervals of 2 TUs for c_2 (blue solid) and 5 TUs for c_5 (red solid). The cases using a 0.2-TU update interval for both c_2 and c_5 are also plotted as dotted lines for reference. The black line marks the "truth" value of c_2 and c_5 (both are 1 in this case).

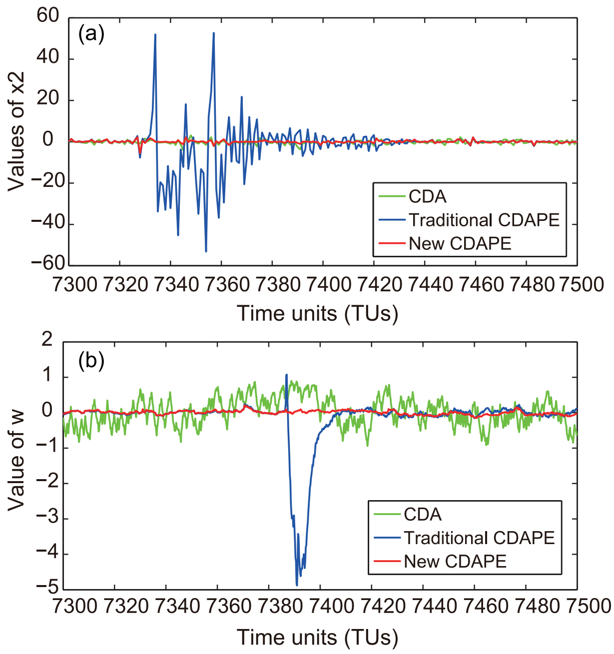

Fig. 7. As in Fig. 3 but for the case using the 2-TU update interval (New CDAPE).

that of I_{obs} (Fig. 5a), while in the c_5 case the $RMSE_{sum}$ is always greater than that of I_{obs} (Fig. 5b) (shown as a coincident case when the statistics of 20 experiments are discussed later). We understand that the parameter estimation is a result of trade-off between reliable state-parameter covariance and the strength of observational constraint. If the update interval is too short, the state-parameter covariance is unreliable, even though with stronger observational constraint. If the update interval is too long, the observational constraint becomes too weak, so the parameter estimation effect is weak, despite reliable state-parameter covariance. This can explain why the $RMSE_{sum}$ increases when the update interval is larger than 5 TUs in both cases—a point we discuss in more depth in the next section.

4.2. *Impact of observational constraint strength on parameter estimation*

To understand the phenomena in the case studies shown in section 4.1 and eliminate the case-dependence of results, in this section, we discuss the results of the whole 20 experiments with independent initial conditions described in section 2.3. The mean $RMSE_{sum}$ of 20 experiments for both the model states and the examined parameters (c_2 and c_5) are shown in Figs. 8a and b and Figs. 9a and b. It is clear that, for the c_2 case, the $RMSE_{sum}$ of both model states and the parameter are less than that of I_{obs} within 6 TUs of update intervals (Figs. 8a and b), while the $RMSE_{sum}$ of the c_5 case is less than that of I_{obs} within 2 TUs of update intervals (Figs. 9a and b). For both cases, when the update interval is greater than a certain magnitude (5 TUs for c_2 and 2 TUs for c_5), the $RMSE_{sum}$ of both model states and the parameter start to increase and quickly exceed that of I_{obs}. As we know, besides the state-parameter covariance, the performance of parameter estimation also relies on the strength of observational constraints. In Fig. 6, compared to the I_{obs} case, the parameter estimation with longer update intervals is more stable but takes much longer to converge due to much weaker observational constraints. Indeed, as the observation is the only information resource to update the model parameter, parameter estimation cannot succeed without sufficient observational constraint. When the update interval increases, the model has a more sensitive response to parameter perturbation, meaning the state-parameter covariance becomes more signal-dominant but the number of observations used to constrain the parameter are obviously less. For example, for parameter estimation with an update interval of 2 TUs, the amount of observational information used to constrain the parameter is only 10% of the amount used in the I_{obs} case. As the update interval significantly increases, although the state-parameter covariance is more reliable than that of I_{obs}, the

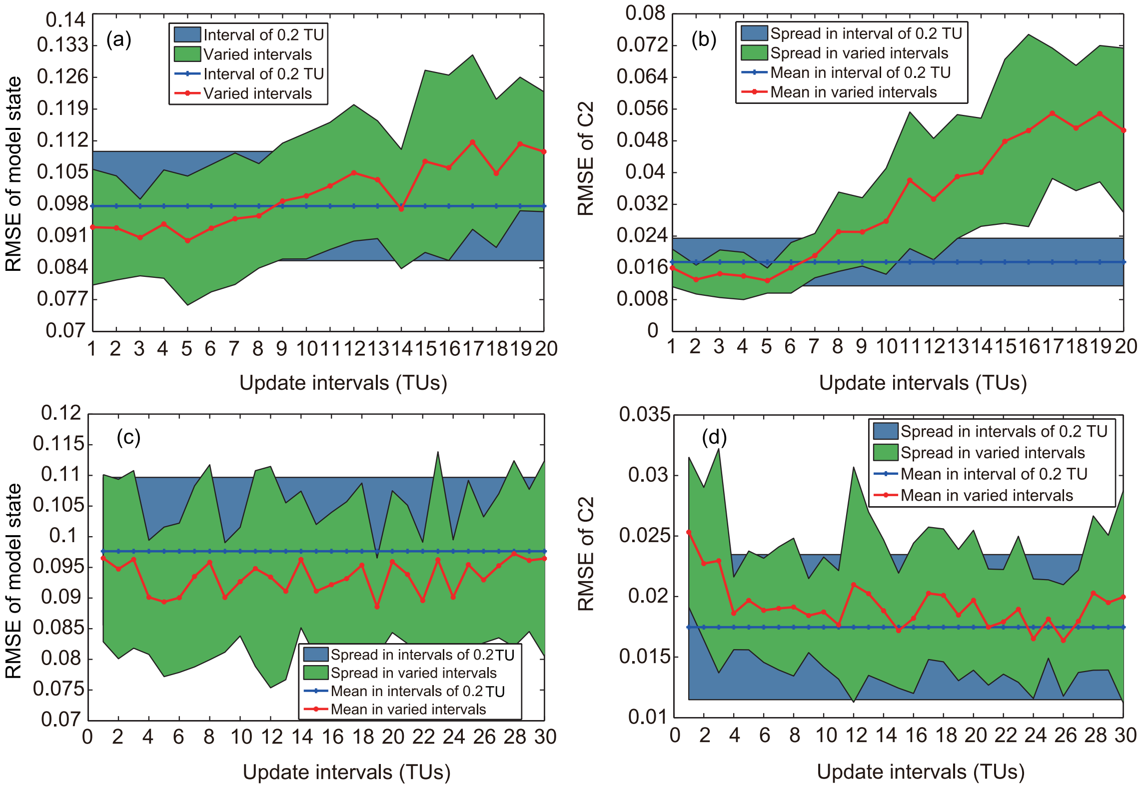

Fig. 8. The variations of 20-case mean RMSE_{sum} of (a, c) model states and (b, d) parameter c_2 in the space of update intervals in parameter estimation experiments (a, b) $\text{CDAPE}_{P_{c_2}(c_2),O_{V,\text{win}}(w)}$ and (c, d) $\text{CDAPE}_{P_{c_2}(c_2),O_{V,\text{win}}(w)}$. The experiments in $\text{CDAPE}_{P_{c_2}(c_2),O_{V,\text{win}}(w)}$ use an observational time window of 0.1 TU (10 observations at each update step). In each panel, the solid line represents the ensemble mean of 20 experiments with independent initial conditions, described in section 2.3, while the shading represents the spread of these 20 cases. The blue line and blue shading are the results of parameter estimation with a 0.2-TU update interval, while the red line and the green shading are the results of using different update intervals. Note that, with or without an observational window, the scope of RMSE convexity is quite different, so panels (a, b) and (c, d) use different horizontal axis scales.

weak observational constraint suppresses the positive impact of reliable covariance, so the parameter estimation diverges.

In the real world, an observational time window is usually used to collect measured data to increase the number of samples of observational information for an assimilation cycle (e.g., Pires et al., 1996; Hunt et al., 2004; Houtekamer and Mitchell, 2005; Laroche et al., 2007). This assumes that all the collected data are the samples of the "truth" variation at the assimilation time (Hamill and Snyder, 2000; Zhang, 2011; Gao et al., 2013). In a coupled system, due to different characteristic time scales in different media, how to choose a suitable observational time window in different media so that while sampling information increases the characteristic variability maintains, is an important and interesting research topic, but one that is beyond the scope of this study. Here, we only discuss the impact of observational constraint strength on parameter estimation when the update interval is long. For simplicity, we apply a comparable observational constraint with the I_{obs} experiment to further understand the impact of model sensitivity response time scales on parameter estimation. Figures 9c and d and Figs. 10c and d are the results of re-running the 20 experiments for c_2 and c_5 estimation but with a 0.1-TU observational time window (each parameter estimation step uses 10 observations), referred to as $\text{CDAPE}_{P_{c_2}(c_2),O_{V,\text{win}}(w)}$ and $\text{CDAPE}_{P_{c_5}(c_5),O_{V,\text{win}}(w)}$ (see Table 2). In this way, for the cases with the 2-TU update interval, the parameter estimation in $\text{CDAPE}_{P_{c_2}(c_2),O_{V,\text{win}}(w)}$ and $\text{CDAPE}_{P_{c_5}(c_5),O_{V,\text{win}}(w)}$ has an equivalent observational constraint strength as I_{obs}. From Figs. 8c and d and Figs. 9c and d, we can see that the errors of parameter estimation exhibit a wide convex shape when the estimation has a reasonable observational constraint. Of course, when the update interval is longer, the observational constraint becomes weaker and the representation of observations also becomes poorer, so the estimation error starts to increase.

From the analyses above, we conclude that the state-parameter covariance requires some response time to establish a reliable signal (reaching equilibrium) as the model responds to parameter perturbations. Thus, it is necessary to update the parameter with an update interval comparable to the model sensitivity response time scale in parameter estimation.

4.3. *Multiple parameter estimation*

In order to test the impact of the model sensitivity response time scales on multiple parameter estimation, we conduct a series of experiments—$\text{CDAPE}_{P_{c_2,c_5}(c_2),O_{V,\text{win}}(w)}$, $\text{CDAPE}_{P_{c_2,c_5}(c_5),O_{V,\text{win}}(w)}$ and $\text{CDAPE}_{P_{c_2,c_5}(c_2,c_5),O_{V,\text{win}}(w)}$ (see

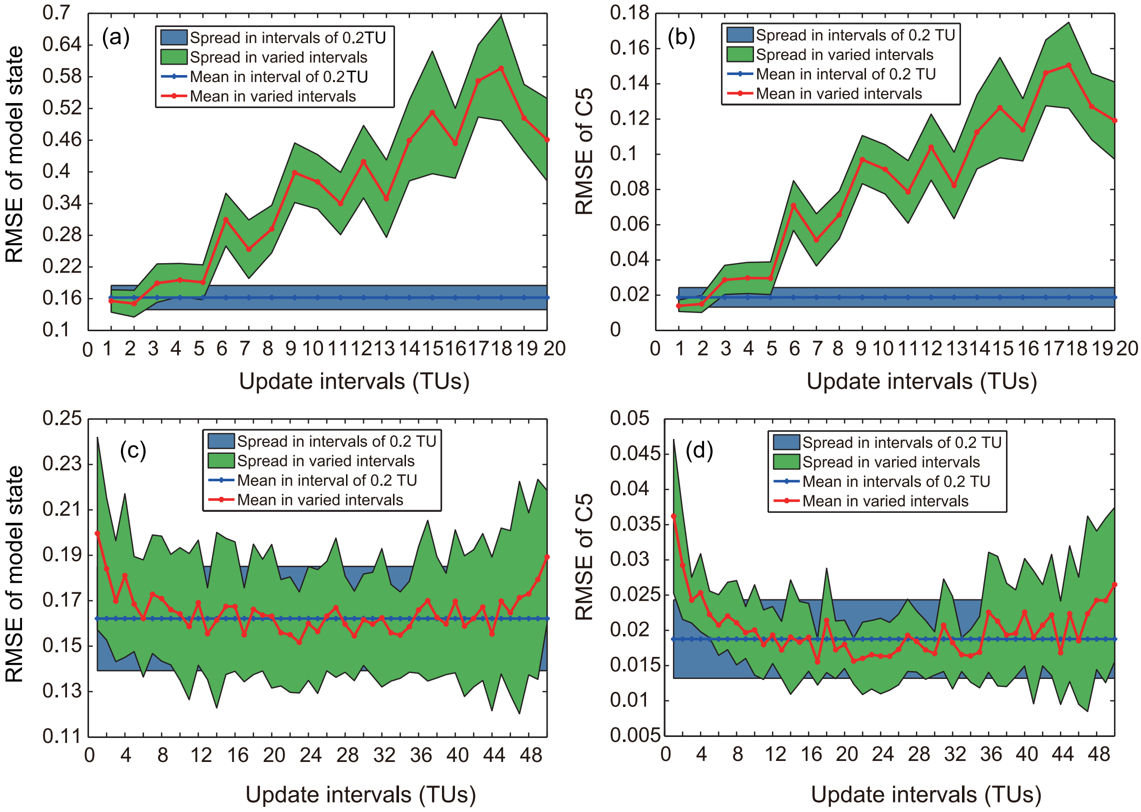

Fig. 9. As in Fig. 8 but for the case of parameter estimation of c_5.

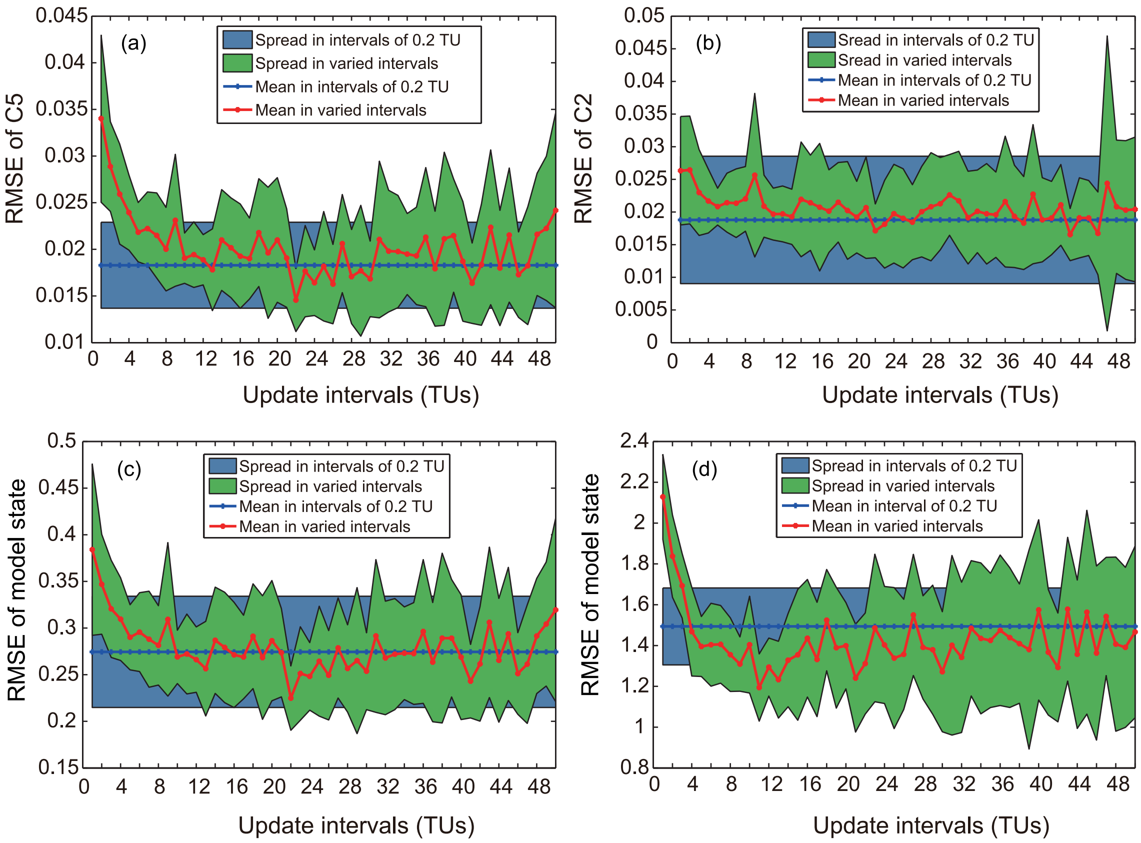

Fig. 10. The variations of $\mathrm{RMSE_{sum}}$ of parameter (a) c_2, (b) c_5 and (c) model states in the space of update intervals in multiple parameter estimation experiments $\mathrm{CDAPE}_{P_{c_2,c_5}(c_2,c_5),O_{V,\mathrm{win}(w)}}$ when c_2 and c_5 are estimated simultaneously with 50% initial bias for both. Panel (d) shows the results of only estimating c_5 when c_2 remains biased ($\mathrm{CDAPE}_{P_{c_2,c_5}(c_5),O_{V,\mathrm{win}(w)}}$). All other notation is the same as in Fig. 8.

Table 2 for detailed descriptions)—with different parameter update intervals that are longer than the 0.2-TU observational interval of w (all experiments with 0.1-TU observational time window). Parameters c_5 and c_2 are perturbed together in all of these experiments. While both are estimated together in $\text{CDAPE}_{P_{c_2,c_5}(c_2,c_5),O_{V,\text{win}}(w)}$, only $c_5(c_2)$ is estimated in $\text{CDAPE}_{P_{c_2,c_5}(c_5),O_{V,\text{win}}(w)}$ ($\text{CDAPE}_{P_{c_2,c_5}(c_2),O_{V,\text{win}}(w)}$). The RMSE_{sum} of model states and parameters from 20-case statistics are shown in Figs. 10a–d. From Figs. 10a–c, we see that the RMSE_{sum} for the model states and parameters (c_5 and c_2) are reduced quickly as the update intervals increase, meaning that the covariance between model states and the parameter is more stable with longer update intervals in multiple parameter estimation. As in the single parameter estimation cases shown before, when the observational constraint strength becomes too weak and with overly long update intervals, the RMSE shows gradual growth. Clearly, the result of multiple parameter estimation is consistent with that of single parameter estimation. Comparing Fig. 10c to Fig. 10d, we can see that the RMSE is much bigger when both c_5 and c_2 are perturbed but only c_5 is estimated (Fig. 10d), meaning the fast oceanic parameter (c_2) has a big influence on the result of model integration if it is not corrected.

5. Conclusion and discussion

Based on filtering theory, parameter estimation with the observation of model states is a promising approach to mitigate model bias. Customized from traditional state estimation, traditional parameter estimation usually updates the parameter being estimated according to observational frequency. Without direct observations on parameters, the covariance between model states and the estimated parameter plays a critical role in parameter estimation. The sensitivity response time scales of model to parameter perturbations in a coupled system can be different, from hourly to decadal, depending on the nature of the associated physics and characteristic variability of the fluid. With an ensemble filter consisting of a simple coupled model, this study addresses the impact of the time scale of model sensitivity response on coupled model parameter estimation. Meanwhile, the influence of observational constraint strength on parameter estimation is discussed. Results show that it is necessary to update the parameter with an update interval comparable to the model sensitivity response time scale in parameter estimation. These results provide a guideline for when real observations are used to optimize the parameters in a CGCM for improving climate analysis and prediction initialization.

Although the new parameter optimization scheme has shown great promise with a simple model, many challenges remain in applying it to CGCMs. Firstly, it is assumed in this study that the errors of model parameters are the only source of model biases. Actually, the dynamical core and physical schemes themselves are also imperfect and serve as significant sources of model biases in a CGCM. How the new parameter estimation scheme works with multiple model bias sources needs to be examined. Secondly, in order to determine the suitable update interval, the sensitivity of a model state to parameters has to be studied first. So, a thorough examination of the sensitivity of a CGCM with respect to its numerous parameters is an important but challenging issue. When a real-world observing system is combined with a CGCM, all of these issues need to be further investigated and addressed.

Acknowledgements. This work was funded by the National Natural Science Foundation of China (Grant No. 41676088), the National Key Research and Development Project of China (2016YFC1401800, 2017YFC1404100, 2017YFC1404102), the Fundamental Research Funds for the Central Universities (HEUCF 041705), and the Foundation of the Key Laboratory of Marine Environmental Information Technology.

APPENDIX

Implementation of Parameter Estimation

We choose the ensemble adjustment Kalman filter (EAKF) to conduct the parameter estimation in this study. The implementation of ensemble filtering for parameter estimation is processed through the following four steps:

Step 1: Draw M Gaussian random numbers, which are set as the default values for the parameter to be estimated (M is the ensemble size, which is set to 20 in this study). The ensemble of the default values of the estimated parameter is the initial prior ensemble of the parameter for parameter estimation.

Step 2: Compute the ensemble observational increments of a state variable at the observational location k. The observational increment $\Delta y_{k,i}$ for the ith ensemble member produced for the kth observation is computed as

$$\Delta y_{k,i} = \frac{\overline{y_k}}{1+r^2(y_k,y_{\text{o},k})} + \frac{y_{\text{o},k}}{1+r^{-2}(y_k,y_{\text{o},k})} + \frac{y_{k,i}-\overline{y_k}}{\sqrt{1+r^2(y_k,y_{\text{o},k})}} - y_{k,i}\ , \tag{A1}$$

where $y_{k,i}$ is the ith prior ensemble member for the kth observation; y_k is the model estimate ensemble for observation $y_{\text{o},k}$; and $r(y_k,y_{\text{o},k})$ is the ratio of the model ensemble standard deviation and the observational error standard deviation.

Step 3: Compute the error covariance between the prior ensemble of the parameter β and the model-estimated observation ensemble of y_k as

$$\text{cov}(\beta,y_k) = \frac{\sum_{i=1}^{M}(\beta_i-\bar{\beta})(y_{k,i}-\bar{y}_k)}{\sigma_\beta\sigma_{y_k}}\ , \tag{A2}$$

where β_i is the ith ensemble member of the parameter being estimated.

Step 4: Apply each observation increment and covariance sequentially to Eq. (2) to update the parameter ensemble until all observations are applied to the estimated parameter, and an updated ensemble of parameter is produced for the next cycle of parameter estimation.

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