AGU100 ADVANCING EARTH AND SPACE SCIENCE

Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

10.1002/2017MS001222

Key Points:
- The ensemble data assimilation method can potentially be used to tune convection parameters in a fully coupled general circulation model
- The climate analysis and prediction are significantly improved by convection parameter estimation
- Parameters with greater sensitivities are more suitable for tuning in the CGCM

Supporting Information:
- Supporting Information S1
- Figure S1
- Figure S2
- Figure S3

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Citation:
Li, S., Zhang, S., Liu, Z., Lu, L., Zhu, J., Zhang, X., et al. (2018). Estimating convection parameters in the GFDL CM2.1 model using ensemble data assimilation. *Journal of Advances in Modeling Earth Systems*, *10*, 989–1010. https://doi.org/10.1002/2017MS001222

Received 3 NOV 2017
Accepted 20 MAR 2018
Accepted article online 25 MAR 2018
Published online 13 APR 2018

Estimating Convection Parameters in the GFDL CM2.1 Model Using Ensemble Data Assimilation

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Abstract Parametric uncertainty in convection parameterization is one major source of model errors that cause model climate drift. Convection parameter tuning has been widely studied in atmospheric models to help mitigate the problem. However, in a fully coupled general circulation model (CGCM), convection parameters which impact the ocean as well as the climate simulation may have different optimal values. This study explores the possibility of estimating convection parameters with an ensemble coupled data assimilation method in a CGCM. Impacts of the convection parameter estimation on climate analysis and forecast are analyzed. In a twin experiment framework, five convection parameters in the GFDL coupled model CM2.1 are estimated individually and simultaneously under both perfect and imperfect model regimes. Results show that the ensemble data assimilation method can help reduce the bias in convection parameters. With estimated convection parameters, the analyses and forecasts for both the atmosphere and the ocean are generally improved. It is also found that information in low latitudes is relatively more important for estimating convection parameters. This study further suggests that when important parameters in appropriate physical parameterizations are identified, incorporating their estimation into traditional ensemble data assimilation procedure could improve the final analysis and climate prediction.

1. Introduction

In a fully coupled general circulation model (CGCM), convection parameterization is of critical importance. Previous studies suggest that misfit in convection parameterization is one major source of biases for model climatology and variability (Bretherton, 2007; Jang et al., 2013; Kim et al., 2011). Therefore, a good convection scheme is crucial to a CGCM (Mukhopadhyay et al., 2010; Randall et al., 1996). Many closure parameters exist in the convection parameterization scheme in a CGCM (Arakawa & Schubert, 1974; Moorthi & Suarez, 1992; Smagorinsky, 1963). Because of limited constraints from direct observations and theories, convection parameter values usually contain large uncertainty (Sexton et al., 2012; Williamson et al., 2015, 2017). This uncertainty is associated with pronounced model biases in the CGCM. For example, tropical variabilities, such as El Niño-Southern Oscillation (ENSO), Madden-Julian Oscillation (MJO), etc., are not simulated well (Bretherton, 2007) where convection parameters play a key role (Jang et al., 2013; Kim et al., 2011; Tokioka et al., 1988). Due to the fact that convection parameter values have such a great impact on global climate, in the CGCM, they are often used as tuning parameters to adjust model states toward the observation (Golaz et al., 2013; Mauritsen et al., 2012).

Traditionally, convection parameters are tuned manually to maintain desired climate properties (Mauritsen et al., 2012). Recent advances in mathematics and computer sciences make it possible to tune convection parameters automatically based on mathematical and statistical frameworks. Various automatic methods have been used for parameter estimation, including the downhill simplex method (Severijns & Hazeleger, 2005; Zhang et al., 2015), annealing method (Jackson et al., 2004, 2008; Liang et al., 2013; Yang et al., 2013; Zou et al., 2014), multiple objective method (Neelin et al., 2010), history matching (Williamson et al., 2015, 2017), Bayesian calibration (Hararuk et al., 2014; Kennedy & O'Hagan, 2001; Rougier, 2007; Sexton et al., 2012), ensemble data assimilation (Schirber et al., 2013), variational method (Emanuel & Živković-Rothman, 1999), and sequential Monte Carlo method (Järvinen et al., 2010). Here an ensemble data assimilation method is used to estimate convection parameters.

Previous studies on estimating convection parameters with the ensemble data assimilation method are mostly conducted in the column-based models and atmospheric general circulation models (AGCMs). These studies showed that the method can help reduce model errors associated with convection parameterization scheme to improve model performance. For example, Golaz et al. (2007) calibrated cloud parameters with the ensemble data assimilation method in a single-column model to improve the model simulation. Ruiz et al. (2013) tuned three convection parameters in a low-resolution AGCM in a twin experiment setting. Nevertheless, due to the computational cost, the ensemble data assimilation method is rarely used in the CGCM. However, given the strong impact of convection on both the atmosphere and the ocean, it is realized that the interactions among convection, other processes and the large-scale circulations, and the coupling between the atmosphere and the ocean are becoming increasingly important in climate simulations (Hourdin et al., 2016; Li et al., 2016). For example, Schirber et al. (2013) estimated four convection parameters in an AGCM in a 1 month time window, finding that the estimated parameter values could help improve short-term forecast. However, in their experiment, the long-term climate simulation error tends to increase, probably because of the neglect of long-term signals of the ocean in both the estimation and the model. Therefore, to understand the impact of convection parameters on the long-term climate modeling, it is necessary to estimate convection parameters in the CGCM systematically. Our study is a first attempt to explore the feasibility of estimating convection parameters in a CGCM with the ensemble coupled data assimilation method.

Different from the previous work of estimating coupling parameters in a CGCM (Liu et al., 2014a, 2014b), estimating convection parameters is more challenging. First, convection is discontinuous in both time and space, making parameter estimation more dependent on time-variant information of local states, since only when convection occurs can model states be influenced by convection parameters. Such a time-dependent feature suggests that flow-dependent techniques that consider both instantaneous and longer-term parameter influences may be more suitable for estimating convection parameters. Second, there are many threshold parameters in a convection parameterization scheme. The relationships between convection parameters and model states could be highly nonlinear and non-Gaussian (Posselt & Bishop, 2012; Posselt et al., 2014; Posselt & Vukicevic, 2010; Van Lier-Walqui et al., 2012, 2014), adding additional difficulties to parameter estimation. Third, due to the relatively small-scale and high frequency nature of convection, the resolution of the observation should be sufficiently high, in both time and space, to capture sufficient convective events.

This study explores the feasibility of estimating convection parameters in a fully coupled GCM with an ensemble-based coupled data assimilation method and examines its impact on climate analysis and simulation in a twin experiment context. After the introduction, a brief description of the model and its convection parameterization, as well as the twin experiment setting is presented in section 2. Results of parameter sensitivity, single, and multiple convection parameter estimation experiments under perfect and imperfect model regimes are presented in section 3. Conclusions and discussions are given in section 4.

2. Model and Methodology

2.1. The CGCM and Its Convection Parameterization Scheme

The CGCM used here is the second generation of the coupled model (CM2) developed at the Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration (GFDL/NOAA) (Delworth et al., 2006). This global climate model simulates the atmospheric and oceanic variabilities from diurnal to multicentury time scales. The version of CM2 used here applies a finite-volume atmospheric dynamical core (so-called CM2.1). The atmosphere and land components are AM2.1 (Lin, 2004) and LM2.1 (Delworth et al., 2006; GFDL Global Atmospheric Model Development Team, 2004) with the resolution of 2° latitude $\times$ 2.5° longitude, and 24 vertical levels. The oceanic component is OM3.1 with the resolution of 1° latitude $\times$ 1° longitude, and 50 vertical levels (Gnanadesikan et al., 2006; Griffies et al., 2005). The meridional resolution

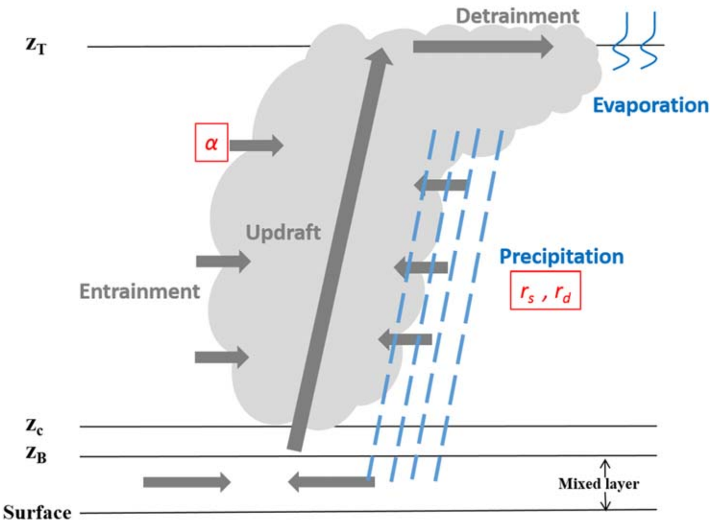

Figure 1. A schematic diagram of a single plume of one cloud type in CM2.1 RAS. z_B is the base of the updraft. z_c and z_T are the cloud base and top, respectively. The air from the mixed layer below z_B and the environment above z_c is entrained into the updraft of the cumulus cloud and is detrained at the level of cloud top, where part of the liquid water becomes precipitation and part is evaporated. Some of the estimated parameters are marked with the red box at corresponding processes.

within 30°N/S becomes progressively higher. The sea ice component is the Sea-Ice Simulator (SIS; Delworth et al., 2006; Winton, 2000). The coupler is the Flexible Modeling System (FMS; http://www.gfdl.noaa.gov/~fms/), where fluxes between each component are exchanged every 2 model hours.

CM2.1 generates long time climatology of atmospheric fields and oceanic surface very close to observations. For the atmospheric fields, the spatial distributions and time evolutions of the shortwave radiation absorption, precipitation, surface temperature, sea level pressure, wind, geopotential height, and temperature profile are consistent with observations (Delworth et al., 2006). For the oceanic fields, the simulations of meridional heat transport, sea surface characteristics, sea ice distributions, and vertical oceanic structures are also stable and credible compared to observations (Delworth et al., 2006; Gnanadesikan et al., 2006). CM2.1 is capable of simulating typical variabilities from interannual to decadal time scales (Delworth et al., 2006; Wittenberg et al., 2006). The climate response of CM2.1 is 3.4 K to a doubling of CO_2. The transient climate response is about 1.6 K to a 1% CO_2 increase (Stouffer et al., 2006). Due to its ability in simulating important climate features, CM2.1 is widely used in climate researches. CM2.1 participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5) and displayed relatively smaller overall simulation errors (e.g., Figure 9.7 in Flato et al., 2013; Nishii et al., 2012).

The convection scheme in CM2.1 is the Relaxed Arakawa-Schubert cumulus convection parameterization (RAS; Moorthi & Suarez, 1992). RAS is one of the improved implementations of the original Arakawa-Schubert cumulus convection parameterization (AS; Arakawa & Schubert, 1974; Lord, 1982). Similar to AS, RAS assumes the balance between the generation of moist convective instability by the large-scale environment and its dispersion by the cloud. It uses the mass flux to calculate the interaction between the convection and the large-scale environment. RAS distinguishes multiple cloud types by their detrainment properties. For each cloud type, as shown in the schematic diagram Figure 1, the atmosphere is divided into two parts: the cloud region from the cloud base z_c to the cloud top z_T, and the subcloud region beneath. The air from the mixed layer below z_B and the air from the environment above z_c are entrained into the cumulus updraft which starts from z_B, and is then detrained at z_T. At z_T, a fraction of the condensed water becomes precipitation. The cumulus cloud work function is calculated based on the profiles of the initial environment. The cloud work function is then relaxed toward the critical value of the cloud work function where the atmosphere is stable. To form a closure, the cumulus mass flux is calculated. A fraction of the mass flux is allowed to modify the temperature and moisture profiles. The above procedures continue to be performed on another cloud type until all cloud types are finished. Compared with the original AS scheme, RAS is more accurate and economical for the CGCM because it generates profiles that are more physically realistic while significantly reducing the computational cost of calculating the quasi-equilibrium in the AS (Moorthi & Suarez, 1992).

2.2. Convection Parameters

In the CM2.1 RAS, five adjustable parameters controlling important physical processes are chosen for parameter estimation experiments in our study (Table 1). The first parameter is the Tokioka parameter α. In RAS, the Tokioka modification (Tokioka et al., 1988) is applied to suppress the convection whose entrainment rate is smaller than the minimum threshold

$$\mu_{\min} = \frac{\alpha}{D} \tag{1}$$

that varies with the planetary boundary layer depth D. The value of α, controlling the cumulus entrainment, has great impacts on the high cloud, sea surface temperature (SST), and precipitation in the tropical region, and further influences the tropical cyclone (Held & Zhao, 2008), MJO (Lee et al., 2008; Sobel et al., 2010), Hadley Circulation (Kang et al., 2008), and ENSO (Jang et al., 2013; Kim et al., 2011). A greater α reduces

Table 1
Results for Single Convection Parameter Estimation

Symbol	Truth and range	IB1	Perturbation	PE_G	PE_T
r_d	0.975 (0,1]	0.550	0.100	0.973	0.974
β	0.250 (0,1)	0.100	0.050	0.258	0.251
α	0.025 [0,0.04]	0.055	0.005	0.024	0.024
A_c	1.000 (0,2]	2.000	0.100	1.019	1.047
r_s	0.500 (0,1)	0.150	0.100	0.489	0.503

Note. The ranges of parameters are derived from Moorthi and Suarez (1992), Tokioka et al. (1988), Kim et al. (2011), Sud et al. (1991), and expert elicitation. IB1 is the first set of initial parameter biases. PE_G and PE_T represent the results of parameter estimations with global and tropical observations.

convection, high clouds, incoming sunlight and global temperature, while enhancing ENSO variability, and eastward shifts of westerly wind stress and El Niño related precipitation anomalies (Jang et al., 2013; Kim et al., 2011). The default value of α in CM2.1 is 0.025 which has been found to produce a good overall tropical simulation, although it leads to a cold bias in the upper tropical troposphere (GFDL Global Atmospheric Model Development Team, 2004). The parameter α has great impact on the entrainment processes that are believed to cause large uncertainties in climate prediction (Klocke et al., 2012; Murphy et al., 2004; Stainforth et al., 2005). Parameters related with the entrainment processes have been used widely for tuning in parameter estimation studies (Li et al., 2016; Mauritsen et al., 2012; Schirber et al., 2013). Therefore, parameter α is very suitable for tuning in CM2.1.

The second parameter is the relaxation parameter β. In RAS, only a fraction β of the total mass flux is used to adjust the cloud, and is allowed to modify the large-scale environment in each step (Moorthi & Suarez, 1992). Given β, the adjustment time scale τ over which the cloud relaxes the atmosphere to the neutral state is defined as

$$\tau=\frac{\Delta t}{\beta}, \tag{2}$$

where Δt is the time step. A greater β corresponds to stronger relaxation of the cloud work function toward the quasi-equilibrium.

The third parameter is A_c, the ratio of the critical cloud work function to the standard cloud work function in AS. In RAS, for each cloud type, the cloud work function is relaxed to a critical value which is the product of A_c and the standard cloud work function defined in the original AS scheme (Lord, 1982; Moorthi & Suarez, 1992). A greater A_c leads to less stable atmosphere. Increasing A_c also leads to reduced convective precipitation and increased large-scale precipitation (Sud et al., 1991).

The fourth and fifth parameters are precipitation efficiencies r_d and r_s. As stated in the last section, when all the liquid water is risen to the detrainment level, part of it is precipitated. The fraction of water condensed as precipitation is defined as the precipitation efficiency. In the CM2.1 RAS, the precipitation efficiency is calculated as a function of the detrainment pressure p:

$$\mathrm{r}=\begin{cases} r_d & p<500\ \text{hPa} \\ r_s+\dfrac{800-p}{800-500}(r_d-r_s). & 500\ \text{hPa}<p<800\ \text{hPa}\,. \\ r_s & p>800\ \text{hPa} \end{cases} \tag{3}$$

r_d and r_s are the precipitation efficiencies specified for the deep convection which detrains above 500 hPa and the shallow convection which detrains under 800 hPa. For the convection which detrains between 500 and 800 hPa, the precipitation efficiency r is linearly interpolated in pressure between r_d and r_s (GFDL Global Atmospheric Model Development Team, 2004; Moorthi & Suarez, 1992). The $(1-r)$ fraction of the condensed water is important condensate for the cloud. The value of the precipitation efficiency can influence the reflectivity of the atmosphere, having a positive correlation with the incoming solar radiation which is essential to the global climate. These five parameters are important to the modeled climate of CM2.1, and are therefore used in the parameter estimation experiments.

2.3. Parameter Estimation Experimental Setup

As a preliminary exploration of estimating convection parameters in a sophisticated CGCM, following Liu et al. (2014a, 2014b) and Ruiz et al. (2013), we carry out experiments in a twin experiment framework which contains two model runs: the "truth" run and the "estimation" run. Within this framework, we estimate convection parameters under both perfect and imperfect model regimes. In the twin experiment framework, CM2.1 is first integrated with the default values (i.e., "truth" values, see Table 1) of all convection parameters. This defines the "truth" run and the simulation is assumed to represent the evolution of the "truth" climate. The "observations" are created from the "truth" simulation after the addition of a white noise error. Then the "observations" are assimilated into the "estimation" run where value(s) of the convection parameter(s) is (are) set with biased and perturbed values (see Table 1).

An idealized observation network is used in our experiment. The atmospheric "observations," which include 6 h model grid temperature, specific humidity, and u/v wind, are assimilated to constrain model states. The oceanic "observations" include the oceanic temperature and salinity profiles projected onto the 2004-Argo network (Gould et al., 2004), and daily model grid SST. Only observations of the atmospheric temperature and specific humidity are used to constrain convection parameters (not much improvement is found by adding wind observations in constraining convection parameters in our experiment). The target of the estimation is to minimize the error of 6 h atmospheric temperature and humidity during the estimation period. The estimated parameter value is assumed to be able to provide better model simulation than that of the unestimated parameter. The observation is created by adding onto the "truth" a Gaussian distributed random error with a mean of zero and standard deviations of 0.5 K for the atmospheric temperature, 0.1 g/kg for the specific humidity, 1 m/s for the u/v wind, 0.5 K for the oceanic temperature, and 0.1 psu for the oceanic salinity. Sensitivity experiments show that larger observational error degrades the estimation.

The ensemble adjustment Kalman filter (EAKF; Anderson, 2001, 2003; Zhang & Anderson, 2003) approach is used for data assimilation and parameter estimation in our study. EAKF is a variant of the ensemble Kalman Filter (EnKF; Evensen, 1994) under an adjustment idea. In the observational space, EAKF adjusts the ensemble mean and ensemble departure separately with an algorithm similar to the Ensemble Square Root Filter (Kalman SRF; Tippett et al., 2003) to obtain the observational increment (Anderson, 2001, 2003; Whitaker & Hamill, 2002). Then the observational increment is projected onto the model space to produce the model state increment:

$$\Delta x_{l,i}^{u} = \frac{cov\left(\Delta x_l^p, \Delta y_k^a\right)}{\sigma_k^a 2} \Delta y_{k,i}^{o}. \tag{4}$$

Here $\Delta x_{l,i}^{u}$ is the adjustment increment of the ith ensemble member of the lth updated model state. On the RHS, $\Delta y_{k,i}^{o}$ is the observational increment of the ith ensemble member of the kth observable model state in the observational space. x_l^p is the ensemble of the lth model state prior to the update, and Δx_l^p is the ensemble of member departures from their ensemble mean. y_k^a is the ensemble of the kth updated model state in the observational space, and Δy_k^a is the ensemble of member departures from their ensemble mean. $cov\left(\Delta x_l^p, \Delta y_k^a\right)$, often called the error covariance, is the covariance of Δx_l^p and Δy_k^a. $\sigma_k^a 2$ is the variance of the kth updated model state in the observational space. This equation of updating the model state means that the adjustment increment of the model state $\Delta x_{l,i}^{u}$ is obtained by the increment of the observable state $\Delta y_{k,i}^{o}$ multiplied by an operator $\frac{cov\left(\Delta x_l^p, \Delta y_k^a\right)}{\sigma_k^a 2}$ (Anderson, 2001; Zhang & Anderson, 2003). More details of the method can be found in Zhang et al. (2007).

The EAKF-based parameter estimation is an extension of the data assimilation by replacing the updated state with the parameter. The parameter adjustment formula therefore becomes:

$$\Delta \varphi_{m,i}^{u} = \frac{cov\left(\Delta \varphi_m^p, \Delta y_k^a\right)}{\sigma_k^a 2} \Delta y_{k,i}^{o} \tag{5}$$

(their equation (2) in Zhang & Anderson, 2003). $\Delta \varphi_{m,i}^{u}$ is the adjustment increment for the ith ensemble member of the mth parameter. $cov\left(\Delta \varphi_m^p, \Delta y_k^a\right)$ is the error covariance calculated between the departure ensembles of the mth parameter prior to the update and the kth updated observable model state in the observational space. $\Delta y_{k,i}^{o}$ and $\sigma_k^a 2$ are the same as in equation (4). EAKF tunes the parameter to minimize the discrepancy between model states and observations during the estimation period. The tuned parameter that minimize the analysis error is assumed to be able to provide better climate simulation and prediction. It is noted that the estimated parameter value may not necessarily be the optimal because the limitation of the minimization target, and approximations in the model and the estimation method.

The EAKF approach is suitable for data assimilation and parameter estimation in the CGCM because it is flow-dependent and easy to be implemented in the CGCM (Anderson, 2001; Zhang & Anderson, 2003). In addition, EAKF does not require very large ensemble size (Anderson, 2001). Zhang et al. (2007) implemented EAKF in the GFDL Ensemble Coupled Data Assimilation System (ECDA). Tests on the ECDA with 6-ensemble, 12-ensemble, and 24-ensemble members showed that no further significant improvement was found with 24-member (Chang et al., 2013; Zhang & Rosati, 2010). Therefore, a 12-member ensemble is used in our study to maintain a small ensemble sampling error (Anderson, 2012; Hamill et al., 2001; Houtekamer & Mitchell, 1998) at an acceptable cost. The EAKF approach has been used widely in many parameter estimation studies from simple models to sophisticated CGCMs (Li et al., 2016; Liu et al., 2014a, 2014b; Schirber et al., 2013; Wu et al., 2012, 2013; Zhang, 2011a).

The covariance localization of Gaspari and Cohn (1999) is used with the influence radii of 1,000 km for oceanic observations and 500 km for atmospheric observations. In addition, the conditional covariance inflation (CCI; Aksoy et al., 2006; Tong & Xue, 2005, 2008b) is applied. After each parameter update cycle, the spread of the parameter ensemble shrinks drastically. Unlike model states that vary with integration, the shrunken parameter ensemble stays unchanged until the next update cycle. The spread of the parameter ensemble soon becomes very small. Too much weight is then given to the prior ensemble and future assimilated observations no longer have any effect. This ensemble spread issue is usually called filter degeneracy. As a remedy CCI predefines a minimum spread. Whenever the spread of the posterior parameter ensemble becomes smaller than this minimum spread, the parameter ensemble is inflated to the level of the CCI minimum spread. It should be noted that the choice of the CCI predefined minimum spread is empirical, and its optimal value varies from parameter to parameter (Aksoy et al., 2006). A smaller CCI spread will lead to a smoother time evolution of the estimated parameter (Tong & Xue, 2005). However, a smaller CCI spread will make the estimated parameter take longer time to converge (Tong & Xue, 2005). In our experiment, the CCI spread is empirically set at 30% of the spread of the initial parameter perturbation for economical reason.

To facilitate parameter estimation, a half year of state-estimation-only (SEO) is conducted (Zhang, 2011a) before parameter estimation is activated. After that, the combined state and parameter estimation (PE) is performed. The initial conditions for the integration are taken from a 12-member GFDL CM2.1 ECDA product. The initial condition for the “truth” simulation is one ensemble member of the ECDA product at 0000 UTC, 1 January 2000. This initial condition is then integrated with the default convection parameter values (Table 1) and temporally varying greenhouse gases and natural aerosols (GHGNA) for a few years. This establishes the “truth” run in the twin experiment. In the “estimation” run, the convection parameter is set to its biased value, and then perturbed with Gaussian distributed random errors of mean zero and corresponding perturbation spread (as listed in Table 1) into a biased and perturbed parameter ensemble. The initial conditions for the ensemble in the biased model are taken as the GFDL CM2.1 12-member ECDA product at 0000 UTC, 1 January 2004. The initial conditions are integrated with the biased parameter ensemble and GHGNA for a half year to 0000 UTC, 1 July 2004, with SEO. During the SEO, the uncertainty of the initial condition is largely constrained. After that, two integrations of 1 year up to 0000 UTC, 1 July 2005 are performed. One is SEO with the biased and perturbed parameter ensemble. The other is PE with both state estimation and parameter estimation activated. The results of the two integrations are compared to examine the influence of convection parameter estimation.

We evaluate the estimation result in three aspects. The first aspect is the time evolution of the estimated parameter. In the perfect model regime, the most desirable result is that the estimated parameter reaches at the “truth” (default) value. This is an anticipation most likely to be achieved in an idealized situation, such as those in the perfect model regime (Liu et al., 2014a, 2014b; Schirber et al., 2013). It should be noted that this parameter convergence is a valid target strictly speaking only in the perfect model study here. In more complex situations, such as multiple parameter estimations under the imperfect model environment, or for the real world study, parameters may not have true values, and, some parameters may not even converge (Aksoy et al., 2006; Annan, 2005; Schirber et al., 2013; Tong & Xue, 2008b). The second aspect for evaluating the result is the error of important model variables during the estimation period. It is desirable that the analysis error is reduced after convection parameter estimation compared with that of SEO, providing a better initial condition for the prediction than that of SEO (Golaz et al., 2013). The third aspect is prediction. It is desirable that the prediction using the PE initial conditions and convection parameters is more accurate than that of SEO. The three aspects above are examined to help form an objective evaluation of the parameter estimation results.

3. Convection Parameter Sensitivity

We first examine the sensitivity of observable model states with respect to convection parameters. One important precondition for successful parameter estimation is that the model variables are sensitive to the change of parameters (Aksoy et al., 2006; Tong & Xue, 2008a, 2008b), called "parameter sensitivity." When the sensitivity of a specific parameter is great, the estimation of this parameter is more likely to be successful and, furthermore, the improved parameter is more likely to improve the model state. In addition, a parameter sensitivity study allows us to identify the regions of observations that are most useful for parameter estimation. Observations located in more sensitive regions may provide more information for parameter estimation due to stronger model response.

In this study, the parameter sensitivity is examined using the perturbed parameter method (Zhang, 2011a). For a single parameter φ, we form a 12-member parameter ensemble φ_i ($i=1, 2, 3\ldots12$) by perturbing the parameter around its default value φ_d with random noise of i.i.d. $N(0, \sigma^2)$. The standard deviation of the perturbation $\sigma=20\%\varphi_d$. The CM2.1 is then integrated freely without observation constraints with the parameter ensemble φ_i from a same initial condition (the first ensemble member of the GFDL ECDA product) for 6 h which is the observational and updating interval (Liu et al., 2014a). After the integration, the standard deviations of model states represent the sensitivities of this parameter. The parameter sensitivity experiment is repeated with 24 initial conditions in January, April, July, and October in the year of 2003. The final result is an average of the 24 results, filtering out the influence of seasonal cycle.

As shown in Figure 2, with the same perturbation, r_d, β, and α are relatively more sensitive while A_c and r_s are less sensitive. Horizontally, the most sensitive areas are located in the convective zones in the low latitudes within 30°N/S (Figures 2a–2j). The sensitive areas shift and extend toward the summer hemisphere due to the seasonal change of radiation. In the real world, convection occurs more frequently in the low latitudes, especially in the western tropical Pacific, northern Indian Ocean, and tropical Atlantic regions (Xie & Arkin, 1997). This distribution is well captured by CM2.1 in its simulation with default convection parameter values (Delworth et al., 2006). In CM2.1, convection parameters affect model states only when convection occurs (Moorthi & Suarez, 1992). Therefore, the response of model states to convection parameter uncertainties is the strongest in the low latitudes. This indicates that the relationships between convection parameters and model states are better established in the low latitudes, and observations of the low latitudes may contribute more signals in estimating the convection parameters.

In the vertical direction, the sensitive areas of most convection parameters are located at the lower troposphere, except for α (Figure 2m) and r_d (Figures 2k and 2p). Parameter α and r_d are closely related to properties of the deep convection which tends to influence the atmospheric state in the upper troposphere. Therefore, they also display great sensitivities there. Especially for r_d, the precipitation efficiency for the deep convection detraining higher than 500 hPa, the sensitivities of both temperature and moisture display local maximums around 300 hPa. It is noted that parameter sensitivity may change when the value of this parameter or other parameters change. Here we examine parameter sensitivities with a uniform perturbation range of 20% of the default parameter value.

4. Results

4.1. Estimation of a Single Convection Parameter

We first discuss the results of single convection parameter estimation in the perfect model regime. In this experiment, in the assimilation model, one convection parameter is set with the biased value (Table 1, IB1) while the other four parameters keep their default values. For each parameter, we conduct three integrations: one SEO integration, one PE using global observations to update parameter (PE_G), and one PE using tropical observations within 30°N/S to update parameter (PE_T). The results of SEO and PE are compared to

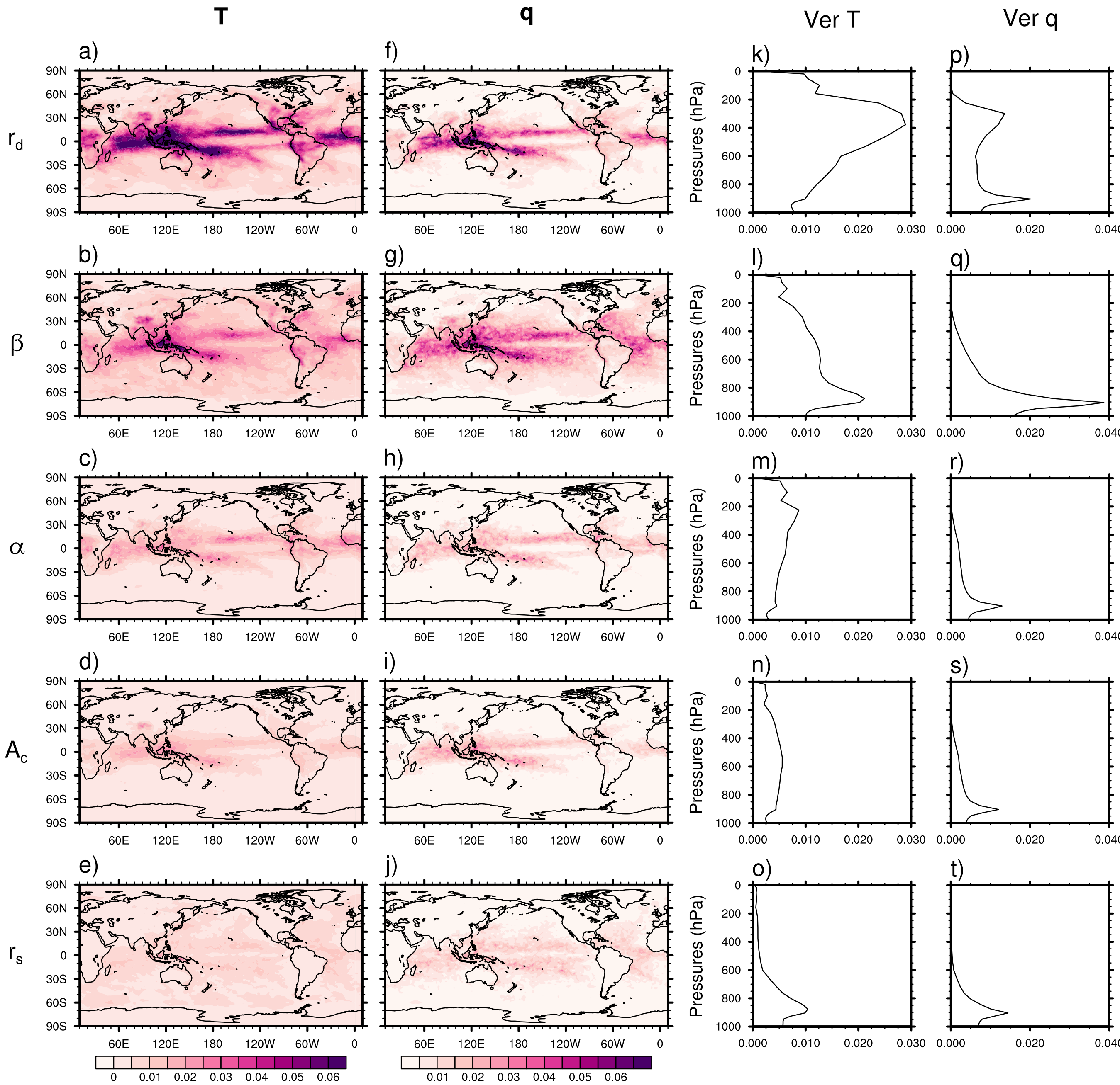

Figure 2. Parameter sensitivities. Global distributions of vertically averaged ensemble spreads of 6 h (a–e) atmospheric temperature (unit: K) and (f–j) specific humidity (unit: g/kg), and the vertical variations of the globally averaged ensemble spreads ((g–o) for the temperature; (p–t) for the specific humidity). The ensemble spread of model state based on a perturbed parameter ensemble serves as a measure of the model's sensitivity to examined parameter. Each row represents the results for a single parameter.

investigate the influence of convection parameter estimation. The results of PE_G and PE_T are compared to further investigate the role of tropical observations in convection parameter estimation.

All estimated parameters converge to the truth values successfully, as shown in Figure 3. A monthly average is applied to filter out small fluctuations. These fluctuations are caused by constantly tuning parameter with multiple observations to reduce the distance between model states and observations (Tong & Xue, 2005, 2008b). Although all estimations converge to the truth, the time evolutions of the parameters show some differences. Parameter r_d and β seem to have the best estimation quality, with relatively smoother and faster convergence within 2 months. The other three parameters show slower convergences and exhibit

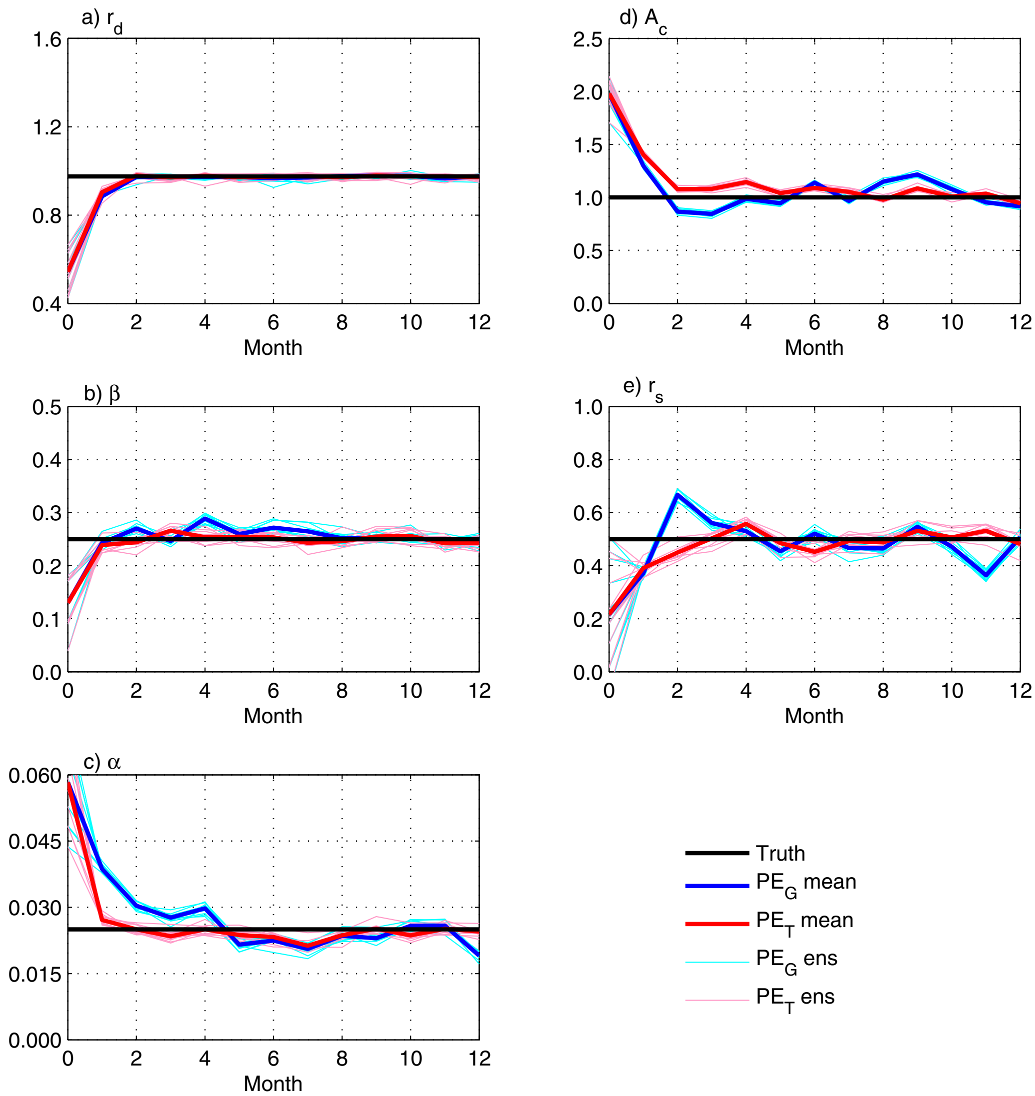

Figure 3. Time evolutions of estimated parameters in the single parameter estimation experiments with global (PE_G) and tropical (PE_T) observations for (a) r_d, (b) β, (c) α, (d) A_c, and (e) r_s. The black line represents the "truth." The cyan lines represent the estimated ensemble members of PE_G while the blue line represents their ensemble mean. The pink lines represent the estimated ensemble members of PE_T while the red line represents their ensemble mean.

some oscillations. The differences in the time evolutions are likely associated with different parameter sensitivities. For parameters with greater sensitivities, model responses are stronger, so that the ensemble estimated error covariances between the parameters and model states [$cov\left(\Delta\varphi_m^p, \Delta y_k^a\right)$ in equation (5)] have higher signal-to-noise ratios. Therefore, these parameters are more likely to be identified quickly and estimated accurately. The estimation quality is also found to be related with the time scale of the parameter sensitivity (Liu et al., 2017). Parameters r_d and β have greater sensitivities at 6 h time scale than other parameters. Therefore, with an updating time scale of 6 h, they have better parameter time evolutions. It should be noted that the sensitivity of one parameter may change when the value of this parameter or other parameter changes. In each update, the change of the sensitivity is reflected in the changes of covariance and variance in equation (5) in the EAKF algorithm. The EAKF automatically uses the real time information to update parameters. Table 1 summarized the statistical estimation results for each parameter as the ensemble mean averaged over the last 10 months of the estimation period after the estimation converges to a stable value (Li et al., 2016; Schirber et al., 2013). The estimation result is assumed to be able to provide better model simulation and prediction than that of the unestimated parameter. The estimation results are very close to the truth with negligible differences. In addition, estimation convergence of PE_T using only tropical observations are faster and smoother than PE_G using global observations. This is because model states are more sensitive to parameter changes in the tropical regions. Therefore, in these regions, there are more chances that convection parameters have direct influences on model states so that the parameter-state relationship is better defined in these regions (Li et al., 2016; Liu et al., 2014a, 2014b). Moreover, during parameter estimation, the spread of the parameter ensemble is found to contract significantly after each update cycle in the tropical regions, suggesting that observations and covariance estimations [$cov\left(\Delta\varphi_m^p, \Delta y_k^a\right)$ in equation (5)] in the tropical regions are more signal-dominant. The single parameter estimation experiment suggests that in general, tropical observations are potentially capable of correcting bias in the convection parameter through ensemble data assimilation method in a fully coupled GCM.

The optimized parameter after the estimation helps improve the climate analysis. Figure 4 displays the time evolutions of the root-mean-square-errors (RMSEs) of the atmospheric temperature, specific humidity, and precipitation for SEO, PE_G, and PE_T. First, the analysis error is significantly reduced after convection parameter estimation. In SEO, although the model states are largely constrained by observations, the biased convection parameter still induces large analysis error. After parameter estimation, the convection parameter is

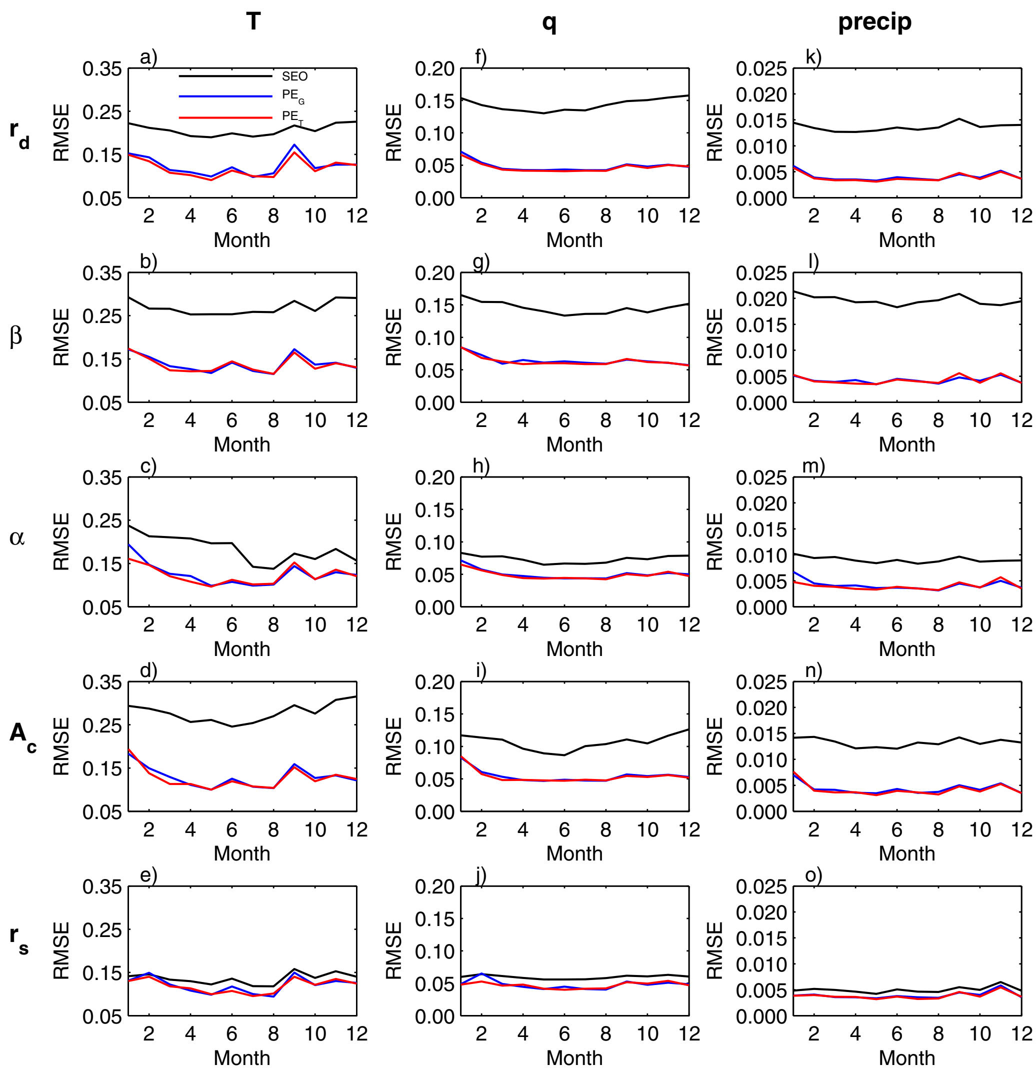

Figure 4. Time evolutions of RMSEs of (a–e) atmospheric temperature (unit: K), (f–j) specific humidity (unit: g/kg), and (k–o) precipitation (unit: mm/d) in single convection parameter estimation experiments. Each row shows the results of one parameter, as denoted on the left. The black line represents the RMSE for the state-estimation-only (SEO). The blue and the red line represent the RMSEs of parameter estimation with global observations (PE_G) and tropical observations (PE_T).

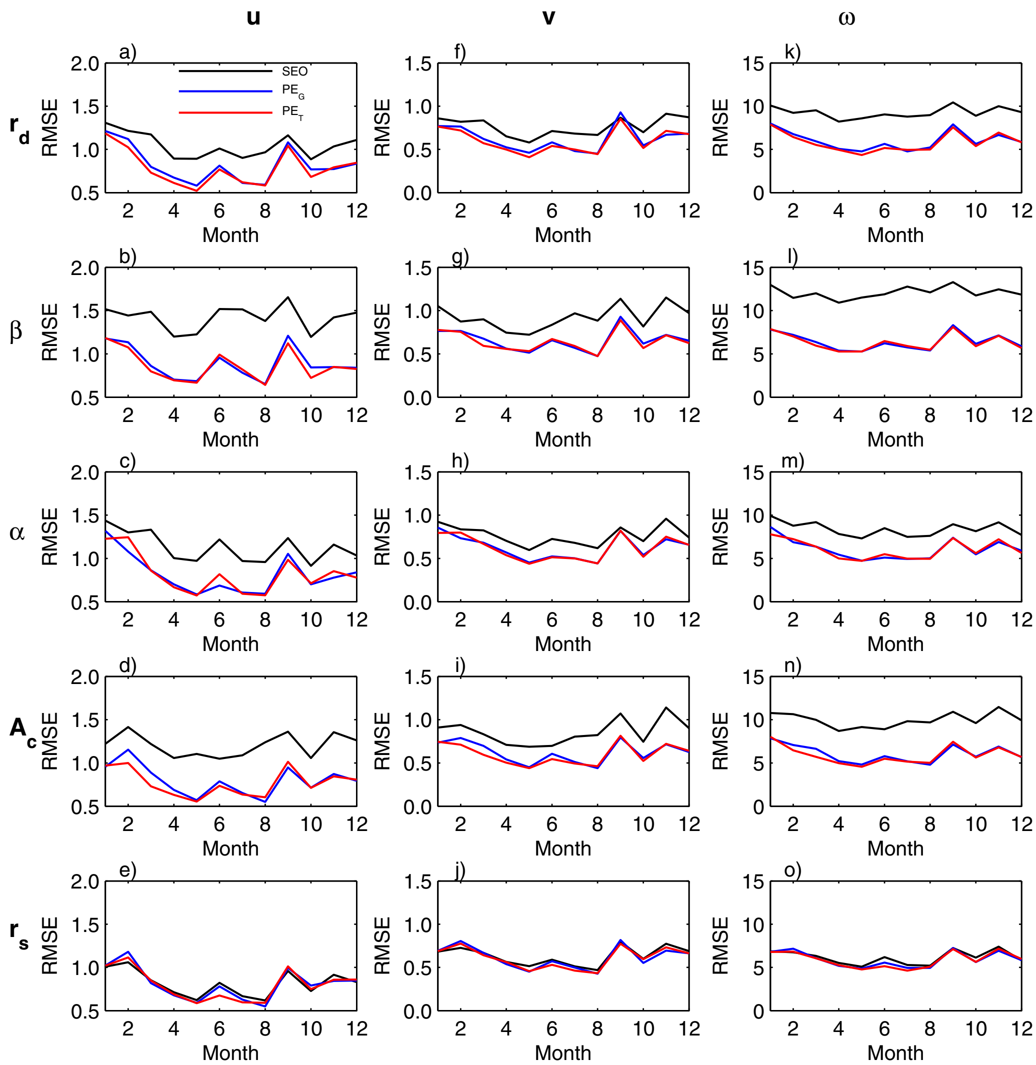

Figure 5. Same with Figure 4, but for the (a–e) zonal wind component (denoted as u, unit: m/s), (f–j) meridional wind component (denoted as v, unit: m/s), and (k–o) vertical motion (denoted as ω, unit: Pa/s).

also constrained, therefore the RMSE is further reduced. Second, parameters with greater sensitivities yield greater reductions of the analysis error. For example, the initial bias for the most sensitive parameter r_d is 44% (Table 1) and the RMSE reduced by correcting r_d is about 40% for the atmospheric temperature. On the contrary, the initial bias for the least sensitive parameter r_s is 70% while the RMSE reduced by correcting r_s is only 11%. This further demonstrates that estimations of parameters with greater sensitivities are likely to provide more improvement for model analysis. Third, RMSEs of PE_T are generally smaller than RMSEs of PE_G, which further suggests the importance of tropical observations in convection parameter estimation. The above conclusions can also be drawn for wind components in Figure 5. Due to the internal dynamic adjustment among atmospheric variables, the analysis errors of the horizontal wind and vertical motion are also reduced after convection parameter estimation, although the reductions are not as significant as for the temperature and humidity.

An improvement is also found for the ocean state even if the estimated convection parameters are all in the atmospheric component of the CGCM (Figure 6). For the surface ocean, the RMSEs of SST and SSS (sea surface salinity) are also reduced after convection parameter estimation, although not as significantly as in the atmosphere, especially for parameter r_s. This is understandable because the surface ocean is dynamically coupled to the atmosphere. The change of the atmospheric temperature, humidity, and precipitation has strong impacts on the SST and SSS. The influence of convection parameter estimation is transferred

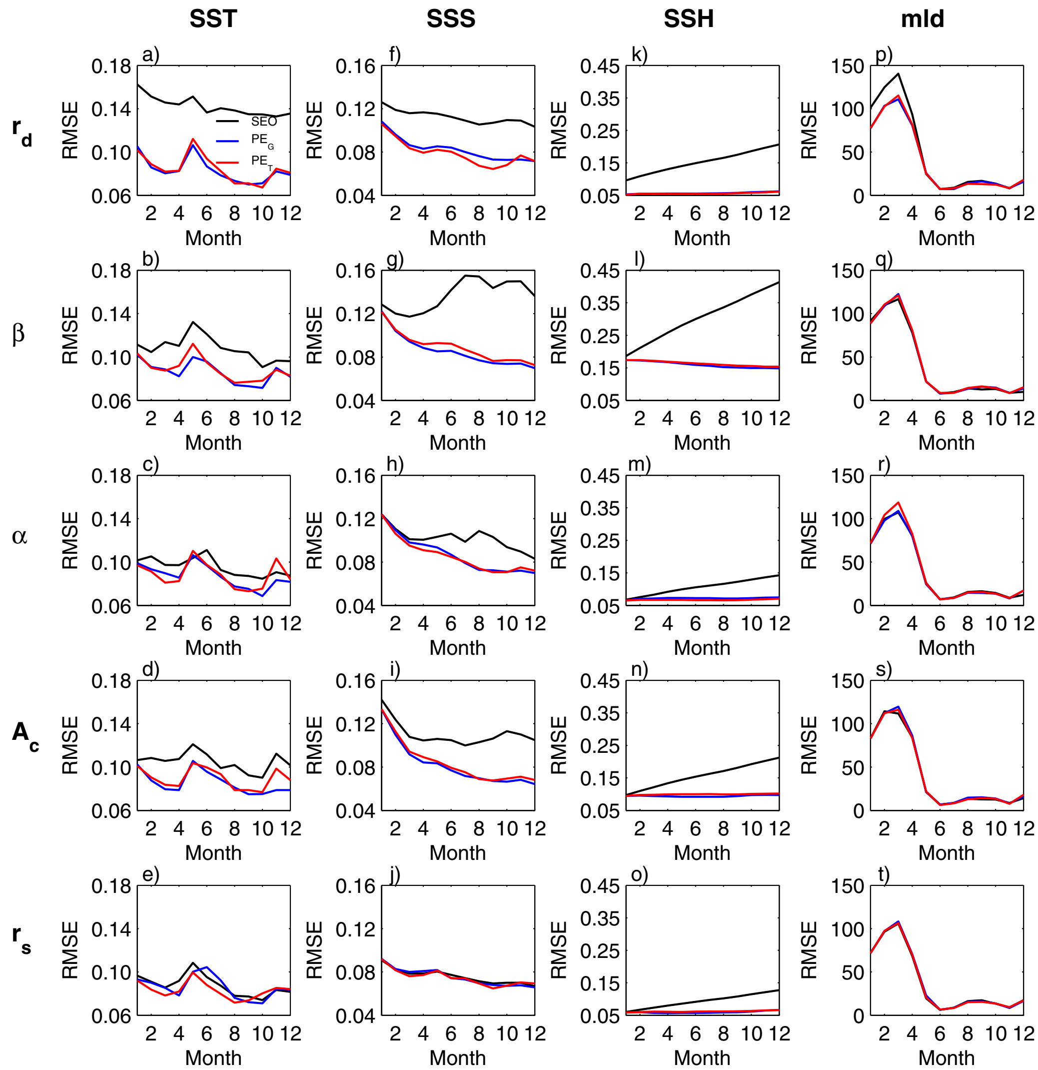

Figure 6. Same with Figure 4, but for (a–e) SST (unit: K), (f–j) SSS (unit: psu), (k–o) SSH (unit: m), and (p–t) mixed layer depth (denoted as mld, unit: m).

from the atmosphere to the ocean, leading to the improvement of the oceanic analysis indirectly. It is interesting that the sea surface height (SSH) cannot be constrained by atmospheric observations using SEO only. Without convection parameter estimation, the biased convection parameter seems to keep dragging the SSH away from the "truth." However, after parameter estimation eliminating the bias in the convection parameter, the drift in the SSH is also constrained. Nevertheless, the optimization of convection parameters does not seem to improve the mixed layer depth (mld), which represents the interaction between the atmosphere and the ocean. In addition, the advantage of estimation with tropical observations becomes marginal for oceanic variables. The experiments of single convection parameter estimation under the perfect model regime suggest that it is potentially possible to use ensemble data assimilation method to correct the bias in a convection parameter and improve climate analysis for both the atmosphere and the ocean in a CGCM. The tropical observation plays an important role in convection parameter estimation. In addition, it is also noted that the improvement on the mixed layer depth is less obvious, indicating a weaker relationship between convection parameter estimation and the simulation of mixed layer depth.

4.2. Simultaneous Estimation of Multiple Convection Parameters

Due to the complexity of a CGCM and multiple uncertainty sources (Zhang et al., 2012), it is usually difficult to attribute model biases to a single parameter. Usually several parameters are tuned simultaneously to

Table 2
Results for Simultaneous Estimation of Multiple Convection Parameters

Symbol	Truth and range	IB1	IB1 result	IB2	IB2 result
r_d	0.975 (0,1]	0.550	0.984	0.6	0.980
β	0.250 (0,1)	0.100	0.231	0.35	0.237
α	0.025 [0,0.04]	0.055	0.018	0.01	0.023
A_c	1.000 (0,2]	2.000	0.997	0.5	0.872
r_s	0.500 (0,1)	0.150	0.291	0.3	0.474

Note. IB2 is the second set of initial parameter biases.

obtain an optimal combination of parameter values such that the model state best fits the observation. In previous studies using the atmospheric models, Aksoy et al. (2006) found that the quality of multiple parameter estimation is worse than that of single parameter estimation, because the parameter-state correlation, which serves as the key in parameter estimation, is significantly reduced by the contamination of other parameters. Tong and Xue (2008b) conducted a series of simultaneous multiple parameter estimation experiments and discovered that multiple modes may exist for multiple parameter estimation. Although results in multiple parameter estimation are not as good as in the single parameter estimation, the quality of model analysis can be improved significantly. Liu et al. (2014b) performed multiple parameter estimation in a CGCM, also showing less robust parameter convergence than the case of single parameter estimation. Annan (2005) estimated multiple parameters simultaneously in an AGCM and discovered that parameters with greater sensitivities are more likely to be accurately estimated. Here we explore the feasibility of estimating multiple convection parameters simultaneously in the GFDL CM2.1 in the perfect model regime. Considering the influence of the initial bias distribution, estimation experiments are conducted starting from two sets of initial parameter guesses, IB1 and IB2, as listed in Table 2.

Multiple parameter estimation still exhibits convergence for some parameters. But, overall, the convergence is not as good as that of single parameter estimation. Figure 7 shows the time evolutions of the estimated parameters. Parameter r_d converges rapidly from both initial parameter sets IB1 and IB2 in about 2 months, comparable to the single parameter estimation. Other parameters tend to converge slowly, some taking almost a year. The estimation accuracy is also degraded in comparison with the single parameter estimation case. Parameter β approaches the truth also in a few months, but then deviates and finally converges to values 8% (IB1) and 5% (IB2) lower than the truth in about a year. For parameter α, the estimation converges to the truth from IB1, overshoots from IB2, and seems to approach a value smaller than the truth. For parameter A_c, the estimation converges quickly and smoothly to the truth starting from IB1, but converges much more slowly from IB2. For parameter r_s, the estimation exhibits large oscillations around the truth and do not seem to converge even after 1 year. The ensemble means of estimated convection parameters averaged over the last 3 months (Table 2) show some reduction of parameter biases from the initial guesses. These average values are used in the forecast experiments that will be discussed later.

The result of multiple parameter estimation is consistent with most previous research using the ensemble data assimilation method (Aksoy et al., 2006; Annan, 2005; Liu et al., 2014a, 2014b; Tong & Xue, 2008b; Zhang, 2011b). The overall degeneration of the accuracy of multiple parameter estimation compared with the single parameter estimation may be contributed partly by a simple statistical reason: given the fixed sample size, the increased number of parameters tends to increase the uncertainty in the constructed ensemble covariance matrix between the multiple parameters and climate variables. When calculating the increment for one parameter using equation (5), model states in the error covariance, state variance, and observational increment are inevitably contaminated by the influences of other parameters. As a consequence, multiple parameter estimation is not as accurate as single parameter estimation where the single parameter bias is the only model error source. This is likely most serious if the effect on the climate state variables are correlated among different parameters. For example, the effect on the climate state may be compensated between parameters. This compensation effect is clearly seen in our experiment. For IB1, on the 6 h time scale, a smaller relaxation time scale β (Figure 7b) leads to less convective heating, resulting in a colder and moister atmosphere (supporting information Figures S1e–S1h). A smaller precipitation efficiency r_s for the shallow convection (Figure 7e) reflects more incoming sunlight, also resulting in a colder

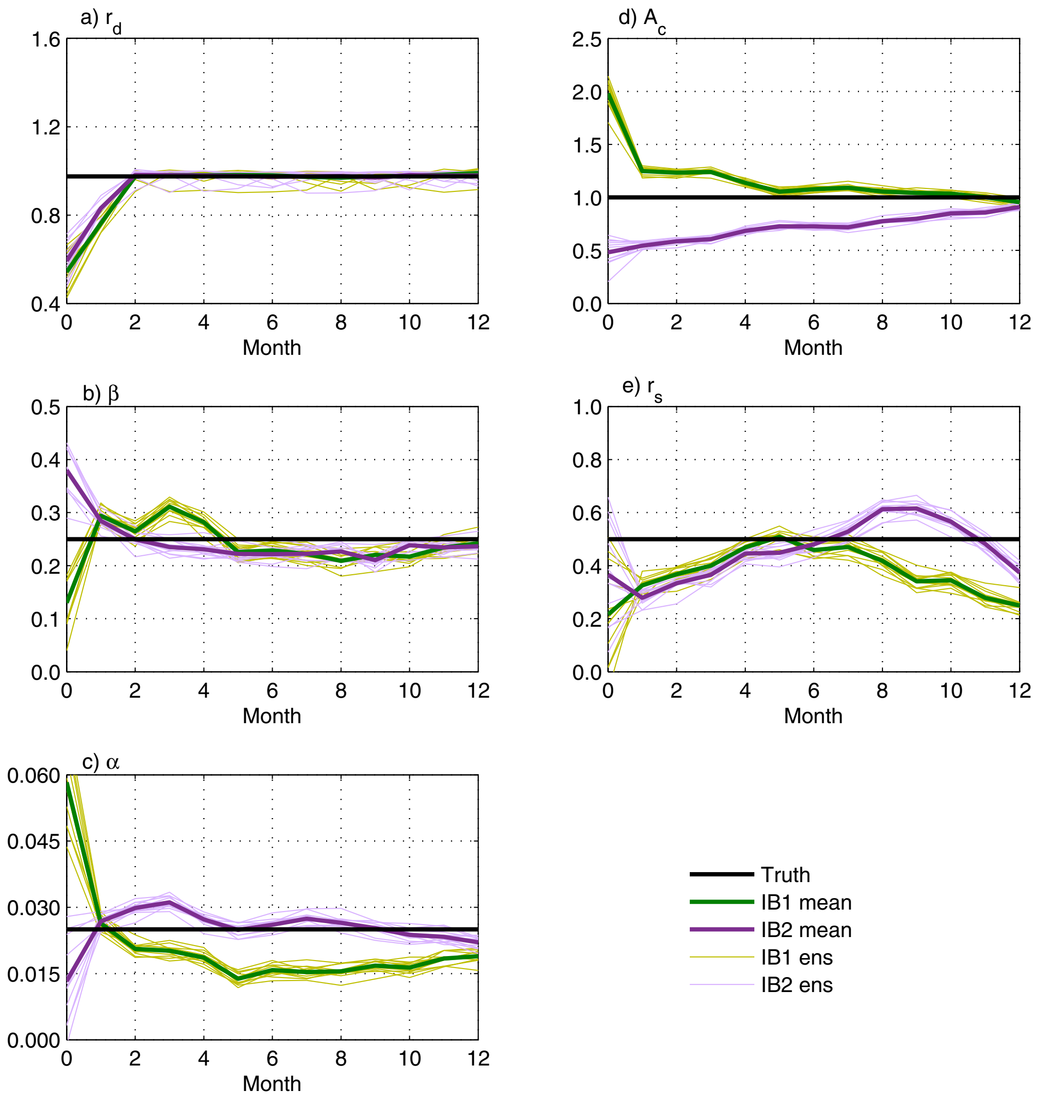

Figure 7. Time evolutions of the simultaneous multiple convection parameter estimation with tropical observations for (a) r_d, (b) β, (c) α, (d) A_c, and (e) r_s. The black line represents the "truth." The light and dark green lines represent the estimated ensemble members and their ensemble means from the first initial parameter bias set IB1 (Table 2). The light and dark purple lines represent the estimated ensemble members and their ensemble means from the second initial parameter bias set IB2 (Table 2). The IB1 mean and IB2 mean overlap the truth in Figure 7a).

and moister atmosphere (supporting information Figures S1q–S1t). On the contrary, a smaller entrainment parameter α (Figure 7c) results in more convective heating and thus a warmer and dryer atmosphere (supporting information Figures S1i–S1l), compensating for the cold and moist bias from β and r_s. This compensation effect is also responsible for the existence of multiple modes in multiple parameter estimation (Tong & Xue, 2008b), especially for convection parameters which usually display multiple peaks in the probability distribution functions of model state responses (Posselt & Bishop, 2012; Posselt et al., 2014; Posselt & Vukicevic, 2010). Under the influence of multiple modes, the estimated parameters may not all converge to the truth values. Instead, they may converge to different values which also tend to minimize the cost function. It should be noted that under this circumstance, the estimation result should be examined carefully in the model to reduce the risk of triggering other problems that are not considered in the cost function. For example, Golaz et al. (2013) estimated several cloud parameters in a CGCM. They discovered that while multiple strategies exist for desired radiation balance and observed climate, these strategies give significantly different aerosol effects that result in different 20th century temperatures. The findings in the twin experiment framework where the "truth" is precisely known are indicative to convection parameter tuning with

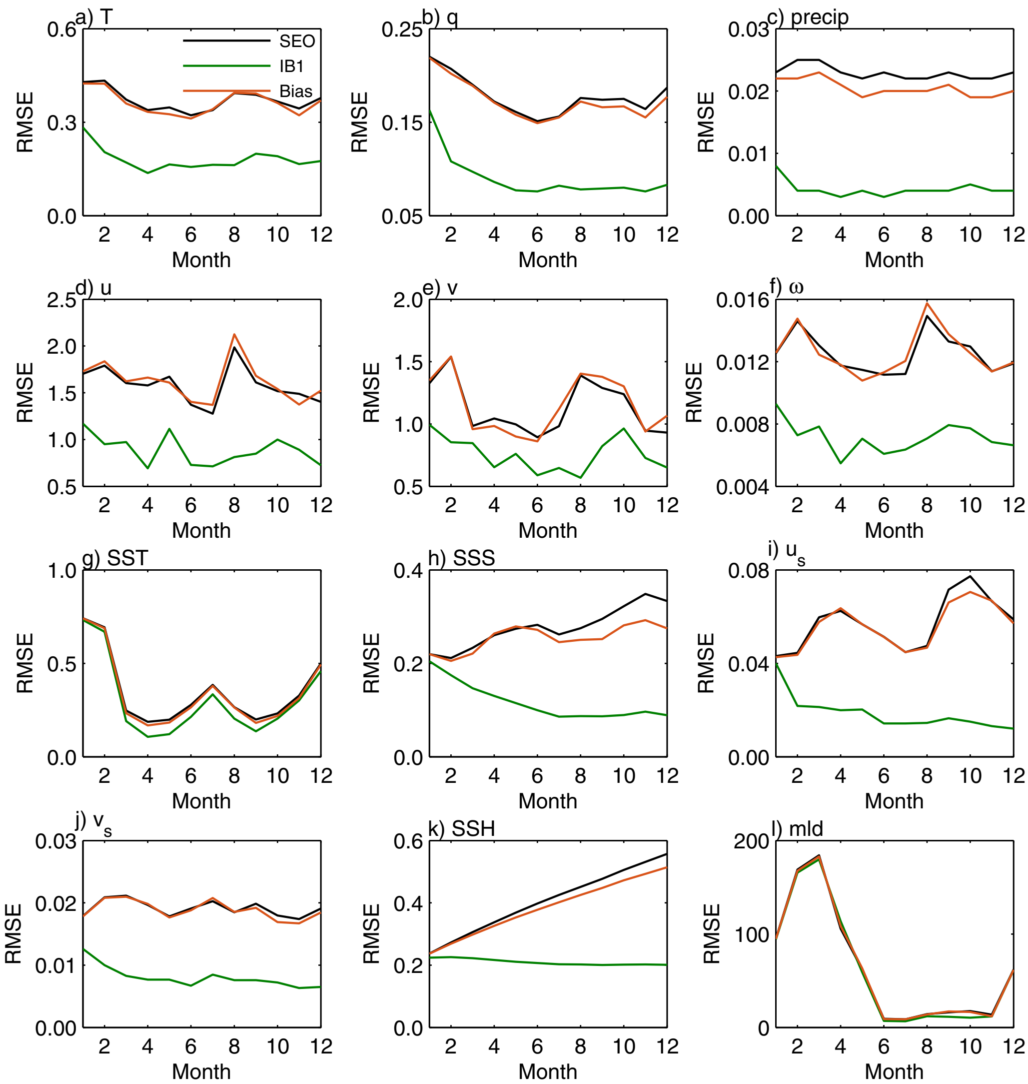

Figure 8. Time evolutions of analysis RMSEs for different model variables (unit for u_s and v_s is m/s) in SEO (black), PE (dark green), and parameter estimation under the imperfect model regime (dark orange) from IB1.

real observations. For simultaneous convection parameter estimation with the ensemble data assimilation method in a CGCM, parameters with greater sensitivities are more likely to converge to the truth of higher physical "reliability" with little "side-effects." Moreover, the final convergence value may depends on the initial parameter biases.

Although not all estimated parameters converge to the truth, multiple parameter estimation is still able to substantially reduce the errors in model states during the analysis period. Figure 8 shows the time evolutions of RMSEs for model variables in SEO and PE from IB1. For both the atmosphere and the ocean, the analysis error is significantly reduced after multiple parameter estimation. The error reduction of mixed layer depth is less obvious compared with other model variables, as in the case of single parameter estimation. Results for IB2 are similar with that of IB1 (supporting information Figure S2). Therefore, under the perfect model regime where all model errors come from the estimated convection parameters, simultaneous parameter estimation can help reduce the analysis error significantly. Furthermore, this improvement seems to be independent of the initial parameter biases.

We further explore the impact of multiple parameter estimation on forecast. For initial parameter bias set IB1, a 1 year forecast is conducted with the estimated parameter values listed in Table 2. The model states at the end of the 6th month of the parameter estimation are used as forecast initial conditions. The forecast

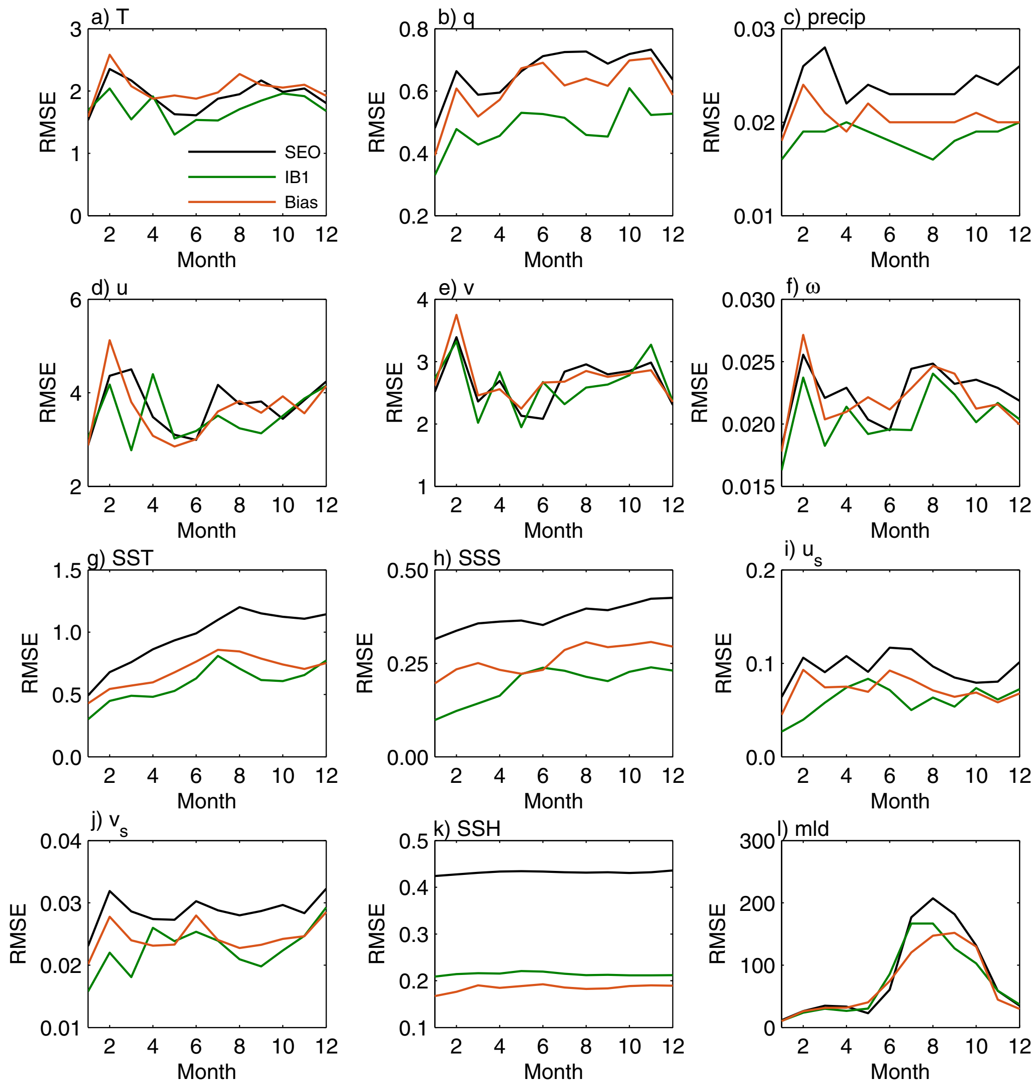

Figure 9. Time evolutions of forecast RMSEs for SEO (black), PE (dark green), and parameter estimation under the imperfect model regime (dark orange) from IB1 (estimating r_d while keeping β, α, A_c, and r_s biased, see section 3.4 for detailed description and refer to Figure 13).

lead time is 1 year. In this way, the SEO forecast using the initially biased parameters and the SEO initial conditions, and the PE forecast using the estimated parameters and the PE initial conditions are compared to demonstrate the influence of convection parameter estimation on the short-term climate forecast. Figure 9 shows the time evolutions of forecast RMSEs for model variables in SEO and PE for IB1. RMSEs of the PE forecast are generally smaller than those of the SEO forecast, indicating that convection parameter estimation helps improve the short-term climate forecast, even though not all the parameters converge perfectly. Results for IB2 are similar with that of IB1 (supporting information Figure S3). This improvement is caused mainly for two reasons: the improved model and the improved initial condition. Through parameter estimation, the model bias associated with the convective process is greatly reduced, providing a better CGCM for the climate forecast. At the same time, the forecast initial condition is improved by incorporating parameters to increase the degree of freedom of tuning.

We have experimented the estimation of convection parameters in a fully coupled CGCM under the perfect model regime. Our evaluations of the parameter convergence, and the associated analysis error and forecast error show that simultaneous estimation of multiple convection parameters in a CGCM can help reduce parametric error, improve climate analysis and forecast. A parameter sensitivity study is necessary because estimations of parameters with greater sensitivities are more likely to have rapid convergences and reliable results.

4.3. Convection Parameter Estimation Under the Imperfect Model Regime

In this section, an imperfect CGCM is used to explore the effect of convection parameter estimation with the ensemble data assimilation method in a situation closer to the real world. Due to model discrepancy arises from our limited understanding of the climate system and approximations in numerical schemes, there are many biases in a CGCM. Some of the biases are unknown or known but cannot be fixed easily. This kind of biases are referred to as "hidden biases" in parameter estimation (Li et al., 2016). Here we explore convection parameter estimation with model discrepancy, i.e., under the imperfect model regime. The hidden convection biases could in principle be any kind of biases, such as parametric biases and structural errors in the parameterization scheme. In this experiment, all five convection parameters are initially biased with IB1 as listed in Table 1. It is assumed that the bias associated with four parameters β, α, A_c, and r_s are unknown or "hidden." The only known adjustable parameter is the precipitation efficiency r_d for the deep convection. So, only r_d is estimated. This simulates the real world case where model discrepancy exists in a CGCM and we tend to tune the most sensitive parameter to try to "nudge" the model toward the observation. The estimation is evaluated in terms of the time evolution of the estimated parameter, analysis error, and forecast error.

In this experiment, the estimated r_d converges rapidly to 0.999 (ensemble mean averaged over the last 3 months) which is 2.5% greater than the truth (Figure 10). This is because all the hidden biases tend to produce a colder and moister atmosphere (supporting information Figures S1e–S1t). As a compensation, therefore, the estimation increases r_d to get a greater precipitation efficiency for the deep convection such that it produces more convective heating (supporting information Figures S1a–S1d). The analysis error is reduced due to the improved estimation of r_d, but not as significantly as in the case of estimating all five convection parameters (Figure 8). In the forecast, the result is more complex. For most model variables, the forecast errors are smaller than those of SEO but greater than those of PE. However, for the atmospheric temperature, the forecast error is even greater than that of SEO. Figure 11 shows the error distributions of the temperature and humidity averaged globally and over the forecast period. Over 400 hPa, a higher estimated precipitation efficiency for deep convection not only compensates for the cold bias but also overcompensates to cause a warm bias there.

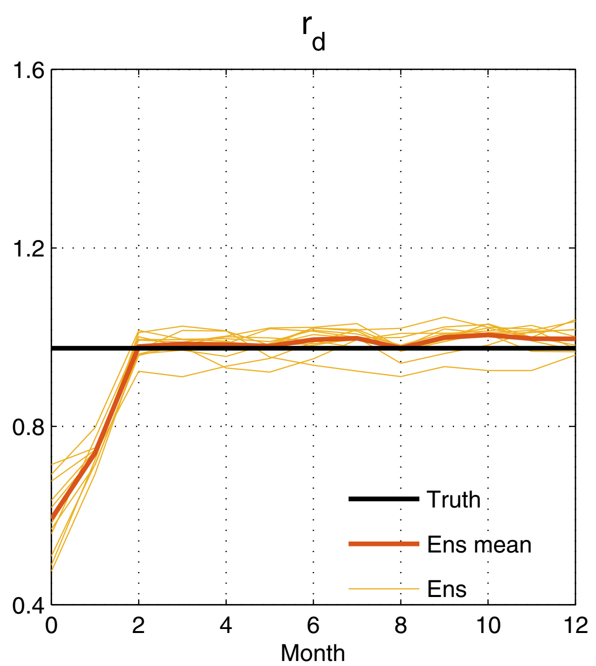

Figure 10. Time evolution of estimated r_d under the imperfect model regime. The black line represents the "truth." The light and dark orange lines represent the estimated ensemble members and their ensemble mean from IB1.

The experimental result under the imperfect model regime reveals the limitation of applying the current data assimilation method when model discrepancy is not accounted for. It is possible to tune parameters in the real world to make the model best fit the observation, but the result could be unpredictable. The estimated parameter may converge to a biased value to compensate for the model discrepancy (Brynjarsdóttir & O'Hagan, 2014). The biased estimation may result in biased physics, giving rise to greater error for some variables in the forecast. Two ways are potentially useful in mitigating this problem. One is to modify equation (5) to include an uncertainty term of model discrepancy. Another is to tune more related parameters, hoping to include key parameters of model discrepancy. However, neither way can fully tackle this problem.

However, parameter estimation result can sometimes serve as a diagnosis of the potential cause of model discrepancy. For example, it is possible that the tuned convection parameter(s) display different values at positive and negative phases of ENSO, indicating that there are hidden biases in the convection parameterization related to ENSO variabilities. Clearly, many challenges remain in convection parameter estimation with the ensemble data assimilation method in a CGCM for the real world application, where model discrepancy could be substantial. The data assimilation should be improved. It is also critically important to combine the deep understanding of physical process in the coupled model with parameter estimation result to achieve a successful real world parameter estimation.

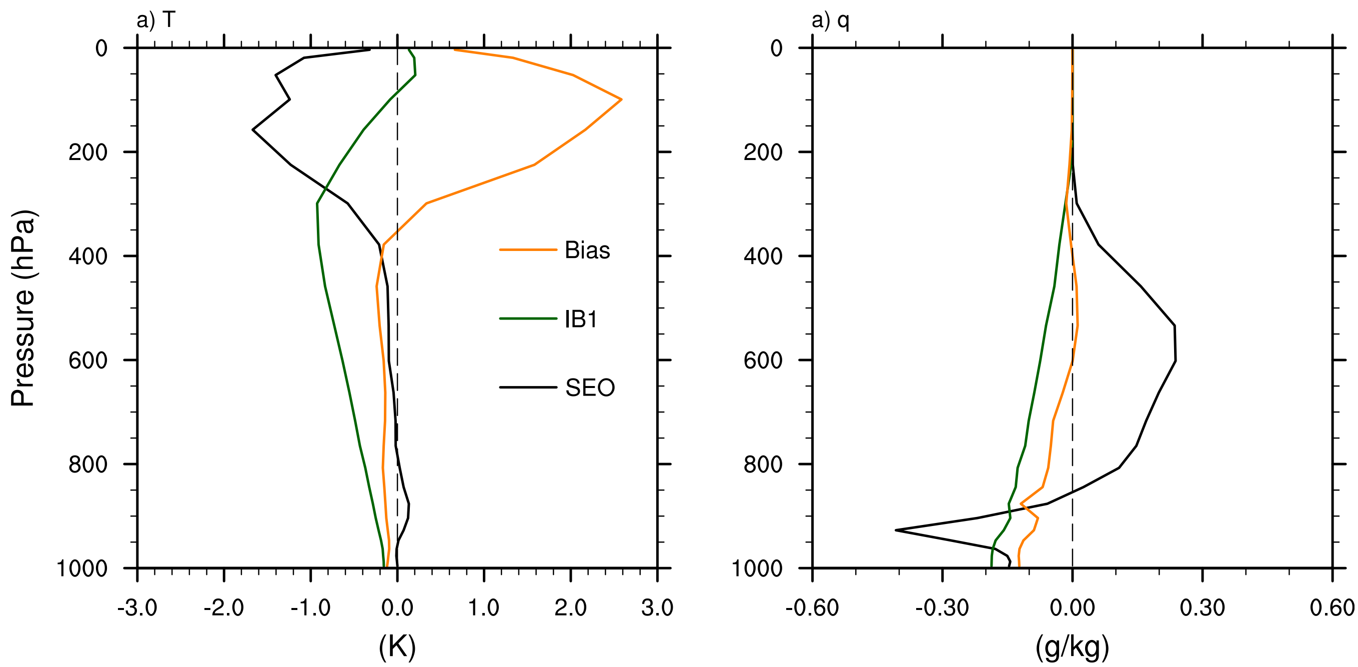

Figure 11. Vertical distributions of forecast errors of global mean temperature and specific humidity for SEO (black), PE (dark green), and parameter estimation under the imperfect model regime (dark orange) from IB1.

5. Conclusions and Discussions

In this study, we explore convection parameter estimation using an ensemble-based coupled data assimilation method in a fully coupled general circulation model (CGCM). The estimation experiments are performed in a twin experiment setting under both perfect and imperfect model regimes. Five important convection parameters in the Relaxed Arakawa-Schubert moist convection scheme (RAS) are estimated: the precipitation efficiencies for the deep and shallow convection (r_d and r_s), the relaxation time scale β, the entrainment parameter α, and the ratio of critical cloud work function to its standard value A_c. Under the perfect model regime, all estimated parameters converge to the truth successfully when estimated individually. The analysis error is significantly reduced by parameter estimation. When the parameters are estimated simultaneously, four parameters converge while the least sensitive parameter fails to converge after an entire year. The convergence of the estimated parameter is closely related to the parameter sensitivity. Parameters with greater sensitivities are more likely to have fast convergence and reliable estimation results. After parameter estimation, the initial parameter bias is reduced. The analysis and short-term forecast are both improved. In the imperfect model regime, the estimated parameter converges to a value 2.5% greater than the truth as a compensation of model discrepancy. The analysis and forecast errors are reduced. The error reduction comes from two aspects. One is the improved model due to the reduced parametric bias. The other is that parameter estimation increases the degree of freedom in the tuning process, leading to a better initial condition.

Some of our findings provide insights to convection parameter tuning for a CGCM with real observations. First, a sensitivity study is necessary to help select tunable parameters. Parameters with greater sensitivities are preferable for tuning purposes because they are more likely to rapidly converge to physically reliable results. In addition, tuning these highly sensitive parameters leads to more improvement in climate analyses and predictions than tuning of less sensitive ones, because the highly sensitive parameters have better-defined relationships with observable model states. Consistent in all our experiments, the estimation of the most sensitive parameter r_d is always the most stable and closest to the truth. The ratio of error reduction to parameter bias reduction of r_d is also the highest among all parameters in the single parameter estimation experiment.

Second, in the case of multiple parameter estimation, the estimation result must be carefully examined due to the compensation effect. This reveals a major challenge to parameter estimation. In our imperfect model experiment, the value of the only estimated deep convection precipitation efficiency parameter is increased to compensate for the hidden bias. In the forecast, the estimated parameter overcompensates and causes too much convective heating in the upper atmosphere. In fact, in the real world, this behavior itself is an indication that hidden bias exist and other convection parameters may also need to be tuned. Researchers should be careful in interpreting and applying these results. With model discrepancy, the estimation may be biased.

Third, tropical observations are important in tuning convection parameters because there are more convection in the tropical regions and hence better-defined parameter-state relationships in these regions.

Fourth, convection parameter estimation is able to constrain the drift of the ocean in the CGCM. However, compared to convection parameter estimation in the AGCM, it takes much longer time for convection parameters to converge in the CGCM where the ocean component is incorporated.

Much further research is needed to explore convection parameter estimation in CGCMs. First, our experiments can be extended to a much longer time scale to fully explore the influence of convection parameter estimation on the ocean and the entire coupled climatology. With longer time scales, the time evolution of the parameter sensitivity can reveal the saturated influence of each parameter on the climate system. The saturated time scale of the parameter sensitivity could also provide guidance for choosing the optimal time scale of the parameter updating interval (Liu et al., 2017). In addition, the estimated convection parameters can be examined in a longer forecast in terms of important climate variabilities such as ENSO with a period of 2–7 years. In this case, CGCMs with a lower resolution but faster integration speed may be more suitable. In a longer climate regime, the role of the ocean in estimating convection parameters can be systematically studied. The major difference between a CGCM and an uncoupled AGCM is whether the role of the ocean is considered. It is obvious that convection parameters have a great impact on the oceanic simulation (Jang et al., 2013; Kim et al., 2011), and the ocean in turn influences the frequency, intensity, and location of convection (Johnson & Xie, 2010; Sabin et al., 2013; Woolnough et al., 2000). Therefore, it is important to include the ocean component when long-term climate simulation is designed. In our work, the ocean is "dynamically coupled" to the convection through air-sea coupling in the model. It is possible that good statistical relationships exist in the cross-covariance between convection parameters and oceanic states on a longer time scale. Recent studies also found that incorporating the air-sea cross-covariance in the coupled data assimilation can improve the initialization and prediction of ENSO (Zheng & Zhu, 2010), which provides insights in coupled data assimilation and improving oceanic simulation through convection parameter estimation.

Second, convection parameter estimation in a CGCM using real observations with the ensemble data assimilation method needs to be studied. The estimation method needs to be improved substantially to account for model discrepancy. And albeit the improvement, it should always be noted that one can never get the "right" parameter value due to model discrepancy. Researchers should be careful in using the estimation result. In addition, for parameter estimation with real world observations, it is possible that some convection parameters may have difficulty converging within valid physical ranges (Schirber et al., 2013). Some parameters may display periodic features corresponding to different phases of the climate variability, vary stochastically (Hansen & Penland, 2007) or geographically (Wu et al., 2012, 2013). Some of these patterns may provide useful information and even help discover other model error sources. It is also possible to apply the estimated time-varying or geographic-varying parameter patterns in climate simulations to help mitigate some model biases and improve the CGCM.

Acknowledgments

The major funding of this research comes from the CMOST National Key Research & Development projects 2017YFC1404100, 2017YFC1404104 and the Chinese National Natural Science Foundation of China (41775100). This research is also sponsored by Chinese 2017YFA0603801, NSFC41630527, China Postdoctoral Science Foundation 2016M601103, and China Scholarship Council (awarded to Shan Li for 2 years' study at GFDL/NOAA) and US NSF 1656907. Data used in producing the figures and analyses in this work are available through the link https://pan.baidu.com/s/1q7_BioI0vavUV1fgApj1DQ (password: sbux) and sending a written request to the corresponding author (Shaoqing Zhang, szhang@ouc.edu.cn).

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