Strongly Coupled Data Assimilation Using Leading Averaged Coupled Covariance (LACC). Part II: CGCM Experiments*

FEIYU LU

Nelson Institute Center for Climatic Research, and Department of Atmospheric and Oceanic Sciences, University of Wisconsin–Madison, Madison, Wisconsin

ZHENGYU LIU

Nelson Institute Center for Climatic Research, and Department of Atmospheric and Oceanic Sciences, University of Wisconsin–Madison, Madison, Wisconsin, and Laboratory for Climate, Ocean and Atmosphere Studies, Peking University, Beijing, China

SHAOQING ZHANG

NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey

YUN LIU

Nelson Institute Center for Climatic Research, and Department of Atmospheric and Oceanic Sciences, University of Wisconsin–Madison, Madison, Wisconsin

ROBERT JACOB

Mathematics and Computer Science Division, Argonne National Laboratory, Argonne, Illinois

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ABSTRACT

This paper uses a fully coupled general circulation model (CGCM) to study the leading averaged coupled covariance (LACC) method in a strongly coupled data assimilation (SCDA) system. The previous study in a simple coupled climate model has shown that, by calculating the coupled covariance using the leading averaged atmospheric states, the LACC method enhances the signal-to-noise ratio and improves the analysis quality of the slow model component compared to both the traditional weakly coupled data assimilation without cross-component adjustments (WCDA) and the regular SCDA using the simultaneous coupled covariance (SimCC).

Here in Part II, the LACC method is tested with a CGCM in a perfect-model framework. By adding the observational adjustments from the low-level atmosphere temperature to the sea surface temperature (SST), the SCDA using LACC significantly reduces the SST error compared to WCDA over the globe; it also improves from the SCDA using SimCC, which performs better than the WCDA only in the deep tropics. The improvement in SST analysis is a result of the enhanced signal-to-noise ratio in the LACC method, especially in the extratropical regions. The improved SST analysis also benefits the subsurface ocean temperature and low-level atmosphere temperature analyses through dynamic and statistical processes.

1. Introduction

Coupled data assimilation (CDA) has shown great promise as a capable and comprehensive strategy for generating climate reanalyses and initial conditions for prediction in the coupled climate system (Zhang et al.

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Corresponding author address: Feiyu Lu, Center for Climatic Research, 1225 W. Dayton St., Madison, WI 53706.
E-mail: flu7@wisc.edu

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2007; Sugiura et al. 2008; Saha et al. 2010; Dee et al. 2011). A CDA system assimilates observations into one or more model components and allows the exchange of information among different components, either dynamically through model fluxes or statistically through the updating algorithm. Recently, a coupled forecast model has been implemented into the reanalysis process at the National Centers for Environmental Prediction (NCEP; Saha et al. 2010). The exchange of information in a CDA system has been suggested to produce more balanced interfaces and better adjusted fluxes between model components, resulting in improved coupled state estimates as well as initialization for coupled model predictions (Zhang et al. 2005, 2007; Sugiura et al. 2008; Zhang 2011).

Most CDA systems so far, however, have been using the ''weakly'' coupled data assimilation (WCDA), in which the first-guess forecast states come from the coupled model, but the observation innovations are applied in each component separately. Therefore, the exchange of information is accomplished only dynamically through cross-component fluxes during the forecast stage. In contrast, ''strongly'' coupled data assimilation (SCDA) uses the coupled error covariance between variables from different model components (hereafter cross covariance for short) and applies cross-component analysis increments (Liu et al. 2013; Han et al. 2013). As a result, the coupling process is achieved not only dynamically during the forecast stage, but also statistically during the analysis stage. Since the observational information is directly projected from one model component to another in SCDA, the coupled adjustments are instantaneous, more comprehensive, and, therefore, could produce more balanced analyses than in WCDA. The additional cross-component update in the SCDA will be referred to as cross update for short.

So far, exploration of the SCDA has been limited to conceptual models (e.g., Liu et al. 2013; Han et al. 2013) with conflicting results. In a simple coupled model consisting of a chaotic atmosphere and a slow ocean, Liu et al. (2013) reported that the SCDA improves the analysis quality in a perfect-model framework compared to the WCDA with a modest ensemble size of 20. In contrast, in a biased climate model of similar complexity, Han et al. (2013) found that the cross update may introduce greater noise than signal and, therefore, deteriorate the quality of model analyses unless the ensemble size increases to about 10^4. In these previous studies of the SCDA, the simultaneous coupled covariance (SimCC) is always used for the cross update. Because ofthe great mismatch of time scales between different components, it tends to be difficult to estimate the simultaneous cross covariance, which is usually small and dominated by the noise from the fast variable (Frankignoul et al. 1998; Han et al. 2013).

In Part I of this study (Lu et al. 2015, hereafter Part I), we proposed the leading averaged coupled covariance (LACC) method for the SCDA. In a typical extratropical coupled ocean–atmosphere system, the cross correlation shows a strong asymmetry with the maximum correlation occurring when the atmosphere leads the ocean by about the decorrelation time of the atmosphere (Hasselmann 1976; Barsugli and Battisti 1998). The LACC method utilizes this asymmetric coupling dynamics by using the leading forecasts and observations of the fast atmospheric variables. This leads to increased cross correlation and enhanced signal-to-noise ratio during cross update (Part I). To further reduce the sampling error, the leading atmospheric states are averaged over time to produce even higher correlations (Dirren and Hakim 2005; Huntley and Hakim 2010; Tardif et al. 2014). In the simple coupled model of Part I, the LACC method significantly increases the cross correlation for the cross update and reduces the analysis error of the slow model variable compared to both the WCDA and the regular SCDA using SimCC.

As an extension of Part I, here we will test SCDA with the LACC method in a CGCM and a perfect-model framework, and compare the results with the WCDA and the SCDA using SimCC. The SCDA in a CGCM has been uncharted territory so far, and to date, we are aware of no publications of successful SCDA in a CGCM. Our study shows that LACC can be successfully applied to a CGCM, and significantly improve the ocean temperature analysis using atmospheric observations compared to WCDA and SimCC. This paper is organized as follows. Section 2 describes the CGCM [Fast Ocean Atmosphere Model, version 1.5 (FOAM)], our SCDA system, and the LACC method. The experiments and results are reported in section 3. More specifically, section 3a shows the benchmark WCDA experiments, section 3b shows the SCDA experiments with the LACC method, and section 3c shows a detailed comparison between the SCDA using SimCC and LACC. Section 4 discusses the results and summarizes the paper.

2. Model and methodology

a. FOAM

The CGCM we used is FOAM (version 1.5). FOAM is a fully coupled global atmosphere–ocean model with parallel implementation (Jacob 1997). The atmosphere component [Parallel Community Climate Model, version 3–University of Wisconsin model (PCCM3-UW; Drake et al. (1995)] is a spectral model with a R15 horizontal resolution (equivalent to $7.5° \times 4.5°$) and 18 vertical levels. The ocean component (OM3) is based on the Modular Ocean Model (MOM; Cox 1984) created by the Geophysical Fluid Dynamics Laboratory (GFDL).

It has a horizontal resolution of 2.8° × 1.4° and a z coordinate with 24 vertical levels. The land surface and sea ice models are based on those of Community Climate Model, version 2 (CCM2; Hack et al. 1993). Without flux adjustment, a 6000-model-yr simulation of FOAM shows no apparent drift in tropical climate (Liu et al. 2007a). FOAM is able to capture most major features of the observed global climatology as in some more advanced CGCMs. It also shows reasonable climate variability in regions such as the tropics (Liu et al. 2000, 2004), the North Pacific (Wu et al. 2003; Liu et al. 2007b), and the North Atlantic (Wu and Liu 2005).

b. Data assimilation scheme

Ensemble-based analysis techniques such as the ensemble Kalman filter (EnKF; Evensen 1994; Houtekamer and Mitchell 1998) and the ensemble adjustment Kalman filter (EAKF; Anderson 2001, 2003) have emerged as viable options for CDA systems in complex systems such as a CGCM. EAKF, in particular, was used by Zhang et al. (2007) to develop the first ensemble-based CDA system in a fully coupled general circulation model. Recently with our collaborators, we have set up a CDA system in FOAM using EAKF and completed the first parameter estimation experiment through ensemble-based data assimilation in a CGCM (Liu et al. 2014a,b). Although EnKF is used in Part I for better illustration of the algorithm of LACC, in Part II here, we will use the existing EAKF scheme in FOAM. A detailed description of the EAKF algorithm can be found in Anderson (2003) or Zhang et al. (2007).

c. The observing system

The output of a 20-yr control simulation is considered the "truth." The observations are constructed by adding Gaussian white noise onto the truth. The available observations are monthly mean sea surface temperature (SST) with an error scale (standard deviation) of 1 K,[1] and daily mean atmosphere temperature (T) and wind components (U, V) with error scales of 1 K and 1 m s^{-1}, respectively. These arbitrary observational errors and frequencies represent typical conditions for such observed variables (Liu et al. 2014a). Observations are taken at all grid points of their corresponding component, so the projection between observation and model spaces is not required. The experiments are repeated with multiple 20-yr control simulations starting from different initial conditions and the results prove to be consistent. In section 3, we only show one set of the experiments.

In the real world, time-averaged observations are usually generated by averaging instantaneous observations rather than independently observed. However, the history file (output) of FOAM is limited to time-averaged model states, so our constructed observations are also time-averaged quantities. All the major conclusions of this paper, we believe, would remain valid if each daily mean atmospheric observation is replaced by the average of four 6-h instantaneous observations and each monthly mean SST observation is replaced by the average of 30 daily instantaneous observations.

d. The WCDA system

To test the impact of the cross update, we will use a WCDA system as the benchmark. In the WCDA system, SST observations are assimilated into the ocean for ocean data assimilation (ODA) and (T, U, V) observations into the atmosphere for atmosphere data assimilation (ADA). The WCDA system uses certain covariances within each component, such as that between temperature and salinity in the ocean, and those between T and (U, V) in the atmosphere. The update between T and (U, V) is only one way, using the observation innovations of T to update (U, V). This type of CDA is still considered weakly coupled because no cross covariance is used. Previous research showed that these in-component covariances could improve the quality of model estimates significantly (Zhang et al. 2007). Different from the cross covariance, simultaneous in-component covariances usually work well because the variables in the same component have comparable time scales and high simultaneous correlations.

Covariance localization is applied in both ADA and ODA with the widely used filter from Gaspari and Cohn (1999), and the horizontal influence radius is set at 1000 km for both. Vertically, each SST observation affects the ocean temperature and salinity down to the depth of 300 m (eight levels) and each cluster of (T, U, V) observations affects three levels both above and below the observed level. For simplicity, the ODA is restricted between 60°S and 60°N and ADA is restricted between 70°S and 70°N. The ADA is also limited to the troposphere.

e. Ensemble configuration

All experiments in this paper use an ensemble size of 16, typical for a CGCM in practice (Zhang et al. 2007; Liu et al. 2014a). Ensemble spread is well maintained

[1] To test the robustness as well as the sensitivity of the LACC method to the quality of ODA, all experiments are also executed with a smaller SST error of 0.2 K. The LACC method is still superior to the WCDA and SimCC, while the optimal averaging length does decreases from 7 to 3–5 days. A similar relation is also found in Part I, where better ODA reduces the optimal averaging length of the LACC method.

and comparable to analysis error in the perfect-model WCDA experiments, so covariance inflation is not applied to ADA and ODA. However, considering the greater noise from sampling the cross covariance, a relax-to-prior scheme (Zhang et al. 2004) is used for the cross update with a relaxation factor of 0.5. In our sensitivity tests, the results are insensitive to the relaxation factor in the range of 0.3–0.8 (not shown).

The initial ensemble consists of the restart files within eight years before and after the start of the truth. For example, if the 20-yr truth starts from model year 10, the initial ensemble for the data assimilation experiments consists of initial conditions at the start of model years 2–9 and 11–18, a total of 16.

f. Cross update and the LACC method

To establish SCDA, cross update between the atmosphere and ocean is added into the WCDA system. As a first attempt of SCDA in a CGCM, we use the coupled covariance between low-level atmosphere temperatures and the SST. More specifically, observations of atmosphere temperature in the bottom four levels (from the surface to about 850 hPa) are used to directly adjust the SST. The cross update is applied at all atmospheric grid points between 50°S and 50°N that have underlying ocean grid points. To simplify the notation, we will use the atmosphere surface temperature (T_s) as a representative in the following description of the cross update.

In Part I, the LACC method was applied to a simple coupled model with the EnKF scheme (Burgers et al. 1998). A WCDA system, including both ADA and ODA, is set up in the simple model. By adding the cross update from the atmosphere to the ocean, the SCDA with both simultaneous observations (SimCC) and time-averaged leading observations (LACC) were found to perform better than the WCDA. However, the LACC method increases the cross correlations by using leading averaged atmospheric states, which further improves the analysis of the variables from the slow component compared to the SimCC method.

The observation and the forecast are usually assumed independent in data assimilation systems. In an SCDA system with the LACC method, however, the atmospheric observations used for cross update have been assimilated into the coupled model at previous ADA steps. As a result, the current model forecast inherits the observed information from previous analysis and, therefore, will be correlated with the leading observations. There are two ways to deal with the additional covariances caused by the LACC method in the framework of EnKF. The first (complete LACC) is to use the general formula of the Kalman gain function that is derived without the assumption of independence between any pair of variables (see the appendix in Part I). The additional covariances can be explicitly estimated from a previously perturbed observation ensemble and the current forecast ensemble. The second way (reperturbed LACC) is to neglect such covariances by implementing a reperturbation on the leading averaged atmospheric observations. Both approaches work well in the simple model, but the reperturbed LACC is preferred because of its simpler implementation and faster computing time (Part I).

Here, LACC is applied to the EAKF. Unlike the EnKF with perturbed observations, there is no perturbed observation ensemble in the EAKF, so the covariance between observation and forecast cannot be calculated explicitly as the complete LACC in Part I. Besides, even if the EnKF is used in our CDA system, the complete LACC method requires the storage of the perturbed ensemble of every observation that will be averaged by the LACC method. Such requirements would command prohibitively large memory space for a CGCM. Therefore, we will use the EAKF and treat the observation and forecast as independent quantities, equivalent to the reperturbed LACC method in the EnKF. The incremental analysis update (IAU) procedure (Bloom et al. 1996) is also used in ADA, ODA, and the cross update to minimize initial shocks (e.g., Sugiura et al. 2008; Yin et al. 2011; Rienecker et al. 2011). For example, the analysis increments in ADA are divided by the number of atmosphere steps in each ADA cycle, and then evenly added onto the atmospheric states at every step in the next ADA cycle. Assuming an averaging length of τ days in this study, our SCDA system with the LACC method is executed as follows:

- (i) ADA is performed at the end of every day based on the observation and forecast of daily mean (T, U, V) states.
- (ii) The forecast of daily mean T_s (T_s^f) is accumulated for every ensemble member.
- (iii) At the end of every τ days, the τ-day-averaged forecast of T_s ($\overline{T_s^f}$) is calculated from the accumulations and its data are transferred to the ocean model. The accumulations are then reset to zero for the next cross-update cycle.
- (iv) The ocean component reads in the atmospheric observations of daily mean T_s (T_s^o) for the previous τ days and calculates the τ-day-averaged observation $\overline{T_s^o}$.
- (v) The observation innovations for the cross update are calculated based on $\overline{T_s^o}$ and the ensemble of $\overline{T_s^f}$. According to the EAKF algorithm from Anderson

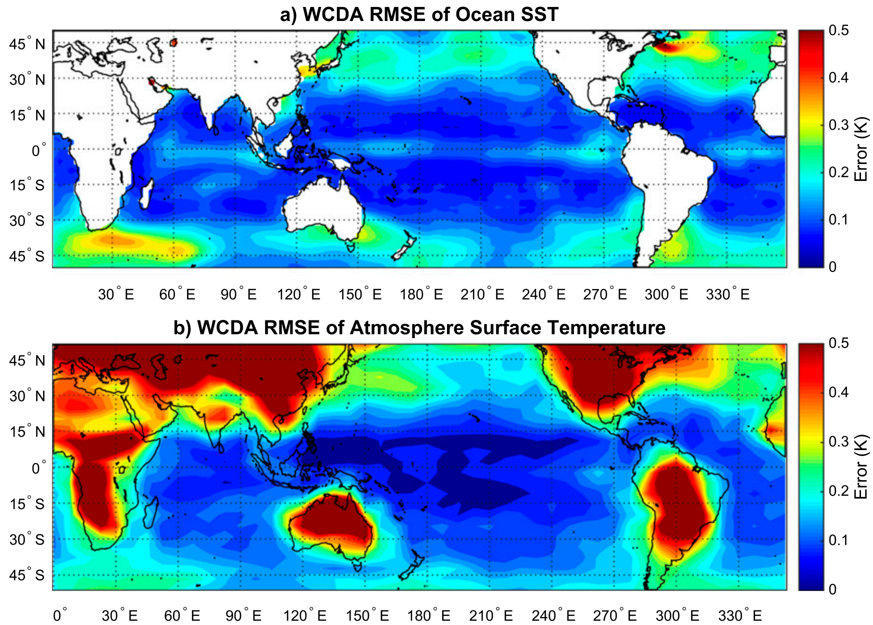

FIG. 1. RMSE of monthly (a) SST and (b) T_s from the WCDA experiment.

(2003), the innovations from the ensemble mean and perturbations are calculated separately [e.g., Eqs. (2)–(5) in Zhang et al. (2007)].

(vi) The observation innovations are then distributed to the SST field through the covariance between the ensemble of $\overline{T_s^f}$ and the ensemble of instantaneous SST states.

(vii) ODA assimilates monthly mean SST observations and is performed at the end of every month. When ODA and the cross update happen at the same time, they calculate and apply their increments separately using the same SST forecast (prior).

These steps follow the so-called chunk scheme in Part I, that is, the cross update is executed every τ days for an averaging length of τ days. In calculating the cross covariance for the cross update, the instantaneous SST state, instead of the averaged one, is used because averaging the slow SST does not significantly change the cross correlation in FOAM. It may be helpful to use the time-averaged SST states in models with diurnal cycles or other high-frequency variability.

3. Experiments and results

a. Benchmark experiment and cross correlation

We start with the WCDA system to provide the benchmark. The experiments are evaluated by the root-mean-square error (RMSE) of the monthly ensemble mean from the truth:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\overline{X_i} - X_i^t)^2},$$

where $\overline{X_i}$ is the ensemble mean of monthly mean output of the ith month, X_i^t is the true monthly mean value, and N is the number of months. The monthly output averages the model states at all time steps, and they are analyses because the IAU adds small increments on the model states at every time step. Similar to Part I, the monthly values are used to conduct a fair comparison between the WCDA, the SimCC, and the LACC method with different averaging lengths. In real-world situations, the truth is unknown and is usually substituted for by observations.

Figure 1 shows the RMSE of SST and T_s from the WCDA experiment. Both SST and T_s are well constrained by the WCDA system across the globe. Larger RMSE of SST is found in a few midlatitude regions with high natural variability, such as the North Atlantic and the Southern Ocean. Over the ocean, RMSE of T_s is comparable to that of the underlying SST. There is no data assimilation for any variables in the land model, so T_s over the land is affected by poor boundary conditions from the land model and the RMSE is relatively large. A detailed figure of T_s analysis as Fig. 1b is important because the performance of the WCDA system provides a baseline before the addition of the cross update. Compared with an ensemble of control simulations without data assimilation, RMSEs of both SST and T_s at every grid point are greatly reduced. For example, in the

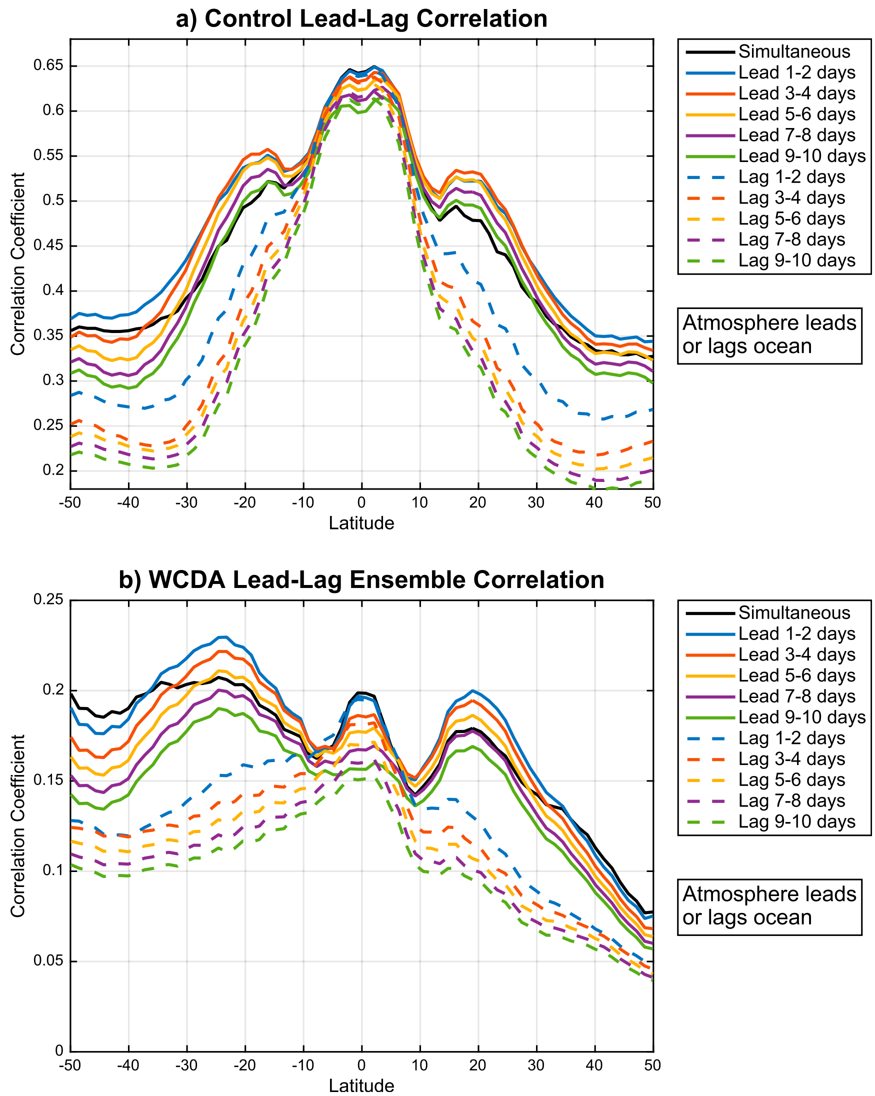

FIG. 2. Zonal-mean lead–lag correlations between daily mean SST and T_s from (a) single-member control simulations and (b) a 16-member WCDA experiment. The control correlations in (a) are the average of correlations calculated from 16 single-member 5-yr control simulations. The WCDA correlations in (b) are calculated from a 16-member 5-yr WCDA experiment.

ensemble of control simulations, the RMSE of both SST and T_s over the ocean ranges from about 1 K in the tropics to 2–3 K in the midlatitudes.

Before implementing cross update, we will first examine the cross correlation between daily mean SST and T_s in FOAM. We should note that the cross update uses instantaneous SST instead of daily mean SST. However, the correlations should be very close because of the slow time scale of the model ocean. Both lead–lag and leading averaged correlations will be estimated. As in Part I, the cross correlations can be obtained from two types of experiments. The first type is single-member control simulations, which show the correlation between SST and T_s associated with their natural variability. The second type is a multiple-member WCDA experiment, which captures the spinup correlation between SST and T_s during the initial error growth. Every correlation from the WCDA experiment is the time average of the instantaneous sample correlation between daily mean SST and T_s ensembles. The first approach is simpler and straightforward using the output of model control simulations. In comparison, the second approach requires the setup of a WCDA system. However, as shown both here and in Part I, the WCDA substantially alters the structure of the cross correlations, and more importantly, the cross correlations from WCDA are

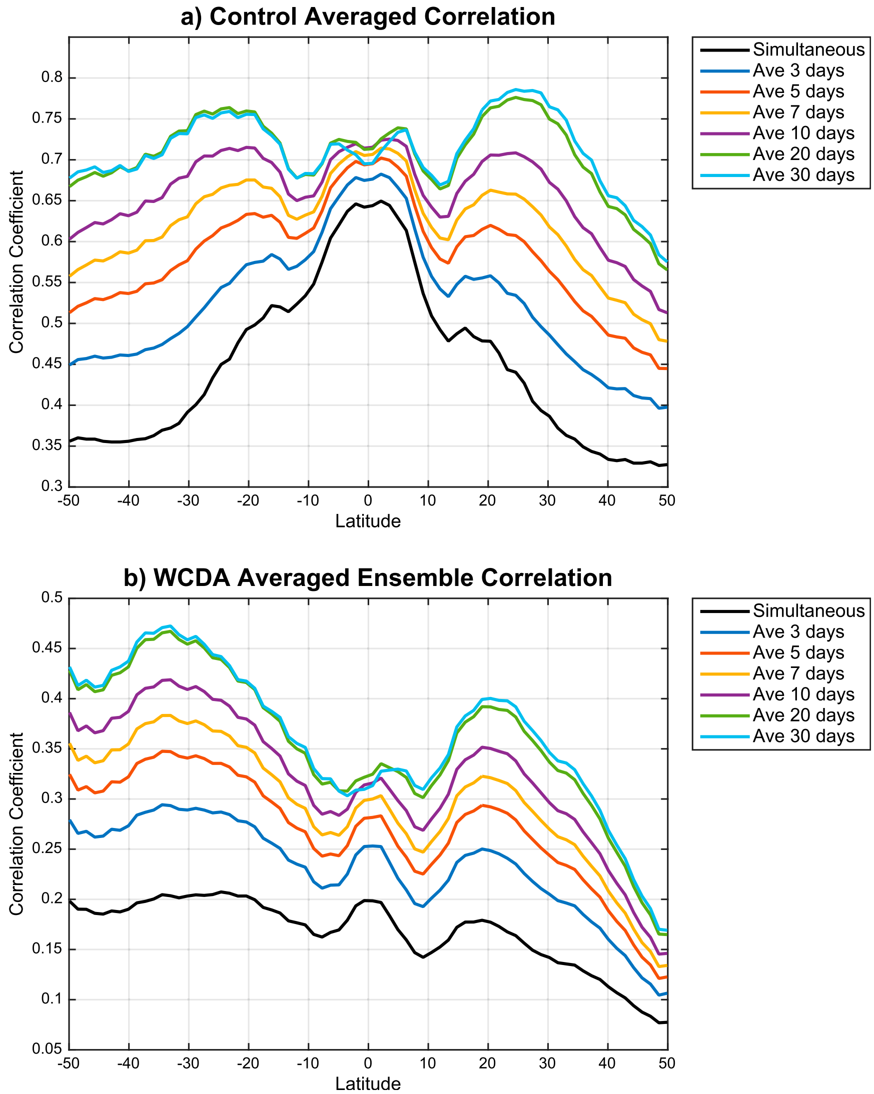

FIG. 3. Zonal-mean correlations between daily mean SST and leading averaged T_s from (a) single-member control simulations and (b) a 16-member WCDA experiment. Figure 3 uses the same model data as in Fig. 2.

direct estimations of those used in the cross update of the SCDA.

The zonal-mean lead–lag correlations from both the control simulation and the WCDA experiment are plotted in Fig. 2. The correlation at ocean grid point (i, j) is estimated between the local SST and the spatial average of T_s at atmosphere grid points within 500 km of the location of (i, j). This accounts for the coarser horizontal resolution of the atmosphere component, as well as the covariance localization used by the cross update. Because of the huge size of daily output files, the correlations in Figs. 2 and 3 are estimated from 5-yr outputs, and the results in each plot are validated by additional experiments with different initial conditions or observations.

The different structures of the ocean–atmosphere cross correlation at different latitudes are shown by the control simulation in Fig. 2a. In the deep tropics (5°S and 5°N), the simultaneous correlation (black) is the greatest, while both the leading (solid lines) and lagging (dashed lines) correlations decrease slowly and almost symmetrically with the leading and lagging times. This symmetric structure reflects the dominant role of ocean dynamics on SST and a strong oceanic feedback on the atmospheric temperature in the tropical system in addition to the atmospheric forcing on the ocean. In comparison, the lead–lag structure is strongly asymmetric outside of 5°S–5°N: the maximum correlation occurs when T_s leads SST by 3–4 days for 5°–30°N

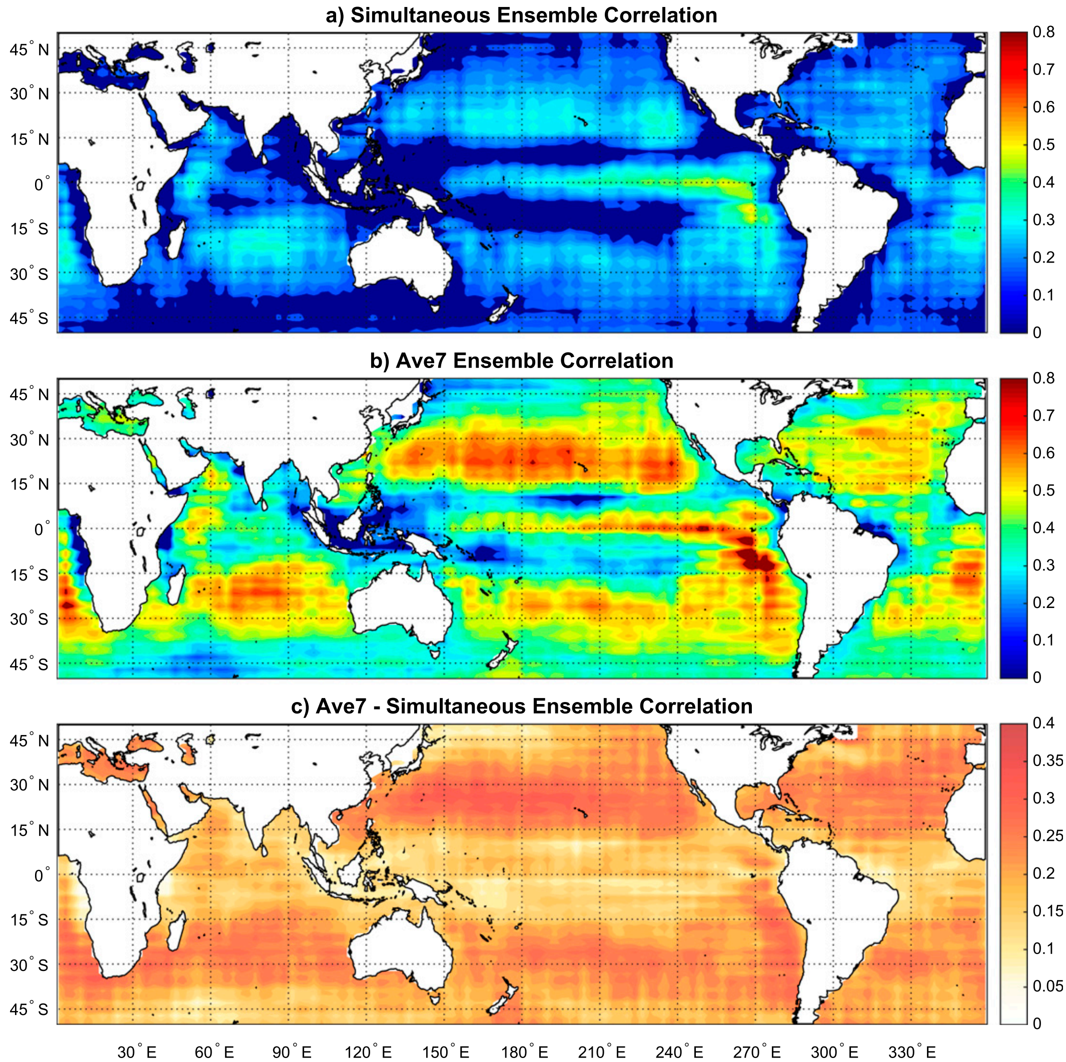

FIG. 4. Time average of the sample ensemble correlation between (a) daily mean SST and same-day T_s and (b) daily mean SST and 7-day-averaged leading T_s. (c) The difference between (b) and (a).

and 5°–25°S, or by 1–2 days for 30°–50°N and 25°–50°S; the leading correlation up to 10 days exceeds the simultaneous value for some latitudes; and the correlation declines rapidly once T_s lags SST. This asymmetric structure reflects the dominant influence of atmospheric internal variability on not only atmospheric temperature variability, but also the SST variability through forcing, as typical in extratropical atmosphere-driven coupled system (Hasselmann 1976; Frankignoul et al. 1998; Barsugli and Battisti 1998).

The asymmetry in the lead–lag correlation is qualitatively maintained in the WCDA experiment in Fig. 2b, although the magnitude is reduced and the structure is altered. The assimilation in the WCDA experiment reduces the ensemble spread and alters the ensemble deviations at every analysis step, so Fig. 2b displays the correlations that result from the initial error growth. Compared to Fig. 2a, the correlations at all latitudes are significantly smaller in Fig. 2b, and the maximum leading correlations occur exclusively when T_s leads SST by 1–2 days (solid blue line). The changes of the correlations from the control in Fig. 2a to the WCDA in Fig. 2b are consistent with those in Part I. Figure 2 may suggest that the optimal averaging length of the LACC method should include the leading days that show significant correlations, or more specifically, those that have correlations higher than the simultaneous correlation. This seems to be the case for many latitudes in this study, since, as will be seen later, the optimal length is 7 days, which uses the average from simultaneous to 6-day leading atmosphere states. However, this criterion for the optimal average may

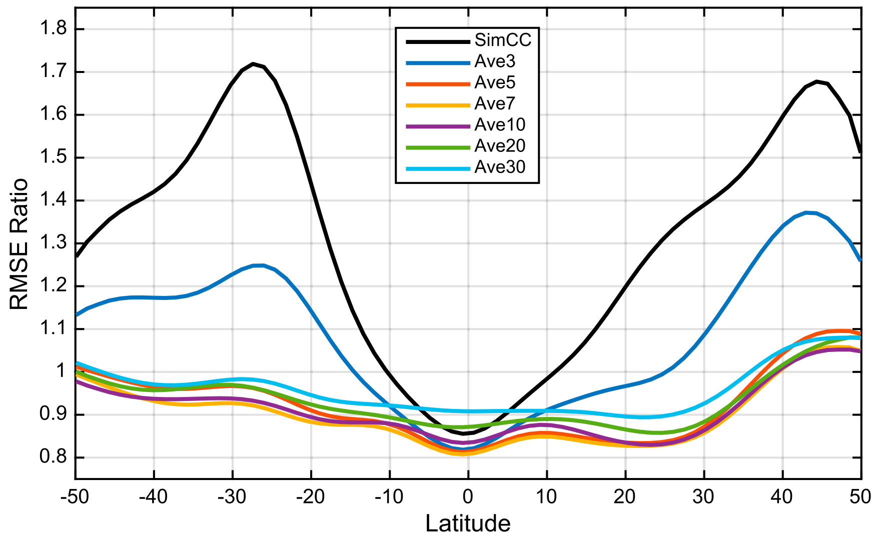

FIG. 5. Zonal-mean RMSE of monthly SST from the SimCC experiment and the LACC experiments with different averaging lengths, normalized by the WCDA experiment.

not be applicable to more general cases. Further studies are needed with different system configurations or even other CGCMs.

To apply the LACC method, the cross correlations between SST and time-averaged leading T_s are also estimated from the output of the control simulation (Fig. 3a) and the WCDA experiment (Fig. 3b). "Simultaneous" indicates the same-day cross correlation as in Fig. 2, and "AveX" means that cross correlation is calculated between SST and the average of X daily mean T_s from $X - 1$ days ago to the current one. Same as Fig. 2, all the time-averaged leading T_s states are also spatial averages in order to account for the coarser atmospheric resolution and the covariance localization. The leading averaged correlations initially increase with the averaging length for all latitudes, and the increases are more noteworthy outside the tropics because of the higher correlations when T_s leads SST in Fig. 2. The correlations plateau when the averaging length reaches 10 days in the deep tropics and 20–30 days in the midlatitudes. As in Fig. 2, the correlations from the WCDA experiment are smaller than those from the control simulation across all latitudes and averaging lengths. Together, Figs. 2 and 3 show that the simple coupled model in Part I captures some important physical and statistical features of the coupled ocean–atmosphere system in a complex CGCM like FOAM, demonstrating the potential application of LACC method to a SCDA system in a CGCM.

Figure 4 shows the spatial distribution of two leading averaged cross correlations from the WCDA experiment, the simultaneous and the Ave7, along with the difference between the two distributions. In Fig. 4a, the simultaneous correlation is small except in the eastern tropical Pacific, which reflects the slow ENSO variability and its strong impact on the atmosphere above. By averaging the 7-day leading T_s (Fig. 4b), the cross correlation is significantly enhanced across the displayed domain. The increases from simultaneous to Ave7 (Fig. 4c) are the most notable in the extratropics, while most tropical locations show much less increase. We should note that, on purpose, all the correlations shown in Figs. 2, 3, and 4 are estimations of the coupled correlations from the control simulation or the WCDA experiment instead of the exact correlations calculated during the cross update of the SCDA experiment. The ability to estimate these correlations from the control or WCDA provides valuable information about how much the SCDA and LACC method would improve the analysis before their implementation.

b. LACC experiments

Now we apply the LACC method to the cross update that assimilates the observations of low-level atmosphere temperature into the SST. We will show that, although the direct SCDA using simultaneous cross covariance (SimCC) fails to improve upon the WCDA, the SCDA with the LACC method can indeed improve upon the WCDA significantly. Figure 5 shows a summary of the performance of the SimCC and the LACC method with different averaging lengths, normalized by the WCDA. Following the notation of Fig. 3, "AveX" means that cross update is done every X days with the X-day-averaged leading T_s. The SimCC method performs poorly across all latitudes except for the deep tropics between 10°S and 10°N, where the simultaneous

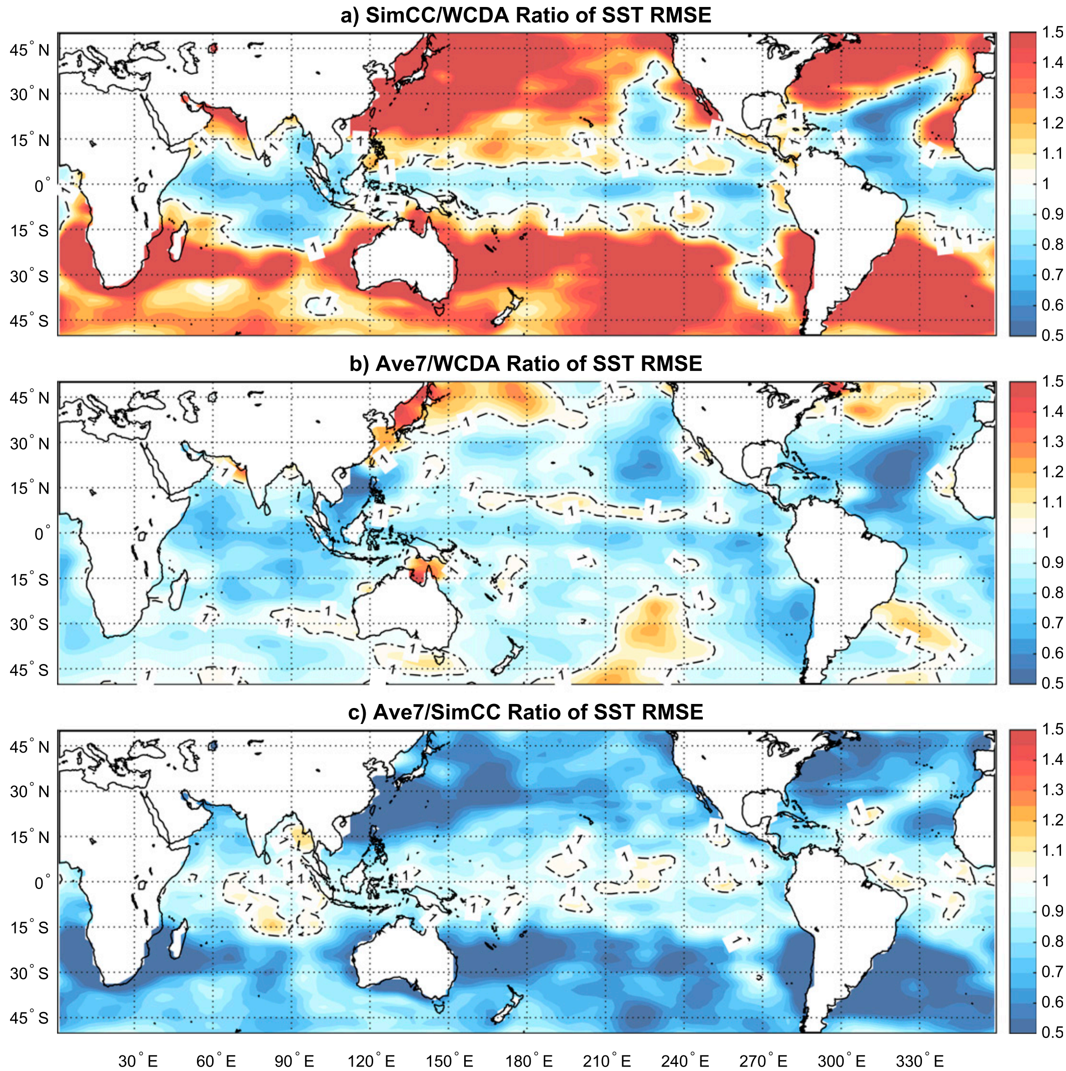

FIG. 6. Spatial distribution of the RMSE of monthly SST from (a) the SimCC experiment (normalized by the WCDA), (b) the Ave7 experiment (normalized by the WCDA), and (c) the Ave7 experiment (normalized by the SimCC).

correlations are the largest and the SimCC can indeed reduce the RMSE of monthly SST by up to 10%. Nevertheless, the SCDA using SimCC is far from an acceptable scheme because of its much poorer analysis outside the equatorial region. In particular, the RSME increases by up to 70% over WCDA in the midlatitude in both hemispheres. As the averaging length becomes longer, the cross update begins to have a consistently positive impact on the system. The optimal case, the Ave7 experiment, notably outperforms the benchmark WCDA experiment: its RMSE of SST is reduced by 10%–20% between 24°S and 33°N, and remains smaller than the WCDA across the entire domain, except for the very north part (>40°N).

As shown in Fig. 5, the averaging length is a critical parameter governing the performance of the LACC method (Part I; Tardif et al. 2014). As discussed in Part I, in a given SCDA system with fixed observations, ensemble size, ADA/ODA frequencies, and analysis schemes, there are two competing factors that determine the optimal averaging length. The first is the magnitude of the leading averaged cross correlation, which controls the signal-to-noise ratio when estimating the sample covariance for the cross update. This correlation usually increases rapidly with the averaging length starting from 1, peaks at a certain length, and eventually declines. The other is the frequency of cross update, since a longer averaging length implies less frequent assimilation through coupled covariance and, therefore, less constraint by atmospheric observations on the ocean. The competing effects of these two factors usually result in an optimal length, which tends to be longer in the case of a system with larger noise (Part I). In a CGCM like FOAM, these factors are not spatially homogeneous, as shown by the spatially varied leading averaged correlation in Fig. 4. Yet, the length of 7 days, which is close to the decorrelation time of the atmosphere surface temperature, seems to be the optimal choice for most latitudes. A longer 10 days is slightly better south of 40°S and north of 40°N, which also agrees with Part I, since the higher latitudes have smaller correlations. Changes in the observations, ensemble size, configuration of ADA/ODA, and analysis schemes could all lead to different optimal averaging lengths, as shown by the sensitivity tests in Part I. The sensitivity of the optimal average length in a complex CGCM like FOAM, however, remains to be studied in the future.

c. SimCC versus Ave7

A detailed comparison is made between the underperforming SimCC and the optimal Ave7. The enhancement in cross correlation from simultaneous to Ave7 is already displayed in Fig. 4. Figure 6 shows the spatial distribution of the RMSE of SST from the SimCC experiment normalized by the WCDA, the Ave7 experiment normalized by the WCDA, and the Ave7 experiment normalized by the SimCC. The zonal average of Figs. 6a and 6b will produce the curves of SimCC and Ave7 in Fig. 5, respectively.

Aside from the zonal-mean features already demonstrated in Fig. 5, Fig. 6a shows that the improved SST in the SimCC experiment expands into higher latitudes in the Atlantic and the eastern Pacific where the simultaneous correlations are relatively large (Fig. 4a). Figure 6b shows that the inferior analysis quality of Ave7 north of 40°N is the result of larger RMSE in the northwestern Pacific and northwestern Atlantic than the WCDA. These inferior analyses, we speculate, are caused by two reasons. First, they could be attributed to the small ensemble correlations north of 40°N (Figs. 2b and 3b) as well as the small correlations in those specific areas (Fig. 4b). Second, they could also be caused by the large T_s errors over land and their westward extension (Fig. 1b). Since the observation innovations for the cross update are calculated from the observation and forecast of T_s, the poor quality of T_s analysis leads to less accurate observation innovations and less effective cross update. Directly comparing Ave7 to SimCC (Fig. 6c), the RMSE ratio in the tropics is very close to 1, while the analysis quality is improved across most grid points in the extratropics.

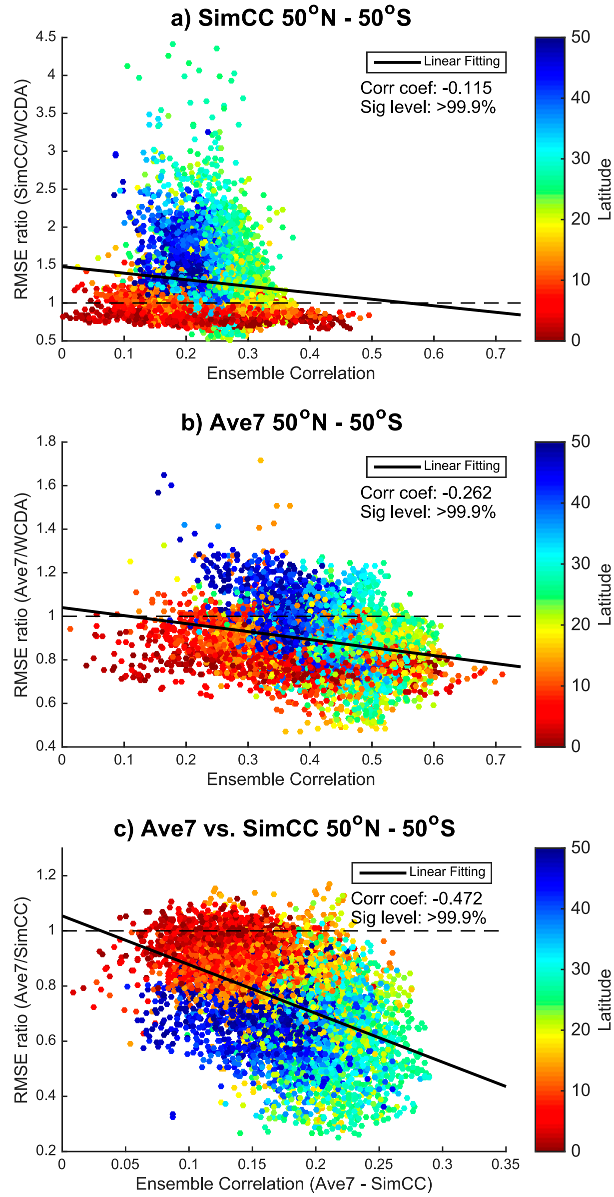

FIG. 7. (a) Scatterplot of the RMSE of the SimCC experiment (normalized by the WCDA) against simultaneous correlations between SST and T_s for all grid points between 50°S and 50°N. (b) As in (a), but for Ave7 experiment and 7-day-averaged leading correlations. (c) As in (b), but with RMSE of Ave7 (normalized by the SimCC) against the differences between the cross correlation of Ave7 and SimCC. The color scale indicates the absolute value of the latitude of each point.

The dependence of the effectiveness of the cross update on the cross correlation is shown in Fig. 7. Here, the RMSE ratio at every grid point in Figs. 6a–c is plotted against the corresponding cross correlation in Figs. 4a–c. The regression coefficients in all three plots are negative with confidence levels over 99.9%. Admittedly, the negative coefficient in Fig. 7a might be distorted by the

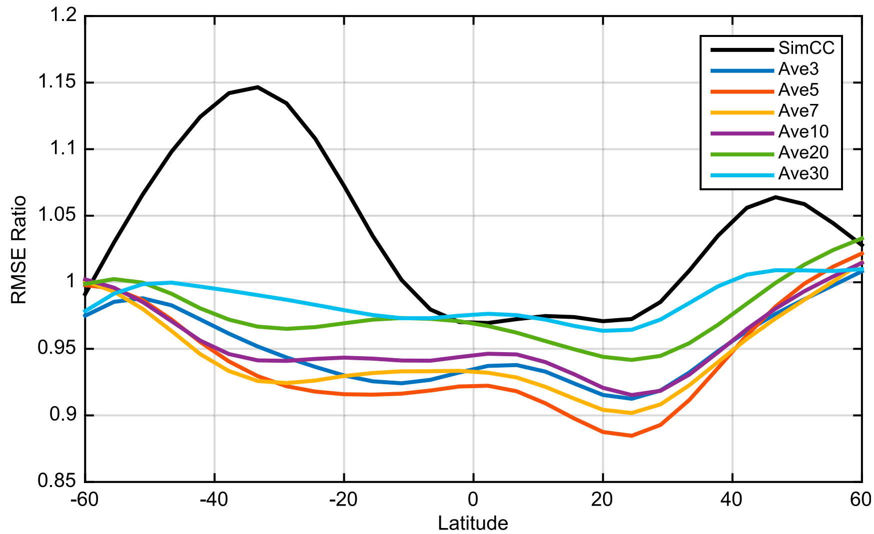

FIG. 8. Zonal-mean RMSE of monthly T_s over the ocean from the SimCC experiment and the LACC experiments with different averaging lengths, normalized by the WCDA experiment.

dramatically different performances at different latitudes. However, the coefficient of Ave7 (Fig. 7b) is more significant not only for all grid points, but also for any latitude band or any specific ocean basin (not shown). The global coefficient of -0.26 indicates that an increase of 0.1 in cross correlation results in a 2.6% reduction in the RMSE of SST on average. A more direct comparison between Ave7 and SimCC is made in Fig. 7c, where the ratio of RMSE between Ave7 and SimCC is plotted against the increase in cross correlation from SimCC to Ave7. The coefficient of -0.47 in Fig. 7c shows that the enhancement in cross correlation by the LACC method has a significant impact on the performance of the cross update in an SCDA system, especially for the extratropics.

The low computational cost is also an advantage of the LACC method. For example, the SimCC experiment costs 16.9% more computational time than the WCDA experiment due to the additional cross update, while the Ave7 experiment costs only 3.3% more than the WCDA because its frequency of cross update is 1/7 of that of SimCC.

d. *Atmosphere surface temperature*

Although the cross update works only one way from the atmosphere to the ocean, the atmospheric analysis could also be improved due to the nature of the CDA system. When the SST analysis is improved, it provides better boundary conditions and surface fluxes for the atmospheric component, thus improving the atmospheric analysis through coupled dynamics. Figure 8 shows the zonal-mean RMSE of T_s analysis over the ocean, normalized by the WCDA. Similar to Fig. 5, the LACC method outperforms the SimCC method across all latitudes. The optimal averaging length of 5 days is slightly different from Fig. 5, but the reduction in the zonal-mean RMSE consistently exceeds 5% from 40°S to 40°N for averaging lengths of 5, 7, and 10 days.

e. *Subsurface ocean temperature*

In addition to the SST analysis, the subsurface temperature analysis is also an important product of CDA systems, because the subsurface ocean states contain the critical "memory" information for seasonal and longer climate prediction (Rosati et al. 1997). The zonal-mean RMSE of monthly ocean temperature analysis down to 1300 m is displayed in Fig. 9 for SimCC and Ave7 experiments, again normalized by the WCDA results. The upper 1300 m include the top 14 levels of the ocean component. The upper eight levels (down to 200 m) are updated by monthly SST observations through ODA, while only the top level (SST) is updated by atmospheric observations through the cross update. For "SimCC" (Fig. 9a), the zonal-mean RMSE ratios demonstrate the different effects of cross update on subsurface temperature analysis at different latitudes and depths. One noteworthy feature is the huge increase of RMSE north of 40°N, which is probably caused by the poor SST analysis of SimCC and strong convection. In contrast, the Ave7 experiment shows reduced RMSE across most latitudes and depths compared to the WCDA.

It is interesting that, even though atmospheric observations only directly affect SST through cross update, the temperature analysis is also improved significantly

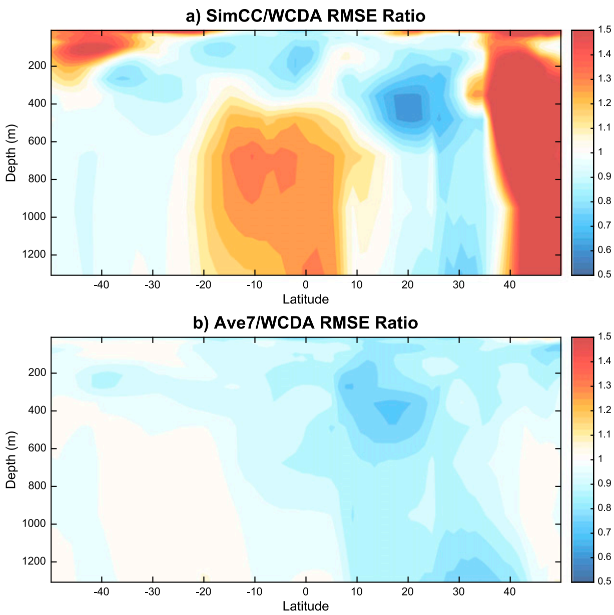

FIG. 9. Zonal-mean RMSE of monthly ocean temperature analysis from (a) the SimCC experiment and (b) the Ave7 experiment, both normalized by the WCDA.

in the subsurface. The improvement of subsurface temperature could be caused by several mechanisms. First, statistically, the improved SST by the LACC method further benefits the subsurface temperature through ODA. Second, dynamically, the improved SST provides better surface conditions and improves the subsurface through convection and ventilation processes. Furthermore, the improved SST also benefits the atmosphere (Fig. 8), which could in turn improve the response in the subsurface.

4. Summary and discussion

In this paper, we demonstrate the success of the SCDA with the LACC method in a CGCM in the perfect-model framework. To our knowledge, this is the first successful application of a SCDA scheme in a CGCM. The SCDA system implements cross update from the atmosphere component to the ocean component, utilizing the coupled covariance between atmosphere temperature and SST. Using the LACC method, the SCDA system could significantly reduce the RMSE of monthly SST analysis over most regions compared to the WCDA. The SCDA with the LACC method also produces a significantly better analysis than the regular SCDA using SimCC. The latter leads to deteriorating SST analysis compared to the WCDA system except in the deep tropics where the cross correlation is high, symmetric in lead and lag, and peaks at zero lag. Compared to SimCC, the improvement from the LACC method mainly comes from the increased cross correlations, compared to the simultaneous correlations, due to the use of leading averaged atmosphere temperature, which enhances the signal-to-noise ratio in calculating the coupled covariance for the cross update. The success of the LACC method indicates the potential to combine coupling dynamics with proper statistical techniques to improve coupled data assimilation systems.

The success of this study demonstrates the potential to apply the SCDA with more coupled covariances, especially those between different model components, in state-of-the-art CGCMs. We have also experimented expanding the cross update from atmosphere temperature directly to subsurface ocean temperature, but without significant further improvement. Because of the longer memory of subsurface ocean temperature, its correlation with atmosphere temperature is even lower and more asymmetric; therefore, a longer averaging length may be required for such cross update (Tardif et al. 2014, 2015). We are also exploring other possibilities such as the coupled covariance between atmosphere wind stress and subsurface ocean temperature, which may be significant due to dynamic processes such as Ekman transport and ventilation.

With an SCDA system, currently assimilated observations can be used more effectively, and information from a well-observed component like the atmosphere can be directly projected to a less-observed or unobserved component such as the ocean or the land. Compared with the WCDA systems that are currently being established for some major reanalysis projects, SCDA systems, in principle, would produce a more accurate and balanced analysis of the coupled state and provide better initialization for predictions.

This study is still very preliminary in the exploration of the SCDA in CGCMs in several aspects. First, the observing system is not very realistic. Second, the sensitivities of the SCDA system to the observation network and frequency and some parameters such as localization radius and relaxation factor remain to be further explored. Third, only a perfect model framework is used, and the model biases that arise from a biased model may deteriorate the results. Based on the above concerns, we plan to develop the SCDA in several directions.

(i) We will use a more realistic observing system with nongridded data. Real-world instantaneous observations instead of time-averaged reanalysis-like ones should be assimilated in the SCDA system.

(ii) We will perform more sensitivity experiments to better assess the performance of the SCDA system and the LACC method. Similar to Part I, the impact of ensemble size, observation quality, ADA/ODA frequency, etc., should be investigated in FOAM.

(iii) Ultimately, an SCDA system needs to assimilate real-world observations and the model bias will be another issue. There are at least two impacts of a biased model. First, model biases could deteriorate the analysis of the WCDA as well as the potential observation innovations for the cross update. Second, the coupled covariance in a biased model may not represent the real-world covariance. The impacts of model biases on the SCDA and the LACC method remain to be studied.

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