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Key Points:

- The local ensemble transform Kalman filter is used for strongly coupled ocean-atmosphere data assimilation
- Atmospheric observations are able to directly improve the ocean with strongly coupled DA
- The method used could easily be used by coupled models with any Earth subsystem

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Assimilating atmospheric observations into the ocean using strongly coupled ensemble data assimilation

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Abstract The local ensemble transform Kalman filter (LETKF) is used to develop a strongly coupled data assimilation (DA) system for an intermediate complexity ocean-atmosphere coupled model. Strongly coupled DA uses the cross-domain error covariance from a coupled-model background ensemble to allow observations in one domain to directly impact the state of the other domain during the analysis update. This method is compared to weakly coupled DA in which the coupled model is used for the background, but the cross-domain error covariance is not utilized. We perform an observing system simulation experiment with atmospheric observations only. Strongly coupled DA reduces the ocean analysis errors compared to weakly coupled DA, and the higher accuracy of the ocean also improves the atmosphere. The LETKF system design presented should allow for easy implementation of strongly coupled DA with other types of coupled models.

1. Introduction

Data assimilation (DA) combines real-world observations with model forecasts to produce an analysis of present conditions. Traditionally, DA systems have analyzed the ocean and atmosphere separately even if the respective models are then run as a coupled system for forecasting. Reasons for this include a higher observational coverage in the atmosphere compared to the ocean as well as asymmetric development in atmospheric and oceanic DA. For example, both National Centers for Environmental Prediction (NCEP) [*Kleist and Ide*, 2015] and European Centre for Medium-Range Weather Forecasts [*Bonavita et al.*, 2012] have operational hybrid ensemble/variational DA systems for the atmosphere while still using a traditional 3-D-variational method for the ocean [e.g., *Saha et al.*, 2014; *Mogensen et al.*, 2012]. The different temporal and spatial scales of the two domains increases the complexity of coupled DA [*Lawless*, 2012]. Practical issues such as different grid types by each model add complications as well.

Coupled DA can broadly be divided into two categories: *weakly coupled* and *strongly coupled*. Weakly coupled DA uses a coupled-model forecast to provide the background while the analysis update is performed separately for the two domains [e.g., *Zhang et al.*, 2007; *Lea et al.*, 2015]. The only method of information exchange between the ocean and atmosphere in this case is through the exchange of surface fluxes and sea surface temperature (SST) during the model integration for the forecast. Additional improvements can be made with weakly coupled DA if the coupled model is used in the outer loop of the otherwise separate variational DA systems [*Laloyaux et al.*, 2015], allowing observations to indirectly impact the analysis of the opposite domain.

Recently there has been some research focused on improving data assimilation for coupled ocean-atmosphere systems by analyzing the two domains as a single system. Strongly coupled DA is able to transfer information between the atmosphere and ocean by using the cross-domain error covariance. Such coupling allows observations in one domain to instantaneously impact the state variables in the other domain during the analysis update. Strongly coupled DA should be able to extract more information from the same observations, retain a better balance between the two domains, and is considered the preferable method for future coupled DA systems, as discussed at the 2012 International Workshop on Coupled Data Assimilation [*Lawless*, 2012]. No operational strongly coupled DA systems currently exist, and few studies have looked at using strongly coupled DA for realistic coupled general circulation models (CGCM). Studies that have focused on strongly coupled DA with a realistic CGCM have relied on averaged atmospheric observations assimilated into the ocean at a lower frequency than that of the atmospheric DA [*Lu et al.*, 2015].

For strongly coupled DA systems to be practical for operational numerical weather prediction (NWP), the ocean and atmosphere DA cycles should use similar observational windows. Ensemble Kalman filters (EnKF), in contrast to variational methods, perform best with short assimilation windows [*Kalnay et al.*, 2007]. Thus, the EnKF allows for both systems to be assimilated at the shorter window length of the atmosphere [*Singleton*, 2011]. Several studies using either an EnKF [*Lu et al.*, 2015; *Liu et al.*, 2013; *Han et al.*, 2013; *Luo and Hoteit*, 2014; *Tardif et al.*, 2013] or four-dimensional variational data assimilation [*Smith et al.*, 2015] have examined idealized models with strongly coupled DA operating at similar time scales for the two domains. *Liu et al.* [2013] found that strongly coupled DA provides substantial improvements, with the greatest impacts seen by assimilating atmospheric observations into the ocean in the extratropics.

This study investigates strongly coupled DA using a realistic CGCM by creating an EnKF system designed with an operational NWP cycle in mind. Two separate local ensemble transform Kalman filters (LETKF) [*Hunt et al.*, 2007], one each for the ocean and atmosphere, are implemented as a strongly coupled DA system by sharing observation innovations between the two systems. As a first step in testing this system we conduct a perfect model observation system simulation experiment (OSSE) with an intermediate complexity CGCM to determine if it can improve both domains when only atmospheric observations are available. As the historical record for ocean observations is extremely sparse, this scenario is particularly relevant for reanalysis in the pre-Argo era, e.g., prior to 2000 [*Roemmich et al.*, 2009], and provides an example of how such a strongly coupled DA system using both atmospheric and oceanic observations simultaneously could be implemented.

2. Methodology

2.1. Model

In this perfect model OSSE we use an intermediate complexity coupled model, SPEEDY-NEMO [*Kucharski et al.*, 2015], chosen for its ability to represent realistic physics with low computational cost. The atmosphere consists of the Simplified Parameterizations, primitivE-Equation DYnamics (SPEEDY) model, version 41 [*Molteni*, 2003; *Kucharski et al.*, 2006]. SPEEDY is a hydrostatic, eight-level sigma coordinate spectral model with T30 resolution and is capable of producing realistic atmospheric phenomenon despite simplified parameterizations. The ocean consists of the Nucleus for European Modeling of the Ocean (NEMO) v3 ocean dynamics model [*Madec*, 2008]. NEMO is configured with 30 vertical levels using z coordinates and a 2° horizontal tripolar grid that tapers to 0.25° latitude along the equator to capture equatorial wave dynamics. We modified the original SPEEDY-NEMO by changing the coupling and model output period from 24 h to 6 h. The model is coupled by exchanging SST from the ocean to the atmosphere, and total heat flux, shortwave solar radiation, wind stress, and evaporation minus precipitation ($E - P$) from the atmosphere to the ocean. Sea ice distribution is prescribed using observed monthly climatology from ERA-15 [*Gibson et al.*, 1999]. Following *Kröger and Kucharski* [2011], a one-way anomaly coupling is applied from the ocean to the atmosphere which corrects a cold bias in the East Pacific and allows for El Niño–Southern Oscillation-type variability to occur.

2.2. Data Assimilation

The LETKF [*Hunt et al.*, 2007] is a type of EnKF, using an ensemble of forecasts $\left\{\mathbf{x}^{b(i)} : i = 1, 2, \ldots, k\right\}$ to determine the statistics of the background error covariance. This information is combined with new observations, $\mathbf{y}^o$, to generate an analysis mean, $\bar{\mathbf{x}}^a$, and a set of new ensemble members, $\mathbf{x}^{a(i)}$. First, the model state is mapped to observation space by applying a nonlinear observation operator H to each background ensemble member $\mathbf{y}^{b(i)} = H\mathbf{x}^{b(i)}$. If the observed and modeled variables are the same, H is simply an interpolation of the model state to the observation locations. The weights $\bar{\mathbf{w}}^a$ are calculated to find the analysis mean $\bar{\mathbf{x}}^a$

$$\tilde{\mathbf{P}}^a = \left[(k-1)\,\mathbf{I} + \left(\mathbf{Y}^b\right)^T \mathbf{R}^{-1}\mathbf{Y}^b\right]^{-1} \tag{1}$$

$$\bar{\mathbf{w}}^a = \tilde{\mathbf{P}}^a \left(\mathbf{Y}^b\right)^T \mathbf{R}^{-1}\left(\mathbf{y}^o - \bar{\mathbf{y}}^b\right) \tag{2}$$

$$\bar{\mathbf{x}}^a = \bar{\mathbf{x}}^b + \mathbf{X}^b\bar{\mathbf{w}}^a \tag{3}$$

where $\bar{\mathbf{x}}^b$ and $\bar{\mathbf{y}}^b$ are the ensemble mean of the background in model space and observation space, respectively, $\mathbf{X}^b$ and $\mathbf{Y}^b$ are the matrices whose columns represent the ensemble perturbations from those

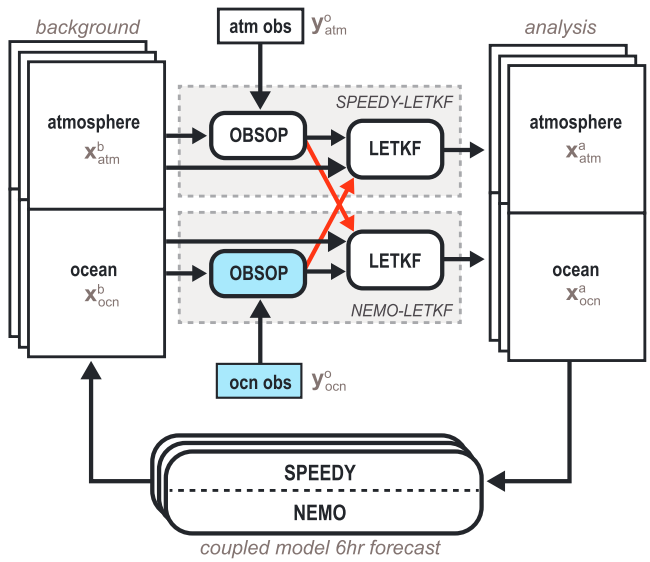

Figure 1. Schematic of the LETKF configuration for the coupled system. Shared observational departures (red arrows) between the separate LETKF systems enable them to perform as a strongly coupled data assimilation system. For this study only atmospheric observations were used and so the components in blue were not utilized.

means, and **R** is the observation error covariance matrix. Last, the set of weights $\mathbf{W}^a$ are calculated to find the perturbations in model space for the analysis ensemble by

$$\mathbf{W}^a = \left[(k-1)\,\tilde{\mathbf{P}}^a\right]^{1/2} \tag{4}$$

$$\mathbf{X}^a = \mathbf{X}^b\mathbf{W}^a \tag{5}$$

In practice, the LETKF is able to calculate the above equations in parallel for each grid point j using the subset of observations, $\mathbf{y}^o_j$, within its localization radius. For weakly coupled DA, $\mathbf{y}^o_j$ contains only observations from the same domain as the grid point being considered, whereas $\mathbf{y}^o_j$ can contain both atmospheric ($\mathbf{y}^o_{atm}$) and ocean ($\mathbf{y}^o_{ocn}$) observations in strongly coupled DA.

The LETKF analysis benefits from strongly coupled DA in two key ways. First, the calculation of $\bar{\mathbf{x}}^a$ by equations (1)–(3) uses the cross-domain error covariance to allow observations in one domain to directly inform the analysis mean calculated at grid points in the other domain. Second, the creation of the analysis ensemble by equations (4) and (5) maintains balance between the two domains within each ensemble member. Neighboring grid points use overlapping sets of observations, and since $\mathbf{y}^o_j$ will be nearly identical for adjacent grid points, $\mathbf{W}^a_j$ will be similar as well [*Yang et al.*, 2009]. Similar weights for neighboring grid

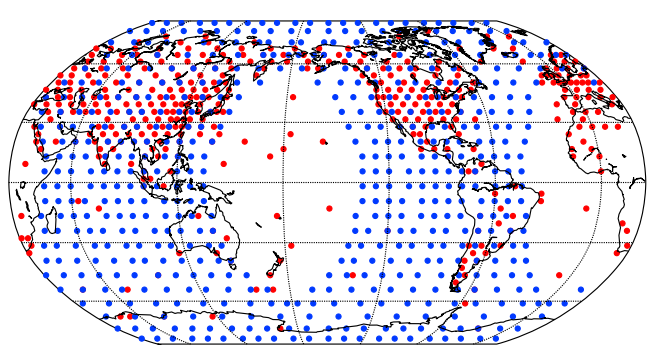

Figure 2. Location of atmospheric observations at 00Z for synthetic rawinsonde observations (red) and satellite retrievals (blue). The location of satellite retrievals changes for 06Z, 12Z, and 18Z to provide global daily coverage.

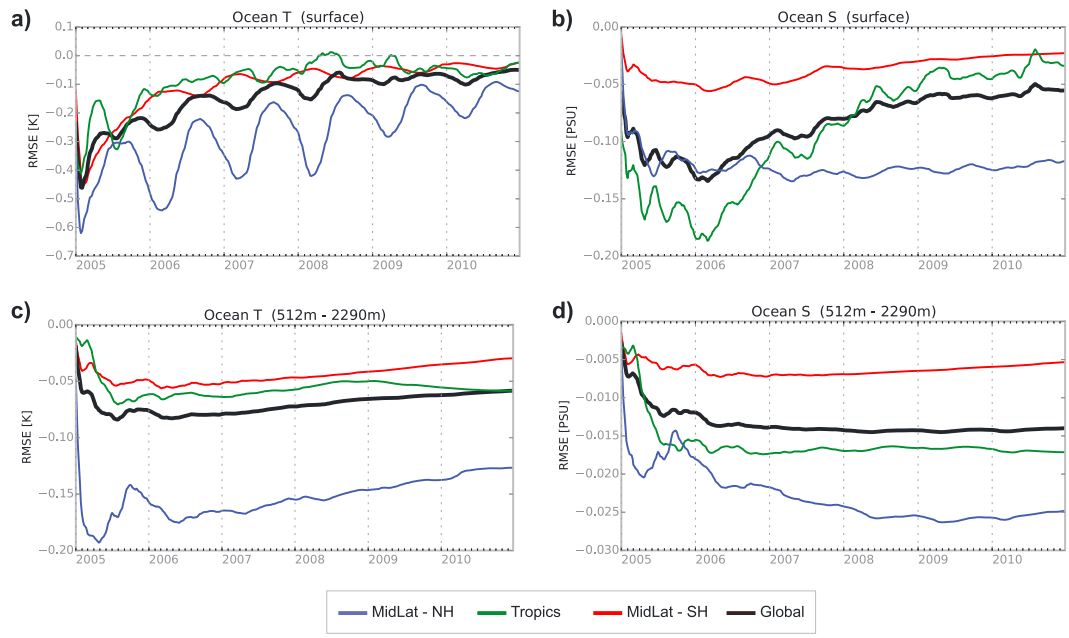

Figure 3. Spatially averaged difference of analysis RMSE for STRONG − WEAK in the Northern Hemisphere midlatitudes (blue), tropics (green), Southern Hemisphere midlatitudes (red), and globally (black). Variables shown are the (a and c) ocean temperature and (b and d) salinity for the surface only (Figures 3a and 3b), and deep ocean (Figures 3c and 3d).

points, both vertically and horizontally, ensure the ensemble perturbations are kept "matched together" at the domain interface. Weakly coupled DA is not able to retain this ocean-atmosphere surface balance within the ensemble members.

3. Experiment Design

We conduct a perfect model OSSE with SPEEDY-NEMO and LETKF using synthetic atmospheric observations and compare weakly coupled DA (WEAK) with strongly coupled DA (STRONG). The atmospheric LETKF developed for SPEEDY by *Miyoshi* [2005] and the ocean LETKF system developed for NCEP by *Penny et al.* [2015] are used. For WEAK the two LETKF systems operate separately. For STRONG the output of the atmospheric observation operator is passed to NEMO-LETKF (Figure 1). For both experiments SPEEDY-LETKF and NEMO-LETKF are run concurrently using 40 members and a 6 h analysis cycle using an identically configured coupled model for the two experiments.

SPEEDY-NEMO is first initialized with climatological ocean temperature and salinity and run freely for 20 years to spin-up. The subsequent 6 years are saved as the nature run and are the truth to which the two experiments are compared. From this run synthetic rawinsonde observations and satellite retrievals are generated every 6 h at the locations shown in Figure 2, providing observations of surface pressure (*Ps*) and vertical profiles of temperature (*T*), humidity (*q*), and wind (*U*, *V*). Independent Gaussian errors are added with zero mean and unit standard deviation (1 hPa, 1°C, 1 g/kg, and 1 m/s). No ocean observations were generated or assimilated in these experiments. For simplicity, observations are only generated at the analysis times, though a 4-D-LETKF using observations throughout a window would be expected to perform similarly.

Starting with an arbitrary date denoted January 2005, both experiments are initialized with identical ensemble members randomly chosen from dates in subsequent years of the nature run. For WEAK, the atmospheric observations are only assimilated into the atmosphere. The ocean is updated in this case every 6 h exclusively by fluxes from the atmospheric model during the integration of the forecast. For STRONG, the atmospheric observational departures are also used by the NEMO-LETKF, enabling the ocean to be corrected by both the atmospheric fluxes from the coupled forecast and by the NEMO-LETKF analysis updates with information from the atmospheric observations. In both cases the atmosphere ($\mathbf{x}^a_{\mathrm{atm}}$) and ocean ($\mathbf{x}^a_{\mathrm{ocn}}$) analyses are generated separately by the respective SPEEDY-LETKF and NEMO-LETKF, though for STRONG this is identical to a single LETKF handling the entire state ($\mathbf{x}^a$), due to sharing cross-domain observational departures.

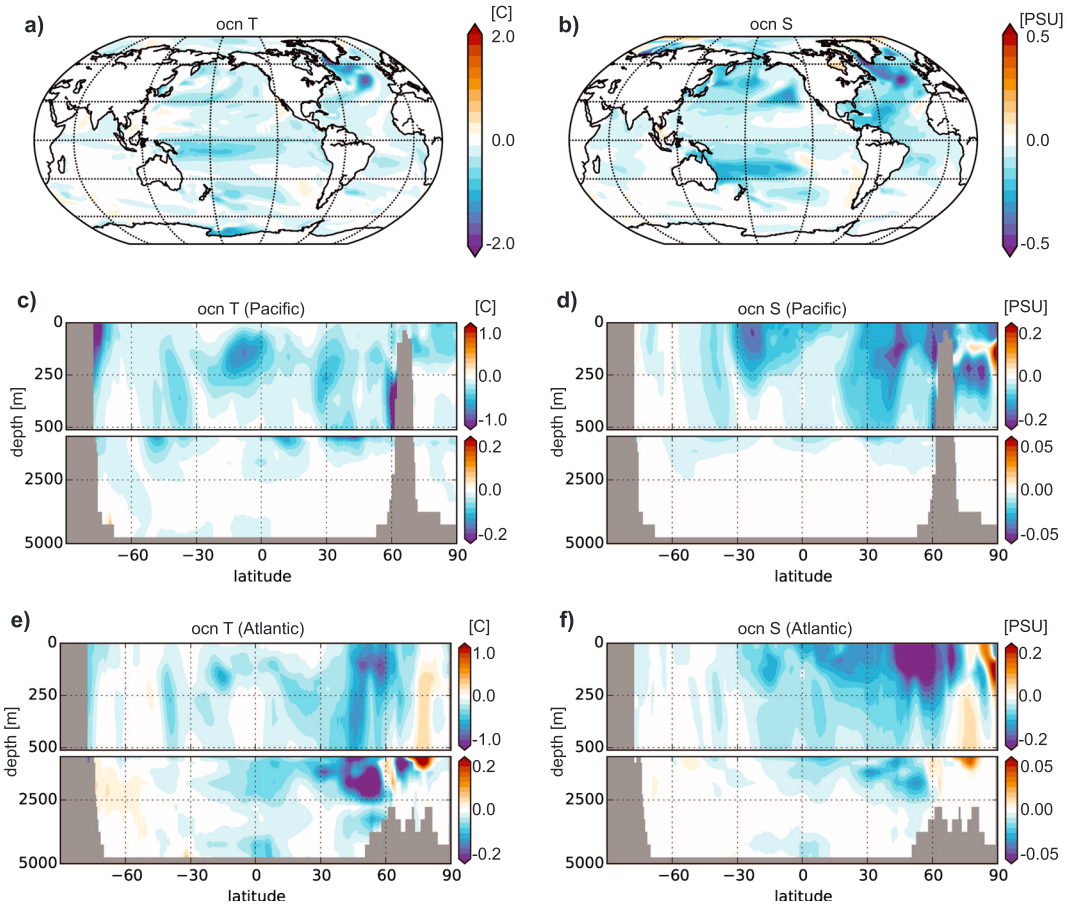

Figure 4. Time mean difference of analysis RMSE for STRONG − WEAK for the final 5 years (2006–2010). Shown are (a, c, and e) ocean temperature and (b, d, and f) salinity over the upper 512 m (Figures 4a and 3b), and latitude-depth cross sections averaged over the Pacific (Figures 3c and 3d) and Atlantic (Figures 3e and 3f) basins.

To account for errors in the background estimate, covariance inflation is required to keep the ensemble spread from collapsing. There are several choices for covariance inflation including constant multiplicative [*Anderson*, 2001], adaptive multiplicative [*Miyoshi*, 2011], additive [*Houtekamer and Mitchell*, 2005], relaxation to prior background [*Zhang et al.*, 2004], and stochastic physics parameterizations, [*Shutts*, 2005; *Berner et al.*, 2009]. We use here the relaxation to prior spread (RTPS) method of *Whitaker and Hamill* [2012]. This method expands the magnitude of the ensemble perturbations after the analysis a percentage, α, toward the prior spread while keeping the direction of the perturbations consistent for each coupled ensemble member. The RTPS parameter was chosen as $\alpha = 0.6$ for the atmosphere and $\alpha = 0.9$ for the ocean, resulting in an ensemble spread of similar magnitude to the root-mean-square error.

A horizontal observation localization of 1000 km is used, defined as the scaling distance of a Gaussian localization function [*Greybush et al.*, 2011; *Gaspari and Cohn*, 1999]. Vertical localization in the atmosphere is carried out by each model level so that observations at one level have minimal impact on adjacent levels. No vertical localization is used within the ocean, which provides better balance within the ocean and reduces the computational cost of the data assimilation by requiring only a single set of weights to be generated for the ocean column. All levels in an ocean column are therefore impacted by the observations in the lowest levels of the atmosphere with strongly coupled DA.

4. Results

The difference in analysis RMSE as compared to the nature run truth for STRONG minus WEAK (Figure 3) shows that the ocean is significantly improved when assimilating only atmospheric observations. Similar results are also found in the background RMSE (not shown). The near-surface ocean temperatures and SSH RMSE are

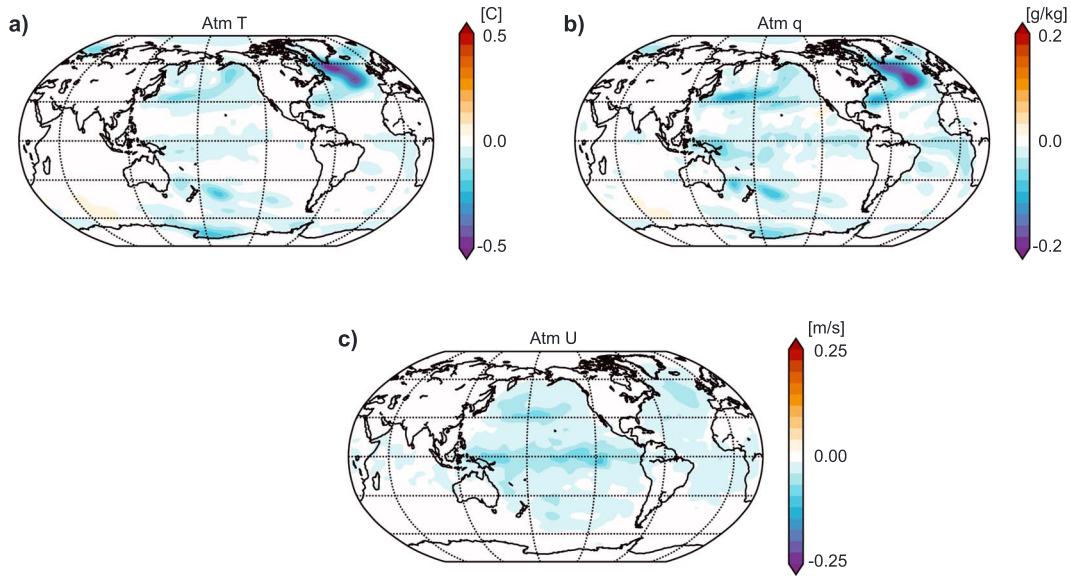

Figure 5. Time mean difference of analysis RMSE for STRONG − WEAK for the final 5 years (2006–2010). Shown are (a) atmospheric temperature and (b) humidity at the lowest model level, and (c) zonal wind speed throughout the troposphere.

reduced compared with the WEAK results by about 50% after a spin-up of a couple of weeks. The Northern Hemisphere (NH) and tropics, which have the largest initial errors in WEAK, also improve the most in STRONG. Ocean salinity errors are reduced more slowly than temperature, but this reduction continues for several years. Globally, the strongly coupled DA reduces errors in salinity and temperature an average of 46% in the upper ocean over the last 5 years of the experiment. Annual variations in the RMSE reduction by STRONG can be seen at the ocean surface (Figure 3a). The NH midlatitudes experience the greatest improvement in SST during the spring months, averaging 52% over the last 5 years while only 37% during the summer months. This result could be expected due to stronger midlatitude atmospheric dynamics driving the ocean during the winter and spring months.

Figure 4 shows the spatial patterns of analysis RMSE reduction between the two cases. The ocean state is improved most in the NH midlatitudes where the greatest density of atmospheric observations is and where the ocean is generally considered to be driven by weather anomalies. The NEMO-LETKF is configured to use no vertical localization in the ocean, which enables observations above the ocean to impact the entire water column, accelerating the improvement of the barotropic mode of the ocean. Though not using any vertical localization risks creating spurious correlations for vertically distant points, the LETKF is shown to perform better in the ocean without vertical localization [*Penny et al.*, 2015]. The strongest improvements in the northern Atlantic extend down below 2.5 km. Although SST errors are not reduced significantly in the tropical Pacific, RMSE errors of the subsurface waters in the upper 250 m are reduced by about 1°C.

Figure 5 shows that by assimilating atmospheric observations into the ocean, the corrected sea surface temperatures in STRONG reflect back on the atmosphere, resulting in a reduction in atmosphere RMSE. Improvements in atmospheric temperature and humidity at the lowest model levels overlap the same areas of the ocean (Figure 4) experiencing corrected SSTs. Precipitation and other fluxes are all improved in these areas (not shown). Zonal winds are improved throughout the troposphere of the tropical Pacific, presumably from an improved Walker circulation, as well as over the oceanic NH midlatitudes.

In addition to the STRONG and WEAK cases using all atmospheric observations, similar experiments were performed using only rawinsonde observations. Though extremely few observations are directly over the oceans, the strongly coupled data assimilation was still able to provide similar improvements in most regions, except for the Southern Hemisphere where there are too few rawinsondes.

5. Summary

By performing strongly coupled DA, where the ocean-atmosphere states and observations are effectively treated as a single system, improvements are seen in both domains compared to weakly coupled DA. Sharing ensemble observational departures between the SPEEDY-LETKF and NEMO-LETKF systems takes advantage of the cross-domain background error covariance and allows atmospheric observations to directly impact the ocean analysis. Balance between the domains within ensemble members is also retained. These benefits lead to a substantial reduction in analysis RMSE of the ocean state in our perfect model experiments, which due to the lack of vertical localization extends throughout the vertical column of the ocean.

For simplicity we performed strongly coupled DA experiments with only atmospheric observations, which the ocean was also allowed to assimilate. Preliminary experiments suggest that the complementary experiment, with ocean observations assimilated by the atmosphere, also results in analysis RMSE reductions compared to weakly coupled DA. This substantial improvement in both the ocean and the atmosphere analysis errors indicates that the strong coupling of the ocean-atmosphere DA has the potential to improve weather and climate forecasts compared to the currently performed weakly coupled DA. The SPEEDY-NEMO model used, however, is only able to exchange fluxes every 6 h, the same time as the assimilation. The strength of the cross-domain covariance information is reduced by not coupling more frequently and prevents all observations, both atmosphere and ocean, from being assimilated at the same time for these experiments. Future research will use a CGCM with more frequent model coupling such as the Climate Forecasting System v2 [*Saha et al.*, 2014].

Given the nearly "black-box" nature of the LETKF, automatic generation of cross-domain background error covariance, and the simple implementation provided by retaining separate LETKF code for each domain, strongly coupled DA has the potential to be applied to data assimilation for all the Earth subsystems, including land, chemistry, sea ice, land ice, ocean surface waves, and clouds.

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