Climate Model State Estimation Using Variants of EnKF Coupled Data Assimilation

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ABSTRACT

Data assimilation (DA) experiments are performed to assess impacts of observations in climate model state estimation through the cross-domain ocean–atmosphere forecast error covariances (cross covariances). Specifically, we explore strongly and weakly coupled DA variants using the Climate Analysis Forecast Ensemble (CAFE) system. This comprises 96 ensemble members of the Geophysical Fluid Dynamics Laboratory (GFDL) CM2.1 climate model assimilating observational data from the ocean, atmosphere, and sea ice realms with the ensemble Kalman filter (EnKF). Sequences of atmospheric synoptic time-scale coupled forecasts (7 days) are carried out with model consistent initialization. Unassimilated forward-independent observations are used to quantify forecast innovation error-growth rates. The results show benefit for the slow components of the atmosphere and ocean subsurface when strongly coupling ocean observations to the atmosphere. In the present system, projecting fast atmospheric observations onto the ocean subsurface through the cross covariances benefits the oceanic and atmospheric near-surface layers; however, this leads to deterioration in the ocean subsurface. Particular variants of coupled DA are able to constrain the ocean and atmosphere. The forecasts initialized with these variants have predictability at intraseasonal time scales. Errors associated with the dominant intraseasonal mode of variability, the Madden–Julian oscillation (MJO), are decomposed into normal mode functions. Consistent with recent studies showing large MJO events are concurrent with rapid error growth associated with nonlinear interactions, we find a clear relationship between the strength of a given MJO event and the related forecast innovations. Our results demonstrate consistent system behavior in relation to capturing real-world disturbances that affect climate predictability.

1. Introduction

State estimation of the atmosphere, ocean, sea ice, land, biogeochemistry, etc., requires data assimilation (DA) to account for observation and model uncertainties. Observations can have dense coverage and be accurate and reliable, but they also can be sparse, imprecise and contain outliers. Models propagate errors in initial conditions, forcing, and physical parameterizations (Sugiura et al. 2008; Zhang et al. 2007). Furthermore, spatiotemporal differences between observations and models give rise to representation error (Hopson 2014; Oke and Sakov 2008; Houtekamer et al.

2009). The ensemble Kalman filter (EnKF) (Evensen 2003) provides a natural method for generating dynamic cross-domain ocean–atmosphere forecast error covariances (cross covariances) in coupled geophysical applications. Due to the different physical and dynamical scales in the ocean and atmosphere, technical difficulties and high computational cost, cross covariances are usually not represented in operational prediction systems. Advances in prediction are limited by model and observation uncertainty. An important motivation for coupled DA is to generate consistent analyses for each domain and to minimize shock when initializing the coupled model (Chang et al. 2013). Recent studies have indicated the potential for consistent coupled DA and forecasting to overcome some of the persistent systematic errors seen in uncoupled systems (Penny et al. 2019; O'Kane et al. 2019; Laloyaux et al. 2018b; Storto et al. 2018; Smith et al. 2018; Sluka et al. 2016; Sluka 2018;

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Laloyaux et al. 2018a, 2016; Penny and Hamill 2017; Lea et al. 2015; Brassington et al. 2015; Saha et al. 2014). In their introduction, Lu et al. (2015) provide an excellent overview of weakly and strongly coupled DA. Strongly coupled DA involves projecting observations from one domain onto another using cross covariances (e.g., Frolov et al. 2016; Sluka et al. 2016). Weakly coupled DA does not consider the cross covariances, rather, separate analyses are performed for the domains and coupling only occurs via air–sea fluxes in the model forecast (e.g., Karspeck et al. 2018; Feng et al. 2018; Zhang et al. 2007). The different spatio-temporal scales in the relatively fast atmosphere and slow ocean make strongly coupled DA challenging (Smith et al. 2017; Fowler and Lawless 2016; Peña and Kalnay 2004; Palmer and Anderson 1994).

The National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) was designed to produce gridded multiyear estimates of atmospheric states for advancing climate studies (Saha et al. 2014) using a coupled model. Sea surface temperature (SST) nudging was employed using an optimally interpolated (OI) gridded analysis at 1 day restoring e -folding time scales. This largely decoupled the atmospheric and ocean models but was required to alleviate emergent biases in the coupled model. In the Coupled Reanalysis of the Twentieth Century (CERA-20C) Laloyaux et al. (2018b) used SST relaxation at 2–3-day time scale presumably for similar reasons. Coupled model SST bias remains a challenge for coupled DA systems and mainly relies on model improvements to address.

Mulholland et al. (2015) proposed coupled DA could be important for reanalysis in providing improved consistency in estimates of global transports and mass, heat and energy. This is correct, but in practice it would demand adequately sampled covariances with concomitant improvements in representation of SST, winds, surface fluxes and precipitation to be expected as a result. Sugiura et al. (2008) suggest coupled DA as a possible source of breakthrough for seasonal to interannual prediction. They acknowledge the use of approximate coupled DA as direct updating of short time scale growing weather modes is a difficult problem, although correcting the shorter time scales would improve the corrected mean state. In an effort to manage the scale separation between ocean and atmosphere, Sugiura et al. (2008) synchronously assimilated 10-day mean gridded OI SST, sea surface height and monthly mean temperature and salinity from the World Ocean Database. They also used their data assimilation framework to spatially optimize exchange coefficient parameters for the bulk fluxes, leading to improvements in estimates of surface air temperature (SAT) and SST.

Laloyaux et al. (2016) found a mostly neutral impact between coupled and uncoupled DA, albeit a slight improvement for lower atmosphere and upper ocean. However, more recently, improvements particularly for air–sea heat fluxes and in the oceanic and atmospheric boundary layers, have been reported in a number of studies (Penny et al. 2019; O’Kane et al. 2019; Laloyaux et al. 2018b; Storto et al. 2018). To date, there has been no study of the relative differences between all variants of strongly and weakly coupled DA in the framework of a complex earth system model assimilating many of the available ocean, sea ice and atmospheric observational data used for ocean and climate prediction. It is widely recognized that the ocean plays a key role in seasonal and near-term climate prediction (e.g., Myers and Weaver 1992; Balmaseda et al. 2013). This emphasizes the importance of ocean models and observations for initializing the ocean subsurface for predictability on seasonal to interannual time scales. A key indicator for climate forecast system performance remains the skill in predicting the ocean subsurface.

The large majority of coupled DA studies have used separate DA schemes and systems for the ocean and atmosphere. The use of separate schemes (e.g., 3DVar for ocean and 4DVar for atmosphere) can be a source of inconsistency with potential to introduce initialization shock. Here we undertake a set of coupled model state estimation experiments, with a consistent coupled DA framework, with various forms of cross covariances employed to characterize the impact and utility of each cross covariance on the quality of the estimated state and forecast errors. In the next section we describe the experimental framework, model, observational data, and EnKF assimilation method. The results and conclusions follow in subsequent sections.

2. Data and methods

a. Experiments

For variants of coupled ocean–atmosphere data assimilation that either consider the error covariances and/or the cross covariances there are 2^4 possibilities of which one is the control case with no data assimilation. These are shown in Table 1 where for atmosphere (A) and ocean (O) represent the observations and superscript the domain onto which the observations project. For example, O^A represents oceanic observations projecting onto the atmospheric domain via atmosphere–ocean cross covariances. The variants are annotated accordingly in Table 1 and used to denote them in the following text and results.

The 16 variants are run over the same 15 month period from 1 January 2010 using the same ensemble of initial

TABLE 1. Variants of strongly and weakly coupled ocean–atmosphere data assimilation (DA) where for atmosphere (A) and ocean (O) represent the observations and superscript the domain onto which the observations project (e.g., O^A represents oceanic observations projecting onto the atmospheric domain via atmosphere–ocean cross covariances). The $\checkmark$ indicates whether the covariances A^A or O^O or cross covariances A^O or O^A are considered in the projection of observations onto a given domain. A weakly coupled analysis only considers covariances. A strongly coupled analysis considers cross covariances. The variants are annotated in column 1 where the following simplifications are made: $A^A A^O = A^{AO}$ and $O^A O^O = O^{AO}$.

Variant	A^A	A^O	O^A	O^O	Atmospheric increment	Ocean increment	Type
$A^{AO} O^{AO}$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	Atmospheric and ocean observations	Atmospheric and ocean observations	Strong
$A^O O^O$		$\checkmark$		$\checkmark$		Atmospheric and ocean observations	Strong
$A^A O^A$	$\checkmark$		$\checkmark$		Atmospheric and ocean observations		Strong
$A^A O^O$	$\checkmark$			$\checkmark$	Atmospheric observations	Ocean observations	Weak
O^O				$\checkmark$		Ocean observations	Weak
A^A	$\checkmark$				Atmospheric observations		Weak
$A^O O^A$		$\checkmark$	$\checkmark$		Ocean observations	Atmospheric observations	Strong
O^{AO}			$\checkmark$	$\checkmark$	Ocean observations	Ocean observations	Strong
A^{AO}	$\checkmark$	$\checkmark$			Atmospheric observations	Atmospheric observations	Strong
A^O		$\checkmark$				Atmospheric observations	Strong
$A^A O^{AO}$	$\checkmark$		$\checkmark$	$\checkmark$	Atmospheric and ocean observations	Ocean observations	Strong
$A^O O^{AO}$		$\checkmark$	$\checkmark$	$\checkmark$	Ocean observations	Atmospheric and ocean observations	Strong
O^A			$\checkmark$		Ocean observations		Strong
$A^{AO} O^A$	$\checkmark$	$\checkmark$	$\checkmark$		Atmospheric and ocean observations	Atmospheric observations	Strong
$A^{AO} O^A$	$\checkmark$	$\checkmark$		$\checkmark$	Atmospheric observations	Atmospheric and ocean observations	Strong

conditions. The first three months are considered a spinup period for the experiments. The initial ensemble was formed in two steps. In the first step we generated 96 instantaneous states for the 1st of January from a multicentury control run of the coupled model. In the second step these were used as initial conditions for a 96-member EnKF strongly coupled (our variant O^{AO}) reanalysis run on a 28-day cycle from 2002 to 2018 as in O’Kane et al. (2019). The ensemble from this reanalysis at 1 January 2018 is used as the initial ensemble for all experiments in this study. This has a major advantage as it provides a relatively balanced initial ensemble with a subsurface initialized to all available observations. The time scale to spin up the subsurface ocean to currently available observations can take many years and depends on global coverage from Argo (Roemmich et al. 2009; Gould et al. 2004). Memory of assimilated observations at depth (e.g., >500 m) can be retained over long time scales; however, assimilation of deep ocean data is challenging as present models contain virtually no variability at depth, likely due to insufficient vertical (and horizontal) resolution. This leads to minimal ensemble spread, with observations having little impact. Results shown in section 3 illustrate that taking 1 January 2018 ensemble and using it to initialize the system to observations at the 1 January 2010, takes around 8–10 cycles (2 months) to spin up the upper ocean.

From the outset we expect that some of the variants, such as those where only atmospheric observations and cross covariances are used to constrain the ocean, will not perform well. These variants, however, will

be interesting as they will provide insight into the nature of the correlations. Variant $A^{AO} O^{AO}$ utilizes all cross covariances. Variant $A^A O^O$ is the weakly coupled DA approach. Strongly coupled variant $A^O O^A$ is of interest as ocean observations are projected onto the atmosphere and atmospheric observations onto the ocean via the cross covariances. Variant A^{AO} , which assimilates atmospheric observations only, is similar to the variant that Sluka et al. (2016) have investigated. They found in their system an improvement to the ocean with a positive feedback to improvements in the atmosphere.

Where a domain is densely observed, as for our experimental atmosphere, the impact of cross covariances should diminish suggesting minor differences between variants $A^A O^O$ and $A^{AO} O^{AO}$. The only difference between weakly coupled variant $A^A O^O$ and strongly coupled variant $A^{AO} O^{AO}$ is that the latter assimilates ocean observations into the atmosphere. Furthermore, we expect in weakly coupled variants O^O and A^A , which either assimilate only atmospheric observations into the atmosphere or only ocean observations into the ocean, that the weakly coupled DA will not be sufficient to constrain the domains that do not assimilate their respective observations.

b. Model

The Climate Analysis Forecast Ensemble (CAFE) (O’Kane et al. 2019) version of the Geophysical Fluid Dynamics Laboratory (GFDL) Coupled Model version 2.1 (CM2.1) (Delworth et al. 2006) is used. This system consists of Atmospheric Model 2.0 (AM2), the Sea ice Simulator version 1.0 (SIS), Modular Ocean Model

TABLE 2. Observations assimilated and used for verification in 2010–11. Number represents mean for 7-day cycle. SO—superobservations. Asynchronous (Asynch.) is accounting for the timing of observations within the cycle. Assigned observation error estimates are shown; † denotes error estimates provided by product vendor for each observation.

Observations	Dataset	Number	SO	Spatial	Asynch.	Error estimate
Sea surface temperature	NAVO-AVHRR, WindSat, AMSR-E	1.02×10^7	6.35×10^5	Point	Yes	†, 0.5 K, 0.5 K
Sea level anomaly	ERS-2, Jason-1, Jason-2, Envisat, CryoSat-2	1.09×10^6	1.25×10^5	Track	Yes	†, †, †, †, †
In situ ocean temperature	Argo, XBT, CTD, TAO, PIRATA	1.48×10^5	7.03×10^4	Profile	Yes	0.5 K
In situ ocean salinity	Argo, CTD, TAO, PIRATA	1.41×10^5	6.44×10^4	Profile	Yes	0.075 psu
Sea surface salinity	SMOS	7.17×10^5	7.55×10^4	Gridded	Yes	0.4 psu
Sea ice concentration	OSISAF	1.24×10^6	8.57×10^4	Gridded	Yes	0.1 [C]
Zonal wind	JRA-55	1.2×10^7	3.16×10^5	Gridded	No	1 m s^{-1}
Meridional wind	JRA-55	1.2×10^7	3.16×10^5	Gridded	No	1 m s^{-1}
Air temperature	JRA-55	1.2×10^7	3.16×10^5	Gridded	No	1 K
Specific humidity	JRA-55	1.2×10^7	3.16×10^5	Gridded	No	0.05 kg kg^{-1}

version 5.1 (MOM5) (Griffies et al. 2009), and a land surface model (LM1). AM2 has a resolution of 2° in latitude, 2.5° in longitude with 24 hybrid sigma-pressure vertical levels. Concentrations of atmospheric aerosols, radiative gases and land cover are based on 1990 conditions. LM1 is on the same horizontal grid as AM2.

MOM5 is configured using the AusCOM 1° ocean grid from the ACCESS (Australian Community Climate Earth System Simulator) Coupled Model (Bi et al. 2013) with extra latitudinal resolution in the tropics, 0.33° at the equator and horizontal resolution in the Southern Ocean of 0.25° at 75°S . The grid is tripolar over the Arctic, north of 65° . The ocean grid has 50 vertical levels with 10-m resolution in the upper ocean increasing to 300 m at abyssal depth. The layer closest to the surface in the ocean model has 10 m thickness approximating SST at 5 m depth. Ocean model settings include the use of a fourth-order Sweby advection method and a scale dependent isotropic Laplacian horizontal mixing scheme as described in Griffies and Halberg (2000). The K -profile parameterization (KPP) vertical mixing scheme (Large et al. 1994) is used. Also included are standard subgrid parameterizations in the CM2.1 ocean model such as neutral physics (Redi diffusivity and Gent–McWilliams skew diffusion), Brian–Lewis vertical mixing profile, and a Lagrangian friction scheme.

The ocean, atmosphere, land, and sea ice exchange fluxes every hour, which is the ocean model baroclinic time step and twice the atmospheric model time step. Fluxes of heat, freshwater and momentum are exchanged between ocean and atmosphere using second order conservative remapping. SIS is on the same grid as the ocean model with 5 ice thickness categories.

c. Observations

Observations listed in Table 2 are converted into superobservations. This involves combining all observations

falling within model grid cells, with known error estimates, into one superobservation with a smaller error estimate (Oke et al. 2008). The superobservation location, values and error estimates are based on a weighted average using inverse error variance of the original observations. Assigned observation errors are also given in Table 2.

Altimetric sea level anomaly (SLA) is taken from the Radar Altimeter Database System (RADS) (Schrama et al. 2000) using tide, mean dynamic topography (MDT), and inverse barometer corrections. SLA observations are limited to water depths greater than 200 m due to the small signal to noise ratio on the shelf and up to the coast. Remotely sensed sea surface temperature (SST) from NAVOCEANO (May et al. 1998), AMSR-E, and WindSat (Gaiser et al. 2004) are used. All available duplicate checked delayed mode in situ temperature and salinity observations from USGODAE, Coriolis, and the Global Telecommunications System (GTS) are also used. These include Argo profiles (Roemmich et al. 2009), TAO, PIRATA and RAMA moored arrays, conductivity–temperature–depth (CTD), and expendable bathythermograph (XBT) profiles. Daily mean zonal and meridional wind, temperature, humidity, and surface pressure from the JRA-55 atmospheric reanalysis (Kobayashi et al. 2015) is assimilated into the model. The direct assimilation of atmospheric observations was not carried out. The assimilation of an atmospheric reanalysis product may cause some degradation as inherent in this are the systematic and random errors of the reanalysis. Nonetheless, we ascribe observation errors to the gridded atmospheric data in order to avoid overfitting. Sea ice concentration data is sourced from the 25-km resolution climate data record EUMETSAT Ocean and Sea Ice Satellite Application Facility (OSISAF) global sea ice concentration reprocessing dataset 1978–2015 (v1.2, 2015) by the Norwegian and Danish Meteorological Institutes. This uses passive microwave

data from SMMR, SSM/I, and SSMIS sensors. SMOS sea surface salinity observations are accessed from IFREMER reprocessed as SMAP product L2OS RE05.

d. Data assimilation

Data assimilation is carried out using the EnKF to constrain the coupled model to observations. The state vector includes ocean temperature, salinity, sea level anomaly, velocity, sea ice concentration and thickness categories, atmospheric pressure, temperature, humidity, and winds. Model SLA is the difference between model sea surface height and mean sea level from a 100-yr control run. The EnKF-C software (Sakov 2018) is used in ensemble transform Kalman filter (ETKF) mode. The analysis equation, Kalman gain, and forecast error covariances can be written as

$$\mathbf{x}^a = \mathbf{x}^f + \mathbf{K}[\mathbf{y} - \mathcal{H}(\bar{\mathbf{x}}^f)], \quad (1a)$$

$$\mathbf{K} = \mathbf{P}\mathbf{H}^T[\mathbf{H}\mathbf{P}\mathbf{H}^T + \mathbf{R}]^{-1}, \quad (1b)$$

$$\mathbf{P} \equiv \frac{\mathbf{A}\mathbf{A}^T}{m-1}, \quad (1c)$$

where $\mathbf{x}^a$ and $\mathbf{x}^f$ are the $n \times 1$ analysis and forecast state vectors, respectively (n is number of state variables); $\mathbf{y}$ is a $p \times 1$ observation vector (p is number of observations); $\mathbf{H}$ is a $p \times n$ observation operator; $\mathbf{K}$ is the $n \times p$ Kalman gain matrix; $\mathbf{P}$ is $n \times n$ model state error covariance matrix; $\mathbf{R}$ is a $p \times p$ observation error covariance matrix; $\mathbf{H} = \nabla \mathcal{H}(\mathbf{x})$; $\mathbf{A}$ is an $n \times m$ matrix representing anomalies with respect to the ensemble mean; m is ensemble size; and superscript T signifies matrix transposition. The forecast state vector $\mathbf{x}^f$ is taken to be an instantaneous coupled model state, whereas $\bar{\mathbf{x}}^f$ is daily mean state; and $\mathbf{P}$ is based on a 96-member ensemble of the coupled model.

Data assimilation cycle length is 7 days. The model is directly initialized to the analysis. Ocean observations are assimilated asynchronously (Sakov et al. 2010) with an asymmetric backward in time observation window. Assimilation of JRA-55 atmospheric data is only performed synchronously on analysis day; however, atmospheric forecast error statistics are calculated every day. To remove spurious long-range correlations we employ horizontal localization. A Gaspari and Cohn (1999) localization function with support radius of 500 km is used for all observations. DA experiments with localization radii of 750 and 1000 km did not produce significantly different results for the 96-member ensemble. We chose 500 km as a minimum scale to improve computational efficiency as the system assimilates a relatively large number of superobservations

per cycle ($\approx 2.3 \times 10^6$). Vertical localization is not used. Covariance inflation of 5% is used. Bias correction of SST (SLA) is applied, similar to [Evensen 2003, Eq. (122)]. We also make the common assumption that superobservations are uncorrelated (i.e., the $\mathbf{R}$ covariance matrix is diagonal).

To estimate the SST (SLA) bias field, the observed SST (SLA) field is assumed to be a sum of the model SST (SLA) field and unknown SST (SLA) bias field. The ensemble of bias fields is initialized to random spatially uniform values. It is then updated similar to other model fields, except that instead of being propagated with the model, the bias ensemble is evolved by slowly relaxing it toward zero and adding random noise using the following first order auto-regressive [AR(1)] function:

$$\mathbf{x}_b^f = \lambda \mathbf{x}_b^a + (1 - \lambda^2)^{1/2} \sigma, \quad (2)$$

where λ is the forgetting factor, $0 < \lambda < 1$, $1 - \lambda \ll 1$, and $\sigma \sim \sigma_0 N(0, 1)$; σ_0 is the standard deviation of the bias state variable $\mathbf{x}_b$, where for SST $\lambda = 0.95$, $\sigma = 0.8$, and for SLA $\lambda = 0.995$, $\sigma = 0.2$. Further, we assume that the SST bias applies to subsurface temperature in the mixed layer, and therefore affects innovations from subsurface observations. While bias correction does not explicitly improve the model it provides detection and correction of systematic biases from initial conditions. Regardless, even when model bias is removed from initial conditions, it finds its way back into the forecasts, growing with lead time.

Sea ice assimilation is carried out by comparing ice concentration in the forecast model to satellite observations. The five thickness categories in the ice model are added to the state vector and sea ice assimilation is strongly coupled to the ocean. Summing the thickness categories provides total sea ice area fraction or concentration. Assimilation uses this as the background concentration. As sea ice assimilation can be highly nonlinear (Barth et al. 2015), the analysis can at times produce values outside physical bounds. The analyzed thickness categories are normalized using analyzed concentration so that the sum is constrained to be between zero and 1. To handle larger errors near the ice edge and reduce overfitting at these locations a prescribed ice-concentration error estimate is applied using the following equation taken from Sakov et al. (2012):

$$\sigma_{\text{ice}}^2 = 0.01 + (0.5 - |0.5 - c|)^2, \quad (3)$$

where c is observed sea ice concentration. This formulation targets where the ice concentration observations are least certain in regions where cover is around 50%. Observations of zero and 100% ice concentration are usually reliable.

FIG. 1. Error-spread probability distribution histograms for global sea surface temperature (K).
(a) Weakly coupled variant A^{AO} and (b) control.

The atmospheric model is on hybrid sigma-pressure levels where vertical grid positions vary in physical height according to surface pressure. To assimilate the atmospheric data from the JRA55 reanalysis into an ensemble of atmospheric states, all with different vertical grids based on surface pressure, it was necessary to regrid all ensemble members onto a common grid to calculate the covariances. The common vertical grid used was the daily mean surface pressure from JRA55 corresponding to analysis time. Initialization of the atmospheric ensemble states was done by regridding the analyzed fields back to the hybrid sigma-pressure levels of the atmospheric model using the analyzed surface pressure for each member. The atmospheric, ice and ocean models are all initialized directly to analyzed fields, no nudging or incremental analysis updating was carried out.

The system adaptively moderates observation impact using the method of [Sakov and Sandery \(2017\)](#) using a K factor of 1. The method was designed to limit the impact of individual observations with large innovations likely to be inconsistent with the state of the DA system. It does this by smoothly increasing observation error variance depending on the projected increment, state error variance and K factor so that the resulting increment does not exceed the estimated state error times K . A benefit of the method is that it minimizes the innovations by modifying the distribution of observation error such that this becomes closer to the distribution of model error thereby increasing the gain and the observation impact. A clear example of the impact of the K factor can be seen in [Fig. 1](#). This compares observations and model uncertainty probability density functions (PDFs)

in observation (innovation) space for the control run and variant A^{AO}. The histograms are constructed using ensemble forecast global innovations of SST from every DA cycle. The innovations use observations prior to assimilation and therefore can be considered as independent, assuming that observation errors are not correlated in time. In the control variant, we ran the complete ensemble system within the DA framework; however, we set all observations errors to infinity to make them have no impact. This allowed us to obtain an equivalent set of ensemble statistics for the control. Figure 1 shows PDFs of absolute forecast innovation, forecast and analysis ensemble spread, observation and modified observation error spread. Figure 1a illustrates the model's representation of uncertainty (i.e., the forecast ensemble spread for weakly coupled variant A^{AO}). This has a relatively narrow range with mean error of 0.26K compared to overall mean absolute deviation (MAD) of 0.47K, suggesting the ensemble is underestimating its own uncertainty with respect to its forecast errors. This can be a reflection of the limitation of the present model's resolution and its ability to represent observed SST. For example, a mesoscale eddy resolving ocean model would certainly achieve greater spread than a climate ocean model and possess smaller representation error. Spread reduction from EnKF assimilation can be seen in the difference between the PDFs of forecast and analysis ensemble spread. For the control variant in Fig. 1b there is no impact on the model from assimilation of observations so the "virtual analysis" and forecast ensemble spread overlap exactly. Here the distribution of absolute forecast innovation flattens to a uniform distribution of errors across the entire range. The effect of K factor is seen in both panels in Fig. 1 by comparing observation error spread and modified observation error spread. In general K factor moves the PDF of observation error closer to the PDF for model forecast error, which is desirable for balance in K .

In EnKF-C, R factors are defined for each observation type and represent scaling coefficients for the corresponding observation error variances affecting the impact of these observations. Increasing R factor decreases the impact of observations and vice versa. Specifying an R factor of k produces the same increment as reducing the ensemble spread by a factor of $k^{1/2}$. We exploit this data assimilation tuning setting to carry out strongly and weakly coupled DA experiments. One can set, for example, R factors for ocean observations to a very large number, corresponding to no impact, and to unity for atmospheric observations to calculate a weakly coupled atmospheric increment, while maintaining sequential propagation of the cross covariances within the

FIG. 2. The 7-day forecast innovations for variant A^{AO} on 1 Oct 2010 for (a) air temperature at 500 hPa (K), (b) zonal velocity at 500 hPa (m s⁻¹), and (c) meridional velocity at 500 hPa (m s⁻¹).

ensemble. This allows us to study all variants of strongly and weakly coupled DA described in Table 1.

Figures 2–4 show the spatial distribution of forecast innovations for assimilated observations on the 1st of October 2010 for variant A^{AO}. These provide examples of observation coverage and model-observation mismatches. Figure 2 shows 500 hPa air temperature, zonal, and meridional velocity and illustrates that the atmosphere in our experiments is densely observed due to the use of 33-km resolution reanalysis data. The innovations represent 7-day forecast lead time error growth, which mainly manifests as corrections of the model to the observed locations of the midlatitude weather systems. Embedded within these innovations are corrections to the positions of the subtropical jets.

Figure 3 shows 7-day forecast innovations for SST, SLA, and subsurface ocean temperature at 200-m depth. In Fig. 3a SST has been strided in space and time by 5 to reduce overcrowding. In this snapshot the forecast innovations are generally larger outside the tropics, driven

FIG. 3. As in Fig. 2, but for (a) sea surface temperature (K) strided by 5, (b) sea level anomaly (m), and (c) ocean temperature at 200 m depth (K).

by errors in air–sea fluxes related to the weather systems, although the eastern equatorial Pacific cold tongue is forecast to be warmer than observations at this particular time. Figure 3 also shows 7-day coverage of altimetry from the RADS database. SLA innovations tend to be small in the tropics and increase with increasing latitude. Ocean temperature innovations are shown at 200-m depth where the TAO array can be seen in the western equatorial Pacific. This highlights the sparsity of subsurface ocean temperature observations, which are very important for near-term climate forecasting.

Figure 4a shows innovations for remotely sensed sea surface salinity (SSS). While there is dense coverage from this platform, there is relatively large measurement uncertainty. The innovations have a larger range compared to surface salinity innovations from Argo (not shown). A large uncertainty means SSS observations have a relatively small impact on the system. Figure 4b shows ice concentration innovations, which are relatively higher in the Arctic than Antarctic. This may be expected for the austral spring as seasonal transition is

FIG. 4. As in Fig. 2, but for (a) sea surface salinity (psu), (b) sea ice concentration [C], and (c) ocean salinity at 200 m depth (psu).

occurring. As the winter ice in the Antarctic is retreating, the DA system is making corrections at the ice edge, where the innovations are generally largest, to account for deficiencies in the model's ability to predict the observed retreat of the ice edge. Innovations for arctic ice concentration show that the model has not maintained enough summer sea ice, which is a known bias, and in the transition to winter the innovations are creating tendencies to increase ice concentration by more than 30% in order to move the model closer to the observed state. As with Fig. 3c for temperature at 200 m, Fig. 4c indicates ocean salinity at this depth is also sparsely observed relying mainly on Argo profiles for coverage.

3. Results

a. Forecast errors

Global mean 7-day forecast innovation MAD for all experiments was calculated for all observation types. In Fig. 5 we show time series of SST, ocean temperature and salinity and in Fig. 6 the same for air temperature,

FIG. 5. Global mean 7-day forecast innovations (MAD) for (a) sea surface temperature (K), (b) temperature (K), and (c) salinity (psu). The coupled data assimilation variants shown in the legend are listed in Table 1.

zonal and meridional wind for all levels of the atmosphere. The different coupled DA variants stratify into classes in terms of forecast performance. For the ocean the weakly coupled variants O^O and A^AO^O and the strongly coupled variants O^{AO} and $A^{AO}O^{AO}$ perform best overall. In terms of SST, the systems that perform almost equally well are those that assimilate ocean

observations into the ocean. Variant O^O that assimilates no atmospheric data is also in this class. The strongly coupled experiments, such as variants $A^{AO}O^{AO}$, $A^O O^O$, O^{AO} , $A^A O^{AO}$, $A^O O^{AO}$, and $A^{AO}O^O$, which all assimilate ocean observations, are also in this class for SST. There are variants that perform worse than the control run. These are variants A^{AO} , A^O , and $A^{AO}O^A$, which all

FIG. 6. Global mean 7-day forecast innovations (MAD) for (a) air temperature (K), (b) zonal wind (m s^{-1}), and (c) meridional wind (m s^{-1}). All levels of the atmosphere are included. The coupled data assimilation variants shown in the legend are listed in Table 1.

assimilate atmospheric observations into the ocean without assimilation of ocean observations. This deterioration suggests apparently spurious behavior in the cross covariances. Paradigm model studies using the nine component Lorenz model as in Peña and Kalnay (2004), configured to study data assimilation with the EnKF as in

O’Kane et al. (2019), suggest it’s virtually impossible to constrain the slow ocean with observations of the fast atmosphere. Similarly, it’s very difficult to properly constrain the fast atmosphere with observations of the slow ocean using strongly coupled DA (Han et al. 2013). Results for the subsurface ocean are also differentiated

TABLE 3. Global and temporal mean 7-day forecast innovations (MAD) for assimilated variables. Sea surface temperature (SST), sea level anomaly (SLA), in situ temperature and salinity (TEM, SAL), sea surface salinity (SSS), sea ice concentration (SIC), air temperature (ART), zonal wind (ARU), meridional wind (ARV); obs = average number of superobservations per cycle. The coupled data assimilation variants in the legend are listed in Table 1.

Variant	SST (K)	SLA (m)	TEM (K)	SAL (psu)	SSS (psu)	SIC [C]	ART (K)	ARU (m s ⁻¹)	ARV (m s ⁻¹)
A ^{AO} O ^{AO}	0.495	0.0617	0.821	0.125	0.318	0.263	3.06	5.9	5.26
A ^O O ^O	0.499	0.0591	0.77	0.12	0.3	0.24	3.06	5.91	4.94
A ^A O ^A	1.06	0.113	0.966	0.153	0.484	0.185	3.04	5.97	5.26
A ^A O ^O	0.477	0.0558	0.603	0.0942	0.263	0.186	3.02	5.87	5.2
O ^O	0.5	0.0559	0.588	0.0903	0.249	0.155	3.15	5.94	4.95
A ^A	1.06	0.116	0.971	0.154	0.489	0.19	3.02	5.87	5.22
A ^O O ^A	1.07	0.134	0.982	0.152	0.452	0.269	3.08	5.98	4.98
O ^{AO}	0.495	0.0559	0.588	0.0903	0.249	0.155	3.15	5.96	4.95
A ^{AO}	1.45	0.178	1.07	0.161	0.485	0.271	3.03	5.91	5.21
A ^O	1.19	0.139	1	0.154	0.471	0.246	3.06	5.92	4.94
A ^A O ^{AO}	0.476	0.0555	0.603	0.0941	0.263	0.186	3.03	5.86	5.23
A ^O O ^{AO}	0.492	0.0591	0.773	0.122	0.3	0.255	3.07	5.94	4.97
O ^A	1.12	0.114	1.01	0.155	0.489	0.148	3.09	6.02	5.01
A ^{AO} O ^A	1.54	0.183	1.11	0.159	0.478	0.266	3.05	5.9	5.23
A ^{AO} O ^O	0.493	0.0617	0.808	0.123	0.317	0.27	3.02	5.81	5.18
Control	1.2	0.114	1.05	0.157	0.493	0.147	3.11	6.01	4.99
Obs	6.35×10^5	1.25×10^5	7.03×10^4	6.44×10^4	7.55×10^4	8.57×10^4	3.16×10^5	3.16×10^5	3.16×10^5

into classes. Any of the strongly coupled variants with atmospheric observations projecting onto the ocean increment deteriorate forecast skill of the subsurface ocean. Looking at Fig. 6 we see that 7-day forecast errors for the atmosphere appear to be saturated with no discernable signal to differentiate the experiments.

Examination of the global and temporal mean 7-day forecast innovation MAD for assimilated variables (Table 3) highlights the need for a more sensitive metric to discriminate atmospheric forecast innovations. In the following section we examine this further with error-growth rates.

b. Error growth rates

In the previous section there was no obvious way to distinguish between the impacts of the respective coupled DA experiments on the atmosphere at 7-day lead time. The summary statistics presented in Table 3 for the atmosphere highlight this. Variants O^O and O^{AO} have the lowest forecast innovation MAD for the subsurface ocean; however, without assimilation of atmospheric data, they contribute little predictability to the fast midlatitude weather modes in the atmosphere. To better distinguish between the respective variants, the predictability of the coupled forecasts is analyzed in terms of error-growth rates (Trevisan 1993) here defined as

$$\dot{\varepsilon}_G(T) = \frac{1}{(T+1)} \ln \left[\frac{\varepsilon_F(T)}{\varepsilon_A} \right], \quad (4)$$

where $\dot{\varepsilon}_G(T)$ is global mean error-growth rate, ε_F is global mean forecast innovation MAD, ε_A is global

mean analysis innovation MAD, and T is forecast lead time. At $T = 0$, $\varepsilon_F = \varepsilon_A$ (i.e., the forecast is initialized to the analysis).

We calculate $\dot{\varepsilon}_G(T)$ using forecast innovations. The best way to interpret $\dot{\varepsilon}_G(T)$ is to know that when growth is close or equal to zero, errors of the forecast system are presumed to be saturated and there is no more skill than that of a control forecast. Figure 7 shows global error-growth rates, for all levels in the atmosphere, for air temperature, zonal, and meridional wind as a function of lead time based on all forecasts between March 2010 and March 2011. The first three months of forecasts were regarded to be in the spin-up period and not included. In contrast to previous error metrics showing global atmospheric forecast errors, the growth rates differentiate forecasts into two main classes, those that have predictability beyond initialization and those that are saturated. All variants that assimilate atmospheric observations into the atmosphere (i.e., any combination with an “A^A”) possess error-growth and atmospheric predictability. There is also some indication that at times the strongly coupled DA in variants that either have in their combination “A^AA^O” or “A^AO^A,” have larger error growth than variant A^A alone, indicating that these strongly coupled variants contribute to increasing atmospheric predictability. This suggests that while strongly coupled DA may not be enough alone to constrain a realm in the absence of observations for that realm that it still nonetheless provides benefit for forecasting in a well-observed realm.

The differences in ocean observations influencing the atmospheric analysis, whether assimilating dense

FIG. 7. Global innovation error-growth rates $\dot{\epsilon}_G(T)$ for (a) air temperature ($K \text{ day}^{-1}$), (b) zonal wind ($m \text{ s}^{-1} \text{ day}^{-1}$), and (c) meridional wind ($m \text{ s}^{-1} \text{ day}^{-1}$). All levels of the atmosphere are included. The coupled data assimilation variants shown in the legend are listed in Table 1.

atmospheric observations or not, are contained in the following results. Figure 8 shows $\dot{\epsilon}_G(T)$ for the ocean variables—SST, SLA and in situ temperature. The error-growth rates differentiate the experiments further into classes according to predictability. SST predictability appears to be enhanced for variants O^O and O^{AO} . These are weakly coupled ocean-only DA and strongly coupled ocean DA including the ocean–atmosphere cross covariance. For these and those additional variants assimilating ocean observations into

the ocean, error growth remains nonzero at day 6. For the control, or where the influence of the ocean observations is absent, assimilation analysis error tends to forecast error. Small negative and positive growth rates can be related to sampling issues. As seen in Fig. 1b the expectation is that analysis error equals forecast error in the control, which represents zero error growth. For the present system this implies virtually zero predictability at spatiotemporal scales of hundreds of kilometers and lead times of days. $\dot{\epsilon}_G(T)$ for SLA is unsaturated at day 6

FIG. 8. As in Fig. 7, but for (a) sea surface temperature ($K day^{-1}$), (b) sea level anomaly ($m day^{-1}$), and (c) in situ temperature ($K day^{-1}$). The coupled data assimilation variants shown in the legend are listed in Table 1.

for variants that assimilate ocean observations into the ocean. In our experiments SLA and in situ ocean temperature displayed nonmonotonic error growth (Figs. 8b,c). $\hat{\epsilon}_G(T)$ for in situ temperature confirms that the subsurface ocean is best represented in variants O^O and O^{AO} .

To study error-growth and atmosphere predictability at larger lead times we ran an additional experiment comprising variant $A^{AO} O^O$ on a 28-day cycle and calculated $\hat{\epsilon}_G(T)$ (Fig. 9). Here we see rapid nearly linear

error growth over the first 3 days after which the rate gradually decays as errors progressively saturate.

c. Seasonal mean increments

In strongly coupled ensemble data assimilation cross covariances are sensitive to scale separation, ensemble rank, spurious correlations, model deficiencies and observation distribution. Figure 10 shows seasonal mean increments (analysis minus forecast) for the austral summer in a zonal section at $2^\circ S$ for the upper

FIG. 9. Global innovation error-growth rates for variant A^{AOO} on a 28-day data assimilation cycle for air temperature ($K \text{ day}^{-1}$), and zonal and meridional wind ($m \text{ s}^{-1} \text{ day}^{-1}$).

500 m of the ocean and the atmosphere in pressure coordinates. The classes that emerged in error-growth rates are also distinguishable in Fig. 10. In the strongly coupled variants A^{OOA} , O^{AO} , A^{OOAO} , and O^A where only ocean observations are used to calculate atmospheric increments, and in particular in the stratosphere, smaller-scale structures are apparent in the mean increment compared to those variants that assimilated JRA55 data into the atmospheric model. Not all cross covariances in these variants are apparently spurious, for example variant O^{AO} has the highest predictability of the variants in this class suggesting some useful information is being communicated from ocean observations to the atmosphere via the cross covariances.

Where atmospheric observations are used to calculate atmospheric increments the spatial scales of the mean increments tend to reflect systematic biases in the coupled atmospheric model, such as cold lower-tropospheric air temperatures over the known equatorial SST cold tongue bias and a warm lower-tropospheric bias over the Maritime Continent. In variant A^{OOA} atmospheric observations drive the ocean increment and ocean observations drive the atmospheric increment. This is an extreme variant of strongly coupled DA that highlights scale separation away from the planetary boundary layer in the tropics between ocean and atmosphere. If we compare variant A^{OOA} to variant O^{AO} , there is a clear signal that the feedbacks of atmospheric observations into the ocean and ocean observations into the atmosphere through cross covariances are attempting to correct the lower-tropospheric cold bias over the equatorial cold tongue in the eastern Pacific Ocean. The feedback seen in strongly coupled variant A^{OOA} in the tropics, where ocean observations from the slow ocean domain lead to small improvements in the atmosphere and in turn small improvements in the ocean subsurface appears to be similar to the effect observed by Sluka et al. (2016). In their intermediate complexity system, atmospheric observations improved the ocean, which in turn improved the atmosphere, through cross

covariances and integration of the forward model. This suggests scale separation was less of an issue in their system. While, due to scale disparity, we saw deterioration of the ocean subsurface in our variant A^{AO} , the atmospheric error-growth rates in variant O^{AO} show benefit for the atmosphere compared to the weakly coupled variant O^O .

d. Global atmospheric circulation

In this section we analyze the impact of strongly and weakly coupled DA on the tropospheric response to deep tropical convection via modulation of the Hadley circulation using the zonal mean meridional mass streamfunction ψ , defined as

$$\psi(\phi, p, t) = \frac{2\pi a \cos\phi}{g} \int_p^{p_s} v(p', \phi, t) dp', \quad (5)$$

where ϕ is latitude, p is pressure integrated from the top of the atmosphere to p_s the surface pressure, t is time, a is Earth radius, g is gravitational acceleration, and v is zonal mean velocity. The seasonal mean streamfunctions for strongly coupled variant A^{AOOAO} , weakly coupled variant A^{AOO} , strongly inversely coupled variant A^{OOA} and the control are shown in Fig. 11. Positive values of the streamfunction are for clockwise and negative for counterclockwise circulation. The color scale represents the difference in streamfunction from JRA55. While the signal from the DA in the streamfunctions is hindered due to the 7-day forecast cycle, the three variants using strongly coupled DA (A^{AOOAO} , A^{AOO} , A^{OOA}) all modify the latitudinal position of the upward and downward branches of the Hadley cells to be closer to the observations. This is particularly evident in comparison to the control, which possesses larger differences extending into the lower troposphere. The small differences between variant A^{AOOAO} and A^{AOO} reflect that with a densely observed atmosphere, the impact of ocean observations on the atmosphere is reduced. Feedbacks occurring in the inverse strongly coupled variant A^{OOA}

FIG. 10. Zonal section through 2°S showing austral summer seasonal mean temperature increments (K) for the atmosphere and ocean upper 500 m. The corresponding coupled DA variant from Table 1 is annotated in the panels. The black horizontal line is the air-sea interface. Gray shading corresponds to ocean bathymetry.

FIG. 11. Seasonal mean differences in 7-day forecasts of atmospheric zonal mean meridional mass streamfunction for strongly coupled variant $A^{AO}O^{AO}$, weakly coupled variant $A^{AO}O^O$, strongly inversely coupled variant $A^O O^A$, and the control. The color scale represents differences in streamfunction compared to JRA55. Units are $10^{10} \text{ kg s}^{-1}$.

lead to improved agreement for the atmospheric circulation compared to the control, indicating positive strongly coupled interactions between atmospheric and ocean observations purely through the cross covariances supporting the findings of [Sluka et al. \(2016\)](#) and [Sluka \(2018\)](#). Variant A^{OO} reduces error in the tropics for about 6 months of the year from January to May. For all seasons and experiments shown in [Fig. 11](#) there is little difference in atmospheric circulation error in the Northern Hemisphere north of the downward branch of the Hadley cell. This region contains significantly less ocean than the tropics and Southern Hemisphere. This highlights the key role that the ocean plays in predictability of the global atmospheric circulation, in particular for the Southern Hemisphere, and that constraining the subsurface ocean to observations is important for weather and climate prediction.

e. Normal mode decomposed growth rates

The Madden–Julian oscillation (MJO) is a tropical phenomenon on intraseasonal time scales resulting from strong coupling between deep tropical convection over the Maritime Continent and atmospheric dynamics modulating convection and directly affecting tropical precipitation ([Madden and Julian 1971](#); [Zhang 2005](#)). The MJO is characterized by an eastward propagating ($4\text{--}8\text{ m s}^{-1}$) envelope of enhanced convective activity traversing the Indo-Pacific warm pool to the date line ([Hendon and Salby 1994](#); [Zhang 2005](#)). The MJO is an important source of predictability in the Northern Hemisphere midlatitudes on subseasonal time scales via its coupling to North Atlantic Oscillation through fluxes of wave activity emerging from the tropics near 120°E and propagating into the area over the Gulf of Alaska ([Lin et al. 2009](#); [Frederiksen and Lin 2013](#); [Hung et al. 2013](#)). While recent intensive observational studies have improved our understanding of the dynamics of the MJO, the skill of current state of the art seasonal weather prediction systems to predict the initiation and evolution of any particular MJO event remains low [e.g., [Zhang \(2005\)](#) and [Vitart and Molteni \(2010\)](#)]. For climate models, which struggle to simulate tropical variability very well and represent the MJO and its teleconnection to the midlatitudes very poorly ([Hung et al. 2013](#)), coupled data assimilation may offer an important approach to improve key ocean–atmosphere coupled modes and better initialize seasonal prediction systems.

Longer time scales of atmospheric predictability are related to larger spatial scales of the evolving flow ([Lorenz 1969](#)). [Dalcher and Kalnay \(1987\)](#) show that saturation error is attained at longer times for larger scales. [Figure 9](#) showed nonzero atmospheric error growth at intraseasonal time scales. This section explores whether error growth on

intraseasonal time scales is related to the large-scale modes with intraseasonal variability, and in particular the MJO. Improvement of the representation of key coupled modes of variability is a major motivation for coupled data assimilation. The ability to attribute error growth at a particular spatiotemporal scale to a given observed coupled mode introduces an additional direct physical interpretation to our analysis and a criterion to determine the relative importance of cross-domain coupling (covariances). Our approach is to project innovations onto normal mode function(s) (NMF) representative of the MJO and compare to the observed MJO variability. Specifically we project the innovations onto the Rossby wave component most closely associated with the MJO and compare this to the realtime multivariate MJO (RMM) index of [Wheeler and Hendon \(2004\)](#). [Kitsios et al. \(2019\)](#) have shown that the representative Rossby wave component and the RMM are highly correlated. As an example we continue the use of variant A^{AO} on a 28-day DA cycle length. The projection of innovations onto normal mode function(s) (NMF) representative of the MJO is calculated. This is compared to the Real-time Multivariate MJO (RMM) index of [Wheeler and Hendon \(2004\)](#). The RMM index of the MJO involves a multivariate singular value decomposition of outgoing longwave radiation, and the longitudinal velocity at 200 and 850 hPa, all meridionally averaged within the region $15^\circ\text{S}\text{--}15^\circ\text{N}$. A time evolving index is then created from the squared magnitude of the first two principal components. Here we show in [Fig. 12a](#) the RMM index calculated from the JRA-55 fields directly, and following [Wheeler and Hendon \(2004\)](#), a centered 91-day moving average applied to the raw time series index. A large amplitude of the moving average is indicative of a heightened period of the MJO.

As mentioned earlier, the RMM index is strongly correlated to a particular NMF ([Žagar and Franzke 2015](#); [Kitsios et al. 2019](#)). NMFs are the eigenvectors of the linearized primitive equations on a sphere, simultaneously capturing the variability in the horizontal velocity field and geopotential height, with the eigenvalues being the temporal period of the mode ([Kasahara and Puri 1981](#)). The NMFs are characterized by a zonal wavenumber (k), meridional wavenumber (n), and vertical mode number (m), which are in turn decomposed into Rossby waves, and westerly and easterly traveling inertial gravity waves. The particular mode that projects most strongly onto the MJO is the Rossby wave component with $(k, n, m) = (1, 1, 8)$. The meridional and vertical dependence of this mode are illustrated in [Figs. 12b and 12c](#), respectively. The component of the daily DA innovations that project onto the MJO representative NMF is illustrated in [Fig. 12a](#). The red dots indicate when the DA

FIG. 12. Characterization of the DA innovations representative of the Madden-Julian oscillation (MJO), via the balanced component (i.e., Rossby wave-like) normal mode function (NMF) of zonal wavenumber $k = 1$, meridional index $n = 1$, and vertical mode index $m = 8$: (a) temporal evolution of the raw Real-time Multivariate MJO (RMM) index of [Wheeler and Hendon \(2004\)](#), its 91-day moving average (MA), and the DA innovations projected onto the NMF representative of the MJO; (b) zonal velocity component of the horizontal structure function (HSF) of the Rossby wave-like NMF for $(k, n, m) = (1, 1, 8)$; and (c) NMF vertical structure function (VSF) for $m = 8$ in σ coordinates scaled by indicative surface pressure $p_0 = 1013$ hPa. Analysis based on variant A^{AO} on 28-day DA cycle as in [Fig. 9](#).

increments are applied to the background fields. During strong MJO events, identified as large values of the raw RMM index, the MJO component of the DA innovations are also large. Note there are periods when the NMF time series is large during periods of low RMM amplitude. This is because the NMF is a global three-dimensional mode projecting onto other events, not necessarily captured by the RMM index, which is defined on only two vertical levels. Regardless, there is clearly a strong positive relationship between the strength of an MJO event and the MJO related innovations. The complexity of the MJO dynamics represents a severe test for coupled DA. The fact that the CAFE system exhibits consistent behavior in relation to capturing error growth in intra-seasonal disturbances demonstrates the importance of cross covariances for forecasting these modes.

4. Conclusions

Variants of strongly and weakly coupled ocean-atmosphere ensemble data assimilation were explored through assessing the role of observations and cross-domain ocean-atmosphere error covariances relevant to climate model state estimation. This was carried out with sequences of 7-day coupled forecasts using a 96-member EnKF system that assimilated a wide range of ocean, atmospheric and sea ice observational data. We detected a benefit for the relatively large spatiotemporal scales in the atmosphere and for the ocean subsurface when strongly coupling ocean observations to the atmosphere via the cross covariances. In the present

climate model state estimation system, projecting fast atmospheric observations onto the ocean subsurface through the cross covariances produced benefits for the oceanic and atmospheric near-surface layers, however, which led to deterioration of the ocean subsurface. We speculate this was due to disparate scales not being accurately accounted for and the inability of sparse subsurface ocean observations to counteract it. Taking account of the lagged correlations between atmosphere and ocean and averaging observations and background states to construct strongly coupled analyses as proposed by [Lu et al. \(2015\)](#) appears to be a way to ameliorate issues associated with scale separation. Additionally, obtaining improved cross covariances would rely on improving the forecast model, ensemble size, and perhaps localization. Our results indicate that in a well-observed climate system the impact of cross covariances diminishes; however, remain important for striving toward a balanced coupled analysis. These results support the findings of the paradigm model studies of [Peña and Kalnay \(2004\)](#) and [O'Kane et al. \(2019\)](#), where the slow ocean was able to constrain the slow atmosphere through flow dependent cross covariances. Global 7-day forecast error metrics for the atmosphere appeared saturated. Global forecast innovation error-growth rates clearly differentiated predictability in the atmosphere and ocean, suggesting nonzero error-growth in certain classes of coupled DA beyond the 7-day time scale considered in this study.

The strongly coupled variant A^{OOA} where atmospheric observations were used to drive the ocean increment and ocean observations were used to drive the atmospheric

increment, purely through cross covariances, was an extreme test of coupled DA. While the overall forecast performance in variant A^OO^A was poor in our complex system, it nevertheless produced meaningful increments in the tropical marine and atmospheric boundary layers. This aligns with the findings of Penny et al. (2019) and Sluka et al. (2016) where strongly coupled DA has been shown to improve representation of the oceanic and atmospheric surface layers. This also suggests vertical localization around the air–sea interface may be beneficial in strongly coupled DA by excluding areas of scale separation from the cross covariances and coupled analysis.

We then analyzed intraseasonal predictability via forecast innovations associated with the Madden–Julian oscillation (MJO) decomposed into balanced (Rossby) and unbalanced (Kelvin) normal modes. Our finding is that in the balanced mode most closely associated with the MJO, there is a clear relationship between the strength of a given MJO event and the related forecast innovations. This demonstrates that through assimilation of atmospheric, oceanic and sea ice observational data the CAFE system is able to capture dynamics that affect intraseasonal predictability in the climate system.

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