Balanced and Coherent Climate Estimation by Combining Data with a Biased Coupled Model

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ABSTRACT

Given a biased coupled model and the atmospheric and oceanic observing system, maintaining a balanced and coherent climate estimation is of critical importance for producing accurate climate analysis and prediction initialization. However, because of limitations of the observing system (e.g., most of the oceanic measurements are only available for the upper ocean), directly evaluating climate estimation with real observations is difficult. With two coupled models that are biased with respect to each other, a biased twin experiment is designed to simulate the problem. To do that, the atmospheric and oceanic observations drawn from one model based on the modern climate observing system are assimilated into the other. The model that produces observations serves as the truth and the degree by which an assimilation recovers the truth steadily and coherently is an assessment of the impact of the data constraint scheme on climate estimation. Given the assimilation model bias of warmer atmosphere and colder ocean, where the atmospheric-only (oceanic only) data constraint produces an overcooling (overwarming) ocean through the atmosphere–ocean interaction, the constraints with both atmospheric and oceanic data create a balanced and coherent ocean estimate as the observational model. Moreover, the consistent atmosphere–ocean constraint produces the most accurate estimate for North Atlantic Deep Water (NADW), whereas NADW is too strong (weak) if the system is only constrained by atmospheric (oceanic) data. These twin experiment results provide insights that consistent data constraints of multiple components are very important when a coupled model is combined with the climate observing system for climate estimation and prediction initialization.

1. Introduction

Nowadays, coupled climate models reasonably simulate the interactions of major components of the earth climate system, such as the atmosphere, ocean, land, and sea ice, and give the assessment of climate changes forced by the changes of greenhouse gas and natural aerosol (Randall et al. 2007). However, because of uncertainties and errors in modeling (e.g., parameterization is only an approximation, numerical implementation is imperfect, etc.), models always tend to produce different climate features and variability from the real world (e.g., Delworth et al. 2006; Collins et al. 2006). Climate estimation is usually performed by assimilating observations into a coupled model, which is called coupled data assimilation. The estimated climate states by combining model and data serve as a continuous time series for climate change and variation assessment and also provide the initial conditions of coupled model for predicting the future climate states. Such a coupled data assimilation can sustain the nature of
multiple time-scale interactions during climate estimation (e.g., Zhang et al. 2007; Sugiura et al. 2008), thus producing a coherent and balanced coupled model initialization that may enhance model predictability (Yang et al. 2013).

The incomplete understanding on physical processes and imperfect numerical implementation make misfittings in modeling. The discrepancy of a model quantity from observations in its time mean or/and climatology is usually referred to as model bias. In the practice of climate estimation and prediction initialization, scientists have recognized that model bias is a major obstacle when a coupled model is used to assimilate observations to produce accurate climate estimation and prediction (Balmaseda et al. 2007a,b; Zhang et al. 2013). The model bias maintains systematic errors in estimated states and produces artifacts in analysis variability (e.g., Dee and Silva 1998; Dee 2005). Because of model bias, the numerical climate prediction tends to drift away from observed states (Smith et al. 2007). However, because of incomplete representation of observations to the real climate system, especially for the ocean, where most of the measurements are only available for the upper part, knowledge of model bias and its influence on long-term climate estimation and prediction still remains limited. For example, model studies have shown that decadal signals exist in the Atlantic meridional overturning circulation (AMOC) (e.g., Delworth et al. 1993; Latif et al. 2006) that are directly linked with the North Atlantic Deep Water (NADW) (e.g., Hopkins 1991; Pickart and Spall 2007), but long-time direct measurements of AMOC and NADW are still unavailable. This makes severe difficulties in understanding the impact of model bias on climate estimation and prediction.

To understand the behavior of a biased coupled model in climate estimation, in this study, we designed a biased twin experiment framework using two coupled general circulation models (CGCMs) developed at the Geophysical Fluid Dynamics Laboratory (GFDL), which are biased with respect each other. In such a twin experiment framework, the observations sampling one model solution that defines the truth are assimilated into the other model. Within this framework, any climate aspect of interests can be assessed by being verified with the truth. As the first step in detecting decadal variability and predictability when an imperfect coupled model is combined with the modern climate observing system, this study focuses on the impact of consistent atmospheric and oceanic constraints on balanced and coherent estimates. To do that, we examine the behavior of the surface heat flux and ocean heat content in three data constraint schemes: atmospheric data constraint only, oceanic data constraint only, and simultaneous atmospheric and oceanic data constraints.

The paper is organized as follows: The methodology is presented in section 2. Section 3 examines the impact of different data constraint schemes in coupled data assimilation on climate estimation. Section 4 gives summary and discussions.

2. Methodology

a. Two biased CGCMs at GFDL

Combining two atmosphere models, atmosphere model 2.0–land model 2.0 (AM2.0–LM2.0) and AM2.1–LM2.1, with the Modular Ocean Model, version 4 (MOM4) and the Sea Ice Simulator (SIS), GFDL has developed two fully coupled general circulation models, Climate Model, version 2.0 (CM2.0) and CM2.1 (Delworth et al. 2006), for the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4; Randall et al. 2007). These two atmosphere models are based on different dynamical cores, B-grid finite difference (Wyman 1996; Anderson et al. 2004) for AM2.0 and finite volume (Lin 2004) for AM2.1, but both have the same vertical (24 levels) and horizontal (2.5° longitude by 2° latitude) resolution as well as identical physical package and land model with their own tuned parameters.

MOM4 is configured with 50 vertical levels (22 levels of 10-m thickness for each in the top 220 m) and 1° × 1° horizontal B grid resolution telescoping to ½° meridional spacing near the equator. The model has an explicit free surface with freshwater fluxes exchanged between the atmosphere and ocean. Parameterized physical processes include K-profile parameterization (KPP) vertical mixing, neutral physics, a spatially dependent anisotropic viscosity, and a shortwave radiative penetration depth that depends on a prescribed Sea-viewing Wide Field-of-view Sensor (SeaWiFS) climatological ocean color. Isolation varies diurnally and the wind stress at the ocean surface is computed using the velocity of the wind relative to surface currents. The SIS in the coupled model is a dynamical ice model with three vertical layers (one for snow and two for ice) and five ice-thickness categories. The elastic-viscous-plastic technique (Hunke and Dukowicz 1997) is used to calculate ice internal stresses, and the thermodynamics is a modified Semtner three-layer scheme (Winton 2000).

Some fundamental difference of the simulated oceans in CM2.0 and CM2.1 in the IPCC AR4 versions can be found in Gnanadesikan et al. (2006). Here, we set the IPCC AR4 version, CM2.0, as the observational model and the updated CM2.1, which serves as the IPCC AR5
decadal prediction model (see Yang et al. 2013), as the assimilation model. Besides code optimization and machine transition (from Altix to Gaea), major changes of CM2.1 from IPCC AR4 version to IPCC AR5 version include an efficient forward time-stepping scheme (Griffies 2005), replacing the leapfrog scheme and some retuned parameters (e.g., in the parameterization of bottom boundary condition processes). These factors make the two models very different. Here we show and comment on the fundamental bias of CM2.1 versus CM2.0. The black lines in Fig. 1 show the difference of time-averaged global mean atmosphere (top panel) and ocean (bottom panel) temperature profiles of CM2.1 and CM2.0 in the last 20 yr of the 29-yr (1971–99) assimilation period. Both models use historical greenhouse gas and natural aerosol (GHGNA) radiative forcings (the date of GHGNA records is referred as the model calendar) and start from their own initial conditions reset as 0000 UTC 1 January 1861 after the coupled spinup run (Stouffer et al. 2004). Figure 1 presents the mean bias of CM2.1 versus CM2.0 (here the term “bias” refers to as the difference of the two models) in terms of the annual mean of atmosphere and ocean temperatures. The atmosphere has a coherent warm bias in the troposphere and stratosphere.

FIG. 1. Annual means (average over the last 20 yr of the assimilation period) of the (a) atmospheric temperature and (b) oceanic temperature in CM2.1 (black), ADA (green), ODA (blue), and CDA (red), all referred to the observational model, CM2.0. The number in the parentheses is the corresponding root-mean-square of the difference. The details of the 200-m upper-ocean temperature difference are shown in a zoom-out version in (b).
While the warm bias of the ocean is mainly observed in the surface layer (above 200 m) and the deep ocean (below 1500 m), the layer between 200 and 1500 m appears to have a severely colder bias.

b. Ensemble coupled data assimilation

A coupled data assimilation scheme (Zhang et al. 2007) based on the ensemble adjustment Kalman filter (EAKF; Anderson 2001) is applied to CM2.1 in this study. The observational increment (the atmospheric temperature and wind as well as the oceanic temperature and salinity in this case) is computed first [see Eqs. (2)–(5) in Zhang et al. 2007]. Then the observational increment is projected onto corresponding model variables using a linear regression formula as

$$\Delta x_{k,i} = \frac{\text{cov}(x, y_k)}{\sigma_k^2} \Delta y_{k,i}. \quad (1)$$

Here, $\Delta x_{k,i}$ represents the observational increment of the $k$th observation $y_k$ at the $i$th ensemble member. The term $\Delta x_{k,i}$ indicates the contribution of the $i$th observation to the model variable $x$ for the $i$th ensemble member. The term $\text{cov}(x, y_k)$ denotes the error covariance between the prior ensemble of $x$ and the model-estimated ensemble of $y_k$. The term $\sigma_k$ is the standard deviation of the model-estimated ensemble of $y_k$. An adaptive inflation scheme is used to increase the deep-ocean adjustment (Zhang and Rosati 2010). Based on this ensemble coupled data assimilation (ECDA) system, GFDL has generated a coupled reanalysis product more than 50 yr long, in which a realistic ocean mean state and variability have been shown by Chang et al. (2013).

c. Biased twin experiment setup

In this section, we describe a biased twin experiment framework by setting CM2.0 and CM2.1 as the observational and assimilation models, respectively. The true solution of the climate estimation problem is a priori defined by the IPCC AR4 historical simulation of the CM2.0 model for the last three decades of the twentieth century (Randall et al. 2007). The modern climate observing system includes the reanalysis atmospheric temperature and wind data and Argo-observed oceanic temperature and salinity. In this study, to simulate the stable evolution of the Argo observing system after 2007, the 2010 Argo network is used repeatedly. In the Argo network, the number of salinity profiles is almost the same as for temperature [e.g., the total number of salinity (temperature) profiles in January 2010 is 20675 (20681)]. The observations of the atmospheric temperature (wind) take the gridded reanalysis format but are superimposed by a random white noise with 1-K (1 m s$^{-1}$) standard deviation as the observational error, at a 6-h frequency. The observations of the oceanic temperature (salinity) are produced through sampling the true ocean states using the 2010 Argo network at a daily frequency. The ocean observational error is 0.5°C (0.1 PSU) at the surface and gradually decays by an $e$-folding depth of 2000 m.

The 12-member ensemble of assimilation model (CM2.1) starts from its states of ensemble historical simulations at 0000 UTC 1 January 1971 and assimilates the atmospheric or/and oceanic data to finish up on 31 December 1999. To examine the role of balanced and coherent atmospheric and oceanic data constraints in climate estimation, we have conducted three assimilation experiments: 1) atmosphere data assimilation (ADA), only assimilating the atmospheric data into the ensemble coupled system; 2) ocean data assimilation (ODA), only assimilating the oceanic data into the ensemble coupled system; and 3) coupled atmosphere–ocean data assimilation (CDA), assimilating both the atmospheric and oceanic data into the ensemble coupled system.

3. Impact of balanced and coherent coupled data constraints on climate estimation

The time-averaged global mean atmosphere and ocean temperatures of ADA (green), ODA (blue), and CDA (red) are shown in Fig. 1. On one hand, ODA only corrects the troposphere warm bias by cooling the surface ocean from the oceanic data constraint, and ADA changes the warm bias in a cold one in the middle troposphere because of direct atmospheric data constraint but a larger warm bias remains near the surface because of the free warmer surface of the ocean. On the other hand, while ADA makes the ocean subsurface (200–2000 m) too cold, ODA produces a too warm deep ocean (below 2500 m). With both atmospheric and oceanic data constraints, CDA dramatically reduces the lower troposphere warm bias (0.2 K) from ADA (0.7 K) but makes the middle troposphere colder. At the same time, CDA produces the best ocean estimate among the three data constraint schemes.

The time series of ocean heat content (gridded-weighted average of ocean temperature) show that all of ADA, ODA, and CDA make the upper-ocean (above 700 m) heat content converge to the truth (Fig. 2a), although each experiment has a different accuracy. While ADA and ODA produce an overcooling and overwarming deep ocean, respectively, only CDA makes the deep-ocean heat content approach the truth (Fig. 2b). Next, we will analyze these three experiments in details and understand the mechanism of these phenomena.
To understand the mechanism of ADA’s overcooling in the deep ocean, we first show the horizontal distribution of the decadal tendency (last 10-yr mean minus the previous 10-yr mean) of 700–6000-m heat content in Fig. 3a. We see that the major cold tendency is observed in the Southern Ocean, especially in the South Atlantic and south Indian Oceans. In particular, to understand the relationship of the cold tendency and meridional transport and overturning, we focus on the area marked by the blue color (simply called the Atlantic channel here). Then we examine the vertical distribution of the decadal tendency in the channel (Fig. 3b). We find the largest cold tendency is in 700–4000 m and south of 65°S, and a weak cold tendency exists in the tropical and extratropical deep ocean (below 2000 m and between 60°S and 50°N), while the high-latitude North Atlantic (north of 50°N) shows a warm tendency. Figure 3c presents the time series of the deep-ocean heat content in the global domain (GLB; black curve), Atlantic channel (ATL; red curve), and the other area (OTH; green curve). From Fig. 3c, we find the most intensive cold tendency occurs between the mid-1980s and the early 1990s, several years after the data assimilation starts. In addition, Fig. 3b also shows some cold tendency in the south Indian Ocean. Next, we will explain these phenomena by
analyzing the ocean responses to the atmospheric data constraint.

Further examination found that the cold and warm tendency pattern in the Atlantic channel is associated with the very strong meridional overturning there, which corresponds to very strong North Atlantic Deep Water (NADW), as shown in Fig. 4a. The strong deep convection in ADA (green curve) is consistent with the distribution of vertical velocities that have strong North Atlantic downwelling and strong Southern Ocean upwelling shown in Fig. 4b. Furthermore, checking the wind stresses over the Southern Ocean, we found that what causes the increasingly strong overturning is the Ekman effect arising from progressively strong wind stress curl in the Southern Ocean. To conveniently make a linkage with the Atlantic meridional transport and
overturning, we analyze $\tau_y$ as an example of wind stress. Figure 4c presents the distribution of the first mode of empirical orthogonal function (EOF1) pattern of $\tau_y$, and the corresponding first principle component (PC1) time series is shown in Fig. 4d. The progressively strengthened wind stress corresponds to the large vertical velocity shown in Fig. 4b.

To understand the progressively strengthened wind stress in ADA, we examine the difference of the surface pressure in CM2.0 and CM2.1 in the assimilation period, which represents the synthetic effect of atmospheric data constraints in this case. With the distribution of the EOF1 pattern that explains 40% of the variance of the two-model difference in surface pressure, we found that the strongest signals of data constraint are over the Antarctic Circumpolar Current (ACC) area of the Southern Ocean (Fig. 5a). The signals of the atmospheric data constraint are also found in the North Pacific and Atlantic areas, although they are quite weak compared to the ACC areas. Based on the EOF1 distribution of the difference of surface pressure anomalies in the two models, we can derive the signals that the CM2.0 atmosphere constrains the CM2.1 atmosphere by computing the geostrophic wind stress. We show the distribution of the wind stress derived from the EOF1 of the different surface pressure anomalies between CM2.0 and CM2.1 in Fig. 5b (again $\tau_y$ as an example). Compared to Fig. 5b, the major features of the ADA wind stress anomalies shown in Fig. 4c can be mainly explained by the geostrophic responses of the CM2.1 atmosphere to the data constraint from the CM2.0 atmosphere. It is worth mentioning that the PC1 of the difference of surface pressure anomalies appears to be neutral instead of showing an explicit increasing trend like Fig. 4d. This means that the strongly increasing wind stress constraint is explained by the CM2.1 atmosphere not the CM2.0 atmosphere.

**FIG. 4.** (a) Time series of North Atlantic Deep Water [the averaged thickness between two isopycnal surfaces of $\sigma_1.5$ over the domain of (55$^\circ$–35$^\circ$W, 45$^\circ$–65$^\circ$N)] in the CM2.0 (solid black) and CM2.1 (dashed black) simulations and ADA (green), ODA (blue), and CDA (red). (b) The vertical motion velocity averaged over the last 20 yr of ADA, shaded in three bands: greater than 0.05 m day$^{-1}$ (red), −0.05 to 0.05 m day$^{-1}$ (green), and less than −0.05 m day$^{-1}$ (blue). (c) EOF1 (which explains roughly 23% of the variance) of meridional wind stress $\tau_y$ anomalies in ADA. (d) Time series of the first principle component of $\tau_y$ in ADA.
in ADA comes from the accumulated effect of the geostrophic adjustment due to the bias of the two different models. In addition, we notice that the Atlantic deep convection reaches its equilibrium (see the green curve in Fig. 4a) by a typical time scale of NADW’s response to the atmospheric forcings (Zhang et al. 2010). It is roughly the same time scale at which the most intensive Atlantic channel cold tendency starts (see the red curve in Fig. 3c).

The same mechanism that shows the strong upwelling in the south Indian Ocean induced by the progressively strengthened wind stress in ADA can explain the cold tendency distributed over the basin shown in Fig. 3a.

Through the analyses above, we understand that the free ocean responses of CM2.1 to the atmospheric-only data constraint from CM2.0 can produce an overcooling ocean through producing much strong deep convection.
and meridional overturning circulation (Gnanadesikan et al. 2006).

b. Oceanic-only data constraint in the coupled model

As discussed in Zhang et al. (2010), opposite to ADA, ODA solves an inverse problem of ocean modeling in a coupled system in which the ocean states are directly adjusted by projecting data-sampled signals (from CM2.0 in this case) and the sea surface maintains a balance with the feedbacks of the atmosphere to the adjusted ocean states. Also, as pointed out in Zhang and Rosati (2010), unlike the vertically consistent atmospheric data constraint, the oceanic data constraint mainly occurs in the upper ocean because of the dramatically decreased variability of ocean circulations by depth and sparse observations (also, compared to low latitudes, the high-latitude data constraint is weak too). The ODA ocean temperature root-mean-square errors (RMSEs) normalized by the RMSEs of CM2.1 (free model control) are plotted in Fig. 6a. Figure 6a clearly shows that the
effective ODA data constraint mainly focuses on the upper ocean (above 1000 m) between 50°S and 60°N. As the result, while the data constraint quickly brings the upper ocean to approach CM2.0 (truth) (the spinup time scale is about 5 yr; see Zhang et al. 2009; see also blue curve in Fig. 2a), the deep ocean tends to stay with the assimilation model after departing to approach the truth in the spinup time (blue curve in Fig. 2b) and eventually appears to be overwarming below 2000 m (see blue curve in Fig. 1b). The deep-ocean responses to the oceanic data constraint consist of two parts: 1) direct data projection through ensemble-evaluated background error covariance from the data above 2000 m, although the ensemble usually underestimates the deep-ocean variability (Zhang and Rosati 2010), and 2) indirect data constraint by model responses to nonlocal data constraints, including the upper-ocean–deep-ocean interaction and the interaction of coupled model components through exchanged fluxes (Zhang et al. 2009). The direct data projection through vertical error covariance is a fast process, while the indirect data constraint is relatively slow. In this case, on one hand, because of the cold surface ocean (above 200 m) of the observational model (CM2.0) (see black curve in Fig. 1b), ODA cools the surface ocean rapidly and, as a feedback of air–sea interaction from the atmosphere, the atmosphere-to-ocean flux dramatically decreases in the first few years of the assimilation period (black curve of Fig. 6b). On the other hand, because of the negative correlation of upper ocean and deep ocean, a dramatic upper-ocean (above 700 m) warming constraint (blue curve of Fig. 2a) can induce a cooling deep-ocean projection through the negative vertical covariance. Therefore, during the ODA spinup period (the first 5 yr), the deep ocean becomes colder toward CM2.0 (see blue curve of Fig. 2b). Starting from the fifth year, ODA reaches quasi equilibrium and the subsurface warming plays an overwhelming role for the whole upper ocean, including the surface, which maintains a persistent heating to the atmosphere. This leads to a gradually increasing atmosphere-to-ocean heat flux from the feedback of the atmosphere (red line of Fig. 6b). We found that, over the quasi-equilibrium period of ODA, the rescaled deep-ocean heat content change is generally consistent with the atmosphere-to-ocean heat flux trend (cf. the green line with the red line in Fig. 6b). This means that, during the period, the role of surface forcings for the deep ocean is suppressing the role of data projection from upper ocean through the vertical covariance. The possible mechanisms include responses of the AMOC to the atmospheric heat flux, appearing to be a slowing-down AMOC (weakening NADW) (blue curve of Fig. 4a).

The analyses above show that, for an imperfect coupled climate system, because of the existence of model bias, an oceanic-only data constraint may produce an overshooting ocean estimate from the feedback of freely responding atmosphere. In addition, limitation of the ocean observing system (e.g., no deep-ocean measurements) and assimilation implementation (e.g., underestimated deep-ocean intrinsic variability by the model ensemble) can worsen the situation.

c. Coupled data constraints with both atmospheric and oceanic observations

Different from ADA and ODA, when both atmospheric and oceanic data constraints are applied to CDA, the ocean estimate is improved significantly. First, compared to the ODA case, the surface forcings provided by the atmospheric data constraint in CDA are consistent with the oceanic data constraint so that the deep-ocean warming is controlled (see the blue and green areas in Fig. 7a). Second, compared to the ADA case, the consistent surface ocean constraint (cf. the red curve to the green curve of Fig. 1b) further reduces the lower-troposphere warm bias (cf. the red curve to the green curve of Fig. 1a). While CDA makes both the upper and deep oceans converge to the truth (cf. red curves to solid black curves in Fig. 2), the consistent atmospheric and oceanic data constraints produce the most accurate estimate for NADW (red curve of Fig. 4a). The RMSEs of the ADA-, ODA-, and CDA-estimated NADW in the last 20 yr are 444, 100, and 75 m, respectively. This means that simultaneously applying atmospheric and oceanic data constraints to the coupled climate system can help the balance between wind driving and thermohaline advection, thus improving the estimate of overturning (deep convection).

Figure 7b presents the relationship of the changes of the atmosphere-to-ocean heat flux and the total ocean heat content anomaly in ADA, ODA, and CDA due to data constraints (the global warming effect due to external radiative forcings is removed), summarizing the different energy balance in different data constraint schemes. In ADA, the ocean is freely forced by the atmospheric data constraint. While the feedbacks between the ocean and atmosphere can produce an overcooling ocean, the cooling of the ocean is balanced with the decreasing atmosphere-to-ocean heat flux (see green lines of Fig. 7b). In ODA, the heated atmosphere by the upper-ocean warming constraint provides an increasing heat flux to the ocean so that the deep ocean keeps in warming that leads to an overwarming ocean estimate (see blue lines of Fig. 7b). In CDA, the consistent atmospheric and oceanic data constraints produce a mostly steady ocean estimate, which remains in balance with the
atmosphere-to-ocean heat flux that is created by the atmospheric data assimilation (see red lines of Fig. 7b). It should be noted that, with the corrected SST forcing, ODA most efficiently corrects the temperature bias within the middle troposphere and CDA shares the same cold bias structure as ADA but the amplitude is larger (Fig. 1a). This suggests that the bias reduction of the troposphere more relies on the correction of atmospheric bottom boundary conditions, while double corrections on the SST and stratosphere unnecessarily help reduce the bias of the middle troposphere, which needs further studies to clarify the mechanism.

4. Summary and discussion

A biased twin experiment framework is designed to study the impact of coherent atmosphere–ocean data constraints on climate estimation. The biased twin
experiment system consists of two coupled general circulation models (CGCMs) (Delworth et al. 2006) that are biased with respect to each other and a coupled ensemble filter (Zhang et al. 2007; Zhang and Rosati 2010). The atmosphere and ocean observations are drawn from one of the models that defines the true solution of the coupled data assimilation problem, based on the modern climate observing system. Then, the synthetic observations are assimilated into the other model. Three different data constraint schemes are examined: atmosphere only, ocean only, and both atmosphere and ocean. The degree to which the assimilation recovers the truth is an assessment of the impact of different data constraint schemes on climate estimation.

Results show that while the atmosphere-only (ocean only) data constraint produces an overcooling (overwarming) ocean estimate, the constraints with both atmospheric and oceanic data create a balanced and coherent ocean estimate as the observational model. Consistently, the balanced and coherent atmosphere–ocean constraints produce the most accurate estimate for North Atlantic Deep Water (NADW), while the NADW appears to be too strong (weak) when the system is only constrained by atmospheric (oceanic) data. These results suggest that, in combining data with an imperfect coupled climate model to perform coupled analysis for climate estimation and prediction initialization, maintenance of the consistent and balanced data constraints in multiple coupled components is of critical importance, especially in initializing the model for decadal predictions.

The present study only analyzes the impact of atmospheric and oceanic data constraints on ocean estimates. Given the importance of sea ice variations in the development of decadal-scale signals, once a physically consistent sea ice data assimilation component (e.g., Zhang et al. 2013) is included in the coupled data assimilation system, the examination of the impact of sea ice constraint on climate estimation shall be set as the first priority in the follow-up studies. In addition, because of the lack of direct observations on decadal-scale climate signals such as AMOC and NADW, extending the biased twin experiment study to detect decadal predictability is another interesting and important research topic in the future.

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