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Development and evaluation of a new 4DEnVar-based weakly coupled ocean data assimilation system in E3SMv2

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Abstract. The development, implementation, and evaluation of a new weakly coupled ocean data assimilation (WCODA) system for the fully coupled Energy Exascale Earth System Model version 2 (E3SMv2) utilizing the four-dimensional ensemble variational (4DEnVar) method are presented in this study. The 4DEnVar method, based on the dimension-reduced projection four-dimensional variational (DRP-4DVar) approach, replaces the adjoint model with the ensemble technique, thereby reducing computational demands. Monthly mean ocean temperature and salinity data from the EN4.2.1 reanalysis are integrated into the ocean component of E3SMv2 from 1950 to 2021, with the goal of providing realistic initial conditions for decadal predictions and predictability studies. The performance of the WCODA system is assessed using various metrics, including cost function reduction, root mean square error (RMSE) differences, correlation differences, and model biases. Results indicate that the WCODA system effectively assimilates the reanalysis data into the climate model, achieving consistently negative cost function reductions and notable improvements in RMSE and correlation across various ocean layers and regions. Significant enhancements are observed in the majority of global ocean regions, particularly in the North Atlantic, North Pacific and Indian Ocean. Model biases in sea surface temperature and salinity are also substantially reduced. Furthermore, analysis of the connections between the ocean states and the regional climate over the US shows that the WCODA system improves the simulation of interannual precipitation and temperature variability over the southern US. The ultimate goal of the WCODA system is to advance the predictive capabilities of E3SM for subseasonal-to-decadal climate predictions, thereby supporting research on strategic energy-sector policies and planning.

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1 Introduction

Climate predictions are essential for understanding and mitigating the impacts of climate variability and change. The accuracy and reliability of climate predictions depends strongly on the initialization of the climate models, which requires realistic and high-quality initial conditions (ICs) for skillful predictions (Dirmeyer et al., 2018). Data assimilation (DA) techniques are important for providing realistic ICs by integrating observational data into the model, thereby enhancing the predictive capabilities of climate models (Tardif et al., 2014). The efficacy of DA techniques has been demonstrated through enhanced predictability on subseasonal to decadal timescales (Zhou et al., 2024).

Numerous studies have focused on the initialization of climate models for decadal predictions (Branstator and Teng, 2012; Polkova et al., 2019). Climate models integrate multiple components, including the atmosphere, ocean, sea ice, and land. For the initialization of climate models in decadal predictions, DA methods can be categorized into uncoupled data assimilation and coupled data assimilation (CDA). In the uncoupled method, DA is performed independently within the uncoupled atmosphere, land and ocean models rather than in a coupled model. The optimal analyses from these uncoupled models are then integrated together to establish the ICs for the climate model's predictions (Yao et al., 2021). For example, some studies directly utilize existing reanalysis data to initialize climate models for decadal predictions (Yeager et al., 2012; Tian et al., 2021). Nevertheless, the uncoupled DA method may lead to imbalances between different model components, potentially inducing initial shocks and diminishing the reliability of climate predictions (Smith et al., 2015; Zhang et al., 2020). Therefore, there is a growing interest in exploring and developing CDA methods to enhance the coherence and accuracy of the ICs for climate predictions.

Many research groups and institutions are actively engaged in the development and refinement of CDA methods. In CDA, the assimilation process is conducted directly within a coupled model. Compared to uncoupled DA, CDA provides balanced ICs that are more coordinated across multiple components of coupled models (Zhang et al., 2014). Previous studies have demonstrated that CDA enhances interannual climate predictions more effectively than uncoupled DA (Zhang et al., 2005; Shi et al., 2022). CDA techniques are divided into weakly coupled data assimilation (WCDA) and strongly coupled data assimilation (SCDA). In the WCDA system, reanalysis data is assimilated independently within each

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component of the coupled model. However, through the coupled model integration, reanalysis information from one component is transmitted to other components through interactions across multiple systems (Browne et al., 2019; He et al., 2020). Sequential DA is distinctly partitioned into two primary stages: the analysis and forecast steps. During the WCDA analysis step, reanalysis information from one component can not directly influence other components due to the lack of cross-component background error covariances. Nonetheless, the coupled model is employed during the forecast step to transfer reanalysis information from single component to others through the integration of the coupled system (Laloyaux et al., 2016; Carrassi et al., 2018). The primary distinction between WCDA and uncoupled DA is the use of the coupled model during the forecast step (Zhang et al., 2020). Recent studies have developed WCDA systems that separately assimilate reanalysis data from the atmosphere (Li et al., 2021), land (Shi et al., 2024), and ocean (He et al., 2017) into coupled models. On the other hand, SCDA employs cross-component background error covariances during the analysis step to directly exert an instantaneous impact of reanalysis information from single component on the state variables of other components, treating all Earth system components as an integrated whole (Sluka et al., 2016). Moreover, SCDA also allows reanalysis information from single component to propagate to other components during the forecast step through the coupled model integration (Yoshida and Kalnay, 2018). Therefore, SCDA offers potential benefits, including reduced model drift and enhanced forecast accuracy (Smith et al., 2015). Nevertheless, the development of SCDA presents considerable obstacles, primarily due to the complexity of accurately establishing cross-component background error covariances (Penny and Hamill, 2017). As a result, most existing CDA systems continue to employ the WCDA systems.

This study presents the development and implementation of the weakly coupled ocean data assimilation (WCODA) system for the fully coupled Energy Exascale Earth System Model version 2 (E3SMv2), utilizing the four-dimensional ensemble variational (4DEnVar) method. The 4DEnVar method is based on the dimension-reduced projection four-dimensional variational (DRP-4DVar) approach, notable for its innovative application of 4DVar by replacing the adjoint model with the ensemble approach (Wang et al., 2010). In the WCODA system, monthly mean ocean temperature and salinity data from the EN4.2.1 reanalysis are incorporated into the ocean component of E3SMv2 to provide realistic ICs for decadal predictions. Although the assimilation process during the analysis step

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is conducted independently within the ocean component, the fully coupled E3SMv2 model is employed during the forecast step to transmit reanalysis information from the ocean to other components (e.g., atmosphere and land) through multi-component interactions. Consequently, the reanalysis information assimilated into the ocean ICs affects other model components through the integration of the fully coupled model, emphasizing the operation of this system as a WCDA system. The primary objective of this WCODA system is to advance our understanding of the ocean's role in climate predictability. Shi et al. (2024) implemented a weakly coupled land data assimilation in E3SMv2 for isolating the land's role in climate predictability. By improving the accuracy of ICs for both land and ocean, we aim to advance the predictive capabilities of E3SM for decadal predictions, ultimately supporting research on energy-sector policy and planning.

This study presents and evaluates the 4DEnVar-based WCODA system for E3SMv2. Section 2 provides a detailed description of the E3SMv2 model, the ocean reanalysis data, and the framework of implementing the 4DEnVar-based WCODA system. Section 3 evaluates the assimilation performance of the WCODA system. Finally, Section 4 provides the conclusions.

2 Methodology

2.1 E3SM Overview

Developed by the U.S. Department of Energy, the Energy Exascale Earth System Model version 2 (E3SMv2) is a state-of-the-art climate model to advance our understanding of climate variability and its future changes (Leung et al., 2020). E3SMv2 integrates multiple components to simulate the complex interactions within the climate system, encompassing the atmospheric, sea ice, ocean, land, and river transport components. The atmospheric component (EAMv2) employs sophisticated representations of turbulence, clouds, and aerosol processes (Zhang et al., 2023) and features a nonhydrostatic dynamical core (Taylor et al., 2020). It operates on a dynamic grid with a horizontal resolution of approximately 110 km and includes 72 vertical layers that extend to the stratosphere (Golaz et al., 2022). The sea ice component (MPAS-SI) simulates the formation, evolution, and melting of sea ice, with detailed thermodynamics and dynamics processes (Turner et al., 2022). The ocean component (MPAS-O) is responsible for modeling the physical state and biogeochemical processes of the ocean, including detailed simulations of ocean currents, temperature, and salinity (Reckinger et al., 2015). The land component (ELMv2) encompasses various land surface processes, including biophysical processes, soil processes, and surface hydrology (Golaz et al., 2019). These simulations are crucial for understanding land-atmosphere interactions and their impact on climate variability. Additionally, the river transport component (MOSARTv2) simulates the hydrological dynamics of water flow through river basins, providing insights into freshwater resources, flood risks, and sediment transport (Li et al., 2013). The CPL7 coupler dynamically integrates all five components through regulating the exchange of energy, water, and momentum fluxes between different components (Craig et al., 2012). The comprehensive evaluation of the E3SMv2 model is presented from Golaz et al. (2022).

2.2 Ocean Reanalysis Dataset

The ocean temperature and salinity data in this study are derived from the EN4.2.1 ocean reanalysis dataset. Produced by the Met Office Hadley Centre, the EN4.2.1 dataset integrates observations from diverse sources such as Argo floats, ship-based measurements, and satellite data (Good et al., 2013). These observations undergo rigorous quality control procedures to ensure the accuracy and reliability of the EN4.2.1 reanalysis (Chen et al., 2020). The comprehensive coverage and high resolution of the EN4.2.1 reanalysis are instrumental for representing the vertical and temporal dynamics of ocean temperature and salinity. The EN4.2.1 reanalysis datasets have been extensively validated and are commonly utilized in numerous climate research (Good et al., 2013; Armour et al., 2016).

To initialize decadal climate predictions, monthly mean ocean temperature and salinity data from the EN4.2.1 reanalysis are assimilated into the fully coupled E3SMv2 model across sixty ocean layers from 1950 to 2021. The choice to utilize monthly mean reanalysis data is based on two primary reasons: Firstly, data with higher temporal resolution (less than one month) might produce unwanted noise, potentially compromising the accuracy of decadal predictions. Secondly, the initialization for decadal predictions requires assimilation cycles spanning several decades, and assimilating complex, real-time observations over such extended periods would be computationally prohibitive. Therefore, in line with most existing studies that use reanalysis data for initializing decadal predictions (Pohlmann et al., 2019; Tian et al., 2021), this study assimilates the monthly mean EN4.2.1 reanalysis through the WCODA

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system for decadal predictions.

2.3 Implementation of the 4DEnVar-based WCODA System

The 4DEnVar method employed by the WCODA system is derived from the DRP-4DVar assimilation approach. The DRP-4DVar technique addresses the high computational demands of traditional 4DVar by employing an ensemble approach rather than utilizing the adjoint model, significantly reducing the computational resources required for implementation (Wang et al., 2010). This advanced method enhances computational efficiency by projecting the high-dimensional state space onto a lower-dimensional subspace defined by an ensemble of historical samples. DRP-4DVar achieves an optimal solution within this sample space by aligning observations with model-generated historical time series over a four-dimensional window (Wang et al., 2010). The DRP-4DVar approach has been effectively implemented across multiple numerical models, demonstrating its accuracy and effectiveness (Zhao et al., 2012; Shi et al., 2021; Zhu et al., 2022). The comprehensive explanation of the DRP-4DVar method is provided in Wang et al. (2010). The DRP-4DVar method has also been implemented in a weakly coupled land data assimilation system in E3SMv2 (Shi et al., 2024).

Figure 1 illustrates the workflow of the 4DEnVar-based WCODA system utilizing the DRP-4DVar approach within the fully coupled E3SMv2 model. The DRP-4DVar algorithm requires three primary inputs: observational innovation ($\tilde{y}'_{obs}$), model background (x_b), and perturbation samples. Initially, fully coupled E3SMv2 simulation is conducted for one month to generate both the model background (x_b) and observational background (y_b). Specifically, the model background (x_b) refers to the monthly initial condition prior to data assimilation, while the observational background (y_b) denotes the monthly mean model states. Subsequently, the observational innovation ($\tilde{y}'_{obs}$) is calculated as the difference in monthly mean ocean salinity and temperature between the EN4.2.1 reanalysis (y_{obs}) and the monthly mean model states (y_b). From 100 years of balanced pre-industrial control (PI-control) simulations, 30 sets of monthly mean forecast samples ($\tilde{y}'$) are selected based on their highest correlations with the observational innovation. More specifically, the monthly mean forecast samples are computed by removing the long-term PI-control monthly climatology from the selected PI-control monthly mean output, which are then divided by the observational error. The observational error is computed based on the statistical variance and covariance of the EN4.2.1 reanalysis. Correspondingly, 30 sets of monthly initial condition samples (x') for the monthly mean forecast samples are derived. The analysis increment is calculated within the perturbation samples, which consist of 30 monthly initial condition samples and their corresponding monthly mean forecast samples. Due to the limited number of samples and to diminish the influence of spurious correlations between distant grid points, a localization procedure is incorporated into the assimilation process (Wang et al., 2018). Finally, the DRP-4DVar algorithm solves for the analysis increment within the sample space, which is then added to the model background to produce the optimal analysis (x_a).

Figure 2 delineates the assimilation process using the DRP-4DVar method within the 4DEnVar-based WCODA system for the fully coupled E3SMv2 model. This assimilation process includes both the analysis and forecast steps through each one-month assimilation window. In the initial stage, the fully coupled E3SMv2 model employs the model background (x_b) as the monthly initial condition to run for one month, producing the monthly mean model outputs for ocean temperature and salinity (y_b^{ocn}). During the analysis step, the observational innovation (y'_{obs}) is computed by comparing the discrepancies between the EN4.2.1 reanalysis (y_{obs}^{ocn}) and the model's monthly mean outputs (y_b^{ocn}) for ocean temperature and salinity. The DRP-4DVar algorithm then utilizes this observational innovation and the PI-control samples to compute the optimal analysis of the ocean component (x_a^{ocn}) at the start of the assimilation window. During the subsequent forecast step, the optimal analysis (x_a) includes both the optimal ocean analysis (x_a^{ocn}) and the background states of other components prior to assimilation. This optimal analysis serves as the new initial condition for the fully coupled E3SMv2 model to run for one month to generate the next month's forecast. During this fully coupled model integration, reanalysis information from the ocean component is transmitted to the other model components through interactions across multiple systems. Although the assimilation is directly applied to the ocean component, the use of the initial conditions of all components from the optimal analysis and the fully coupled climate model during the forecast step ensures that the reanalysis information from the optimal ocean analysis influences other components through interactions across multiple systems. Therefore, according to the definition of the WCDA system from previous studies (Carrassi et al., 2018; Zhou et al., 2024), this assimilation system is designated as the WCODA system. Using the same DA approach, Shi et al. (2024)

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documented the implementation of DRP-4DVar as a weakly coupled land data assimilation system in E3SMv2.

2.4 Experiment Design

Two distinct numerical experiments are performed in this study to assess the effectiveness of ocean data assimilation within the 4DEnVar-based WCODA system. (1) The control simulation (CTRL) is a free-running fully coupled integration over a 72-year period from 1950 to 2021, driven exclusively by observed external forcings. This free-running simulation allows unrestricted interactions among the various Earth system components, including the atmosphere, land, and ocean. The CTRL simulation serves as a baseline for evaluating the assimilation effectiveness of the WCODA system. (2) The assimilation experiment (ASSIM) incorporates monthly mean ocean temperature and salinity data from the EN4.2.1 reanalysis into the ocean component of the fully coupled E3SMv2 model across sixty ocean layers. This assimilation is conducted using a one-month assimilation window, covering the same 72-year period from 1950 to 2021. At the beginning of each monthly assimilation window, the EN4.2.1 reanalysis information is incorporated into the ocean state variables, after which the fully coupled model continues with free integration. During this free integration process, the reanalysis information assimilated into the ocean ICs influences other model components through interactions across multiple systems. The historical external forcings for both the ASSIM and CTRL experiments are derived from the CMIP6 protocol (Guo et al., 2020).

2.5 Assessment Criteria

To comprehensively evaluate the effectiveness of the WCODA system, multiple quantitative metrics are employed, including the root mean square error (RMSE), correlation coefficient, and cost function reduction. The reduction rate of the cost function serves as a fundamental measure to assess the assimilation system's accuracy, calculated using the formula:

$$\frac{\frac{1}{2}(y_{obs}-y_a)^T\boldsymbol{R}^{-1}(y_{obs}-y_a)-\frac{1}{2}(y_{obs}-y_b)^T\boldsymbol{R}^{-1}(y_{obs}-y_b)}{\frac{1}{2}(y_{obs}-y_b)^T\boldsymbol{R}^{-1}(y_{obs}-y_b)} \tag{1}$$

Here, y_{obs} denotes the EN4.2.1 reanalysis, y_b represents the pre-assimilation observational

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background, y_a indicates the post-assimilation monthly mean model analyses, and $\boldsymbol{R}$ denotes the observation error covariance matrix. Negative values of the cost function reduction signify the successful integration of reanalysis data into the model's state variables. To validate the correctness of this assimilation system, the EN4.2.1 reanalysis continues to be utilized as the reference data for evaluation.

3 Results

3.1 Cost Function Reduction

In Figure 3, the monthly variation in the reduction rate of the cost function for the 4DEnVar-based WCODA system is presented for the 72-year period from 1950 to 2021. A negative value of the cost function reduction signifies the successful assimilation of reanalysis data into the coupled model. The cost function reduction rate reaches -12.03% in the first month. Over the entire 72-year period from 1950 to 2021, the average monthly cost function reduction rate is -4.20% for all months in ASSIM. More importantly, the reduction rate of the cost function remains negative in each month of assimilation, underscoring the effectiveness and stability of the WCODA system. These findings demonstrate the successful implementation of the WCODA system, confirming that the EN4.2.1 reanalysis data have been effectively integrated into the fully coupled model.

3.2 Performance of RMSE Differences

Figure 4 illustrates the RMSE differences of monthly ocean temperature between ASSIM and CTRL from 1950 to 2021 across nine ocean layers. Negative values indicate a reduction in RMSE, signifying improvements due to assimilation, while positive values denote an increase in RMSE, indicating degradations. Overall, the assimilation from the WCODA system leads to marked improvements in ocean temperature simulations across most global regions. Both upper and deeper ocean layers exhibit widespread negative RMSE differences, indicating improvements after assimilation, particularly in the tropical and mid-latitude ocean regions. Notable regions of improvement include the North Atlantic, tropical and North Pacific, Indian Ocean, and parts of the Southern Ocean. In the deeper layers, this pattern of improvements persists, though with more pronounced degradation observed in the South Atlantic and specific areas of the southern Pacific Ocean. This degradation in the deeper layers may be attributed to larger observational errors in these regions or limitations in the model's ability to accurately represent deep-ocean dynamics (Wunsch and Heimbach, 2007; Balmaseda et al., 2013).

The RMSE differences for ocean salinity between ASSIM and CTRL across various ocean layers are presented in Figure 5. The majority of ocean regions display notable improvements for ocean salinity after assimilation, as evidenced by the prevalence of negative RMSE differences. Both upper and deeper ocean layers show relatively consistent areas of improvements. Significant enhancements are particularly evident in the North Atlantic, North Pacific, and parts of the Indian Ocean. However, certain areas exhibit degradation in RMSE. These regions are primarily located in parts of the southern Pacific Ocean. The degradation in these areas could be attributed to the inherent challenges of accurately assimilating data in regions with complex ocean dynamics or limited observational data availability (Edwards et al., 2015; Stammer et al., 2016).

3.3 Performance of Correlation Differences

Figure 6 illustrates the differences between ASSIM and CTRL in their correlations with observed monthly ocean temperature from 1950 to 2021 across nine ocean layers. Positive values denote an increase in correlation following assimilation, indicating improvements, whereas negative values suggest a decrease in correlation. Across the majority of global ocean regions, assimilation has generally led to significant improvements in correlation for ocean temperature simulations, with positive values in correlation differences widely distributed. The overall behavior of the upper and deeper ocean layers is largely consistent. Notably, the equatorial Pacific Ocean exhibits substantial improvements across multiple depths, indicating potential enhancements in modeling phenomena such as the El Niño-Southern Oscillation (ENSO). The North Pacific and parts of the Indian Ocean also demonstrate considerable improvements. However, certain areas exhibit diminished performance, possibly due to sparse observational data or complex ocean dynamics. In summary, ASSIM has demonstrably enhanced ocean temperature simulations by reducing RMSE (Fig. 4) and improving correlation (Fig. 6) across many ocean regions, particularly in the tropical and North Pacific, Indian Ocean, and parts of the North Atlantic.

The correlation differences for ocean salinity between ASSIM and CTRL across various ocean layers are depicted in Figure 7. The majority of global ocean regions exhibit marked improvements for ocean salinity, with positive correlation differences dominating. These enhancements are consistently observed from the upper layers to deeper layers. Noteworthy improvements are particularly evident in the tropical and North Pacific, North Atlantic, equatorial Atlantic, and parts of the Indian Ocean. Nevertheless, some regions display a decrease in correlation, such as parts of the Southern Ocean. Overall, ASSIM has significantly improved simulations of ocean salinity in many ocean regions, as evidenced by reduced RMSE (Fig. 5) and improved correlation (Fig. 7), particularly in the North Atlantic, North Pacific, and parts of the Indian Ocean.

3.4 Vertical and Temporal Analysis of RMSE and Bias for Ocean Temperature and Salinity

Figure 8 presents the vertical profiles of the globally averaged RMSE variations in ocean temperature and salinity comparing ASSIM and CTRL. Negative values in the RMSE difference indicate a reduction in the global mean RMSE due to assimilation. For ocean temperature, the RMSE differences are relatively small but become more negative within the upper 85 meters of the ocean. As the depth increases beyond 135 meters, the RMSE differences become significantly negative, indicating a marked improvement in ocean temperature after assimilation. Unlike temperature, the salinity RMSE differences show substantial deviations in the upper layers, specifically within the first 155 meters of the ocean, reflecting significant improvements. However, the RMSE differences gradually decrease as depth increases, possibly due to the complexity of salt transport mechanisms in deep waters or larger observational errors in these layers (Jacobs et al., 2021; Wang et al., 2015). This suggests that the assimilation of salinity data has a more pronounced effect in the upper ocean layers compared with the deeper regions. In summary, these results emphasize the capability of the WCODA system in enhancing the simulation accuracy for both ocean temperature and salinity.

The temporal evolutions of the global mean bias and RMSE for vertically averaged ocean temperature and salinity are illustrated in Figure 9. The temperature bias (Fig. 9a) in CTRL is persistently positive, indicating a systematic overestimation of ocean temperature. In contrast, ASSIM consistently reduces this bias, with values approaching the zero line. Similarly, the temperature RMSE (Fig. 9b) highlights a significant decrease in RMSE for ASSIM compared to CTRL, reflecting a more accurate alignment with observed temperature. For ocean salinity, the salinity bias (Fig. 9c) reveals that CTRL

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maintains a consistent negative bias, suggesting an underestimation of ocean salinity. However, ASSIM effectively mitigates this bias, bringing the bias values closer to the zero line. Furthermore, the salinity RMSE (Fig. 9d) is notably lower in ASSIM than CTRL, indicating enhanced model performance and a closer match to observed salinity. Overall, ASSIM exhibits superior performance relative to CTRL in reducing bias and RMSE for both ocean temperature and salinity.

3.5 Climatological Mean Differences for Sea Surface Temperature and Salinity

Figure 10 presents the climatological mean differences for both sea surface temperature (SST) and salinity (SSS) from 1950 to 2021. Pronounced cold biases are evident in the SST difference between CTRL and observation (Fig. 10a), particularly in the tropical and North Pacific, North Atlantic, and parts of the Indian Ocean. Significant warm biases are observed in the Southern Ocean and parts of the South Atlantic. In contrast, these SST biases found in CTRL are substantially reduced by ASSIM (Fig. 10b), especially in the North Pacific and North Atlantic, where the cold biases are diminished, and in the Southern Ocean, where the warm biases are corrected. The SSS difference between CTRL and observation highlights a global pattern of salinity biases (Fig. 10c). The CTRL simulation generally underestimates salinity across most global oceans, indicating a widespread lower salinity. This fresh bias is particularly pronounced in the North Atlantic and North Pacific. Compared with CTRL, ASSIM significantly increases the salinity estimates, thereby reducing the overall fresh biases in CTRL (Fig. 10d). Notable improvements are observed in the North Atlantic, North Pacific, and parts of the Southern Ocean. In summary, ASSIM demonstrates marked improvements in both SST and SSS biases compared to CTRL, emphasizing the importance and effectiveness of the WCODA system in enhancing model accuracy and reliability.

3.6 Influence of ocean data assimilation on the regional climate over land

To further assess the effectiveness of the WCODA system, a preliminary analysis is conducted to examine the impact of ocean data assimilation on the regional climate over land through the weakly coupled data assimilation system. Motivated by the influence of the El Niño-Southern Oscillation and the North Atlantic Oscillation on the US regional climate (e.g., Higgins et al., 2000), we focus our

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analysis on the simulation of interannual precipitation and temperature variability over the contiguous US. Correlations between the observed and simulated time series of detrended annual precipitation and temperature anomalies for multiple US regions show higher correlations for ASSIM compared to CTRL, although the correlations are generally low (not shown). For the southern US where statistically significant differences are found for the correlations between ASSIM and observations relative to the correlations between CTRL and observations, Fig. 11 demonstrates notable improvements in ASSIM to capture the observed interannual variability in both annual precipitation and temperature anomalies. For precipitation, the wet-dry transitions from 1982 to 1989 and from 2008 to 2016 are more accurately represented in ASSIM compared to CTRL. ASSIM also effectively reproduces the temporal evolution of temperature anomalies during the periods 1982-1993 and 2006-2013. The correlation between ASSIM and observed precipitation is 0.51, much higher than 0.02 in CTRL. Similarly, the correlation for temperature increases from -0.05 in CTRL to 0.42 in ASSIM. Both correlations for precipitation and temperature in ASSIM are statistically significant at the 95% confidence level. The enhanced simulation of interannual climate variability in ASSIM may be attributed to its improved representation of oceanic variability, particularly ENSO-related variability, which is critical for driving regional climate anomalies through air-sea interactions (Ropelewski and Halpert, 1986; McPhaden et al., 2006). Further research is needed to understand the influence of the WCODA system on improving predictability of regional climate over land.

4 Conclusions

This study documents the development and assessment of the new 4DEnVar-based WCODA system in the fully coupled E3SMv2 model, employing the DRP-4DVar method. The DRP-4DVar approach significantly reduces computational demands by replacing the traditional adjoint model with the ensemble technique. As a weakly coupled assimilation system, the WCODA system independently assimilates ocean reanalysis data within the ocean component during the analysis step. However, during the subsequent forecast step, the reanalysis information from the optimal ocean analyses is propagated to other components of the Earth system through interactions across multiple systems, thereby enhancing the coherence of ICs across the climate model.

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Monthly mean ocean temperature and salinity data from the EN4.2.1 reanalysis are integrated into the ocean component of E3SMv2 from 1950 to 2021, which can be used to provide realistic ICs for decadal climate predictions. The effectiveness of the WCODA system has been assessed using several metrics, including cost function reduction, correlation differences, RMSE differences, and model biases. The cost function reduction consistently shows negative values in each month over the 72-year period, indicating successful assimilation of the EN4.2.1 reanalysis data into the climate model. Compared to CTRL, ASSIM achieves significant reductions in RMSE and enhancements in correlation across various ocean layers and regions, with notable improvements observed in the North Atlantic, North Pacific and Indian Ocean. ASSIM substantially mitigates model biases for SST and SSS observed in CTRL, particularly reducing cold biases in the North Pacific and North Atlantic, correcting warm biases in the Southern Ocean, and significantly increasing salinity estimates to reduce the model fresh biases. Moreover, the temporal evolutions of interannual precipitation and temperature variability over the southern US are more effectively captured by ASSIM compared to CTRL through the influence of the ocean data assimilation in the coupled climate system.

Despite these advancements, the WCODA system exhibits limitations in certain regions, particularly in the deeper layers of the southern Pacific Ocean and South Atlantic. These challenges are likely due to sparse observational data and the complexities of representing deep-ocean dynamics. Future efforts should focus on enhancing observational data coverage and refining assimilation techniques for these challenging areas. To further improve the system's capabilities, plans are underway to assimilate more satellite-based ocean observations into the WCODA system. Furthermore, expanding the application of the WCODA system to other components of the climate model, such as the atmosphere and sea ice, could enhance overall predictive skill. These developments are essential for providing more accurate and reliable long-term climate predictions, ultimately aiding in the formulation of energy-sector policies and management strategies.

Code and data availability. The E3SMv2 code is publicly available under an open-source license through the Zenodo repository at https://zenodo.org/records/13259801. The EN4.2.1 monthly ocean temperature and salinity data are provided by the Met Office Hadley Centre via https://www.metoffice.gov.uk/hadobs/en4/. The model data generated and analyzed during this study can be accessed on Zenodo at https://zenodo.org/records/13283117.

Author contributions. PS and LRL designed the experiments. PS developed the ocean assimilation code and conducted the experiments. BW proposed technical advice. PS and LRL analyzed the data. PS and LRL drafted the paper. All authors contributed to the revisions.

Competing interests. The authors declare no competing interests.

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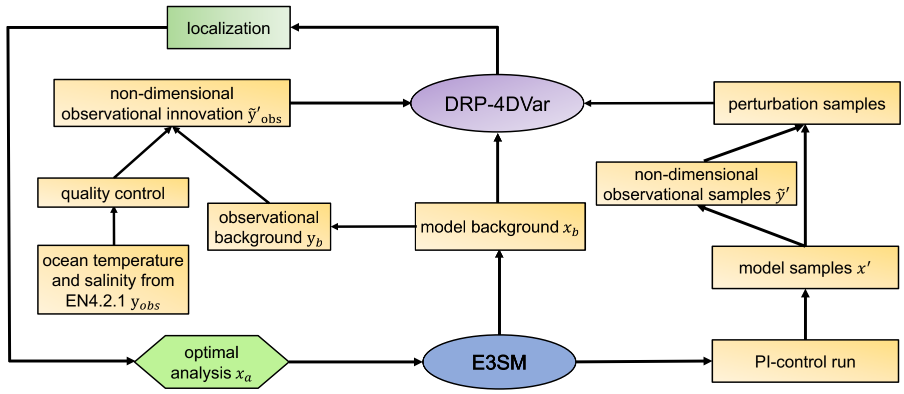

Figure 1. Workflow of the 4DEnVar-based WCODA system utilizing the DRP-4DVar method for the E3SM model (modified from Fig. 1 in Shi et al. (2024)).

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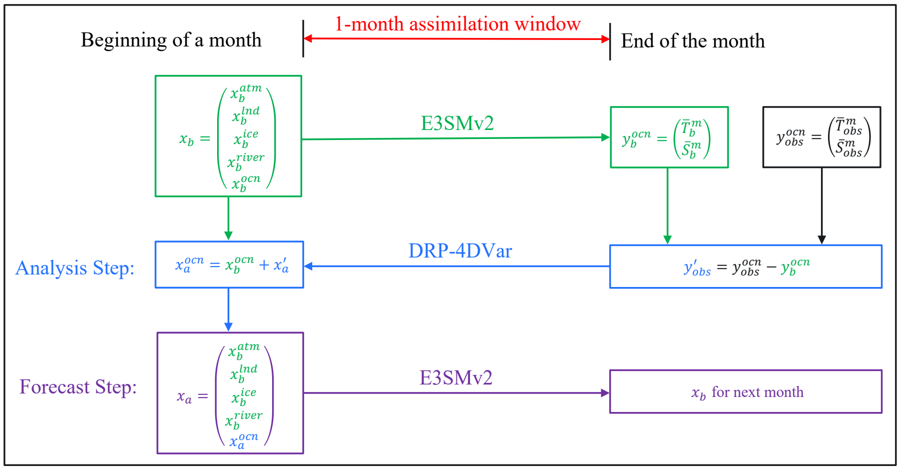

Figure 2. Schematic diagram of the DRP-4DVar assimilation process within the 4DEnVar-based WCODA system for E3SM. The model background (x_b) includes atmospheric (x_b^{atm}), land (x_b^{lnd}), ice (x_b^{ice}), river (x_b^{river}), and oceanic (x_b^{ocn}) components of the fully coupled E3SMv2. The observational background (y_b^{ocn}) is defined by the model outputs of monthly mean ocean temperature ($\bar{T}_b^m$) and salinity ($\bar{S}_b^m$) using x_b as the initial state. The ocean observation (y_{obs}^{ocn}) represents the observed monthly mean ocean temperature ($\bar{T}_{obs}^m$) and salinity ($\bar{S}_{obs}^m$) from the EN4.2.1 reanalysis. The observational innovation (y_{obs}') is calculated as the difference between the observed ocean temperature and salinity (y_{obs}^{ocn}) and the model's observational background (y_b^{ocn}). x_a' denotes the analysis increment. The optimal analysis (x_a) encompasses both the optimal analysis of the ocean component (x_a^{ocn}) and the background states of other components. This optimal analysis (x_a) is used as the initial condition to produce the next month's forecast, transferring ocean reanalysis information to other components.

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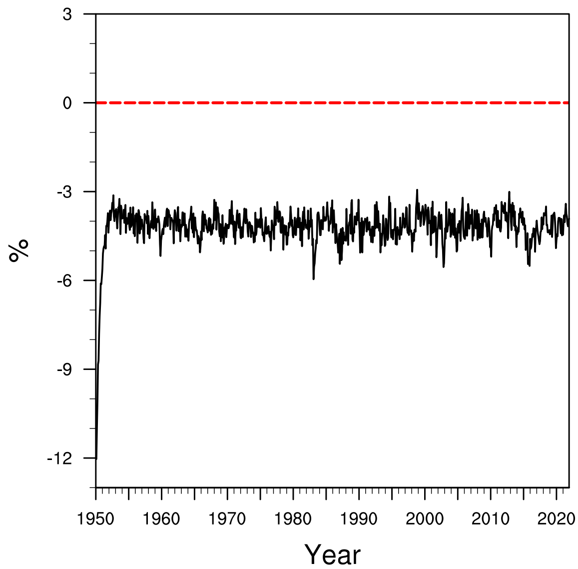

Figure 3. Temporal variation of the cost function reduction in the WCODA system based on the 4DEnVar method from 1950 to 2021.

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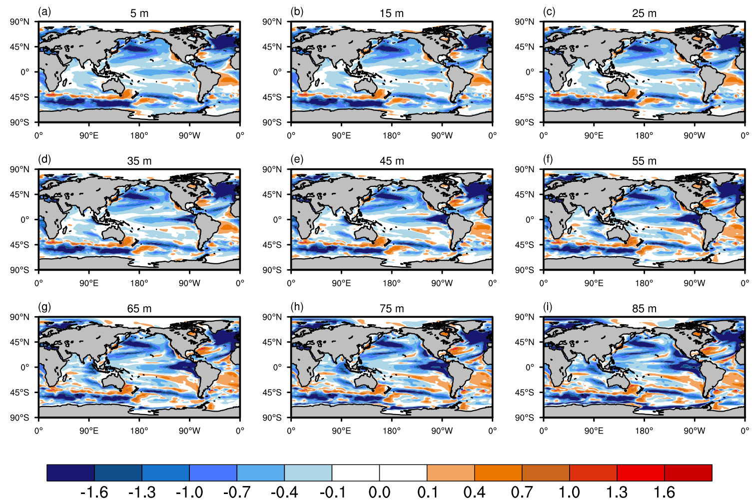

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607 **Figure 4.** Spatial patterns of the root mean square error (RMSE) differences in ocean temperature
608 between ASSIM and CTRL across nine ocean layers from 1950 to 2021. The RMSE differences are
609 shown for nine different ocean depths: (a) 5 m, (b) 15 m, (c) 25 m, (d) 35 m, (e) 45 m, (f) 55 m, (g) 65
610 m, (h) 75 m, and (i) 85 m.

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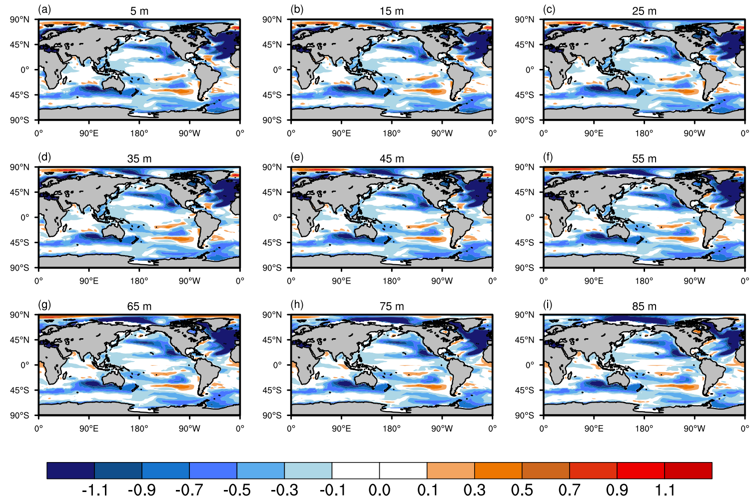

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612 **Figure 5.** Similar to Figure 4 but for ocean salinity.

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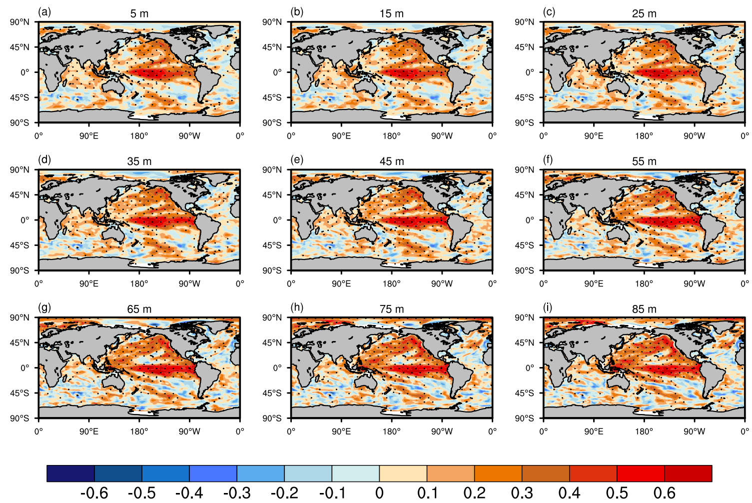

Figure 6. Spatial patterns of the differences between ASSIM and CTRL for their correlations of ocean temperature with observations across nine ocean layers for the period 1950-2021. Regions with stippling indicate statistical significance at the 95% confidence level. Panels (a) to (i) represent different ocean depths: (a) 5 m, (b) 15 m, (c) 25 m, (d) 35 m, (e) 45 m, (f) 55 m, (g) 65 m, (h) 75 m, and (i) 85 m.

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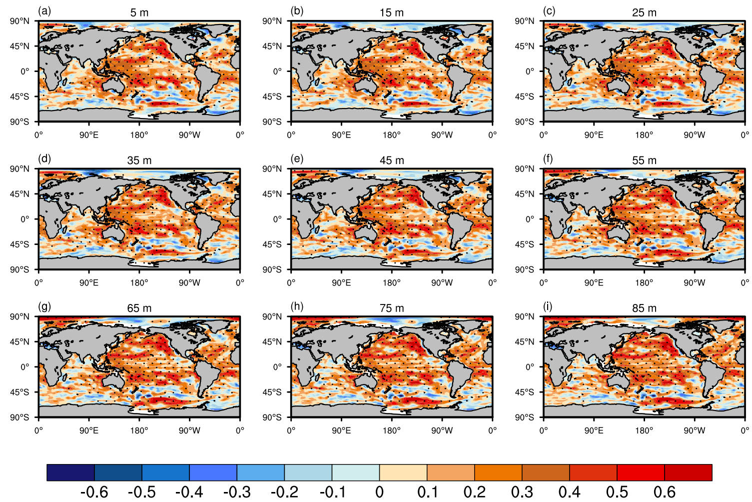

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619 **Figure 7.** Similar to Figure 6 but for ocean salinity.

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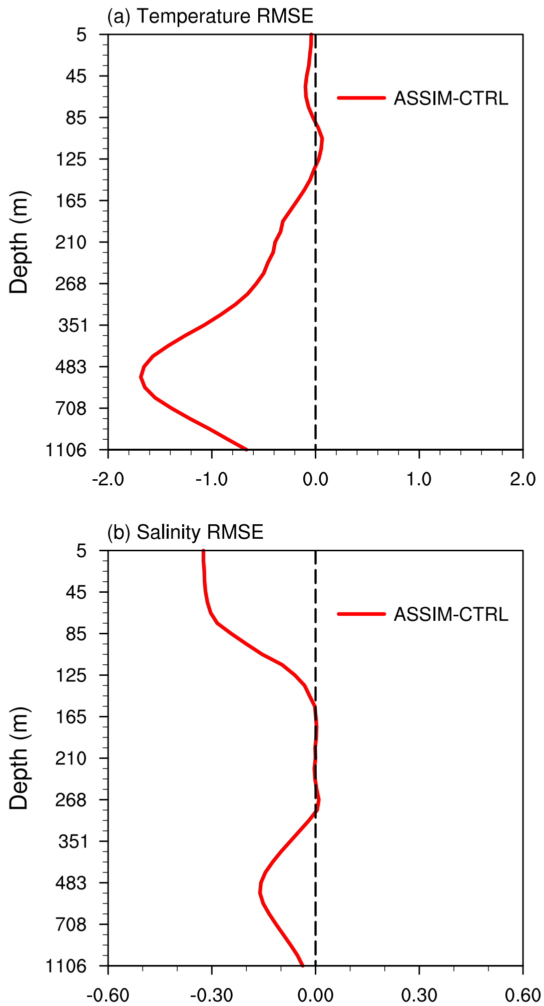

Figure 8. Vertical profiles of the globally averaged RMSE differences between ASSIM and CTRL for (a) ocean temperature and (b) ocean salinity over the period from 1950 to 2021.

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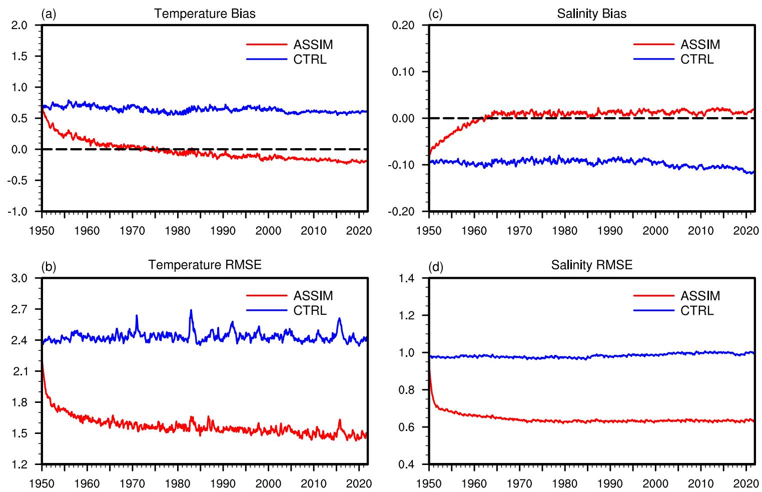

Figure 9. Temporal variations of bias (a, c) and RMSE (b, d) for the global mean ocean temperature and salinity averaged over the top 1000 meters from 1950 to 2021. The red lines represent ASSIM, while the blue lines represent CTRL.

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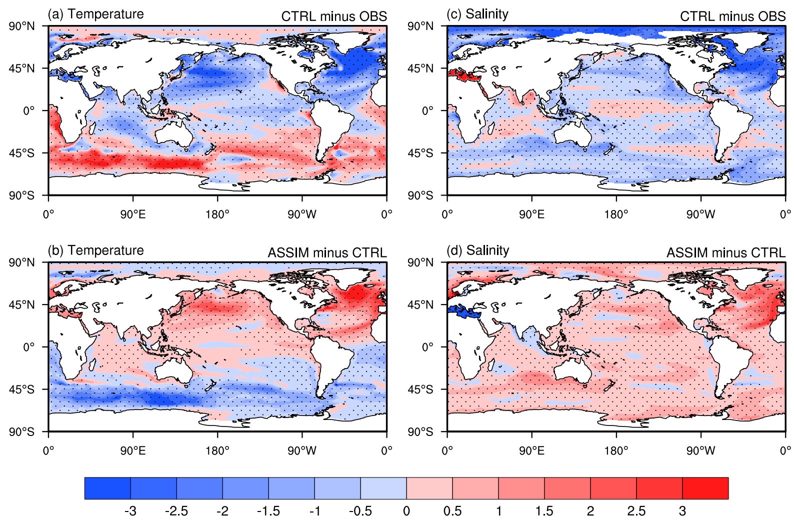

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628 **Figure 10.** Climatological mean differences in sea surface temperature (left) and salinity (right) from
629 1950 to 2021. The top panels show the differences between CTRL and observation, while the bottom
630 panels show the differences between ASSIM and CTRL. Dotted areas indicate regions where the
631 differences are statistically significant at the 95% confidence level.

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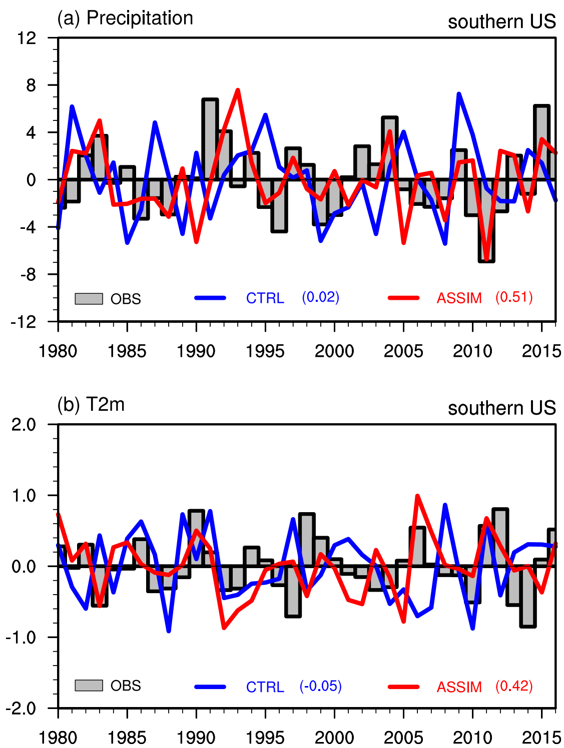

Figure 11. Time series of interannual (a) precipitation and (b) surface air temperature anomalies in the southern US (24°-36°N, 105°-75°W). Gray bar: observation; blue line: CTRL; red line: ASSIM. Correlation coefficients of CTRL and ASSIM with observations are also shown. Both precipitation and temperature anomalies are computed after removing the climatology and its long-term trend from 1980 to 2016. The observed precipitation and temperature are sourced from the GPCP precipitation data and ERA5 reanalysis, respectively.