We thank Reviewer #2 for the constructive comments and suggestions, which greatly help to improve the quality of our manuscript. We have made revisions and replied to all the comments. Please find the point-by-point responses to the comments below. Our responses are shown in "Blue" and the changes in the manuscript are shown in "Red". The line numbers correspond to those in the clean version of our revised manuscript.

Response to the comments from Reviewer #2

General Comment:

This manuscript compares representations of Earth system variability in coupled E3SM simulations running with and without an implementation of the ocean data assimilation framework described in an earlier GMD paper (Shi et al. 2025). They find that assimilation improves correlations between the model and observations across multiple metrics with climate relevance, including cross-variable relationships that motivate using (weakly-) coupled DA. The paper is clearly written. I am suggesting major revisions because I think that more evidence is needed to support the conclusions of the paper and to establish it as a standalone contribution. Shi et al. (2025) already demonstrated the modeling capabilities underpinning this work and the capability of better aligning E3SM with an observational product. I encourage the authors to emphasize how this work is distinct from that earlier work, beyond the choice of different regional and time averages selected for climate scales. Also, given that this is GMD, please also emphasize any model development advances, since I am not sure what has been done on that front.

Response:

We sincerely thank the reviewer for the thoughtful assessment. We appreciate your constructive comments and suggestions, which have significantly contributed to enhancing the quality of our work. We would like to clarify that the previous paper by Shi et al. (2025) served as a "Development and Technical paper", which focused on the technical architecture and algorithmic implementation of this 4DEnVar-based WCODA system within E3SM, including algorithmic formulation, computational design, and basic verification. In contrast, the present study is designed as a "Model Evaluation paper" to provide the comprehensive evaluation of how this WCODA system affects large-scale Earth system variability within the fully coupled E3SM framework. Hence, this study was submitted under the manuscript type "Model Evaluation paper", rather than "Development and Technical paper". The WCODA system evaluated in this work is currently being used to generate realistic initial conditions for seasonal-to-decadal (S2D) hindcast experiments using E3SM model. The main objective of this work is to thoroughly document the performance, strengths, and limitations of this newly implemented WCODA system for the broader modeling community, with particular emphasis on large-scale climate modes and their remote impacts relevant to S2D prediction. We have explicitly clarified this evaluation focus in both the Introduction (L81-87) and the Conclusions (L455-457) of the revised manuscript.

L81-87: This 4DEnVar-based WCODA system is intended to provide realistic initial conditions for developing seasonal-to-decadal (S2D) hindcast experiments using the E3SM model. The primary objective of this study is to evaluate the strengths and limitations of this newly developed WCODA system and to document its capability in capturing global and regional climate variability for the broader modeling community, with particular emphasis on large-scale climate modes and their remote impacts that are essential for generating realistic initial conditions for S2D hindcast experiments.

L455-457: This study aims to thoroughly document the capabilities and limitations of this WCODA system in simulating global and regional climate variability.

To strengthen the distinct contribution of this manuscript, we have incorporated additional dynamical analyses (e.g., Hadley circulation diagnostics in the **Figure A2** and lagged ENSO regressions in the **Figure A3**) to enhance the dynamical insight of the results. Specifically, the **new Figure A2** examines the zonal-mean meridional streamfunction to provide a dynamical interpretation of tropical precipitation improvements, and the **new Figure A3** presents a one-month lagged regression analysis to test the temporal coherence of ENSO teleconnections (in response to **Comment #7**). We have also clarified methodological details to distinguish our 4DEnVar approach from nudging methods (in response to **Comments #1 and #2**), and provided a detailed justification for the Arctic exclusion in the assimilation (in response to **Comment #3**). Furthermore, we have refined our conclusions to distinguish improvements in phase alignment from intrinsic changes in modes of variability (in response to **Comments #5 and #8**), and to discuss the potential tradeoffs of the assimilation (in response to **Comments #4 and #13**). In addition, we have included additional quantitative metrics (e.g., spatial pattern correlations) to strengthen our conclusions (in response to **Comments #10 and #11**).

We hope that these revisions address your concerns and highlight the contributions of this work. Please find our point-by-point responses to each of your specific comments below.

Comment#1:

This work assimilates output from a reanalysis product (EN4). I would likely not consider this to be data assimilation by the conventional definition, and certainly not "direct assimilation" (l. 375) since there are no actual observations being assimilated. Would the authors please justify why their scheme should be considered DA and not a sort of 4D nudging? I think that justifying how this procedure is DA is important because directly ingesting raw data is considerably more challenging and has accompanying benefits, so we should reserve terms like "direct data assimilation" and "data assimilation" for those efforts.

Response:

Thank you for this insightful comment. We agree that the term "direct assimilation" may cause confusion in this context. The assimilation method used in this study is a four-dimensional ensemble variational (4DEnVar) approach based on the dimension-reduced projection 4DVar (DRP-4DVar) algorithm (Wang et al., 2010). Unlike nudging which typically applies empirical relaxation terms to the model's prognostic equations, our 4DEnVar approach minimizes the cost function of 4DVar. Specifically, this approach obtains the optimal analysis in the ensemble subspace by fitting the ocean reanalysis along the trajectory of the model solution within the assimilation window. Therefore, despite assimilating the ocean reanalysis, the methodology itself is a formal data assimilation scheme and not a form of nudging.

It is common practice in Earth system modeling to assimilate quality-controlled ocean reanalysis products for initializing climate models or coupled data assimilation experiments. For example, He et al. (2017) assimilates the ds285.3 ocean reanalysis into the FGOALS model, and Wang et al. (2017) assimilates the EN4.2.1 reanalysis into the NorCPM model. This choice is primarily made because the initialization for decadal predictions requires assimilation cycles spanning several decades, and directly assimilating complex, real-time raw observations over such extended periods would be computationally prohibitive. In the revised manuscript, we have explicitly describe this assimilation process as "assimilating ocean reanalysis" rather than "assimilating ocean observations" to clearly distinguish the nature of the assimilated data.

In response to this comment, we have added a detailed explanation (L123-127) to distinguish the DRP-4DVar method from nudging. In addition, we have removed the phrase "direct assimilation" and updated the descriptions of the assimilated data as "ocean reanalysis" (L28, L57, and L63) throughout the revised manuscript to reflect the nature of the assimilated data.

L123-127: Unlike nudging methods, which typically apply empirical relaxation terms to the model's prognostic equations, the DRP-4DVar scheme obtains the optimal analysis by minimizing the cost function of 4DVar. Specifically, observational information is assimilated along the trajectory of the model solution within the assimilation window, ensuring that the optimal analysis is dynamically consistent with the model physics (He et al., 2017).

L28: assimilating ocean reanalysis

L57, L63: reanalysis products

Comment#2:

Please provide greater detail on your assimilation procedure. How is observational uncertainty propagated through EN4? Are there concerns with ensemble collapse or any inflation used? Does observational density influence results?

Response:

The observational uncertainty of the EN4.2.1 reanalysis is represented through the observation error covariance matrix, which is estimated statistically based on the variance of the EN4.2.1 ocean temperature and salinity data. To mitigate ensemble collapse, the DRP-4DVar algorithm employs a specific inflation technique. As described in Wang et al. (2010), a zero initial condition perturbation sample is introduced to reconstruct the ensemble projection space into a full-rank matrix, and this procedure is explicitly characterized as an inflation technique inherent to the DRP-4DVar algorithm. The spatiotemporal density of observations within the EN4.2.1 product influences the assimilation impact. Regions with high observational density are expected to exhibit more pronounced improvements. Conversely, in areas with limited data coverage, such as the Indian Ocean, the assimilation constraint is relatively weaker.

In response to this comment, we have revised the manuscript to clarify the inflation technique (L127-130), the representation of observational uncertainty (L135-137), and the influence of observational density on assimilation impacts (L137-140).

L127-130: To mitigate ensemble collapse, the DRP-4DVar algorithm employs an inflation technique that introduces a zero initial condition perturbation sample to reconstruct the ensemble projection space as a full-rank matrix (Wang et al., 2010).

L135-137: The observational uncertainty of the EN4.2.1 reanalysis is represented through the observation error covariance matrix, which is statistically derived from the variance of ocean temperature and salinity data.

L137-140: The spatiotemporal density of observations within the EN4.2.1 product modulates the assimilation impact. Regions with dense observational coverage are expected to exhibit more pronounced improvements, whereas in data-sparse areas such as the Indian Ocean, the assimilation constraint is relatively weaker.

Comment#3:

Please give more discussion and justification on eliminating the Arctic. DA natively handles uncertainties large and small, and this seems like a relevant/proximal area for CONUS analysis.

Response:

The exclusion of the Arctic Ocean is primarily due to the lack of a coupled ice-ocean assimilation scheme. Much of the Arctic Ocean is characterized by year-round sea-ice cover. In the current assimilation system, assimilating only ocean temperature and salinity without simultaneously updating sea ice variables could introduce physical inconsistencies at the ice-ocean interface. To avoid such imbalances, assimilation over the Arctic Ocean is not implemented in the current system. Nevertheless, addressing this limitation remains a key priority for future system development.

Following your suggestions, we have included a detailed justification for the exclusion of the Arctic Ocean from the assimilation (L184-190).

L184-190: However, the Arctic Ocean is excluded from the assimilation domain due to sparse observational coverage and the current absence of a coupled ice-ocean assimilation scheme. Much of the Arctic Ocean is characterized by pervasive year-round sea ice cover. Without simultaneously updating sea ice variables, assimilating ocean temperature and salinity alone could introduce physical inconsistencies at the ice-ocean interface. Addressing this technical limitation remains a high priority for future system development.

Comment#4:

A repeating refrain throughout the results section is about the benefits or critical importance of ocean DA for representing various kinds of variability. However, there are many other observations available as well, e.g. in the atmosphere, with better-established assimilation pipelines that might constrain climate modes as well or better. Currently this point is only briefly acknowledged in the Discussion. To me the experiments in this paper demonstrate that ocean constraints are sufficient but not that they are necessary to improve Earth system variability -- please adjust conclusions accordingly.

Response:

We thank the reviewer for this thoughtful comment. We agree that ocean data assimilation in this study provides an effective constraint for improving the representation of climate variability, but the present experiments do not establish that ocean constraints are uniquely necessary for such improvements. Some statements in the original Results section may have overstated the necessity of ocean data assimilation.

In response to this comment, we have carefully reviewed the manuscript and adjusted our phrasing throughout the Results and Conclusions sections to avoid implying necessity. Statements referring to the "critical role" or "importance" of ocean data assimilation have been replaced with more precise descriptions of its demonstrated benefits (L296-297, L376-377, L410-411, and L442-443). Furthermore, we have also strengthened the Discussion (L481-485) to acknowledge the potential contributions of other observational constraints, such as those from the atmosphere.

L296-297: These results demonstrate that ocean data assimilation provides an effective constraint on tropical Pacific SST variability.

L376-377: These results indicate that ocean data assimilation serves as an effective pathway for constraining Pacific-basin SST variability.

L410-411: The spatial coherence of these improvements suggests that incorporating realistic ocean states can better capture U.S. winter precipitation variability.

L442-443: These results demonstrate that the improved phase alignment of ENSO variability enhances the simulation of U.S. winter surface air temperature and precipitation.

L481-485: While our results demonstrate that assimilating ocean reanalysis provides a sufficient constraint to improve the phase alignment of key climate modes, incorporating additional observational constraints from the atmosphere and sea ice may further enhance the representation of coupled climate variability and associated regional impacts.

Comment#5:

Regarding experimental design, I think that comparing an assimilating model to a free-running model for its ability to fit observations is a low bar. Many of the results seem consistent with phase aligning internal variability with observations and I don't think that sections 3.2, 3.3, and 3.4 do much to support the climate that assimilation improves simulation of Earth system variability. I suggest that the authors qualify their conclusions to distinguish between phase alignment versus actual process representation improvement, including the fact that assimilation introduces nonconservative effects.

Response:

We agree that improvements observed in the assimilation experiment may primarily reflect the phase alignment of internal variability with observations, rather than intrinsic enhancement of how climate variability is represented, although several results (Fig. 6 for the power spectrum of Niño3.4, Fig. 9 for the EOF pattern of PDO, and Fig. 14 for the regression patterns of ENSO responses over the U.S.) indicate some improvements in representing the modes of variability. Since the primary objective of our assimilation system is to provide realistic initial conditions for seasonal to decadal hindcast experiments using the E3SM model, improving the phase alignment is an important metric for establishing realistic initial conditions. This distinction is important and was not sufficiently emphasized in the original manuscript.

In response to your valuable feedback, we have revised the manuscript to clearly delineate that the ultimate objective of this assimilation system is to provide realistic initial conditions for seasonal-to-decadal hindcast experiments using the E3SM model (L81-83). Accordingly, we have carefully qualified our statements throughout Sections 3.2, 3.3, and 3.4 to distinguish between phase alignment effects and process-level improvements. Previous descriptions of "improvements" have been moderated to clarify that the enhanced correlations primarily reflect improved phase alignment of internal variability with observations (L293-294 for ENSO, L319-321 for SOI, L336-337 for IOD, L377-378 for IPO, and L387-388 for AMO). In addition, we have added explicit discussion regarding the phase alignment distinction and the nonconservative effects to the Conclusion section (L485-488).

L81-83: This 4DEnVar-based WCODA system is intended to provide realistic initial conditions for developing seasonal-to-decadal (S2D) hindcast experiments using the E3SM model.

L293-294: Compared with CTRL, ASSIM exhibits markedly improved phase agreement with the observed ENSO variability.

L319-321: These results indicate that assimilating ocean reanalysis not only constrains SST but also enhances the phase agreement of ENSO-related atmospheric variability with observations in coupled models.

L336-337: These results highlight the effectiveness of ocean data assimilation in improving the temporal agreement of IOD variability with observations.

L377-378: enhancing the phase alignment of the observed Pacific SST variability on decadal timescales.

L387-388: This improved phase agreement of AMO variability in ASSIM

L485-488: It should be noted that the improved temporal correlations primarily reflect enhanced phase alignment of the model's internal variability with observations, rather than intrinsic changes in modes of variability, and the assimilation increments may locally affect energy and mass budgets.

Comment#6:

Please note in the paper to what extent HadISST is "out-of-sample" relative to the EN4 reanalysis and the implications for how we should interpret any improved fits. It seems that you are assimilating EN4 and then demonstrating that the assimilation improves fits to a different product with largely the same underlying data, which seems like more of a demonstration that DA is functioning rather than having process-specific significance.

Response:

We agree that the HadISST dataset and the assimilated EN4.2.1 reanalysis share a partial overlap in underlying in situ ocean observations, and thus HadISST cannot be considered a fully independent dataset. However, these two products are constructed using different data sources, processing pipelines, and quality-control procedures, resulting in distinct analyzed fields (Rayner et al., 2003; Good et al., 2013). Therefore, the enhanced agreement with HadISST indicates that the assimilation system effectively constrains the ocean states, rather than as a fully independent validation.

In response to this comment, we have added a clear statement (L201-205) to explicitly note this data overlap and to guide readers in interpreting this comparison as a verification of the assimilation system's effectiveness.

L201-205: Since the HadISST dataset and the assimilated EN4.2.1 reanalysis partially share a common pool of underlying in situ ocean observations, HadISST does not serve as a fully independent validation dataset. Nevertheless, the improved agreement with HadISST still demonstrates the effectiveness of the assimilation system in constraining the ocean states.

Comment#7:

I think that the strongest parts of the paper are 3.1 and 3.5 that argue for an improvement in cross-variable correlations as a result of assimilation an ocean product. I recommend the authors explore these results further as a way of making the paper a more distinct contribution. What are the origins of significant improvements in correlation relationships?

Response:

We thank the reviewer for this insightful suggestion. To further investigate the dynamical insight of these improvements, we have added new Figures A2 & A3 and incorporated additional analyses in the revised manuscript. Specifically, new Figure A2 in Section 3.1 presents the zonal-mean meridional streamfunction to examine assimilation-induced changes in the Hadley circulation. The results indicate that ocean data assimilation reduces the excessive ascending motion in the northern branch of the Hadley cell present in CTRL, thereby mitigating tropical precipitation biases. This large-scale adjustment of the Hadley circulation provides a dynamical explanation for the improvement in tropical precipitation biases. In addition, in Section 3.5, we have included a one-month lagged regression analysis shown in new Figure A3. The resulting lagged patterns remain highly consistent with the simultaneous winter regressions presented in Figure 14), reinforcing the linkage between ENSO variability and U.S. winter climate anomalies.

In response to this comment, we have added new Figure A2 in Section 3.1 and new Figure A3 in Section 3.5, and revised the corresponding text (L277-282 and L438-442) to more explicitly clarify the dynamical origins of the strengthened correlations.

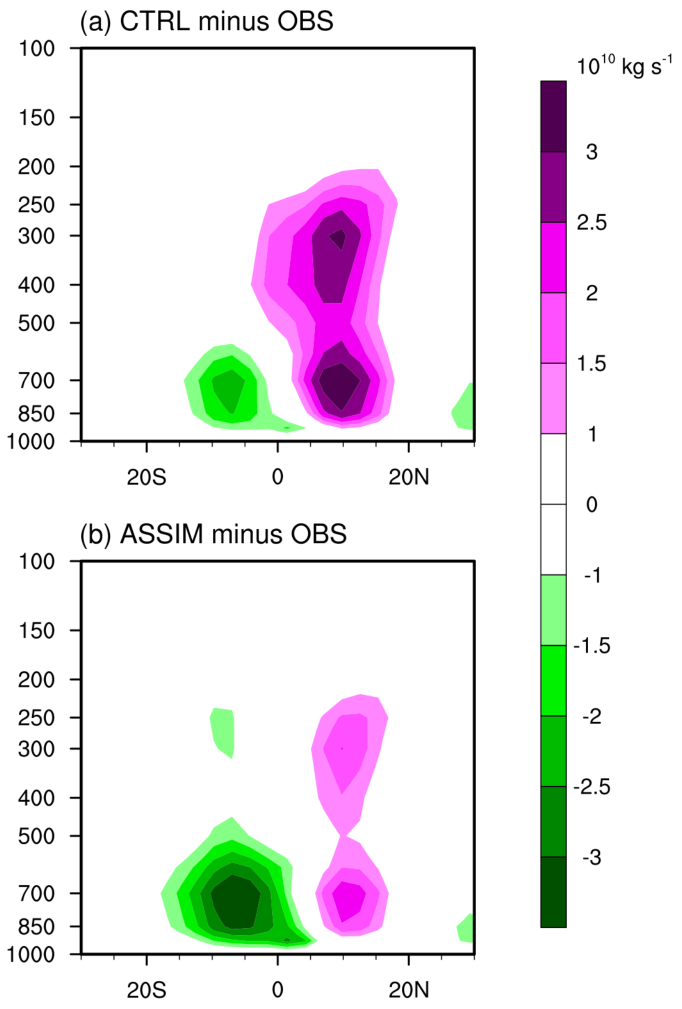

Figure A2. Zonal-mean meridional streamfunction differences (units: 10^{10} kg s^{-1}) between model simulations and observations averaged over the period 1980–2016. Panel (a) shows the difference between CTRL and observations, and panel (b) shows the difference between ASSIM and observations. The vertical axis represents pressure levels (hPa), and the horizontal axis denotes latitude.

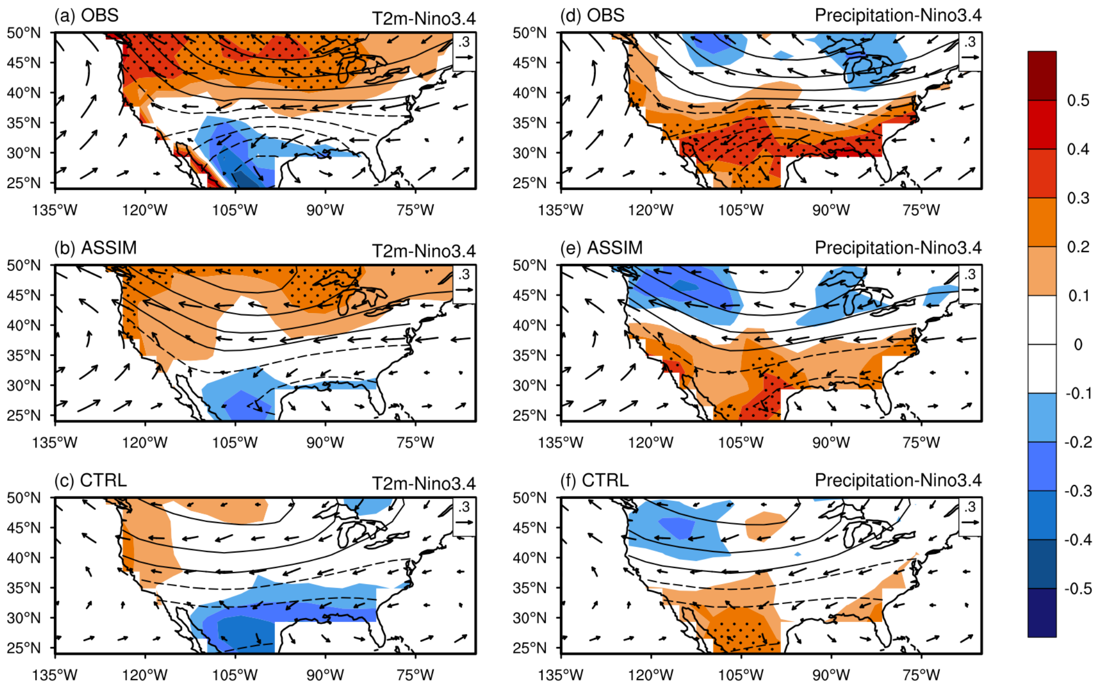

Figure A3. Lagged regression patterns of monthly winter (DJF) surface air temperature (left; shaded), precipitation (right; shaded), 500hPa geopotential height (contours), and 850hPa winds (vectors) onto the preceding month's (NDJ) standardized Niño 3.4 index for (a, d) the observation, (b, e) ASSIM, and (c, f) CTRL. Specifically, monthly atmospheric variables from December to February (DJF) are regressed onto the standardized monthly Niño 3.4 index from November to January (NDJ), corresponding to a one-month lead time. The Niño 3.4 index is calculated separately from each corresponding dataset. Dotted areas denote statistical significance at the 95% confidence level.

L277-282: The improvement in tropical precipitation is closely linked to changes in the large-scale meridional circulation. As illustrated in Fig. A2, CTRL exhibits an anomalously strong ascending branch of the Hadley circulation in the northern tropics, which sustains a pronounced wet bias over the tropical Pacific. In contrast, this anomalous ascent is effectively suppressed in ASSIM, contributing to a more realistic precipitation distribution across the tropical and subtropical regions.

L438-442: To account for the potential delayed impact of ENSO, a one-month lagged regression analysis is also presented in Fig. A3. The resulting lagged patterns are highly consistent with the simultaneous winter regression results (Fig. 14), reinforcing the linkage between ENSO variability and U.S. winter climate anomalies.

Comment#8:

l. 232: Weak correlations could just as well result from incorrect phase of tropical SST variability (as we expect for internal variability) as from the its "evolution" (which sounds more like a dynamical process) -- please clarify

Response:

We agree that weak correlations in CTRL may mainly reflect poor phase agreement with the observed tropical SST variability, rather than deficiencies in its dynamical evolution.

To clarify this point, we have removed the term "evolution" and revised the text (L292-293) to indicate that the weak correlations indicate poor phase agreement with observations.

L292-293: indicating poor phase agreement with the observed Niño 3.4 index.

Comment#9:

l. 345 Please provide more justification for the focus on winter conditions. Should we expect similar behavior in other seasons?

Response:

The analyses focus on boreal winter because previous studies have shown that ENSO teleconnections to North America are strongest and most coherent during winter (Ropelewski and Halpert, 1986; Higgins et al., 2000). As noted by Ropelewski and Halpert (1986), ENSO-related impacts in other seasons are generally weaker and less spatially coherent over the U.S.

To clarify this rationale, we have added a brief statement in the revised manuscript to explain this focus on winter conditions (L414-417).

L414-417: Boreal winter is the focus of this analysis because ENSO teleconnections to North America are strongest and most coherent during winter, while ENSO-related impacts in other seasons are generally weaker and less spatially coherent over the U.S. (Ropelewski and Halpert, 1986; Higgins et al., 2000).

Comment#10:

l. 357 "closely resemble" -- please be more quantitative here and throughout this paragraph

Response:

We have computed the spatial pattern correlation to quantify the similarity between the simulated and observed regression patterns. For surface air temperature, the spatial correlation increases from 0.35 in CTRL to 0.86 in ASSIM. For precipitation, the spatial correlation increases from 0.67 in CTRL to 0.72 in ASSIM.

Following your suggestions, we have added additional quantitative descriptions of the spatial pattern correlations in the revised manuscript (L429-432).

L429-432: The spatial pattern correlation between ASSIM and observations is 0.86 for surface air temperature, much higher than that of CTRL (0.35). For precipitation, the spatial correlation increases from 0.67 in CTRL to 0.72 in ASSIM.

Comment#11:

l. 361 "superior performance" and l. 362 "notable deviations" -- it is not clear that either of these is statistically significant by your criteria. Are there significant differences you can point to?

Response:

The stippled regions in Figures 12 and 13 have indicated statistically significant differences at the 95% confidence level. In the revised manuscript, we have explicitly referenced these statistically significant regions and revised the text to avoid qualitative expressions such as "superior performance" and "notable deviations" (L434-438).

L434-438: The stippled regions in these figures denote statistically significant differences at the 95% confidence level. Specifically, for winter surface air temperature, statistically significant increases in correlation and concurrent reductions in RMSE are primarily found in parts of Arizona and Iowa (Fig. 12), while for winter precipitation, such improvements are mainly located over parts of California and Alabama (Fig. 13).

Comment#12:

l. 374: This language appears to be repeated from the Introduction

Response:

We have removed the repetitive sentence and replaced it with a new sentence (L452-453).

L452-453: To address this limitation, a new 4DEnVar-based WCODA system has been implemented within the E3SM model to provide realistic initial conditions for S2D hindcast experiments.

Comment#13:

l. 381 "improves the representation" -- I think this statement needs more exploration of pros and cons. The procedure used has improved the phase relationship with observations, but at the cost of introducing physical inconsistencies in process representations due to a state increment at each month. Please discuss tradeoffs.

Response:

Thank you for this insightful comment. The phrase "improves the representation" may appear overly broad. In this study, the improved agreement with observations primarily reflects enhanced phase alignment of internal variability, which is an important metric for our assimilation system to generate realistic initial conditions for prediction experiments. And the assimilation procedure generates monthly analysis increments that may introduce localized nonconservative effects.

In response to this comment, we have revised the manuscript to refine the phrase "improves the representation" to specifically refer to the enhanced phase agreement (L459-463), and to expand the discussion to clarify these tradeoffs (L476-478).

L459-463: Our results show that the WCODA system significantly improves the phase agreement of both interannual and decadal climate variability with observations. Beyond phase alignment, minor but noteworthy improvements are also found in representing the modes of variability, as indicated by the improved Niño3.4 spectrum, PDO EOF pattern, and ENSO teleconnection response over the contiguous U.S.

L476-478: It is worth noting that these improvements primarily reflect enhanced phase alignment of internal variability with observations, and the use of monthly assimilation increments may introduce localized nonconservative effects.

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