

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. Our responses are shown in "Blue" and the changes in the manuscript are shown in "Red".

Response to the comments from Reviewer #2

General Comment:

This paper presents experiments assimilating soil moisture and soil temperature from the GLDAS modeling system into the E3SM model using 4DEnVar. The use of Hybrid DA method for the land DA is unusual, and is an interesting development that I am curious to see more work on. Unfortunately, the experimental design is badly flawed, and the information presented in the paper is vague, out-dated, very often incorrect, and difficult to follow.

Response:

Thank you very much for taking time to review our manuscript and providing us very useful comments. We are sorry for any confusions or misrepresentations that our initial draft might have conveyed. We value your comments and have revised the relevant contents on the experimental design. We have rewritten the introduction section of the manuscript and revised the manuscript carefully according to your comments and suggestions. Please refer to the point-by-point responses in the following.

Comment#1:

This work is assimilating model output soil moisture and soil temperature into a different model, with no accounting for the systematic differences between the two models. Data assimilation is not typically applied to assimilate fields from one model into another (unless conducting a synthetic twin experiment to test aspects of the DA, which is not how this is presented). There is also extensive literature discussing the fact that soil moisture cannot be transferred from one model to another without rescaling it, which makes the approach here invalid. For example, see: RD Koster, Z Guo, R Yang, PA Dirmeyer, K Mitchell, MJ Puma, On the nature of soil moisture in land surface models, *Journal of Climate* 22 (16), 4322-4335. And many references in that paper. Additionally, the assimilated fields are monthly means, which is not the obvious choice, and this is not adequately discussed. To be publishable, the authors would need to assimilate actual observations, not model output, and would need to apply adequate bias correction/rescaling to those observations (particularly to soil moisture - see work by Rolf Reichle, Randy Koster, etc).

Response:

Many thanks to your detailed comment on the data assimilation (DA) approach used in our study. We recognize that DA is widely applied to produce high-quality real-time reanalysis data by assimilating actual observations such as satellite data for numerical weather predictions (NWP). However, in this study, the weakly coupled data assimilation (WCDA) system we built is intended to be used to initialize decadal climate predictions (DCPs) with an earth system model that fully couples various component models including the atmospheric model, land

surface model, oceanic model, sea ice model, and so on. The initialization for DCPs is quite different from that of NWP, primarily due to the large difference in temporal scales. Almost all initializations for DCPs in CMIP5 and CMIP6 incorporated monthly mean reanalysis data as observations (Table 1). This preference is based on two key considerations. Firstly, for decadal-scale applications, data signals with temporal resolutions shorter than one month could introduce undesirable noise, which can adversely affect DCPs when high temporal resolution data are assimilated into the ICs. This is why almost all initialization approaches for DCPs used in CMIP5 and CMIP6 assimilate monthly mean data. Secondly, the DA approaches utilized in the coupled data assimilation (CDA) for initializations of decadal prediction are generally much simpler than those used in NWP, due to the complexity of the coupled model. For examples, many initialization systems used in CMIP5 and CMIP6 adopted the nudging method (Table 1). Because of the simpler DA approaches and more complex coupled models, actual observations cannot be assimilated directly into the WCDA system. Furthermore, unlike NWP where long-term DA cycles aren't necessary, the initialization for DCPs requires DA cycles of at least ten years which makes it very difficult or even impossible to assimilate actual observations due to the very high computational cost.

Table 1. Brief summaries of assimilation strategies used in CMIP5 and CMIP6 decadal prediction experiments through assimilation of reanalysis data.

Model	Assimilation Strategies	Method	References
BCC-CSM1.1	Ocean: assimilate the SODA reanalysis	Nudging	Xin et al., 2013
CanCM4	Atmosphere: assimilate the ERA reanalysis	Nudging	Merryfield et al., 2013
CNRM-CM5	Ocean: assimilate the NEMOVAR reanalysis	Nudging	Voltaire et al., 2014
HadCM3	Atmosphere: assimilate the ERA-40 reanalysis	Nudging	Smith et al., 2013
FGOALS-g2	Ocean: assimilate the ds285.3 reanalysis	Nudging	Wang et al., 2013
EC-Earth3	Ocean: assimilate the ORAS4 reanalysis	Nudging	Bilbao et al., 2021
NorCPM1	Ocean: assimilate the HadISST reanalysis	EnKF	Bethke et al., 2021
CanE3M5	Ocean: assimilate the ORAS5 reanalysis	Nudging	Sospedra-Alfonso et al., 2021

GLDAS product generates optimal fields of land surface states and fluxes in near-real time because the atmospheric forcing is based on actual observations (Rodell et al., 2004). These reliable and high-resolution global land surface datasets from GLDAS are extensively utilized in weather and climate research (Chen et al., 2021; Zhang et al., 2018). In our search for the most suitable long-term land surface dataset, GLDAS emerged as a top choice. Therefore, we employed the advanced WCDA approach to incorporate the GLDAS monthly mean soil temperature and soil moisture into the fully coupled E3SMv2 model. It is noteworthy that

GLDAS products were also assimilated in another coupled model (FGOALS-g2), showing significant improvements in the interannual prediction skills over East Asia and Europe, as shown in previous studies by Shi et al. (2021, 2022).

Furthermore, it's important to clarify that assimilating the GLDAS data into E3SM does not mean directly transferring soil moisture data from one model to another, because our employed DRP-4DVar method, which is a 4DVar approach, does not input the full information of the GLDAS data in the initial conditions (ICs) of E3SM but instead this approach only incorporates part of the GLDAS information by fitting reanalysis data with historical samples produced by the model to form consistent forecast states (Wang et al., 2010). More detailed descriptions of the DRP-4DVar method can be found in Wang et al. 2010.

We have added a detailed reason for assimilating monthly mean reanalysis (L245-252) in the revised manuscript.

L245-252: In contrast to decadal timescales, data signals with temporal resolutions shorter than one month can potentially introduce undesirable noise, which can adversely affect DCPs when high temporal resolution data are assimilated into the ICs. Moreover, it is very computationally demanding to assimilate complex actual observations in the initialization for DCPs that requires long-term DA cycles. Therefore, similar to most existing initialization approaches for DCPs that assimilate reanalysis data, this study describes the implementation of a data assimilation approach for initializing DCPs by assimilating monthly mean GLDAS data within the one-month assimilation window.

We recognize the current limitations of the weakly coupled land data assimilation (WCLDA) system implemented for E3SMv2. Specifically, our current assimilation system lacks the design of the observation operator, making it challenging to assimilate actual observations (e.g., satellite data) at this stage. The observation operator is important in providing the linkage between the model variables and actual observations that differ in spatial and temporal resolutions. We have noted the design of the observation operator as a direction for future development, and highlighted this limitation in the discussions of the revised manuscript (L446-450).

L446-450: Our current WCLDA system has some limitations such as the lack of an observation operator to integrate actual observations (e.g., satellite and station data). An observation operator is crucial in providing the linkage between the model variables and actual observations, which differ in spatial and temporal resolutions. Hence future exploration will focus on developing observation operators suitable for assimilating various satellite data, such as the AMSR-E and GRACE data.

In light of your comments, we have changed the experiment design to add the bias correction to GLDAS data before assimilation (L168-171), and then conducted the anomaly assimilation through assimilating observed anomalies into the model in the revised manuscript. Due to the modifications of our experimental design, we have revised all of the figures (Figure 3 to 10)

and relevant descriptions to illustrate the assimilation performance with bias correction in our revised manuscript.

L168-171: In this study, we conduct the anomaly assimilation for the WCLDA system with bias correction applied to GLDAS data before assimilation. For bias correction, the difference between GLDAS data and its long-term average is calculated as anomalies and then added to the simulated model climatology.

Comment#2:

The background information presented in the introduction demonstrates very little understanding of the standard methods used in land DA and coupled land/atmosphere DA, and presents a picture of modern data assimilation practices that is incorrect. Much of the introduction is also rather vague-with references to coupled and uncoupled systems that are unclear. I recommend completely re-writing the introduction by first identifying the modeling system that you are working with (land /atmosphere?), and introducing examples related to that system. Then, then make sure it is always clear what you are referring to when referencing a coupled model or coupled DA system (with a clear distinction between coupling in the model and coupling in the DA). Of greatest concern, the method is presented as ‘coupled data assimilation’ but the experiments assimilate land “observations” into only the land component of their model (a coupled land/atmosphere model)-this is not coupled DA! In general, the paper seems confused between coupled modeling, and coupled DA. There’s also no mention of weakly or strongly coupled DA, which is very relevant.

Response:

We appreciate very much this valuable comment that greatly benefits the improvement of the introduction of our manuscript and the whole paper. According to this comment, we've completely rewritten the introduction. In the revised manuscript, we first elucidate our focus on the initialization of a climate model that fully couples various component models, including atmospheric model, land surface model, ocean model, sea ice model and so on. Subsequently, we delve into both uncoupled data assimilation (DA) and coupled data assimilation (CDA) methodologies. Within the domain of CDA, we draw distinctions between weakly coupled data assimilation (WCDA) and strongly coupled data assimilation (SCDA), providing detailed descriptions for each approach. To address the comment, we have added a description of the fully coupled climate model and the initialization of the climate model (L41-56) in the introduction of the revised manuscript.

L41-56: Much work has been devoted to initializing climate system models for practicable decadal climate predictions (DCPs). These models couple various components, such as models of the atmosphere, land surface, ocean, sea ice, and so on. Due to their much higher complexity, coupled models are often more susceptible to initial conditions (ICs) than their individual model components, underscoring the importance of dedicated data assimilation (DA) (Sakaguchi et al., 2012). The capability of DA methods is essential to incorporate available observations into the components of coupled model and produce the optimal estimate of ICs to improve DCPs. The initialization for DCPs uses uncoupled DA and coupled data assimilation

(CDA) methods. Uncoupled DA performs DA under the framework of an individual component model (e.g., standalone land surface model forced by atmospheric observations or reanalysis data rather than coupled with an atmospheric model), and then the uncoupled DA analyses from different individual components are combined to form the ICs of a coupled model (Zhang et al., 2020). For example, most existing reanalysis data were produced using uncoupled DA approaches, and these reanalysis datasets are then directly used to initialize DCPs in some studies (Du et al., 2012; Bellucci et al., 2013). However, such uncoupled DA often exhibits poor consistency among the ICs of different component models, and eventually produces low prediction skills (Balmaseda et al., 2009; Boer et al., 2016; Ardilouze et al., 2017).

We have also revised our Introduction (L57-80) to include descriptions of both weakly coupled data assimilation (WCDA) and strongly coupled data assimilation (SCDA). We distinguish between WCDA and SCDA by highlighting the characteristics of coupling in the model and coupled DA.

L57-80: To obtain balanced multi-component ICs in coupled models, recent studies focus on the development of CDA methods under the coupled modeling framework (Penny and Hamill, 2017; He et al., 2020a). The purpose of CDA is to produce balanced and coherent ICs for all components within the climate system by incorporating observational information from one or more components in the coupled model, providing great potential for improving seamless climate predictions (Dee et al., 2014). Some studies underscore the superior advantages of CDA over traditional uncoupled DA methods (Lea et al., 2015; Zhang et al., 2005). CDA methods are categorized into two main types: weakly coupled data assimilation (WCDA) and strongly coupled data assimilation (SCDA). WCDA assimilates the observations or existing reanalysis into the respective component of the coupled model and then transfers the observational information to the other components through the coupled model integration (He et al., 2020b; Zhang et al., 2020). Considering that sequential DA encompasses both the analysis and the forecast steps, WCDA allows no direct influence of observations from a single component to other components in the analysis step as the cross-component background error covariances are not used, but coupling in the forecast step allows interactions across different components during the model integration (Browne et al., 2019) and propagates the observational information to other components. In contrast, SCDA utilizes cross-component background error covariances to directly assimilate the observational information from one component into all components, treating the entire Earth system model as one unified system (Penny et al., 2019). Furthermore, similar to WCDA, SCDA also allows coupling in the forecast step to propagate the observations from one component to the other components (Yoshida and Kalnay, 2018). Several studies indicate that SCDA typically exhibits more pronounced improvements in assimilation performance relative to WCDA (Smith et al., 2015; Sluka et al., 2016). However, the application of SCDA poses substantial technical challenges, particularly in the establishment of effective cross-component background error covariances. Consequently, the majority of contemporary CDA systems still utilize the WCDA framework.

According to the aforesaid introduction to uncoupled DA and CDA, their main difference is the use of forecast model at the forecast step. If the forecast model is the coupled model, the

DA is categorized as CDA. Otherwise, if the forecast model is an individual component model, the DA is referred to as uncoupled DA. Additionally, it's important to note that CDA does not necessarily require assimilating observations from multiple components. Even if CDA assimilates the observations just from a single component, it can still enhance the ICs of all components within the coupled model.

In this study, the WCDA system was built and used to produce ICs for all components of E3SM by incorporating GLDAS reanalysis. During the analysis step, our WCDA system only assimilates land reanalysis data into the land component of an earth system model. However, it's crucial to highlight that in the forecast step, the entire E3SM climate model rather than the land surface model is used as the forecast model to forecast the IC backgrounds of all components for the next assimilation window and the land reanalysis information can propagate to the other components (e.g., atmosphere and ocean) dynamically through the coupled integration of E3SM during the one-month forecast. In general, when the coupled model is used in the forecast step while the optimal assimilation analysis is updated separately for the respective component, the assimilation approach is identified as WCDA (Penny et al., 2019; Zhang et al., 2020). Thus, the assimilation approach in this study is referred to as a WCDA system.

We have added a detailed description (L221-228, L268-278 and L288-294) of the implementation of weakly coupled assimilation system and updated the name of our data assimilation system from CDA to WCDA throughout the manuscript. This modification is intended to provide a clearer depiction of the WCDA system in this manuscript.

L221-228: In the analysis step, only the land state variables are updated to the optimal analysis (x_a^{lnd}). Subsequently, we proceed with a one-month freely coupled integration of the E3SMv2 model during the forecast step. This integration is initialized from the optimal land ICs (x_a^{lnd}) along with the background fields as the ICs of other components (e.g., atmosphere and ocean). Throughout this one-month free integration, the interactions among the model components indirectly enhance the background states of these components (e.g., atmosphere and ocean) for the next assimilation window due to the more realistic land state variables. Moreover, this coupled integration also contributes to the balance between the ICs of different components.

L268-278: The incorporation of GLDAS data into the E3SMv2 model consists of the analysis step and the forecast step. In the analysis step, the differences between monthly mean GLDAS data and model outputs are calculated and utilized to produce the optimal assimilation analysis at the beginning of a one-month assimilation window. Subsequently, in the forecast step, this optimal assimilation analysis is used as the land ICs combined with the background ICs for other components to conduct one-month forecast using the E3SMv2 model. This forecast generates the backgrounds of all model components for the next assimilation window. As a result, the forecasted backgrounds for all components are influenced by the land reanalysis information incorporated into the ICs of the land component. In general, when the coupled model is used in the forecast step while the optimal assimilation analysis is updated separately

for the respective component, the assimilation approach is identified as WCDA (Penny et al., 2019; Zhang et al., 2020).

L288-294: To assimilate the monthly mean GLDAS product, fully coupled integration by the E3SMv2 model is performed twice within each one-month assimilation window: first to generate the observational innovation by computing the differences between the GLDAS data and model outputs for analysis, and second to forecast the backgrounds of all components for the next assimilation window. When the fully coupled model is executed for the second one-month run, the land reanalysis information is transferred to the other components through multi-component interactions.

Comment#3:

Paragraph starting L37. I had a lot of trouble following the argument in this paragraph, largely because the terms used have not been defined (and I suspect are not being applied in their standard usage). The distinction between coupling in the model and in the DA is unclear, and I really don't know what the "uncoupled" option is. Perhaps using an explanatory example might help.

Response:

We are sorry for any confusion caused. We understand your concerns about the unclear distinction between coupling in the model and the DA. In the revised manuscript, we have rewritten this paragraph (L41-56 in the revised manuscript) to clearly differentiate between uncoupled and coupled data assimilation. Uncoupled DA implies that DA is conducted using a standalone component model (e.g., a standalone land surface model forced by atmospheric reanalysis data or observations rather than coupled with an atmospheric model) as the forecast model to produce the IC background, and then the uncoupled DA analyses from different components are combined to form the ICs of the coupled model (Zhang et al., 2020). For example, most existing reanalysis data were produced by uncoupled DA, and some decadal predictions were initialized directly using reanalysis data for different components (Du et al., 2012; Bellucci et al., 2013).

We have introduced a new paragraph (L57-80 in the revised manuscript) dedicated to elucidating the concept of coupled data assimilation (CDA), as explained in our response to the last comment.

Comment#4:

L38: I'm not sure what is meant by "uncoupled initialization" here or "uncoupled data assimilation". I suspect you mean weakly coupled data assimilation (as in separate DA systems for each model component, each assimilating obs from that component) - which is still coupled DA.

Response:

We have revised the relevant descriptions (L48-54) to provide a clearer definition on "uncoupled initialization". In this context, "uncoupled initialization" is not the same as WCDA.

Instead, in "uncoupled initialization" reanalysis data are directly used to initialize the individual components of the coupled models, and this approach is defined as uncoupled DA.

L48-54: Uncoupled DA performs DA under the framework of an individual component model (e.g., standalone land surface model forced by atmospheric observations or reanalysis data rather than coupled with an atmospheric model), and then the uncoupled DA analyses from different individual components are combined to form the ICs of a coupled model (Zhang et al., 2020). For example, most existing reanalysis data were produced using uncoupled DA approaches, and these reanalysis datasets are then directly used to initialize DCPs in some studies (Du et al., 2012; Bellucci et al., 2013).

We agree with your opinion about the definition of weakly coupled data assimilation. In this study, soil moisture and temperature data from GLDAS are assimilated into the land component of the climate model during the analysis step. Subsequently, during the forecast step, the entire E3SM climate model is used as the forecast model to forecast the IC backgrounds of all components for the next assimilation window and the observed land information is transferred to the other components (e.g., atmosphere and ocean) through the coupled model integration. Thus, our DA process under the coupled modeling framework is referred as the WCDA system.

Comment#5:

L39: what is a "stand-alone" model state?

Response:

"Stand-alone" model refers to the individual component models, such as the atmospheric or land surface models, which operate independently without interactions with other components. For example, a standalone land surface model is forced by atmospheric observations or reanalysis data but not coupled with an atmospheric model.

Comment#6:

L40: I assume the Prodhomme paper refers to a hydrological system, so it's a bit misleading to say "some modeling centers ..." and then refer to a single product that is not their main product.

Response:

Thank you for bringing this to our attention. The phrase "some modeling centers" has been revised to "some studies" for clarity. Furthermore, we have decided to remove the citation of the Prodhomme paper and replaced it with references to other relevant articles. This sentence (L51-54) is revised as "For example, most existing reanalysis data were produced using uncoupled DA approaches, and these reanalysis datasets are then directly used to initialize DCPs in some studies (Du et al., 2012; Bellucci et al., 2013)."

In response to this comment, we have made adjustments to this sentence (L51-54) in the revised manuscript.

L51-54: For example, most existing reanalysis data were produced using uncoupled DA

approaches, and these reanalysis datasets are then directly used to initialize DCPs in some studies (Du et al., 2012; Bellucci et al., 2013).

Comment#7:

L41: again, I don't know what you mean by "uncoupled methods". If you're applying DA to multiple model components in a coupled model, there is some coupling introduced via the model forecasts - at a minimum, this is weakly coupled DA.

Response:

The "uncoupled methods" here refer to the direct use of reanalysis data as ICs for the coupled model. We have explained what "uncoupled DA" implies. Please refer to the responses to Comments #3 and #4 for the details.

According to your comments, we have revised the manuscript (L48-54) to explicitly define the "uncoupled DA", and we have also added detailed descriptions (L113-118) to emphasize that the data assimilation system employed in our study is a weakly coupled DA system. This will help delineate the differences between the uncoupled methods we initially mentioned and the weakly coupled approach we utilized.

L48-54: Uncoupled DA performs DA under the framework of an individual component model (e.g., standalone land surface model forced by atmospheric observations or reanalysis data rather than coupled with an atmospheric model), and then the uncoupled DA analyses from different individual components are combined to form the ICs of a coupled model (Zhang et al., 2020). For example, most existing reanalysis data were produced using uncoupled DA approaches, and these reanalysis datasets are then directly used to initialize DCPs in some studies (Du et al., 2012; Bellucci et al., 2013).

L113-118: In this WCLDA system, monthly mean anomalies of soil moisture and temperature from a global land reanalysis product are assimilated into the land component of a coupled climate model in the analysis step, and subsequently during the forecast step, the land reanalysis information incorporated into the ICs of the land component is propagated to the other components (e.g., atmosphere and ocean) through the fully coupled model integration and influences the ICs of all components for the next assimilation window.

Comment#8:

L44 "each coupled model individually". Do you mean each component of the coupled model?

Response:

"Each coupled model individually" refers to each climate system model, rather than each component of the coupled model. What we intended to express was that distinct DA systems could be constructed for different climate models to obtain high-quality and well-balanced initial conditions. To avoid further ambiguity, we have removed this sentence in the revised manuscript.

Comment#9:

L50: Again, without concrete examples it is hard to follow the argument in the paragraph. I am unclear what the actual application being discussed is, since the text just refers to “modeling centers” or “models”. The references come largely from atmospheric DA, with some coupled atmosphere / other component examples. If this is the case, then the information presented in this paragraph about the usage of different methods is largely incorrect and very outdated.

Response:

According to your comments, we have made consistent modifications throughout the manuscript, replacing "modeling centers" with more appropriate terms like “some studies” and "previous studies". This ensures a clearer depiction of the source of our references and the focus of our work.

Furthermore, to improve clarity, we have started this paragraph by emphasizing the use of coupled data assimilation methods to initialize decadal climate predictions (DCPs) (L81-82): "Recent research efforts have started to implement the CDA system to initialize DCPs, using a diverse range of DA techniques from simple to complex." Based on our careful review of literature, most of DCPs do not assimilate land observations or reanalysis data.

We have rewritten this paragraph (L81-108) to introduce the development of CDA methods by providing more recent and relevant literature.

L81-108: Recent research efforts have started to implement the CDA system to initialize DCPs, using a diverse range of DA techniques from simple to complex. The simplest method is nudging which adjusts the model states towards the observations or existing reanalysis (Hoke and Anthes, 1976; Zhang et al., 2020). Although the nudging method is time-saving and easy to implement, its application in CDA is restricted primarily due to the limited types of observations and the required interpolation of observations at every time step of model integration (He et al., 2017). Previous studies have developed advanced CDA systems using variational and filtering approaches, such as the three-dimensional variational data assimilation (3DVar) (Laloyaux et al., 2016; Yao et al., 2021), and ensemble-based techniques like the ensemble Kalman filter (EnKF) (Zhang et al., 2007). The former generally utilizes the stationary background error covariance and assimilates observations sequentially (Lin et al., 2017). In contrast, the latter uses the flow-dependent forecast error covariance and recursively integrates observations into the model (Lei and Hacker, 2015). Several studies also show encouraging progress in constructing CDA systems using four-dimensional variational data assimilation (4DVar) method (Smith et al., 2015; Fowler and Lawless, 2016). The objective of 4DVar is to optimize four-dimensional model states and provide a compatible temporal trajectory that matches observational records across each assimilation window (Mochizuki et al., 2016). The 4DVar method is an advanced assimilation technique that exhibits superiority over other assimilation techniques like nudging and 3DVar in multiple aspects. Initial shocks that influence prediction skills can be significantly minimized by the 4DVar approach due to the dynamical consistency between the model and ICs (Sugiura et al., 2008). However, it is difficult to apply the 4DVar method for CDA systems in the fully coupled model because of

the challenge in adjoint integration of the coupled model and its high computational cost in the analysis step. Finally, to capitalize on the strengths of both ensemble and variational techniques, recent studies focus on developing new hybrid data assimilation methods (Wang et al., 2010; Buehner et al., 2018). The hybrid approach utilizes an ensemble forecast to generate flow-dependent forecast error covariances and presents a way to perform 4DVar optimization without the need for tangent linear and adjoint models (Lorenç et al., 2015). However, most studies on CDA have focused on assimilating observations or reanalysis data of ocean, atmosphere and even sea ice. There have been relatively few instances of CDA studies assimilating land observations or reanalysis data.

Comment#10:

L52: Here you are talking about the method used to add the analysis increment to the model states, which is a secondary detail to how the increment is calculated - the discussion is very misleading. For example, the Bloom paper you cite is from NASA GMAO. They currently use 4DEnVar to calculate the increment, and IAU to add it. You may also be mixing up the “nudging” DA method with nudging methods to add increments. If so, nudging is also a very old DA technique, and has not been standard use for decades.

Response:

In light of this comment, we have revised our overview of the nudging methods (L82-86). Furthermore, we have removed the citation to the Bloom paper and have replaced it with more recent and relevant references. Additionally, we have highlighted the limitations and potential drawbacks associated with nudging to offer a comprehensive perspective.

L82-86: The simplest method is nudging which adjusts the model states towards the observations or existing reanalysis (Hoke and Anthes, 1976; Zhang et al., 2020). Although the nudging method is time-saving and easy to implement, its application in CDA is restricted primarily due to the limited types of observations and the required interpolation of observations at every time step of model integration (He et al., 2017).

Comment#11:

L54: IAU (and nudging schemes I know of) do not "recover the observations". They move the model towards the observations, by some amount determined by the respective observation and background errors.

Response:

We recognize that this phrasing "recover the observations" is not accurate in describing the nudging and IAU methods. We have removed this phrasing from the revised manuscript to ensure clarity and accuracy.

Comment#12:

L59: The information presented here is very outdated. Major NWP / reanalysis all use hybrid DA methods now - 3Dvar was two generations of DA schemes ago. I'm not familiar with the

Yao paper, but the Lin paper was conducted at a university, not a “modeling center”. Likewise the Santonello paper - that’s a research paper, not linked to an operational DA system.

Response:

We have replaced "some modeling centers" with "previous studies". This sentence (L86-87) is revised as "Previous studies have developed advanced CDA systems using variational and filtering approaches". Although we acknowledge that major NWP now utilize hybrid DA methods, our focus in this paragraph is on the research progress of coupled data assimilation systems in coupled models. The development of coupled data assimilation in the coupled models is still at its early stages (Zhang et al., 2020) compared to DA used in NWP due to the complexity of the coupled models. Additionally, we have removed the citation to the Santonello paper and have chosen to cite other relevant research articles instead.

In light of this comment, we have revised the sentence (L86-89) in the revised manuscript.

L86-89: Previous studies have developed advanced CDA systems using variational and filtering approaches, such as the three-dimensional variational data assimilation (3DVar) (Laloyaux et al., 2016; Yao et al., 2021), and ensemble-based techniques like the ensemble Kalman filter (EnKF) (Zhang et al., 2007).

Comment#13:

L71: This sentence is wrong (or at least, extremely misleading). If we’re talking about Earth system modeling - so NWP, reanalysis, etc (which the references imply is what we’re talking about) then most centers did use 4DVar, but have now moved on to more sophisticated hybrid methods.

Response:

We have removed this sentence "few modeling centers utilize 4DVar-based initialization methods". To better convey our point, we have revised this sentence (L99-100) as "However, it is difficult to apply the 4DVar method for CDA systems in the fully coupled model" to emphasize the challenges of applying the 4DVar method.

In our revised manuscript, we have revised this sentence (L99-101) accordingly.

L99-101: However, it is difficult to apply the 4DVar method for CDA systems in the fully coupled model because of the challenge in adjoint integration of the coupled model and its high computational cost in the analysis step.

Comment#14:

L121: how many soil layers?

Response:

Totally ten soil layers. We have revised this sentence (L152-153) that monthly mean soil moisture and soil temperature data in a total of ten soil layers are produced by the Global Land Data Assimilation System (GLDAS; Rodell et al., 2004).

L152-153: Monthly mean soil moisture and soil temperature data in a total of ten soil layers are produced by the Global Land Data Assimilation System (GLDAS; Rodell et al., 2004).

Comment#15:

L123: GLDAS does not produce observations! These are modeled output.

Response:

We agree that GLDAS data are land reanalysis data from model outputs. In response to your feedback, we have revised the term "Observational Dataset" to "Land Reanalysis Dataset" (L151).

L151: 2.2 Land Reanalysis Dataset

Comment#16:

There is not enough information here on the 4DEnVar / DRP-4Dvar technique for the reader to understand how it works. Also, how is the ensemble created? How do you ensure the ensemble has reasonable spread near the land? How do you estimate the B matrix?

Response:

The DRP-4DVar method has been extensively introduced in Wang et al. (2010), Shi et al. (2021, 2022) and He et al. (2017, 2020) in the context of its application in another climate system model FGOALS-g2. Therefore, we did not provide a detailed introduction to the DRP-4DVar method. In the revised manuscript, we have rewritten Section 2.3 "Data Assimilation Scheme" to provide a comprehensive and clear introduction to the DRP-4DVar method (L178-228), especially to the process of ensemble creation and the estimation of the background error covariance matrix B .

L178-228: DRP-4DVar is an economical approach that minimizes the cost function of the standard 4DVar by using the ensemble technique instead of the adjoint technique (Wang et al., 2010). The background error covariance matrix B is estimated using the pure ensemble covariance. The ensemble members originate from historical or ensemble forecasts. Considering the high computational cost of ensemble forecasts for the coupled model in our study, we utilize outputs from the pre-industrial control (PI-CTRL) experiment of E3SMv2 to generate ensemble members. The instantaneous state at the beginning of each month and the corresponding monthly mean state of this month from the 100-year balanced PI-CTRL simulation are used as the samples of initial condition (x_i) and forecast samples (y_i). The corresponding perturbation samples are calculated as $x'_i = x_i - \bar{x}$ and $y'_i = y_i - \bar{y}$, where \bar{x} and \bar{y} are the 100-year average values of x_i and y_i at the same month, respectively. Then, m pairs of perturbation samples ($x'_1, x'_2, x'_3, \dots, x'_m$) and ($y'_1, y'_2, y'_3, \dots, y'_m$) are selected at each DA analysis step according to the correlations between y'_i and the observational

innovation $y'_{obs} = y_{obs} - y_b$ and the independence between y' samples. In this study, $m = 30$. Then the estimation of the background error covariance matrix B is represented by the formula in Eq. (1), utilizing the selected x' samples. To remove the spurious remote correlations in the B matrix, the localization approach is applied to optimize the assimilation performance (Wang et al., 2018).

$$\begin{cases} B = bb^T \\ b = \frac{1}{\sqrt{m-1}} \times (x'_1 - \bar{x}', x'_2 - \bar{x}', x'_3 - \bar{x}', \dots, x'_m - \bar{x}') \\ \bar{x}' = \frac{1}{m} (x'_1 + x'_2 + x'_3 + \dots + x'_m) \end{cases} \quad (1)$$

According to Wang et al. (2010), DRP-4DVar produces the analysis increment (x'_a) by minimizing the 4DVar cost function in the incremental form (Courtier et al., 1994):

$$\begin{cases} J(x'_a) = \min_{x'} J(x') \\ J(x') = \frac{1}{2} (x')^T B^{-1} x' + \frac{1}{2} (\tilde{y}' - \tilde{y}'_{obs})^T (\tilde{y}' - \tilde{y}'_{obs}) \end{cases} \quad (2)$$

Here $x' = x - x_b$ represents the increment of model variables relative to the background; $\tilde{y}'_{obs} = r^{-1} y'_{obs} = r^{-1} (y_{obs} - y_b)$ denotes the weighted observational innovation for monthly mean anomalies of soil moisture and temperature, and $R = rr^T$ is the observational error covariance matrix that is usually diagonal; $\tilde{y}' = r^{-1} y' = r^{-1} (y - y_b)$ is the weighted projection of the increment (x') onto the observation space; the superscript T represents the transpose.

To simplify the calculation of the minimization, the increment of model state variables x' and the corresponding weighted observation increment \tilde{y}' are projected onto the dimension-reduced sample space through the following projection transformations:

$$\begin{cases} x' = P_x \alpha \\ \tilde{y}' = P_y \alpha \end{cases} \quad (3)$$

where α is the m -dimension column vector containing the weight coefficients ($\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_m$); P_x and P_y denote the projection matrices that incorporate the initial condition perturbations and the corresponding monthly mean samples as follows:

$$\begin{cases} P_x = (x'_1, x'_2, x'_3, \dots, x'_m) \\ P_y = (\tilde{y}'_1, \tilde{y}'_2, \tilde{y}'_3, \dots, \tilde{y}'_m) \end{cases} \quad (4)$$

where $\tilde{y}'_i = r^{-1} y'_i$ ($i = 1, 2, \dots, m$). Then the original 4DVar cost function defined in Eq. (2) is transformed into the following new cost function and the analysis can be computed in the sample space by minimizing this new cost function:

$$\begin{cases} \tilde{J}(\alpha_a) = \min_{\alpha} \tilde{J}(\alpha) \\ \tilde{J}(\alpha) = \frac{1}{2} \alpha^T B_{\alpha}^{-1} \alpha + \frac{1}{2} (P_y \alpha - \tilde{y}'_{obs})^T (P_y \alpha - \tilde{y}'_{obs}) \\ x_a = x_b + x'_a = x_b + P_x \alpha_a \end{cases} \quad (5)$$

The solution to this minimization problem is formulated as:

$$\alpha_a = (B_{\alpha}^{-1} + P_y^T P_y)^{-1} P_y^T \tilde{y}'_{obs} \quad (6)$$

In this study, the DRP-4DVar-based WCLDA system is used to incorporate the land reanalysis data only. The optimal analysis for the land state variables (x_a^{land}) is obtained by adding the

analysis increment ($x'_a{}^{lnd}$) to the background of land ICs ($x_b{}^{lnd}$), as expressed in Eq. (7):

$$x_a{}^{lnd} = x_b{}^{lnd} + x'_a{}^{lnd} = x_b{}^{lnd} + P_x (B_\alpha^{-1} + P_y^T P_y)^{-1} P_y^T \tilde{y}'_{obs} \quad (7)$$

In the analysis step, only the land state variables are updated to the optimal analysis ($x_a{}^{lnd}$). Subsequently, we proceed with a one-month freely coupled integration of the E3SMv2 model during the forecast step. This integration is initialized from the optimal land ICs ($x_a{}^{lnd}$) along with the background fields as the ICs of other components (e.g., atmosphere and ocean). Throughout this one-month free integration, the interactions among the model components indirectly enhance the background states of these components (e.g., atmosphere and ocean) for the next assimilation window due to the more realistic land state variables. Moreover, this coupled integration also contributes to the balance between the ICs of different components.

Comment#17:

L152: This paragraph implies that there is no atmospheric DA in these experiments? In which case this is not coupled DA. It is land data assimilation into a coupled model.

Response:

This study did not include atmospheric DA because our focus is on investigating the role of land component in initialization for climate predictions, with an initial interest in decadal climate predictions, as very few CDA studies incorporated land observations or reanalysis data.

As we mentioned in our response to Comment#2, our data assimilation system is a WCDA system. The CDA system can provide ICs for all components of the coupled model no matter if the assimilated observations (or reanalysis data) are from one or more components. The ICs of all components are influenced by the observations directly or indirectly through the fully coupled model integration. Please refer to our response to Comment #2 for more details.

In light of this comment, we have incorporated additional clarifications (L221-228) to reflect the influence of land DA on other components (e.g., atmosphere and ocean) under the coupled modeling framework.

L221-228: In the analysis step, only the land state variables are updated to the optimal analysis ($x_a{}^{lnd}$). Subsequently, we proceed with a one-month freely coupled integration of the E3SMv2 model during the forecast step. This integration is initialized from the optimal land ICs ($x_a{}^{lnd}$) along with the background fields as the ICs of other components (e.g., atmosphere and ocean). Throughout this one-month free integration, the interactions among the model components indirectly enhance the background states of these components (e.g., atmosphere and ocean) for the next assimilation window due to the more realistic land state variables. Moreover, this coupled integration also contributes to the balance between the ICs of different components.

Comment#18:

L157 it's not clear what "freely coupled" means. Which components are coupled? Likewise "externally forced", which components are externally forcing used for?

Response:

The term "freely coupled" here refers to the mode of interaction among the various components of our Earth system model, namely the atmosphere, land, river, ocean, and sea ice. The term "freely coupled" implies that the model components interact dynamically without any restraints. The term "externally forced" refers to "forced by solar radiation, greenhouse gases, aerosols and so on". These external forcings mainly act on the atmospheric component and then influence other components (e.g., land surface, ocean, and sea ice) through their coupling with the atmosphere.

In response to this comment, we have revised our manuscript (L236-239) to clearly state that external forcings are used to drive the fully coupled climate system model, namely the atmosphere, land, river, ocean, and sea ice.

L236-239: In the freely coupled simulation, the various components of the Earth system model, namely the atmosphere, land, river, ocean, and sea ice, interact dynamically without any restraints. The observed external forcing mainly acts on the atmospheric component and then influences other components (e.g., land surface, ocean, and sea ice) through their coupling with the atmosphere.

Comment#19:

L187: Some discussion here of how you updated the model states from monthly means would have been useful, as this is not straight forward. There has been a lot of work done on this within the context of assimilation GRACE terrestrial water storage. Also, assimilating monthly means to update instantaneous states is not the obvious way to do it - given that you're assimilating model output, you had the option of assimilation instantaneous output.

Response:

To assimilate the monthly mean GLDAS product, fully coupled integration by the E3SMv2 model is performed twice within each one-month assimilation window: first to generate the observational innovation by computing the differences between the GLDAS data and model outputs for analysis, and second to forecast the backgrounds of all components for the next assimilation window. When the fully coupled model is executed for the second one-month run, the land reanalysis information is transferred to the other components through multi-component interactions. Similarly, to assimilate the monthly GRACE-based TWS observations, previous studies employed the "two-step" scheme in which the land model integration is performed twice within the same month (Houborg et al., 2012; Girotto et al., 2016). The primary reason for assimilating monthly averages rather than updating instantaneous states is that observational information on timescales shorter than one month can potentially introduce undesirable noise, adversely affecting DCPs upon assimilation into the ICs.

In light of this comment, we have included more detailed discussions (L288-297) on how we assimilate monthly mean GLDAS data and previous work about assimilating monthly GRACE data in our revised manuscript.

L288-297: To assimilate the monthly mean GLDAS product, fully coupled integration by the E3SMv2 model is performed twice within each one-month assimilation window: first to generate the observational innovation by computing the differences between the GLDAS data and model outputs for analysis, and second to forecast the backgrounds of all components for the next assimilation window. When the fully coupled model is executed for the second one-month run, the land reanalysis information is transferred to the other components through multi-component interactions. This approach is similar to previous studies that employed the "two-step" scheme in which the land model integration is performed twice within the same month to assimilate the monthly GRACE-based TWS observations (Houborg et al., 2012; Giroto et al., 2016).

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