We thank Reviewer #3 for the constructive comments and suggestions, which greatly help to improve the quality of our manuscript. We have made revisions and replied to all 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 #3

General Comment:

This manuscript presents the implementation of a 4DEnVAR method in the E3SMv2. The authors assimilate monthly mean soil moisture and temperature from a land re-analysis product and evaluate the performance of the new data assimilation system vs a control experiment (no assimilation). I find the approach of 4DEnVAR for land data assimilation very interesting. However, there are several shortcomings of the paper that need to be addressed before it is ready to be published in GMD.

Response:

We would like to express our sincere gratitude for your time and effort in reviewing our manuscript. We truly appreciate your constructive comments and suggestions, which have significantly contributed to enhancing the quality of our work. We have carefully addressed each comment, as outlined below, and have made the necessary revisions to our manuscript.

Comment#1:

The authors need to differentiate between coupled data assimilation and coupled modelling, the study is presented as "land coupled data assimilation" however it is land data assimilation only. Please consider to re-write parts of the introduction to make this clear.

Response:

Thank you for your valuable feedback. We apologize for any ambiguities in our original manuscript. In response to your comment, the introduction of our manuscript has been thoroughly rewritten. Effort has been made to clearly distinguish between weakly coupled data assimilation (WCDA) and strongly coupled data assimilation (SCDA) by highlighting the differentiations between coupled modeling and coupled data assimilation. WCDA implies coupling in the forecast step, but no coupling in the analysis step. In contrast, SCDA allows coupling in both the analysis and forecast steps.

We have incorporated a more thorough description of our assimilation process and clarified that the assimilation method used in our study is referred as the WCDA system. In this study, 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 utilized to produce the optimal assimilation analysis. Subsequent to this, 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.

In the revised introduction, we first elucidate the distinctions between uncoupled data assimilation (DA) and coupled data assimilation (CDA). Uncoupled DA implies that DA is conducted using an individual component model (e.g., land surface model forced by atmospheric observations or reanalysis data rather than coupled with an atmospheric model) as the forecast model that does not consider any interactions with other components. For example, most existing reanalysis data are generated by uncoupled DA, and previous studies employ uncoupled DA that directly utilizes reanalysis data as initial conditions (ICs) to initialize decadal climate predictions (DCPs) based on coupled models (Du et al., 2012; Bellucci et al., 2013). However, such uncoupled DA often exhibits poor consistency between ICs of component models, and eventually produces low prediction skills (Balmaseda et al., 2009; Boer et al., 2016; Ardilouze et al., 2017).

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. Then CDA methods are categorized into two main types: weakly coupled data assimilation (WCDA) and strongly coupled data assimilation (SCDA).

When introducing WCDA and SCDA, we make a clear distinction between coupling in the model and coupling in the DA. 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).

In response to this comment, we have revised our introduction to first elucidate the distinctions between uncoupled DA and coupled data assimilation (L41-56), and then distinguish between WCDA and SCDA by highlighting the characteristics of coupling in the model and coupled DA (L57-80). We hope that these modifications can better distinguish between uncoupled DA and CDA, as well as more effectively illustrate that the data assimilation system we developed in this study is referred to as the WCDA system.

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).

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.

To better elucidate that our data assimilation approach in this study is referred as WCDA, we have augmented our manuscript with a more comprehensive description (L113-118, L221-228, L268-278, and L288-294) of each assimilation process with both the analysis and the forecast steps. Specifically, in the forecast step, we have emphasized that the entire E3SM climate model is utilized for forecasting, and coupling in the forecast step transfers the land reanalysis information to the other components (e.g., atmosphere and ocean) through multi-component interactions. This DA process under the coupled modeling framework is referred as the WCDA system. To distinctly differentiate our assimilation approach (WCDA) from SCDA, we have changed the terminology coupled data assimilation (CDA) to weakly coupled data assimilation (WCDA) throughout the manuscript to accurately represent our utilization of weakly coupled data assimilation. As a result, our assimilation system in this study is explicitly named the weakly coupled land data assimilation (WCLDA).

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.

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#2:

As pointed out by Referee #2, the authors assimilate model derived soil moisture and temperature without taking into account the systematic differences between the two models. I fully agree with Referee #2 that the authors need to do some kind of bias correction before the assimilation step. It is not clear to me why monthly mean values are chosen and also not why you do not assimilate actual observations, please make this clear to the reader. In my opinion the authors should consider changing the experiment design and either assimilate (and evaluate) their system against actual observations or create a synthetic twin experiment study.

Response:

Thank you for your insightful comments. In light of your suggestions, we have now applied bias correction before assimilation and incorporated detailed explanations for our selection of monthly mean values, and assimilating land reanalysis products rather than actual observations in our revised manuscript.

Following your advice, we have modified our experiment design to add bias correction before assimilation (L168-171), and then conducted the anomaly assimilation through assimilating observed anomalies into the model. Due to the modifications of our experimental design, we have comprehensively updated all figures (Figure 3 to 10) and relevant descriptions that depict 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.

Regarding the use of monthly mean values, we realize that our initial manuscript did not sufficiently explain this decision, which is driven by our initial interest in using data assimilation to produce initial conditions for decadal climate predictions (DCPs). Almost all initializations for DCPs in CMIP5 and CMIP6 incorporated monthly mean reanalysis data as observations (Table 1). This preference is primarily driven by two critical factors. Firstly, for decadal-scale climate predictions, assimilating data with temporal resolutions shorter than one month may introduce undesirable noise, which can adversely affect DCPs when high temporal resolution data are assimilated into the initial conditions. Hence, the prevalent practice in both CMIP5 and CMIP6 is to assimilate monthly mean data for DCPs. Secondly, the DA techniques applied in the coupled data assimilation (CDA) for initializations of decadal prediction are generally much simpler than those used in NWPs, attributed largely to the increased complexity in coupled climate models. For examples, many initialization systems used in CMIP5 and CMIP6 adopted the simple nudging method (Table 1). Therefore, these much simpler DA approaches and much more complex coupled models do not allow the direct assimilation of actual observations. Furthermore, unlike NWPs where long-term DA cycles aren't necessary, the initialization for DCPs requires DA cycles spanning at least ten years which makes it very difficult or even impossible to assimilate complex 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	Voldoire 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

To clarify our choice of using monthly mean GLDAS reanalysis, we have incorporated detailed explanations (L245-252) in our 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.

The key challenge we face in assimilating actual observations, particularly satellite data, arises from the lack of the observation operator within our current system. The observation operator plays a critical role in establishing the connection between the model variables and actual observations, accounting for the discrepancies in spatial and temporal resolutions between the two datasets. It takes us one year to build this weakly coupled land data assimilation (WCLDA) system for the E3SMv2 model. Unfortunately, our current WCLDA system lacks the design of the observation operator, thereby presenting a significant obstacle to incorporating actual observational data effectively. Recognizing this limitation, we will focus on the development of the observation operator for future improvement of our WCLDA system.

To shed light on the current limitations of our WCLDA system, we have incorporated the reasons (L446-450) for its inability to assimilate actual observations in our revised manuscript. Our objective in adding these explanations is to provide readers with additional reasons behind our decision not to assimilate actual observations.

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.

GLDAS product generate optimal fields of land surface states and fluxes in near-real time (Rodell et al., 2004), and these reliable global GLDAS datasets are extensively utilized in weather and climate research (Chen et al., 2021; Zhang et al., 2018). In identifying an optimal long-term land surface dataset for our study, we found the GLDAS to be exceptionally suitable. Additionally, 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). Therefore, we employed the advanced WCDA approach to incorporate the GLDAS monthly mean soil temperature and soil moisture into the fully coupled E3SMv2 model.

In response to your suggestion, we have expanded our analysis by further evaluating our assimilation performance against MODIS satellite observations from 2003 to 2014. We have introduced a new figure (Figure A1) in the Appendix and incorporated detailed descriptions about the assimilation performance compared with MODIS data (L348-357) in our revised manuscript. Figure A1 shows the spatial pattern of the AE index for surface soil moisture and land surface temperature between MODIS data and model simulations. For surface soil moisture, the comparison with MODIS data suggests that the majority of global regions exhibit reduced RMSE after assimilation. The reduction of RMSE is pronounced in central North America, South America, southern Africa, Australia, and Europe. However, in high-latitude areas, significant degradations are observed in northern Russia, which may be possibly related to model deficiencies in simulating the complex frozen ground and snow processes (Edwards et al., 2007; Ireson et al., 2013). Regarding land surface temperature, improved performances are evident over South America, Australia, southern Africa, and parts of Eurasia when compared to MODIS data. In contrast, some degradations appear over parts of North America and central Asia, which still require further improvement.

L348-357: We further perform an analysis of the spatial pattern of the AE index for surface soil moisture and land surface temperature between MODIS data and model simulations (Figure A1). For surface soil moisture, the comparison with MODIS data suggests that the majority of global regions exhibit reduced RMSE after assimilation. The reduction of RMSE is pronounced in central North America, South America, southern Africa, Australia, and Europe. However, in high-latitude areas, significant degradations are observed in northern Russia, which may be possibly related to model deficiencies in simulating the complex frozen ground and snow processes (Edwards et al., 2007; Ireson et al., 2013). Regarding land surface temperature, improved performances are evident over South America, Australia, southern Africa, and large parts of Eurasia when compared to MODIS data. In contrast, some degradations appear over parts of North America and central Asia, which still require further improvement.

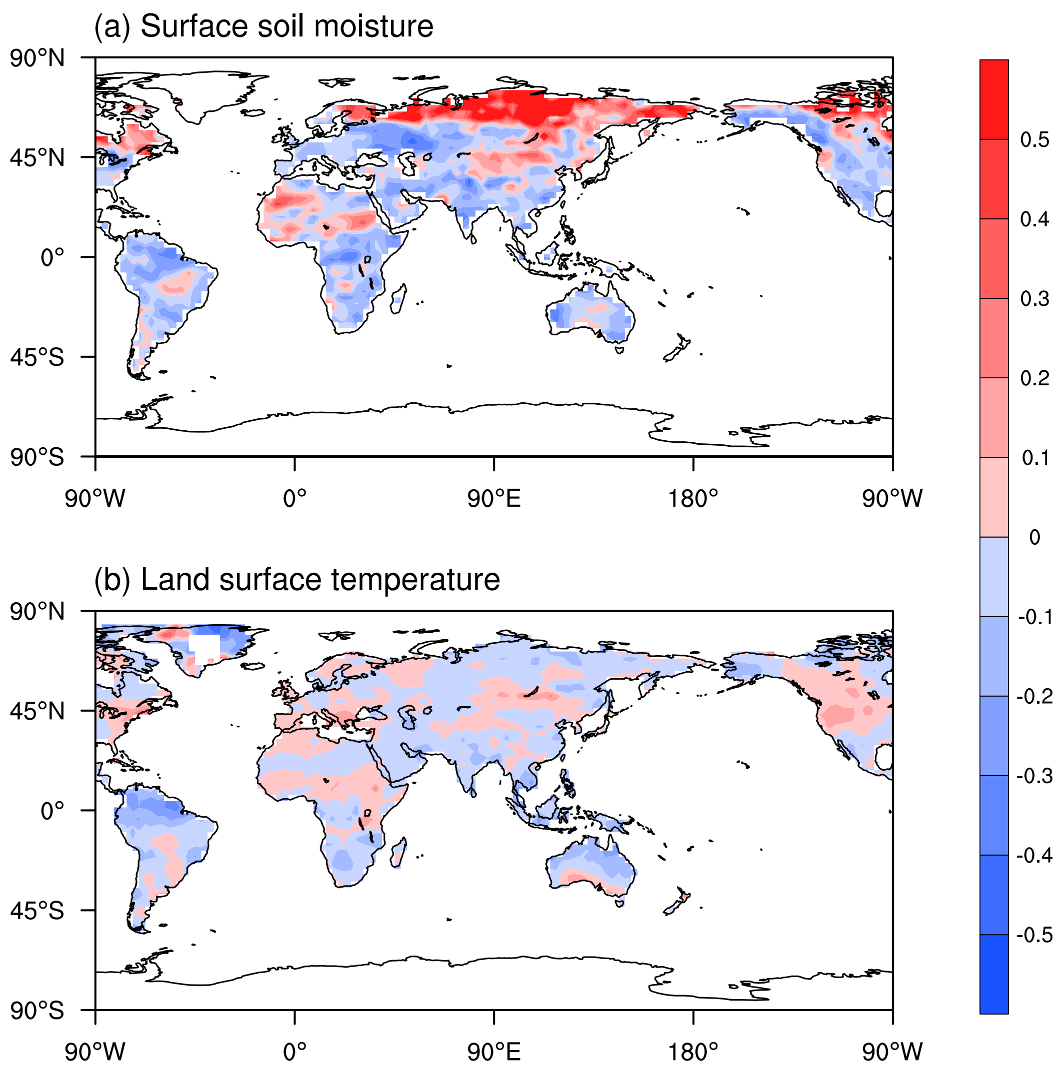

Figure A1. Spatial distribution of the AE index for (a) surface soil moisture and (b) land surface temperature during the 2003-2014 period. The observations are derived from monthly MODIS satellite data.

Current initialization techniques consist of two main categories: full-field initialization with observed values, and anomaly initialization with observed anomalies. The optimal strategy for model initialization (full-field versus anomaly initialization) is still an active research topic (Hu et al., 2020; Polkova et al., 2019). The full-field assimilation is commonly performed to reduce the influence of systematic model biases by replacing the initial model state with the optimal available estimate of the observed state (Volpi et al., 2017). However, the model trajectory tends to drift away from the observations and revert to the model's inherent preferred state because of model deficiencies (Smith et al., 2013). This problem is partially addressed with the anomaly assimilation by assimilating the observed anomalies added to the model climatology (Carrassi et al., 2014).

We have incorporated a discussion (L161-168) to outline the advantages and disadvantages of both full-field and anomaly assimilation in our revised manuscript. This discussion also clarifies our decision to select the anomaly assimilation for the WCLDA system, emphasizing our methodology of applying bias correction to the GLDAS data before assimilation.

L161-168: Current initialization techniques are broadly classified into two categories: full-field assimilation with observed values, and anomaly assimilation with observed anomalies (Hu et al., 2020; Polkova et al., 2019). The full-field assimilation is commonly performed to reduce the influence of systematic model biases by replacing the initial model state with the optimal available estimate of the observed state (Volpi et al., 2017). However, the model trajectory tends to drift away from the observations and revert to the model's inherent preferred state because of model deficiencies (Smith et al., 2013). This problem is partially addressed with the anomaly assimilation by assimilating the observed anomalies added to the model climatology (Carrassi et al., 2014).

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