

Article

The Impact of Spatial Dynamic Error on the Assimilation of Soil Moisture Retrieval Products

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Abstract: Soil moisture is a key factor affecting the exchange of heat and water between the land and the atmosphere. Land data assimilation (LDA) methods that leverage the strengths of both models and observations can generate more accurate initial conditions. However, soil moisture exhibits significant spatial heterogeneity, implying strong local characteristics for both observational and background errors. To elucidate the impact of error localization on LDA, we constructed a land data assimilation system (LDAS) suitable for the Common Land Model (CoLM), based on the simplified extended Kalman filter (SEKF) method. Through practical assimilation experiments using soil moisture retrieval products from the Soil Moisture Active Passive (SMAP) and Fenyun-3D (FY3D) satellites, we investigated the influence of spatial static and dynamic observational and background errors on LDA. The results indicate that by incorporating dynamic errors that account for the spatial heterogeneity of soil, LDAS can adaptively absorb observational information, thereby significantly enhancing assimilation impact and subsequent model forecast accuracy. Compared to experiments applying static errors, dynamic errors increased the spatial correlation coefficients by 17.4% and reduced the root mean square error (RMSE) by 11.2%. The results clearly demonstrate that for soil variable assimilation studies with strong spatial heterogeneity, progressively refined dynamic error estimation is a crucial direction for improving land surface assimilation performance.

Keywords: soil moisture; land data assimilation; error estimation; satellite; retrieval



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1. Introduction

The global land water, energy balance, and carbon cycles are significantly influenced by soil moisture [1]. Soil moisture plays a key role in evaporation and precipitation by regulating the exchange of latent and sensible heat, particularly in areas where wet and dry transitions occur and the coupling between soil moisture and rainfall is more evident [2]. In the surface soil layer, soil moisture influences plant transpiration and growth by controlling precipitation infiltration, and it can also have an impact on the global carbon cycle [3]. Therefore, accurate soil moisture measurements can improve surface conditions, as well as the accuracy of weather forecasting and climate prediction.

Soil moisture monitoring relies heavily on satellite data with high spatial coverage to address the strong spatial heterogeneity of soil moisture [4,5]. As remote-sensing re-

retrieval techniques have developed rapidly, soil moisture products that can be directly applied in research have been established, achieving a balance between data quality and spatial coverage [6–8].

Over the past few decades, significant developments have been made in the field of soil moisture retrieval using microwave remote sensing signals. These retrieval products rely predominantly on active and passive microwave radiometers. Considering their remarkable ability to penetrate clouds and atmospheric aerosols, microwave sensors enable surface data detection across various weather conditions and effectively discriminate between the dielectric properties of wet and dry soils [9]. Passive microwave sensors operate in the X-, C-, and L-bands. Specifically, the X-band encompasses the Microwave Radiometer Imager (MWRI) [10]; the C-band comprises the Scanning Multichannel Microwave Radiometer [11], the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) [9], and the AMSR2 [12]; and the L-band is composed of the microwave sensor equipped with a soil moisture and ocean salinity (SMOS) instrument [7]. Active microwave radiometers predominantly operate within the C-band and include the active microwave instrument wind scatterometer [13], the Advanced Scatterometer (ASCAT) [14], and Sentinel-1 [15]. Soil Moisture Active Passive (SMAP) [16] combines active and passive radiometers operating in the L-band. Scientists have developed soil moisture retrieval products for these sensors. However, the practical application of soil moisture remote-sensing products also faces several limitations, including uncertain retrieval errors, non-uniform spatiotemporal distribution, and irregular missing data, all of which need to be addressed for the actual application of retrieval products.

Many studies have shown that land data assimilation systems (LDASs) can optimally merge soil moisture retrieval products with land surface models, generating soil moisture variables that are temporally and spatially continuous, with greater accuracy [17,18]. Therefore, research on the land assimilation of soil moisture retrieval products has gained widespread attention. For instance, Khaki et al. [19] achieved noteworthy enhancements in soil moisture and groundwater prediction by assimilating total water storage (TWS) and soil moisture data from AMSR-E and SMOS using the square root analysis method. Researchers were able to improve predictions for the Western United States of America (USA) by assimilating soil moisture products from SMAP and ASCAT. They were able to better assess the intensity of drought events in 2015 and 2016 [20]. For weather forecasting, assimilating ASCAT soil moisture retrieval data into land surface models can improve land–atmosphere water and energy exchange simulations, which is beneficial for precipitation and temperature forecasts [21].

Consequently, many countries have developed their own LDASs, tailored to their respective land surface models. In the USA, the North American LDAS assimilates TWS data using the ensemble Kalman smoother method [22]. The European Center for Medium-Range Weather Forecasts (ECMWF) improves surface conditions through the assimilation of 2 m temperature and relative humidity using a simplified extended Kalman filter (SEKF) [23]. China's CLDAS (CMA LDAS) not only assimilates individual data, such as soil moisture and surface temperature, retrieved from FY-3C satellites, but also achieves the joint assimilation of multiple data, such as surface and microwave brightness temperatures [24].

Accurate prior observations and background error information are important for data assimilation methods to reasonably adjust the background field [25,26]. Data assimilation has been extensively employed in weather and climate forecasting for the land, atmosphere, and ocean [22,27,28]. However, unlike the assimilation of fluid variables, such as for the atmosphere and ocean, land variables are non-fluid and exhibit a predominant characteristic of high spatial heterogeneity. Consequently, land data assimilation (LDA) is inevitably

affected by the strong spatial localization arising from land variable heterogeneity. The estimation of prior information has a direct impact on background and observational errors.

These errors determine whether the analysis field in the assimilation process absorbs more observational information or preserves the model background field characteristics [29]. Regarding observational errors, in the process of satellite remote sensing for soil moisture retrieval, multiple auxiliary parameters (such as soil temperature) are required, and parameter uncertainties are the primary source of observational errors. A primary source of background errors is soil parameter uncertainty. Soil thermodynamic and hydraulic parameters affect the transfer of energy and water, respectively. Parameter inaccuracies can lead to deviations in the simulation results [30].

The strong spatial heterogeneity of soil moisture tends to lead to increased local background characteristics and observational errors [31]. Many LDA studies have focused on local differences in land surface variable errors. Muñoz-Sabater et al. [32] attempted to relate background errors to soil texture using the percentage of water-holding capacity, which is the difference between soil moisture at field capacity and the wilting point, as an estimate of background errors. They suggested that the deeper the soil, the smaller the background error. This method established a correlation between soil texture and depth and achieved a neutral positive assimilation effect. Triple collocation (TC) is frequently used for error estimation in observational data, using three independent datasets to estimate errors relatively objectively [33,34]. Vural et al. [35] used TC to calculate observational errors in soil moisture and assimilated the soil moisture data into the SURFEX model. They found that assimilation has a positive impact in certain regions. Qin et al. [36] performed two cycles to assimilate soil moisture and simultaneously optimize the parameters to estimate background and observational errors and model parameters. A key factor influencing the LDA effect and a major goal of this study is to introduce error estimation results with strong local characteristics based on soil moisture characteristics in data assimilation.

A key issue in clarifying the effects of errors on assimilation is the selection of a suitable assimilation algorithm. The optimal interpolation method was initially used in land surface data assimilation, and subsequently, in more commonly used atmospheric data assimilation algorithms, such as the SEKF [37]; the ensemble Kalman filter (EnKF) [25], the ensemble square root filter [38], and three-dimensional variational (3DVar) algorithms [39] have also been applied in land surface data assimilation. The SEKF method was selected in this study to avoid the huge computational demand of EnKF and to overcome the difficulties in handling the adjoint aspect of land surface models in 3DVar.

The application of SEKF in satellite remote-sensing data assimilation has also received scientific attention. Draper et al. [40] first assimilated AMSR-E soil moisture products using the SEKF in combination with the interaction between the soil, biosphere, and atmosphere (ISBA) scheme. Later, ASCAT soil moisture products were also applied to the SEKF assimilation system and showed more positive improvements, particularly in regions with sparse ground observational networks [41,42]. As ISBA has developed from including two to multiple layers, the SEKF method has shown great potential for improving deep soil moisture predictions and simulating soil moisture under inaccurate external forcing conditions [43]. Muñoz-Sabater et al. [44] directly assimilated the L-band brightness temperature of SMOS using the community microwave emission model and found a seven-fold increase in the impact of SMOS brightness temperature data assimilation on surface soil moisture compared to that of assimilating surface variables alone. In recent years, researchers have begun to use the SEKF to jointly assimilate additional surface variables. For example, Albergel et al. [45] used the SEKF to jointly assimilate soil moisture from the ESA Climate Change Initiative and the leaf area index (LAI) from GEOLAND2 version 1 (GEOV1). They found that the LAI had a greater impact on root-zone soil moisture

assimilation. Albergel et al. [46] combined the assimilation of the soil water index from ASCAT and LAI from GEOV1, and the assimilation results performed well in detecting heat waves and other extreme weather events.

In previous studies, the SEKF has been widely applied to the ISBA, primarily by assimilating satellite products from SMOS, Sentinel-1, ASCAT, and TRMM. However, there has been limited research on the assimilation applications of other land surface models and satellite products. In this study, we applied the SEKF to construct an LDAS suitable for the Common Land Model (CoLM). Simultaneously, we conducted a joint assimilation of the soil moisture products from SMAP and Fenyun-3D (FY3D). By assessing the assimilation impact of the spatial static and dynamic error estimation results and comparing the assimilation results from different satellite products, we further explored the influence of error estimation on the assimilation impact of different soil moisture retrieval products.

The remainder of this paper is organized as follows. Section 2 introduces the LDA methods and data. The design of the assimilation experiments is described in Section 3. The results and analysis of the assimilation experiments are presented in Section 4. Finally, the conclusions and discussion are presented.

2. Data

2.1. SMAP

SMAP consists of four levels and 22 types of soil moisture products released by the Distributed Active Archive Center at the National Snow and Ice Data Center (NSIDC). All SMAP products can be accessed through the NSIDC. The soil moisture product L2_M_P_E from the SMAP Level-2 data from June to August 2022 was used in the experiment. The original spatial resolution of the SMAP radiometer was 36 km, whereas the L2_M_P_E product was an interpolated soil moisture product with a spatial resolution of 9 km, derived from SMAP Level-1B using the Backus–Gilbert optimal interpolation technique. This product provides the surface soil volumetric water content (m^3/m^3) at depths of 0–5 cm on a 9 km EASE-Grid 2.0 projection.

2.2. FY3D

FY3D carries the MWRI, which provides global microwave radiance data twice daily. Based on the MWRI radiance data, the Satellite Meteorological Center of the China Meteorological Administration developed a dataset for soil moisture retrieval [47]. The FY3D daily soil moisture products include ascending and descending orbits, which are synthetic values of soil moisture at a horizontal resolution of 25 km on the EASE-Grid projection derived from the MWRI ascending/descending channel brightness temperature data using inversion models. Soil moisture refers to the volumetric water content in the surface layer of the soil, which is defined as the volume of water per unit volume of soil and is the product of soil moisture by weight and bulk density. Daily soil moisture products from June to August 2022 were selected for analysis.

2.3. Observational Data Preprocessing

Accurate observational data is crucial for effective data assimilation, so it is necessary to strictly control the quality of the assimilated observational data. Satellite retrieval data provides us with reliable quality indicators, allowing for quality control based on these indicators. For SMAP satellite data, the study selected data with quality indicators of 0 and 8 for assimilation. As for FY satellite data, the provided quality indicators are only 0 and 1, so here, only data with a quality indicator of 0 are chosen for assimilation.

From the previous description, the horizontal resolution of FY3D soil moisture data is 25 km, while SMAP soil moisture has a spatial resolution of 9 km. However, the CoLM used in the study has a grid size of 128×256 , with a horizontal resolution of approximately 1.406° . To properly apply the observational data in subsequent assimilation experiments, preprocessing of the observational data is required. Considering that the horizontal resolution of satellite retrieval products is much higher than that of the land surface model, in order to avoid introducing excessive small-scale perturbations from the high-resolution observational data, the study spatially averages all the satellite retrieval soil moisture products that fall within the model grid points to obtain gridded observational data of 128×256 globally.

2.4. Evaluating Data

The GLDAS generates different products using four land surface models (Mosaic, Noah, Community Land Model (CLM), and VIC). The products consisted of 22 physical parameters, with temporal resolutions of 3 h and monthly and spatial resolutions of 1.0 and 0.25° , respectively. The soil moisture products from Noah were divided into four layers at depths of 10, 40, 100, and 200 cm below the surface [48]. This study employed Noah soil moisture products from the top three layers for the period 1 June to 31 August 2022.

The in situ data includes soil moisture at a depth of 10 cm, provided by ISMN hosts and the China Meteorological Administration. Since 1952, the ISMN has collected in situ soil moisture measurements from 35 international networks, encompassing over 1400 monitoring stations. The purpose of the ISMN is to validate, calibrate, and improve the accuracy of remote sensing soil moisture retrieval algorithms and land surface soil moisture outputs. Additionally, it provides measurements of other variables, including soil temperature and precipitation, to enable better interpretation of soil moisture data [49]. The soil moisture measurements in this study cover the period from June to August 2022. In this study, we spatially matched satellite-derived products with in situ data using a regional averaging method, with a spatial window of 70 km. For the temporal matching, we used a time window of 6 h. However, it should be noted that the current collocation scheme does not consider the spatiotemporal representativeness of either the station data or the satellite-derived products. Future studies could improve the representativeness of these two datasets by applying spatial and temporal averaging.

3. Methods

3.1. CoLM

A research institute in China developed the CoLM land surface model to simulate land surface ecohydrological processes. Initially, the CoLM and CLM were jointly developed by the National Center for Atmospheric Research and the Institute of Atmospheric Physics, Chinese Academy of Sciences. They integrated land surface models, biosphere–atmosphere transfer schemes, and the IAP94 model. In the latest version of CoLM (2014), several key improvements in Earth physics and physiological ecological processes were achieved, such as updated soil parameter calculations and two big-leaf schemes [50,51].

The CoLM requires atmospheric forcing data for model simulations, such as downward longwave and shortwave radiation, precipitation rate, and surface pressure, as well as near-surface specific humidity, air temperature, and wind speed. In this study, the CoLM was driven by near-surface meteorological data from the ECMWF. The spatial resolution of the atmospheric forcing data was 1.406° , updated every 3 h, and covered the period from 1 January 1979, to 31 December 2022.

3.2. Assimilation Method

The variational assimilation method and the Kalman filter assimilation method are currently the two main approaches used in data assimilation. In land surface assimilation research, scientists have conducted practical assimilation studies for each method [52–54]. Each method also has multiple variations tailored to specific research objectives. Variational assimilation is primarily divided into 3D-Var (three-dimensional variational assimilation) and 4D-Var. The 4D-Var (four-dimensional variational assimilation) method requires the adjoint model of the forecast model, but due to the strong nonlinear characteristics of land surface models, the accuracy of their adjoint models is severely limited, which restricts the application of 4D-Var in land surface assimilation. Similarly, while the 3D-Var method does not require the adjoint model of the forecast model, its cost function minimization still relies on the continuous adjoint equation corresponding to the observation operator. This severely limits the simultaneous assimilation of unconventional and multi-layer observational data [55]. As a result, the Kalman filter assimilation method is more widely used in land surface assimilation research because it does not require a strict continuous adjoint model. However, the Kalman filter's assumption of linearity in the observation operator underpins its lack of an adjoint model. To extend the Kalman filter to nonlinear systems, scientists have developed various modifications [56,57]. A representative method is the ensemble Kalman filter (EnKF), which utilizes statistical methods to obtain the error propagation characteristics of nonlinear systems through the superposition of disturbances. However, the EnKF faces computational challenges due to its need for numerous computational resources, limiting its practical use in operational systems. To address operational needs, scientists proposed the extended Kalman filter (EKF), which employs partial linearization of the numerical model to better apply the Kalman filter to nonlinear systems. However, how to effectively linearize partial modules of the land surface model remains a point of debate in land surface assimilation research. Hess [37] and Balsamo [58] proposed the simplified extended Kalman filter (SEKF), which approximates the gradient of the nonlinear system by superimposing disturbances of appropriate magnitudes. This method produces results that are more consistent with the physical model, avoids the partial linearization issue, and allows for real-time gradient updates, thereby retaining the flow-dependent characteristics of the errors, to some extent. This has made the SEKF a favored method at the European Center for Medium-Range Weather Forecasts (ECMWF). However, the SEKF requires a disturbance for each variable, meaning that as the number of variables to be assimilated increases, the computational cost can become prohibitive. This study, focused on the soil moisture assimilation of a single-column land model, easily meets the computational requirements, making the SEKF the method of choice for this research.

The SEKF is similar to the Kalman filter equation, and KF's equation is as follows:

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - \mathbf{H}(\mathbf{x}_b)) \quad (1)$$

$\mathbf{x}_a$ is the analyzed field, $\mathbf{x}_b$ is the background field, and y is the observation. Here, H represents the observation operator, and $\mathbf{K}$ is referred to as the gain matrix. If H is a linear observation operator, its operation can be represented using the matrix $\mathbf{H}$. The gain matrix $\mathbf{K}$ can be expressed by the following formula:

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1} \quad (2)$$

$\mathbf{B}$ and $\mathbf{R}$ are the covariance matrices of the background and observational errors, respectively, where the background covariance matrix does not evolve over time. $\mathbf{H}^T$ represents the adjoint of the observation operator. However, in practical applications, we often encounter nonlinear problems, and the linearity assumption of the observation operator H severely limits the practical applicability of the KF method. To extend KF to nonlinear systems, scientists have attempted to linearize the observation operator and model, leading to the development of the EKF [59]. However, since EKF requires a tangent linear approximation of the model, it is difficult to apply it to other land surface models, and it significantly increases the complexity of updating and maintaining the assimilation system. To further enhance the generalizability of the KF method while avoiding the complexity of maintenance, the SEKF was proposed by Hess [37] and Balsamo [58]. This method calculates the first-order derivative of the observation operator using a perturbation approach, as shown in Equation (3).

$$\mathbf{H}_{ij} = \frac{H(\mathbf{x}_i + \delta\mathbf{x}_j) - H(\mathbf{x}_i)}{\delta\mathbf{x}_j} \quad (3)$$

The matrix $\mathbf{H}$ elements are composed of the first-order derivative values of the observational operator obtained from perturbing each component x_j of the control vector $\mathbf{x}$. Fairbairn et al. [59] found that in dry regions, $\mathbf{H}$ was much greater than 1, and affected by weather processes, $\mathbf{H}$ can be smaller than 0. Therefore, lower and upper limits of 0 and 1 are set for $\mathbf{H}$, and interpolation was conducted for these grids.

3.3. Perturbation Scale

The definition of derivatives implies that, within appropriate perturbation sizes, the value of the first-order derivative of a linear model should remain constant, irrespective of the perturbation value. Furthermore, for a given perturbation value, the calculated first-order derivatives of the positive and negative perturbations should be equal. Therefore, to compute the first-order derivative of the observational operator, it is crucial to establish a reasonable range of perturbation values appropriate for operator $\mathbf{H}$. By employing perturbation values within this range, the computed first-order derivative $(\mathbf{H}^+ + \mathbf{H}^-)/2$ tends to stabilize around a specific value. Additionally, $|\mathbf{H}^+ - \mathbf{H}^-|$ should be minimized to approach zero as closely as possible [60], where $\mathbf{H}^+$ and $\mathbf{H}^-$ represent the linearized operators $\mathbf{H}$ obtained from the positive and negative perturbations, respectively.

To avoid the influence of weather systems on the estimation of the observational operator derivative, we first computed $(\mathbf{H}^+ + \mathbf{H}^-)/2$ and $|\mathbf{H}^+ - \mathbf{H}^-|$ for each grid point under different perturbation conditions and then calculated the global average for all grid points. Figure 1 shows the global average characteristics of H as the perturbation size changes in different model layers. It should be noted that the global $\mathbf{H}$ -average value here is used only for calculating the size of the perturbations and is not consistent throughout the assimilation process. As shown in Figure 1b, when the perturbation value is $1 \times 10^{-3} \text{ m}^3\text{m}^{-3}$, $(\mathbf{H}^+ + \mathbf{H}^-)/2$ stabilizes at approximately $0.35 (\text{m}^3\text{m}^{-3})$, whereas $|\mathbf{H}^+ - \mathbf{H}^-|$ is very close to 0. Therefore, it can be considered that when the perturbation is $1 \times 10^{-3} (\text{m}^3\text{m}^{-3})$, the derivative of the observation operator for the second layer of soil moisture is $0.35 \text{ m}^3\text{m}^{-3}$. From Figure 1, it can be observed that there is a large range that meets the above criteria from the second layer to the seventh layer, and in the first layer, a small portion of the range also satisfies these requirements. By searching for the smallest $|\mathbf{H}^+ - \mathbf{H}^-|$, the following perturbation values were selected for the first seven layers: 0.001, 0.0001, 0.0001, 0.0001, 0.0005, 0.001, and 0.0005 m^3m^{-3} .

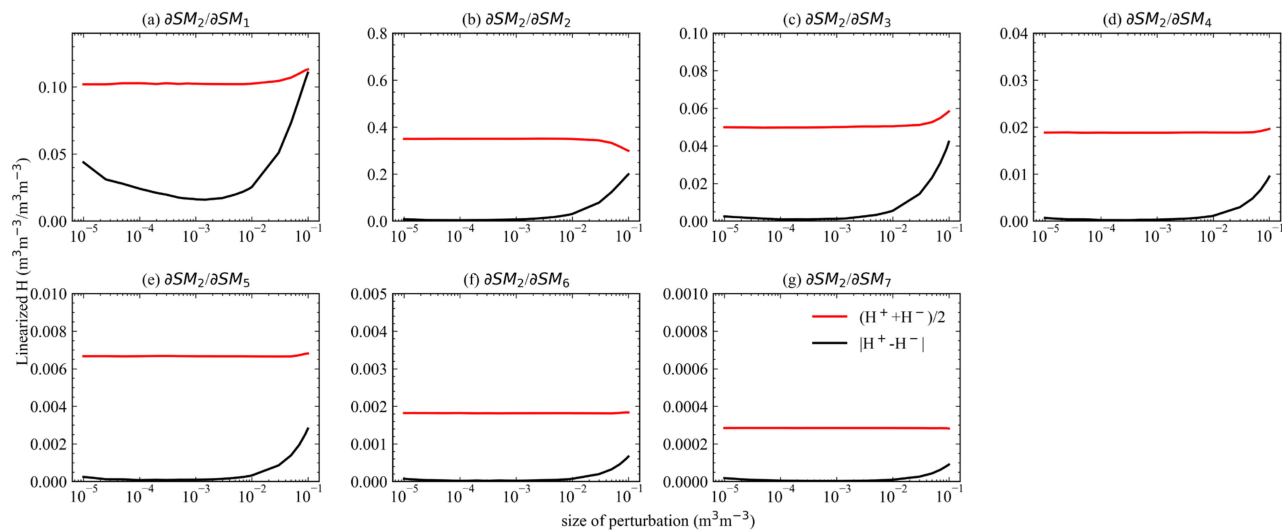


Figure 1. The $\partial SM_2 / \partial SM_n$ characteristics with respect to size of perturbation in different layers are shown. The black line represents $|H^+ - H^-|$, and the red line represents $(H^+ + H^-)/2$.

4. Experimental Designs in Assimilation and Results

4.1. Comparison of CoLM and In Situ Soil Moisture

The standard deviation (STD) spatial distribution of hourly soil moisture differences between in situ soil moisture and the CoLM model from June to August 2022, as well as the differences under various vegetation types, are presented in Figure 2. The CoLM model grid consists of subgrids, and we assigned the dominant subgrid vegetation type within each grid as the vegetation type for that grid. The vegetation type classification is listed in Table 1. The figure reveals significant regional variations in STD. In arid regions, such as the western United States, the STD is relatively small, typically below $0.012 \text{ m}^3 \text{ m}^{-3}$. In contrast, much larger STD values, generally exceeding $0.06 \text{ m}^3 \text{ m}^{-3}$, are observed in flat areas like the Central United States, Europe, and Eastern China. Moreover, there are also notable differences across different vegetation types. The STD in CORN is nearly twice as large as that in BDS Temperature. Furthermore, the land surface model grid consists of multiple subgrids representing different vegetation types, with the calculation of water and heat fluxes being independent in each subgrid. There is no horizontal diffusion between the subgrids. Given the significant local characteristics of the surface variables, the accuracy of soil moisture simulations by CoLM may exhibit considerable regional variability. Background errors are crucial prior information for data assimilation, and accurately specifying them is a prerequisite for appropriately incorporating background information. In data assimilation studies, considering the stochastic nature of reanalysis data errors, the STD of the difference between model simulations and reanalysis data is often used as an estimate of model background errors. Therefore, it is necessary to perform regional adjustments to the background errors throughout the assimilation process.

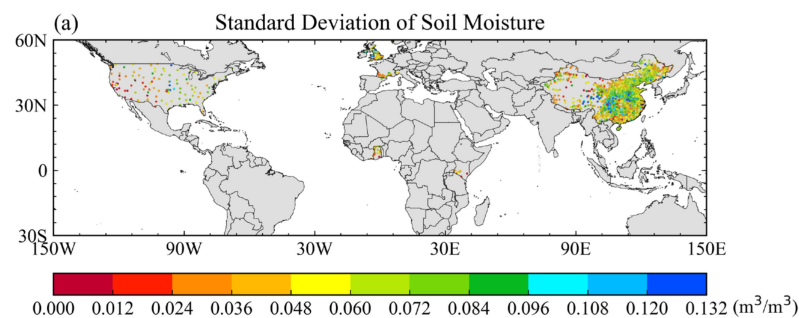


Figure 2. Cont.

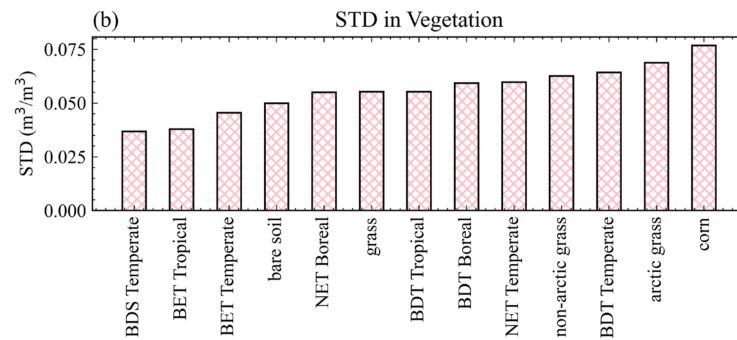


Figure 2. Spatial distribution STDs of the difference between (a) in situ and CoLM simulated soil moisture from June to August 2022, and (b) the STDs across different vegetation types.

Table 1. Vegetation types.

Abbreviation	Type	Abbreviation	Type
BDS Temperate	Broadleaf deciduous temperate shrub	BDT Temperate	Broadleaf deciduous temperate tree
BDT Boreal	Broadleaf deciduous boreal tree	NDT Boreal	Needleleaf deciduous boreal tree
BET Tropical	Broadleaf evergreen tropical tree	NET Temperate	Needleleaf evergreen temperate tree
BDT Tropical	Broadleaf deciduous tropical tree	BDS Boreal	Broadleaf deciduous boreal shrub
BET Temperate	Broadleaf evergreen temperate tree	NET Boreal	Needleleaf evergreen boreal tree

4.2. Comparison of Satellite Products and in Situ Soil Moisture

Figure 3 presents the average root mean square error (RMSE) and bias of FY3D and SMAP soil moisture retrievals compared to the in situ soil moisture at different altitudes and ascending/descending orbits. As shown in Figure 3, below 1000 m in elevation, the RMSE of FY3D retrievals gradually decreases with increasing altitude, with a maximum reduction of approximately $0.045 \text{ m}^3 \text{m}^{-3}$. In contrast, the RMSE of SMAP retrievals initially increases and then decreases. However, above 2000 m, both FY3D and SMAP exhibit a similar trend of gradual increase. The RMSE of SMAP increases abruptly and continues to amplify with further elevation, reaching approximately $0.14 \text{ m}^3 \text{m}^{-3}$ at 4000 m. Overall, the RMSE of SMAP is generally lower than that of FY3D. Both satellite products exhibit certain systematic biases. The bias of the FY3D and SMAP retrievals shows a clear trend of initially decreasing, followed by an increase as terrain elevation rises, with subsequent oscillations for decreases and increases. A comparative analysis of the average bias and RMSE indicates that the increase in RMSE for FY3D at both high and low altitudes is primarily due to an increase in positive bias. SMAP performs better than FY3D in low-altitude regions, while it is less accurate than FY3D at higher altitudes.

Polar-orbiting satellites provide global coverage twice daily, and differences in observational times can lead to varying retrieval errors. Figure 3a–d present the statistical results of RMSE and the bias for different orbits, while Figure 3e,f show the differences between the statistical results of two orbits. A comparison reveals that the soil moisture retrievals exhibit significant differences between the ascending and descending orbits, with the FY3D ascending orbit generally performing better than the descending orbit. The RMSE and bias of the descending orbit are generally higher than those of the ascending orbit. The difference in bias between the ascending and descending orbits is also influenced by terrain height, with larger discrepancies observed at both low and high altitudes. In contrast, the differences between the ascending and descending orbits of the SMAP satellite are less pronounced than those of the FY3D satellite, and the trend of accuracy differences reverses as the altitude increases. In low-altitude areas, the ascending orbit retrievals are more accurate, whereas in high-altitude areas, the descending orbit accuracy gradually outperforms that of the ascending orbit.



Figure 3. The average RMSE (left) and bias (right) between FY3D (first line) and SMAP (second line) soil moisture compared to that of the in situ results at different altitudes during the ascending (top) and descending orbits (middle), and the difference between ascending and descending orbits (bottom, ascending–descending orbits).

The vegetation type is also an important factor affecting the accuracy of retrieval products [9]. Based on in situ soil moisture data, Figure 4 illustrates the average RMSE and bias of the FY3D or SMAP soil moisture retrievals compared to the in situ soil moisture across different vegetation types and orbital passes. The vegetation type categories are listed in Table 1. The vegetation type is determined based on the most prevalent vegetation type in the CoLM grid. As shown in Figure 4, the RMSE of both FY3D and SMAP soil moisture retrievals relative to the in situ soil moisture increases with the density of surface vegetation. In the process of soil moisture inversion based on satellite microwave radiance data, surface temperature information is often required to ascertain the intensity of ground radiation. In densely vegetated areas, not only are microwave detection signals more likely to be affected by vegetation, but studies also indicate that surface temperature information provided by the background field is subject to increased errors due to vegetation interference [61]. Consequently, under the combined influence of radiation data errors and surface temperature errors, the accuracy of soil moisture retrieval products is generally lower in densely vegetated areas compared to in sparsely vegetated regions. When a sufficiently large sample size is considered, the RMSE is the smallest in bare soil and the largest in NET boreal areas. The retrieval performance of FY3D and SMAP is best in bare soil, with an RMSE of $0.09 \text{ m}^3/\text{m}^3$. In low-vegetation types, the retrieval accuracy of FY3D and SMAP is similar, while in high-vegetation types, SMAP outperforms FY3D in terms of retrieval accuracy. Although the errors of the two retrieval products slightly increase in regions with low vegetation cover, both the L-band and X-band demonstrate good penetration capabilities for low vegetation. Therefore, the retrieval accuracy of SMAP and FY3D remains comparable in these areas. However, in regions with high vegetation cover, significant differences in errors between the two datasets are observed. The MWRI product exhibits notably larger errors in areas with high vegetation cover compared to the

results for SMAP. This discrepancy may be attributed to the weaker penetration capability of the X-band in densely vegetated areas, which causes the MWRI retrieval to include more surface-level vegetation information. Consequently, this leads to increased errors in soil moisture retrieval products. In contrast, the superior penetration capability of SMAP ensures greater stability in regards to retrieval accuracy.

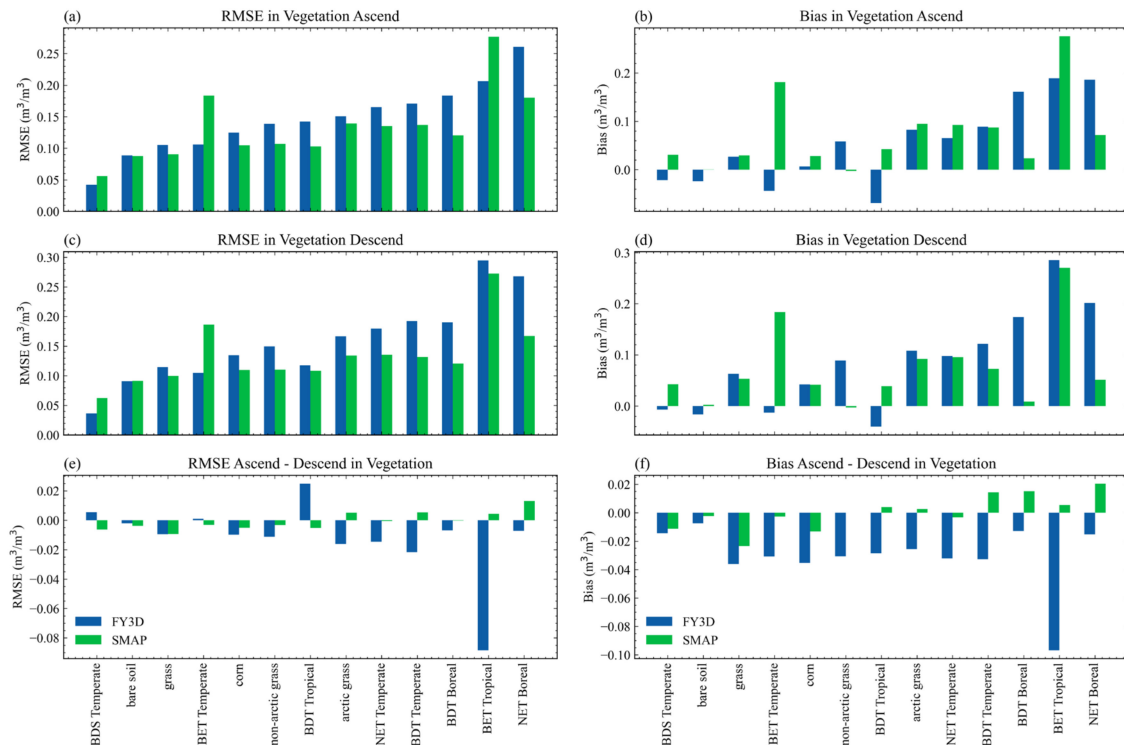


Figure 4. The average RMSE (left) and bias (right) between FY3D and SMAP soil moisture compared to that of in situ results for different vegetation types during the ascending (top), and descending orbits (middle), and the difference between ascending and descending orbits (bottom).

It is crucial to note that the purpose of this comparative analysis is not merely to discern the error characteristics of the observational data. Rather, the intent is to illustrate that local soil features, such as topographic elevation and types of vegetation, can significantly influence the observational data's errors, leading to pronounced local characteristics. Consequently, the spatially uniform background errors and observational error estimates commonly applied in atmospheric data assimilation may not be suitable for land surface data assimilation.

4.3. Design of Assimilation Experiments

The CoLM model first underwent a cold start and ran continuously for 342 years to ensure the stabilization of deep-layer variables in the land surface model. Based on this, sensitivity experiments were conducted. Three sets of experiments were designed, as follows:

The first experiment, referred to as the Control Experiment (CTL), involved the warm-start operation of the CoLM model. It performed a two-month prediction from 2 June 2022 to 2 August 2022, without any assimilation. The results serve as the control group. The second experiment, termed the Single Observation and Background Error Experiment (singleOB), incorporated the SEKF assimilation module, differing from the CTL. This experiment performed one month of assimilation from 2 June 2022 to 3 July 2022, followed by one month of prediction from 3 July 2022 to 2 August 2022. The final assimilation analysis field on 3 July served as the initial condition for the subsequent continuous one-month

forecast. During the assimilation period, SMAP and FY3D soil moisture data were assimilated daily at 0000 UTC, with observation errors set at $0.08 \text{ m}^3/\text{m}^3$ and $0.11 \text{ m}^3/\text{m}^3$, respectively. The static background errors for layers one through seven were set to 0.2, 0.14, 0.14, 0.13, 0.13, 0.12, and $0.12 \text{ m}^3/\text{m}^3$, respectively. The third experiment, named the Changed Observation and Background Error Experiment (changeOB), was identical to the singleOB, except for the observation and background errors. In this experiment, the observation and background errors were dynamically adjusted for each grid point based on differences from the GLDAS data, using the errors in singleOB as a baseline for scaling. Table 2 summarizes the differences among the three experiments.

Table 2. Experimental design.

Experiment	Background Error	Observational Error	Observational Data
CTL			
singleOB	Static	Static	FY3D, SMAP
changeOB	Dynamic	Dynamic	FY3D, SMAP

4.4. Results

Figure 5 shows the SMAP and FY3D soil moisture after grid processing on 3 June 2022. As shown in the figure, the high soil moisture areas in FY3D were primarily distributed near the equator and in mid- to high-latitude regions. For example, the soil moisture was relatively high in northern South America, Central Africa, Southeast Asia, and Siberia. Areas with low soil moisture were primarily distributed within the continental and desert regions. For example, the soil moisture was lower in the Sahara Desert, the Middle East, and Mongolia. The SMAP low soil moisture areas were similar to those of FY3D. However, in the FY3D high soil moisture areas, the SMAP soil moisture was lower, and there was a serious lack of measurements. The most significant differences between the two datasets occur in mid-latitude terrestrial regions. The MWRI product displays large areas of anomalously high soil moisture in mid-latitude regions, with maximum soil moisture values exceeding $0.4 \text{ m}^3/\text{m}^3$. In contrast, the SMAP product classifies these areas as low-quality retrieval regions, resulting in extensive mid-latitude areas being excluded through quality control processes. This may be attributed to the MWRI product's vegetation parameterization scheme, which only accounts for leaf components, while neglecting the impact of stems. Consequently, soil moisture tends to be overestimated in mid- to high-latitude regions [62]. Another notable difference is observed in Southern China, where MWRI-retrieved soil moisture is significantly lower than that of SMAP. This difference may also be attributed to variations in penetration capability. Land cover data indicate that Southern China is predominantly characterized by NET temperate vegetation types, which are associated with reduced MWRI accuracy for high-vegetation areas. As a result, the SMAP product exhibits higher reliability in this region. In the Southern Hemisphere, differences are mainly found in Central South America and Eastern Australia, where MWRI shows relatively wetter characteristics. This might be due to the combined effects of temperate climates and the prevalence of agricultural lands in these regions, with agricultural activities influencing soil moisture values. Meanwhile, SMAP estimates vegetation optical thickness using MODIS climate data, which may lead to an underestimation of human activity impacts on soil moisture [63].

Figure 6 shows the spatial distribution of the difference between the soil moisture of SMAP and FY3D and that of the background field on 3 June 2022. As shown in Figure 6a, the SMAP is generally slightly lower than the background field, with prominent positive values observed in regions such as Eastern Siberia, high-altitude areas of Africa, and Eastern Australia. However, the Eastern European Plain exhibits notable negative values. The

FY3D Observation Minus Background (OMB) pattern is similar to that of SMAP, and in the mid- to high-latitude regions, the FY3D OMB absolute value is higher. However, it showed the opposite characteristics in Northwestern and Southern China. In these areas, the soil moisture in FY3D is significantly lower than that in the background field, whereas the soil moisture in SMAP is generally higher than that in the background field. In contrast, in the Eastern European Plain, the FY3D soil moisture is significantly higher than that in the background field, whereas that of SMAP is lower.

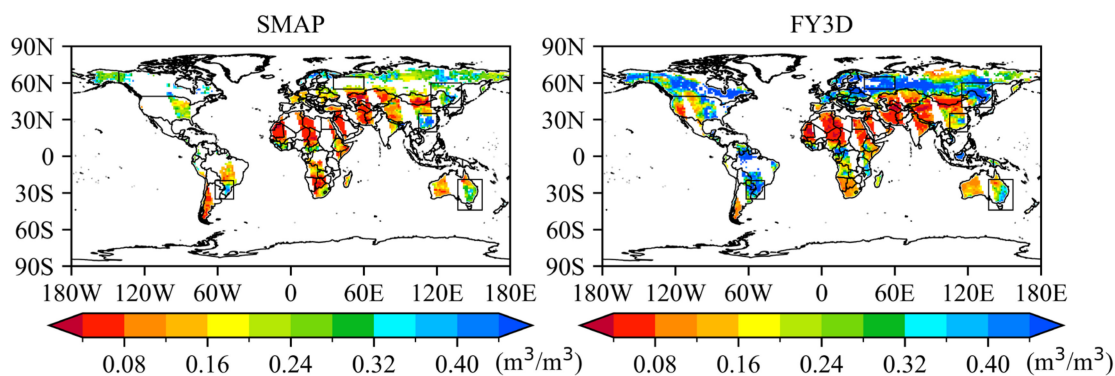


Figure 5. The spatial distribution of soil moisture on 3 June 2022 for SMAP (left) and FY3D (right). Black rectangles illustrate the areas with significant differences.

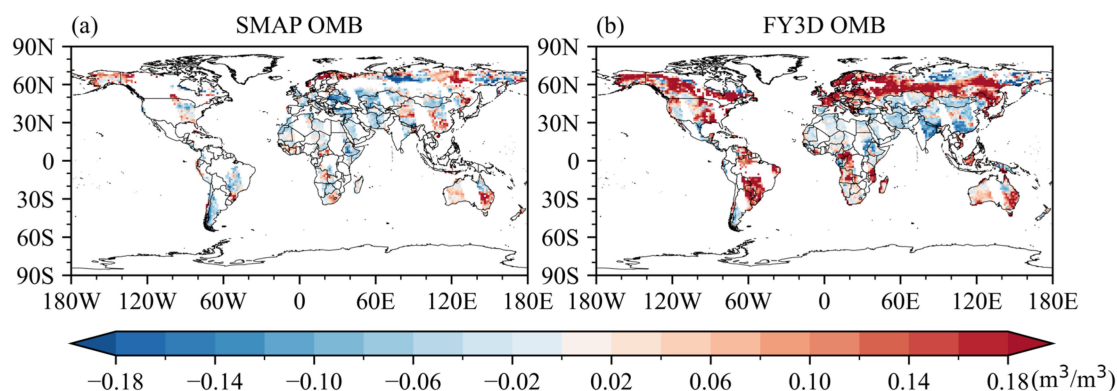


Figure 6. The spatial distribution of the difference between the soil moisture of SMAP (a) or FY3D (b) and the background field on 3 June 2022.

Figure 7 shows the assimilation results after the first assimilation cycle. After SEKF assimilation, the difference between the analysis field and the observed values is significantly reduced. The FY3D and SMAP's observations minus analysis (OMA) for the changeOB and singleOB experiments is noticeably lower than that of the OMB, particularly in regions with a higher OMB, such as Siberia and eastern Australia, where the reduction in the difference is more pronounced. Comparing the changeOB and singleOB experiments (Figure 7e,f), it can be observed that the OMA for the changeOB experiment is lower than those of the singleOB experiments in Central South America, Southern Africa, Siberia, and Eastern Australia. In the Northern European and Western Siberian regions, the OMA is higher for both FY3D and SMAP than for the singleOB experiment. More complex variations are observed in the mid- to low-latitude regions. For example, in the Southern Region of China, the difference between the analysis field of the changeOB experiment and SMAP is lower than that in the singleOB experiment, whereas in the Northern Region of China, the difference between the analysis field of the changeOB experiment and SMAP is higher than that in the singleOB experiment. The difference between the analysis field and FY3D showed an opposite trend. This indicates that the SMAP data had a greater impact on the analysis field

in the singleOB experiment, which may be due to the smaller specified observational error of SMAP in the assimilation system. As shown in Figure 7e,f, the values are predominantly positive in low-latitude regions and predominantly negative in mid-latitude regions. This indicates that the analysis field obtained from the changeOB experiment is closer to the observations in low-latitude regions, whereas in high-latitude regions, the analysis field from the singleOB experiment is closer to the observations. Previous analyses suggest that the errors of the two retrieval products are significantly larger in mid-latitude regions compared to low-latitude regions, with the SMAP data even exhibiting extensive missing areas. However, the singleOB experiment fails to capture the variation in retrieval accuracy with latitude. As a result, the analysis field in mid-latitude regions absorbs excessive observational information, with large errors.

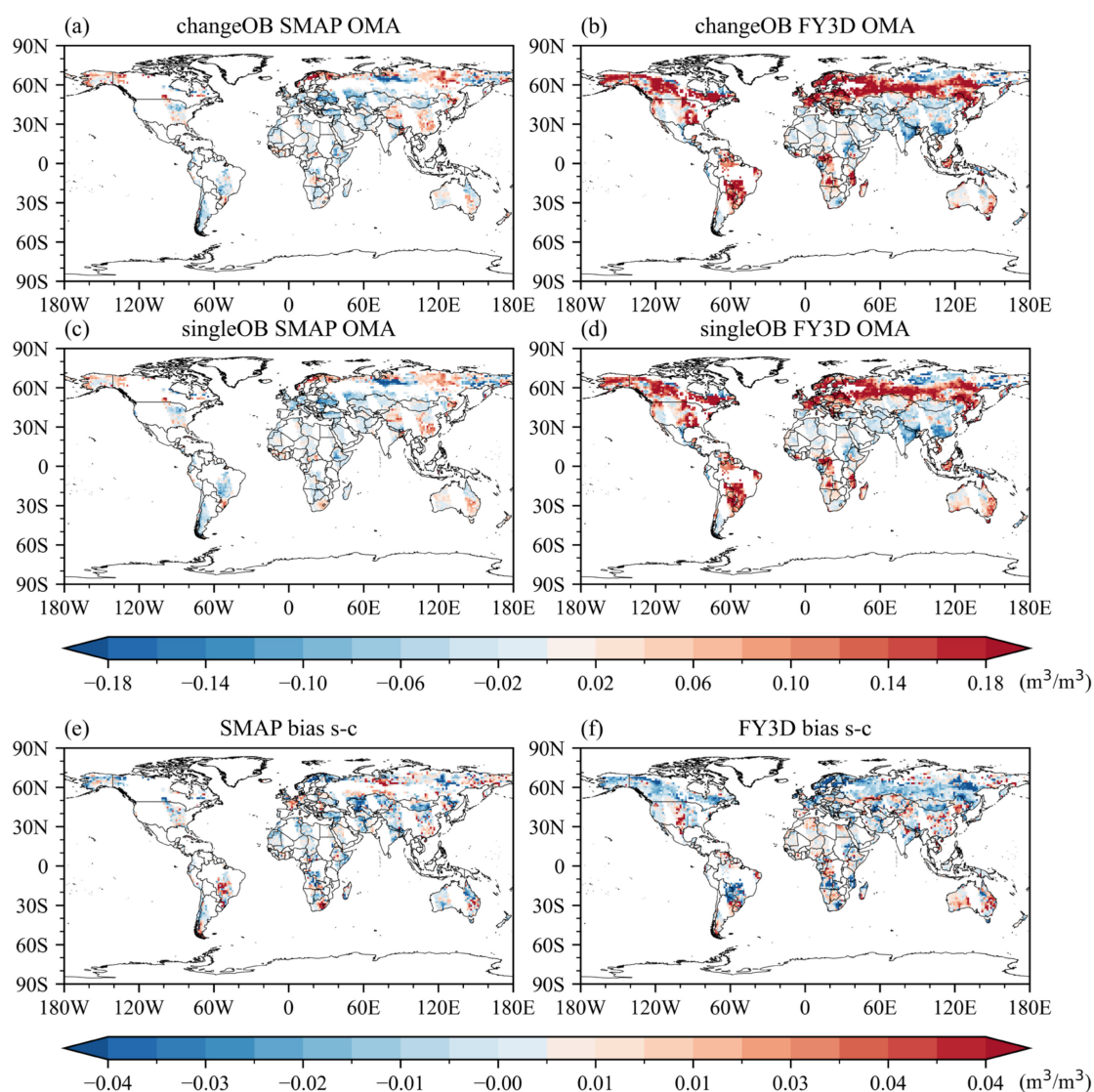


Figure 7. The spatial distribution of the difference between the soil moisture of SMAP (a,c) and FY3D (b,d) with changeOB (a,b) and singleOB (c,d) analysis fields on 3 June 2022. Spatial distribution of the $|O-A|$ difference between the singleOB and changeOB experiments (singleOB–changeOB) for the retrieved soil moisture of the SMAP (e) and FY3D (f) satellites.

To further analyze the differences in the assimilation effects between the changeOB and singleOB experiments, surface soil moisture analysis increments at 00:00 UTC on 3 June 2022 are shown separately in Figure 8. As shown in Figure 8, the analysis increments of both experiments exhibited similar spatial structures in most regions, with an overall

increase in soil moisture. The high-value areas of positive increments are primarily located in the Great Plains of the United States, the Amazon, the La Plata Plain in South America, Northern Europe, Central Africa, Siberia, and Southeastern Australia. Negative increases are observed primarily in the Anatolian Peninsula, Western Siberia, India, and Northern China. The differences between the changeOB and singleOB experiments primarily occurred in high-value areas, with positive and negative increments. In the Amazon and La Plata Plains in South America, Siberia, and Southeastern Australia, the soil moisture increase in the changeOB experiment is substantially higher than that in the singleOB experiment, whereas in Northern and Eastern Europe and Northern North America, the soil moisture increase is more pronounced in the singleOB experiment.

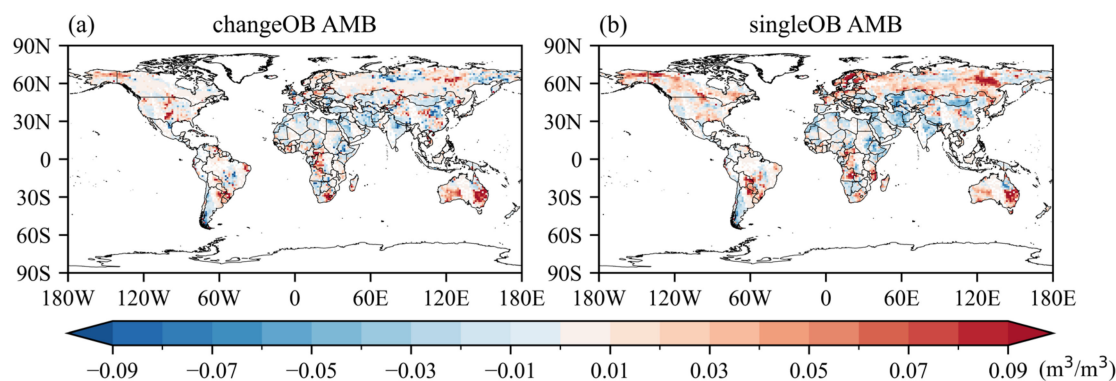


Figure 8. Spatial distribution of the analysis increments of the changeOB (a) and singleOB (b) experiments at 0000 UTC on 3 June 2022.

To confirm the correctness of the results from the changeOB and singleOB experiments, GLDAS soil moisture reanalysis data are used for the validation analysis. Figure 9 shows the spatial distribution of first-layer soil moisture for the changeOB and singleOB experiments and GLDAS. The high soil moisture areas in the GLDAS data are primarily distributed near the equator and in some mid- to high-latitude regions. For example, the soil moisture is relatively high in northern South America, Central Africa, Southeast Asia, and Siberia. Areas with low soil moisture are primarily distributed within the continental and desert regions. For example, soil moisture is lower in the Sahara Desert, Northern and Western Australia, and the Western USA.

In general, the results of both experiments are similar to the spatial distribution of soil moisture in the GLDAS reanalysis data in most areas. They can effectively reproduce wetter regions in southeast Asia, Northern South America, Northern North America, and Northern Eurasia, as well as drier regions in Western North America, Central South America, Western Australia, and large parts of Africa and Western Asia. The regions in which the analysis field differed significantly from the reanalysis data are comparable to the areas with high-value analysis increments, as shown in Figure 7. The regions with noticeable differences, as indicated by the rectangular regions in Figure 9, are as follows: in Siberia, the changeOB experiment effectively reduced the simulated wet bias; in the Northeastern China rectangle, the changeOB experiment reflected the drier characteristics of that region more accurately; in Central South America and Southern China, the soil moisture distribution and values in the changeOB experiment are closer to the GLDAS; in Southeastern Australia, the analysis field of the changeOB experiment is significantly higher than that of the singleOB experiment, with the wet–dry distribution more closely matching the GLDAS data.

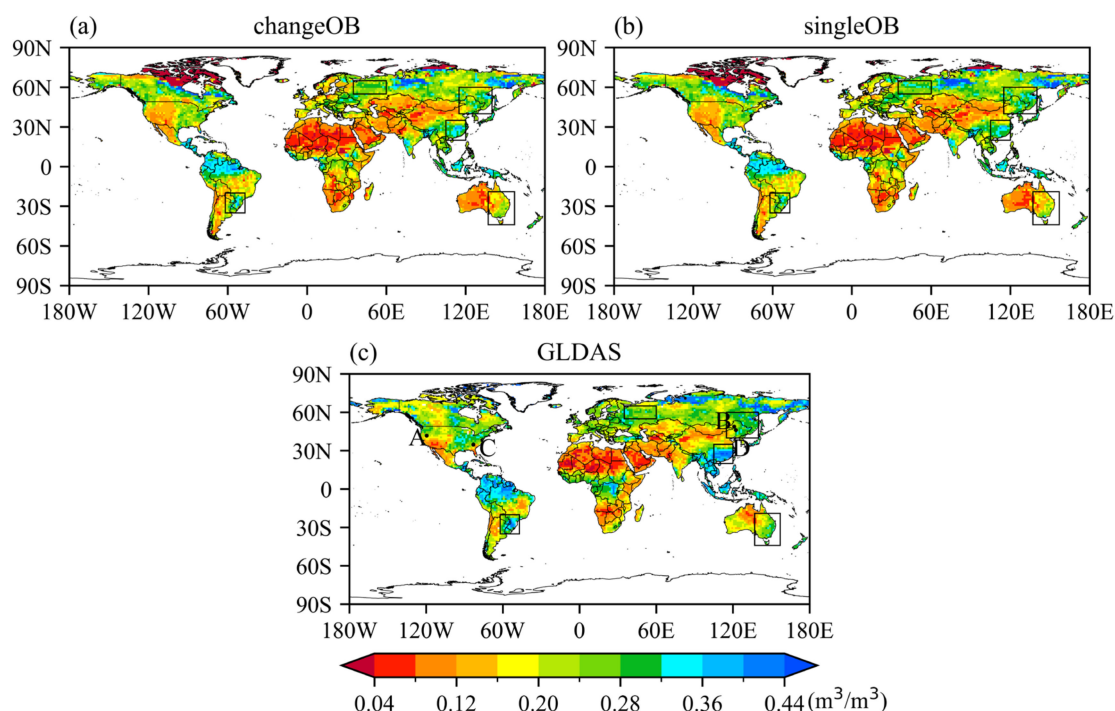


Figure 9. Spatial distribution of the first-layer soil moisture for the changeOB (a) and singleOB (b) experiments and GLDAS (c) at 0000 UTC on 3 June 2022. Black rectangles illustrate areas with significant differences. The black dots marked as A, B, C, and D in the figure respectively represent the locations of the stations.

Figure 10 presents the difference between the analysis fields of the two assimilation experiments and the corresponding GLDAS at the same time (singleOB—GLDAS, changeOB—GLDAS). The rectangular regions in Figure 10 highlight areas with significant differences between the two experiments. In Siberia, the soil moisture analysis fields of both experiments are slightly larger than those of GLDAS. However, the regions with large differences are significantly smaller in the changeOB experiment compared to in the singleOB experiment. In Central South America, Southern China, and Southeastern Australia, the soil moisture in both experiments is lower than that of GLDAS, but the overall differences in the changeOB experiment are notably smaller. These results demonstrate that the analysis field of the changeOB experiment aligns more closely with the GLDAS.

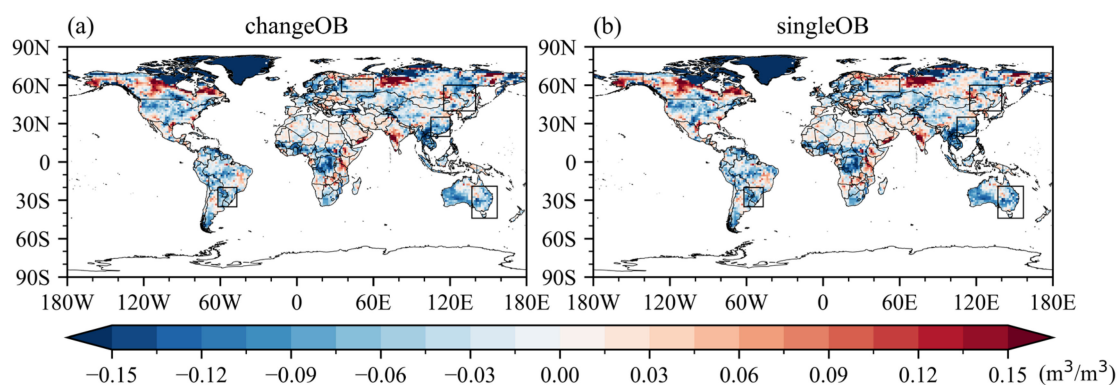


Figure 10. Spatial distribution of the differences between changeOB (a) and singleOB (b) compared to GLDAS. Black rectangles illustrate areas with significant differences.

To gain a deeper understanding of how spatial dynamic errors contribute to the enhancement of assimilation outcomes, this analysis focuses on four representative indi-

vidual points. The locations of these points are denoted by the black circles in Figure 9c. Figure 11 illustrates the temporal evolution of soil moisture at each point, both pre- and post-assimilation. In situ data serves as the benchmark for this comparative analysis. The black dots signify soil moisture retrieved from FY3D data, while the red dots indicate SMAP data. The histograms within the figure depict the magnitudes of background errors and the two types of observational errors involved in the assimilation. The horizontal axis represents the values of the background error (B), FY3D observation error (R_f), and SMAP observation error (R_s) at the corresponding points for the two assimilation experiments. The red color corresponds to the errors utilized in the singleOB experiment, and the blue to those employed in the changeOB experiment.

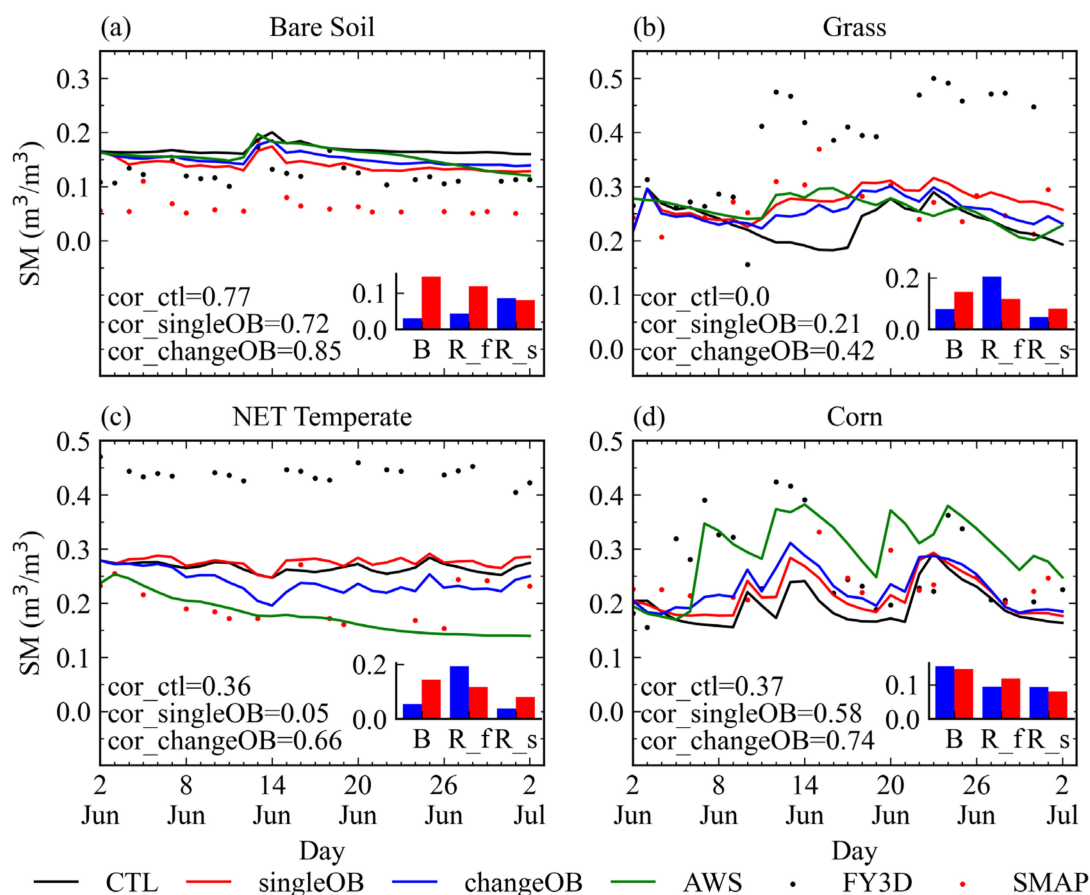


Figure 11. The daily variation in the first-layer soil moisture over time from 1 June to 2 July 2022 under different vegetation types. The small chart in the lower right corner displays the background error (B) and the observation errors of FY3D (R_f) and SMAP (R_s) for the singleOB (red) and changeOB (blue) experiments at that point. The black solid line represents the control experiment, the red solid line represents the singleOB experiment, the blue solid line represents the changeOB experiment, the green solid line represents in situ data, the black dots represent FY3D, and the red dots represent SMAP. AWS represents in situ observations.

Examining the histograms of the error magnitudes reveals that the singleOB experiment implemented a globally consistent set of background and observational errors, with the background error being markedly higher than the two observational errors. Additionally, the observational error associated with the FY3D product is marginally greater than that of the SMAP data. Conversely, the changeOB experiment applied varying errors at different points; at point A, the background error is the smallest, while the SMAP observation error is the largest. For points B and C, the FY3D observational error is the most substantial, with SMAP's error significantly lower than that of the FY3D data, and the background

error falling between the two observational errors. However, at point D, the observational errors are considerably less than the background error.

The errors provide a clear depiction of the assimilation's transformative rule on the background field. At point A (41.8°N, 119.5°W), SMAP soil moisture is significantly lower than that in the in situ data. Despite this, the singleOB experiment's assimilation outcome (red line) is significantly drawn towards the SMAP values (red dots in Figure 11a) due to the specified SMAP observational error being less than the background error. Although the background field is relatively similar to the in situ data, the analysis field from the singleOB experiment remains substantially lower than the background field. In contrast, the changeOB experiment's statistical findings reveal that the SMAP error at this point is substantially greater than the background field error, causing the analysis field to be only slightly lower than the background value and bringing it closer to the in situ data. The correlation coefficients, indicative of the temporal variation characteristics, also demonstrate that the changeOB experiment has a correlation coefficient of 0.85, significantly higher than the singleOB result and superior to the CTL experiment's outcome.

Points B (48.9°N, 120.9°E) and C (34.7°N, 82.9°W) are characterized by the SMAP data's observational error being markedly lower than those of FY3D and the background field. However, the singleOB experiment failed to capitalize on this feature effectively, as the FY3D's observational error is relatively small, resulting in the assimilation results being unduly influenced by the FY3D data. As a result, at point B, the assimilation did not adequately incorporate the characteristic decline in SMAP soil moisture over time, instead mirroring the FY3D product and showing excessive fluctuations, becoming significantly higher than that of the in situ data after 16 June. In the evergreen forest region, where point C is situated, the SMAP data accurately depict the gradual decline in soil moisture observed by the station in the earlier period. However, due to FY3D interference, the singleOB experiment displays pronounced fluctuation patterns, with a correlation coefficient of only 0.05, which is significantly lower than the results of both the CTL and changeOB experiments.

In the crop region at point D (46.1°N, 122.3°E), the observational errors for both datasets are considerably lower than those of the background. A comparison of the time series curves indicates that both retrieval datasets are capable of accurately replicating the fluctuating characteristics of the in situ soil moisture. In contrast, the CTL experiment also exhibits oscillations, but with a frequency notably lower than that of the station data. Both assimilation experiments are designed with the premise that the observational errors are smaller than the background errors, enabling the analysis fields from both to closely mirror the in situ soil moisture. However, regarding the sudden increase in soil moisture recorded by FY3D on 8 June, the changeOB experiment, which assigns a notably smaller error to FY3D compared to the singleOB experiment, achieves a higher correlation coefficient (0.74) with the in situ data. This suggests that the error configuration in the changeOB experiment is more adeptly attuned to the nuances of the FY3D data, resulting in a more precise correspondence with the in situ soil moisture.

The single-point analysis results compellingly confirm that only by incorporating observational and background field errors tailored to the specific site conditions can we effectively assimilate observational data and subsequently improve the analysis outcomes. It should be acknowledged that, while the analysis results reference the in situ soil moisture data, they are inevitably influenced by the inherent inaccuracies of the in situ dataset. However, more significantly, the experimental findings adeptly highlight the distinctions between the atmospheric and land surface data assimilation processes. Contrary to atmospheric data assimilation, where observational and background errors are characterized by strong spatial uniformity, the intense spatial variability of soil can result in pronounced local characteristics regarding both observational and background errors. Consequently,

spatial dynamic error estimation methods are particularly well-suited for research on soil data assimilation. The experimental outcomes presented here further substantiate the significance of spatial dynamic error estimation methods in the context of global land surface assimilation studies.

To quantitatively assess the accuracy of the analysis fields in the two experiments, the spatial correlation coefficients and RMSE between the analysis fields and GLDAS data are calculated. As the soil depths in the CoLM model differed from those in GLDAS, the weighted average interpolation method is first used to interpolate the first eight layers of the CoLM to depths corresponding to the first three layers of GLDAS. The layer averages are calculated at the corresponding depths. Figure 12 shows the temporal variations in the spatial correlation coefficients and RMSE at different depths compared with that of GLDAS. In the changeOB experiment, the correlation coefficients between the soil moisture analysis fields and the GLDAS reanalysis data are significantly better than those in the CTL experiment for different soil layers. The singleOB experiment only showed relatively minor improvements in correlation for deeper layers but more significant improvements for surface layers. The RMSE in both experimental analysis fields is consistently reduced. A comparison between the results of the two experiments shows that the spatial correlation coefficients of the changeOB experiment were consistently better than those of the singleOB experiment, and the RMSE reduction is also more pronounced. The changeOB experimental results are superior to those of the singleOB experiment, not only during the assimilation phase but also during forecasting regarding spatial correlation and lower RMSE. Improvements in forecasts are not significant in the singleOB experiment. During the forecast period, the correlations in the surface layers quickly decreased and stabilized, whereas the spatial correlation coefficients for deeper layers maintained a relatively stable increasing trend with longer assimilation time. This may be due to the greater influence of external forcing on surface soil moisture. However, in both assimilation experiments, the soil moisture RMSE in each layer continuously improved during the assimilation period.

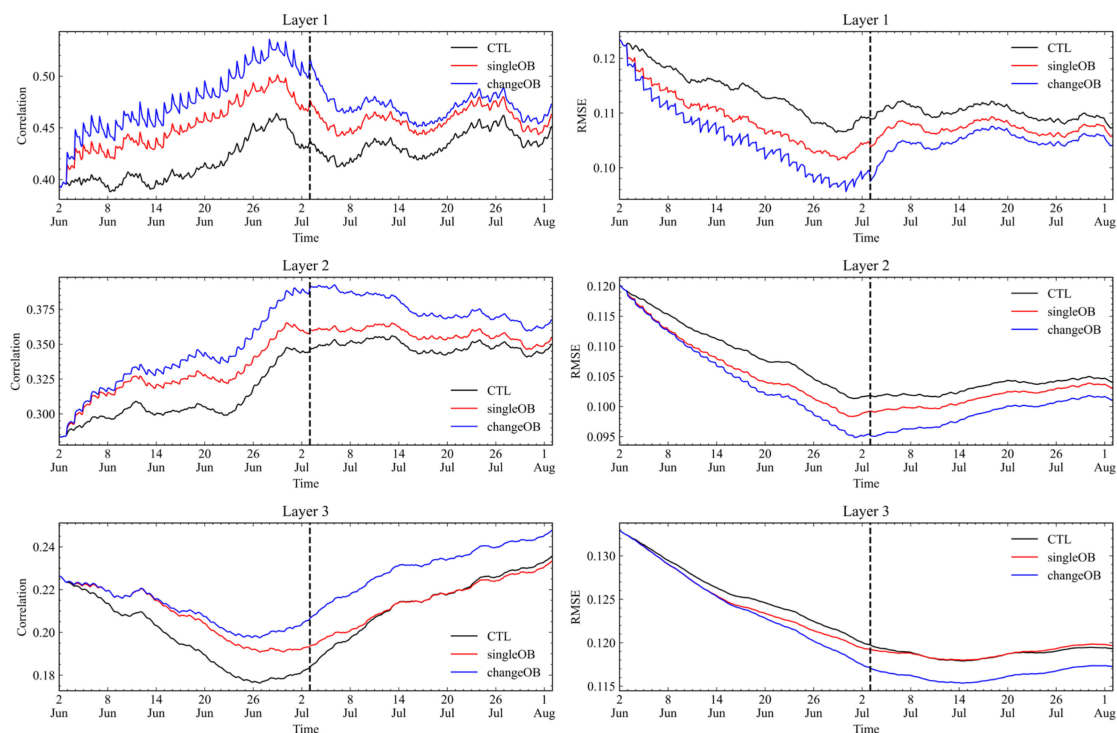


Figure 12. The temporal variation in spatial correlation coefficients (left) and RMSE (right) among the CTL (black solid line), singleOB (red solid line), and changeOB (blue solid line) experiments and the GLDAS first-layer (top), second-layer (middle), and third-layer (bottom) soil moisture.

To objectively assess the differences in the assimilation effects of various experiments, we also calculated the correlation coefficients between the analysis fields during the assimilation period and the nearby site soil moisture observations. To better highlight the differences in the assimilation effects of different experiments, we statistically analyzed the probability density distribution curves of the correlation coefficient differences between the assimilation experiments (singleOB and changeOB) and the control (CTL) experiment (Figure 13a), as well as the mean value differences for various vegetation types (Figure 13b). As shown in Figure 13a, both assimilation experiments improved the correlation between the analysis fields and the in situ data. On average, the changeOB experiment increased the correlation by 0.16, while the singleOB experiment increased it by 0.09. The probability density distribution of the correlation coefficient differences better illustrates the differences in the improvement effects of the experiments. As seen in Figure 13a, the coefficient differences for both assimilation experiments are predominantly positive, indicating that both experiments enhance the accuracy of the analysis fields. However, the improvement in the singleOB experiment is mainly concentrated in the lower range of the coefficient differences, while in the higher range, the changeOB experiment shows a significantly better improvement, suggesting that the changeOB experiment, which better integrates various observational sources and model results, can achieve a more significant improvement in analysis field accuracy across a wider region. Further analysis of the performance improvements for different vegetation types (Figure 13b) shows that for most vegetation types, both assimilation experiments result in positive coefficient differences, indicating that both experiments yield better analysis results across most vegetation types. However, the improvement effect of the changeOB experiment is more pronounced in all vegetation types, except for the BDS temperate vegetation type. This also demonstrates that the changeOB experiment, through dynamic adjustment of background field and observation errors, can more reasonably integrate background field and observational information.

Nevertheless, there are differences in the assimilation results across vegetation types. As shown in Figure 13b, for the BDS temperate vegetation type, the improvement in correlation for the changeOB experiment is slightly lower than that for the singleOB experiment. This is mainly due to the limited number of sites (only six sites) in this vegetation type, making the statistical error characteristics insignificant. Therefore, more data should be introduced for long-term systematic evaluation in future studies. Additionally, for the BET tropical and NET boreal vegetation types, a negative effect was observed in the assimilation results. This may be due to the generally low quality of the observation data for these vegetation types, while the model results are relatively accurate, meaning that assimilation did not improve the model's performance. However, it is still evident that, in regions with relatively poor assimilation effects, the changeOB experiment helps to mitigate the impact of erroneous information as much as possible.

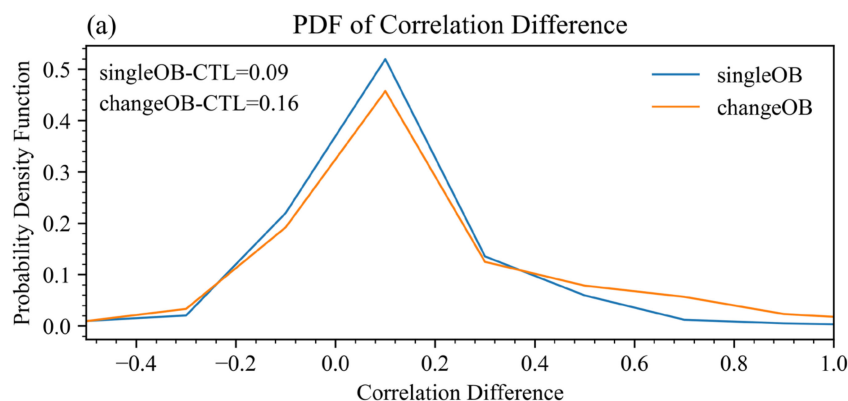


Figure 13. Cont.

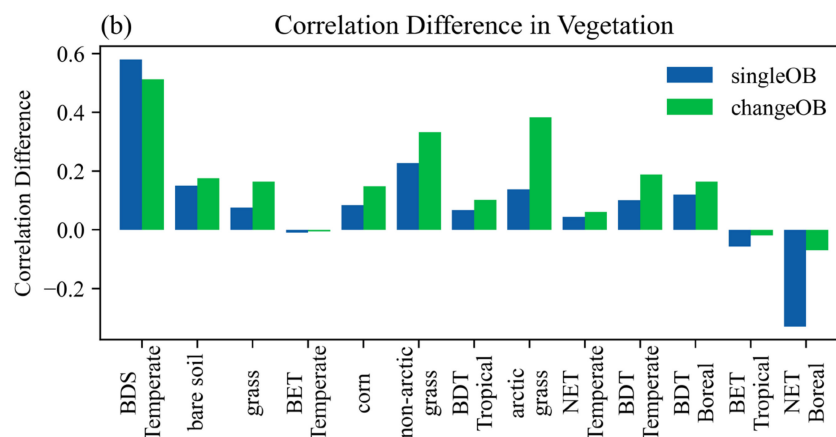


Figure 13. Probability density distribution of correlation coefficient differences between assimilation and control experiments with in situ data (a). Histogram of correlation coefficient differences in different vegetation types (b). Blue and green represent the singleOB and changeOB experiments, respectively. The number in the top-left corner represents the mean value.

5. Discussion

The results indicate that the dynamic error experiment can significantly improve the spatial correlation and RMSE of soil moisture at different depths during both the assimilation and forecast periods. The spatial correlation coefficient increased by 17.4%. The static error experiment exhibited a smaller and more unstable improvement in the spatial correlation of the deep layer but showed a noticeable increase in the correlation coefficient of surface soil moisture, which can reach up to 8.7%. Both the dynamic and static error experiments showed significant improvements in soil moisture RMSE at different depths, with reductions of up to 11.2 and 4.7%, respectively. The comparative results demonstrated that dynamic observational and background errors better represented the spatial heterogeneity characteristics of soil moisture, thereby achieving better assimilation performance. For time series, dynamic errors can also fully consider the characteristics between model results and observations in different regions, thereby improving the time correlation coefficient.

However, we are acutely aware that our study's reliance on GLDAS and in situ data as references introduces a degree of susceptibility to its inherent errors, which is an unavoidable factor in our statistical results. Consequently, the principal value of our findings is to emphasize the pivotal role that spatial dynamic error estimation methods play in the realm of global land surface assimilation research. For real-world applications, it is imperative to adopt more refined analytical techniques, leveraging site-specific observational data to more accurately gauge the background field errors and observational errors across various grid points. In addition, this research only analyzed the assimilation impact of soil moisture retrieval products from a global average perspective, and there may be regional differences in the results. Using long-term data to obtain more stable estimates of dynamic observational and background errors, as well as high-resolution land surface models, would facilitate a more systematic exploration of the localized characteristics of soil moisture product assimilation effects. Introducing observational data with a finer vertical resolution would help analyze the vertical differences in the assimilation effects of soil moisture products retrieved from different frequency instruments. Additionally, considering the sensitivity of root-zone soil moisture to the surface LAI [64], integrating LAI assimilation into the existing system to obtain more reliable root-zone soil moisture data is a future research direction.

6. Conclusions

The data assimilation method is based on prior information from background field errors and observation errors. It integrates the background field and observational data on an optimization basis to establish the analysis field closest to the true values. The reasonable prior information of observational and background errors is a prerequisite for obtaining the optimal soil moisture analysis field. However, unlike fluid variables, such as atmospheric and oceanic variables, soil variables are solids, which leads to significant spatial heterogeneity. The error estimation results indicate that the CoLM model exhibits considerable differences in performance across different vegetation types, and satellite retrieval products also show varying accuracy at different altitudes and for different vegetation types. This proves that in land surface data assimilation research, observation errors and background field errors need to be dynamically set according to the underlying surface type to better adapt to the assimilation of land surface data with strong spatial heterogeneity.

Based on the aforementioned error analysis results, the study applies both dynamic and static spatial observational errors and background field errors. The study integrates SMAP and FY3D soil moisture retrieval products using the CoLM model and the SEKF method. Through actual assimilation experiments, the improvement effect of dynamic errors on land surface soil moisture assimilation was verified. The results show that, compared with static spatial errors, dynamic spatial errors can significantly improve the spatial correlation of soil moisture at different depths, with the correlation coefficient increasing by approximately 17.4%, while reducing the root mean square error (RMSE) by about 11.2%. Comparisons with station data indicate that, compared to static spatial errors, dynamic spatial errors can better consider the quality of soil moisture from different sources in the joint assimilation of multi-satellite soil moisture products, improving the correlation coefficient by 0.07. The evaluation results fully demonstrate the improvement effect of dynamic spatial errors on soil moisture assimilation.

This research effectively illustrates the influence of dynamic errors on the assimilation performance of soil moisture. However, the findings are inevitably affected by the stability of errors due to the constraints regarding the volume of available data. Sufficient data are a prerequisite for obtaining more accurate dynamic errors. Therefore, in practical applications, long-term soil moisture data should be included for error estimation in order to obtain more accurate observation and background errors. Under data-rich conditions, adopting the relatively objective triple collocation (TC) method is also an important approach to obtaining more precise and unbiased dynamic error estimates [65]. With the ongoing enhancement in the precision and detail of dynamic error estimation, we can anticipate a continuous improvement in the assimilation and forecasting accuracy of soil moisture.

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