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Evaluation of ERA5 reanalysis and ECV satellite soil moisture products based on *in situ* observations over Jiangsu, China

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Accurate and spatially continuous soil moisture data are essential for applications including numerical weather prediction, hydrological forecasting, and data assimilation. This study evaluates the global ERA5 reanalysis soil moisture (SM_{ERA5}) and Essential Climate Variable (ECV) satellite-derived soil moisture (SM_{ECV}) against *in situ* measurements from 2013 to 2015 in Jiangsu Province, China. Five evaluation indices accuracy metrics and Triple collocation methods are used in this study. Taking $SM_{in\text{-}situ}$ as the reference, the SM_{ERA5} outperforms the SM_{ECV} in terms of correlation coefficient (0.56 for SM_{ERA5} and 0.42 for SM_{ECV}) and Triple Collocation (TC) errors (0.01 m^3 m^{-3} for SM_{ERA5} and 0.025 m^3 m^{-3} for SM_{ECV}). However, the SM_{ECV} can better characterize the soil moisture with smaller random differences (ubRMSD = 0.045 m^3 m^{-3} for SM_{ECV} and 0.052 m^3 m^{-3} for SM_{ERA5}relative to the $SM_{in\text{-}situ}$ data. Both SM_{ECV} and SM_{ERA5} exhibit consistent spatial patterns across seasons, although with notable magnitude differences. These two products effectively capture *in situ* soil moisture ($SM_{in\text{-}situ}$) temporal dynamics in the northern region, while larger discrepancies occur in the southern region. In addition, we evaluate these products from the perspective of soil moisture sensitivity to precipitation. Results show that SM_{ERA5} data more effectively capture soil moisture response to heavy precipitation events than SM_{ECV}. Overall, SM_{ERA5} demonstrates superior performance in temporal correlation and precipitation sensitivity, whereas SM_{ECV} excels in minimizing random errors. Both datasets exhibit uncertainties linked to sensor limitations and model parameterization, suggesting targeted improvements (e.g., multi-sensor fusion, bias correction) could enhance their reliability.

KEYWORDS

spatial pattern, temporal dynamics, correlation coefficients, triple collocation, differences, uncertainties

1 Introduction

Soil moisture is an essential component of the surface energy balance that influences sensible and latent heat fluxes. Changes in soil moisture exert feedbacks through these energy fluxes and evapotranspiration, linking land surface process to boundary layer and upper troposphere through complex interactions (Dorigo et al., 2017; Hagan et al., 2025; Miralles et al., 2014). Applications of soil moisture include the characterization of land-atmosphere interactions, hydrological analysis, flooding and drought monitoring, and weather forecasting (Jia et al., 2020; Zhang et al., 2021).

In-situ observation provides accurate records of soil moisture (An et al., 2016; Dorigo et al., 2015). In China, soil moisture observations are obtained through gravimetric and Frequency Domain Reflectometry (FDR) techniques (Dorigo et al., 2011), both of which are widely used globally. The FDR provides better temporal resolution compared to the gravimetric technology, and has therefore been widely used in China (An et al., 2016). Though *in situ* observation can provide accurate measurements of soil moisture at point scale, it is limited by the density and spatial distribution of stations and cannot adequately capture the detailed spatial variations (Hagan et al., 2020).

Remote sensing has emerged as a critical observational tool for soil moisture monitoring, offering spatially continuous data through both active and passive microwave techniques (Lal et al., 2022; Zou et al., 2021). Active remote sensing methodologies (Bartalis et al., 2007; Dharssi et al., 2011), rely on backscattering principles to deduce surface conditions. In contrast, passive systems measure the natural emissions emanating from soil surfaces (Shellito et al., 2016). The recent strides in passive sensing technology have been largely propelled by satellite missions. Notably, the European Space Agency's Soil Moisture and Ocean Salinity (SMOS) satellite (Kerr et al., 2012; Kang et al., 2016) and the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) on board NASA's Aqua satellite have played pivotal roles. These passive products are renowned for their high accuracy; however, their spatial resolution remains relatively coarse, which is a notable limitation. On the other hand, active microwave systems have achieved remarkable operational success. The Soil Moisture Active Passive (SMAP) mission launched by NASA (Entekhabi et al., 2010) stands as a widely adopted active product, further enhanced by the Advanced Scatterometer (ASCAT) on MetOp satellites. ASCAT is capable of providing high-resolution spatiotemporal data that effectively capture the dynamics of global land surfaces. Nevertheless, active systems encounter challenges in operational scalability, primarily due to their susceptibility to surface interference, the complexity of their algorithms, and their limited global coverage. To overcome these limitations, the ESA Climate Change Initiative (CCI) Soil Moisture product (SM_{ECV}) ingeniously integrates multi-sensor data from both active and passive systems. By synergizing the complementary strengths of different sensor types, this product achieves enhanced representativeness, a claim that has been substantiated through *in situ* comparisons (Dorigo et al., 2017; Yuan et al., 2020; Zhu et al., 2019). According to Ma et al. (2019), ESA CCI and SMAP products outperformed SMOS and AMSR2 products over the world, exhibiting slightly smaller ubRMSE and bias. In the specific context of the Yellow River Basin in China, Lou et al. (2018) reported a consistent agreement between *in situ* measured soil moisture ($SM_{in\text{-}situ}$) and SM_{ECV} regarding interannual variations and long-term drying trends observed from 1998 to 2010.

Reanalysis datasets also provide gridded soil moisture estimates by integrating observations from multiple platforms. These include NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al., 2011), the NCEP-National Center for Atmospheric Research (NCAR) Reanalysis Project (NNRP) (Kistler et al., 2001) and the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis ($SM_{ERA\text{-}Interim}$) (Dee et al., 2011). In 2017, ECMWF released its new ERA5 (SM_{ERA5}) global atmospheric and land-surface reanalysis with hourly temporal resolution at 0.28125 spatial resolution (Hersbach et al., 2020). The ERA5-Land dataset incorporates major upgrades achieving higher spatiotemporal resolution (Albergel et al., 2018). Multiple studies have evaluated these reanalysis datasets' performance in capturing soil moisture dynamics (Kokkalis et al., 2024; Li et al., 2020). Peng et al. (2015a) compared $SM_{ERA\text{-}Interim}$ with SMOS and AMSR-E data in southwest China, finding it accurately captured large-scale dynamics and seasonal variations. Dong et al. (2022) further assessed $SM_{ERA\text{-}Interim}$ against SM_{ECV} and the Noah land surface model using Tibetan Plateau *in situ* data, demonstrating $SM_{ERA\text{-}Interim}$'s superior performance among all evaluated products.

Both SM_{ECV} and $SM_{ERA\text{-}Interim}$ products are recognized as reliable soil moisture products, with extensive evaluations conducted across diverse regions (Hagan et al., 2020; Ullah et al., 2018; Zeng et al., 2015). However, evaluations of SM_{ERA5} remain limited due to its recent release. In addition, eastern China lacks robust assessments owing to sparse *in situ* observations. Jiangsu Province—a critical economic hub and grain-producing area—exhibits intense land-atmosphere interactions through its summer monsoon precipitation band, yet the mechanistic role of soil moisture in modulating local atmospheric processes is poorly quantified. Given the demand for precise soil moisture data to support agricultural and climate research, this study selects Jiangsu as the target region. We validate ERA5 reanalysis data (SM_{ERA5}) and SM_{ECV} satellite products against *in situ* measurements, assessing their accuracy and reliability. The study area, datasets used and methodology are presented in Section 2, the results are presented in Section 3, discussions are presented in Section 4, and conclusions are presented in Section 5.

2 Materials and methods

2.1 Study area

Jiangsu Province, located in eastern China, is among the nation's most developed regions. It spans 30°45′-35°20′ N and 116°18′-121°57′E, covering approximately 107,200 km^2. The region experiences a dominant East Asian Monsoon climate, with mean annual precipitation of ~1,020 mm—over 50% occurring during summer (Wang and Chen, 2012). Mean annual air temperature is ~15.3 °C, closely tracking the hydrological cycle. Precipitation variability significantly drives soil moisture dynamics at seasonal and interannual scales. Recent studies further emphasize climate change impacts on regional hydrology, underscoring the need for precise spatiotemporal monitoring of soil moisture (Parinussa et al., 2018; Yin et al., 2016).

The topography of Jiangsu Province is characterized by flat terrain with low hills in the western and southern parts (Figure 1). Based on these physiographic divisions, three representative areas were selected in the northwest (NW), northeast (NE), and southeast (SE) sectors of the study area (Figure 1). The spatial attributes of

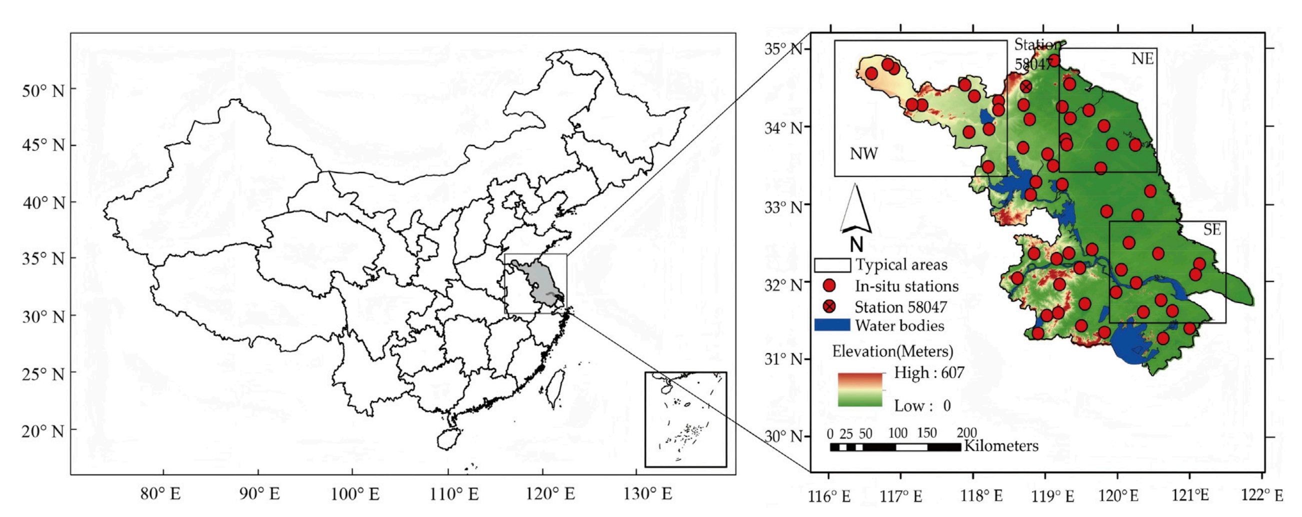

FIGURE 1
Topography of the Jiangsu Province and the selected regions for temporal analysis (Typical areas are shown as squared areas i.e. NW, NE, SE and typical station 58047 is shown as Red dots).

TABLE 1 Specifications of three typical areas used in this study.

Region	Number of stations	Longitude (°C)	Latitude (°C)
NW	12	116.5–118.5	33.4–35.0
NE	10	119.2–120.5	33.4–35.0
SE	10	119.9–121.5	31.5–32.6

these areas are categorized in Table 1 according to the Köppen-Geiger climate classification system (Chen et al., 2017).

2.2 Datasets

2.2.1 Satellite-derived soil moisture

The European Space Agency (ESA) Climate Change Initiative (CCI) soil moisture (SM_{ECV}) product is employed for validation. Version 3.2 integrates passive microwave sensors (e.g., SMOS, AMSR-E) and active radar systems (e.g., Sentinel-1), achieving soil moisture retrievals down to 5 cm depth with unprecedented spatial-temporal consistency (Dorigo et al., 2017). SM_{ECV} consists of three surface soil moisture datasets: the active data derived from scatterometers, the passive data derived from radiometers, and the combined data that merges both. In this study, we use the combined soil moisture daily product with a spatial resolution of 0.25° for the period of 2013–2015 (Gruber et al., 2019).

2.2.2 ERA5 reanalysis soil moisture

ERA5 (SM_{ERA5}) is the fifth generation global atmospheric and land-surface reanalysis product developed by the ECMWF (European Centre for Medium-Range Weather Forecasts), covering the period from 1950 to near real time. Compared to its predecessor (ERA-Interim reanalysis dataset), ERA5 incorporates more satellite-based data and offers considerably higher spatial and temporal resolutions. Hourly reanalysis fields are available at a horizontal resolution of 0.28125° (Albergel et al., 2018).

SM_{ERA5} provides soil moisture estimates at four depth layers: 0–7 cm, 8–28 cm, 29–100 cm, and 101–289 cm, respectively. Given that satellite soil moisture products typically retrieve soil moisture at the top ~5 cm depth from the data of C and L bands (An et al., 2016), we use the SM_{ERA5} of the top layer (0–7 cm) during 2013–2015 to match the satellite-based SM_{ECV} product.

2.2.3 *In-situ* observations

The hourly *in situ* soil moisture observations ($SM_{in\text{-}situ}$) from 60 stations during 2013–2015 are obtained from the Jiangsu Meteorological Information Center. The spatial distribution of these stations (marked as red solid dots) is shown in Figure 1. Measurements are collected using Frequency Domain Reflectometry (FDR) sensors, which are considered more accurate and physically less destructive than the traditional gravimetric technique (Dorigo et al., 2010; 2011). Soil moisture is recorded at an interval of 10 cm depth down to the depth of 1 m. In this study, only the observations of the top layer (0–10 cm) are used to evaluate the remotely sensed and reanalysis soil moisture products.

2.3 Methods

2.3.1 Accuracy metrics

The accuracy of soil moisture estimates is conventionally evaluated by comparing them against *in situ* observations, allowing for the computation of performance metrics such as the correlation coefficient (R), unbiased root-mean-square difference (ubRMSD) and bias (Albergel, Brocca, et al., 2013; Albergel, Dorigo, et al., 2013).

To quantify pattern similarity, the Pearson's correlation coefficient is calculated (Equation 1):

$$R = \frac{\sum_{n=1}^{N} \left(SM_{in-situ} - \overline{SM_{in-situ}}\right)\left(SM_e - \overline{SM_e}\right)}{\sqrt{\sum_{n=1}^{N} \left(SM_{in-situ} - \overline{SM_{in-situ}}\right)^2 \cdot \sum_{n=1}^{N} \left(SM_e - \overline{SM_e}\right)^2}} \tag{1}$$

where, SM_e denotes as the estimate product of soil moisture SM_{ECV} or SM_{ERA5} in this study, n is the time step and N is the length of the data.

To quantify deviation in magnitude from the *in situ* observations, both root-mean-square difference (RMSD) and ubRMSD are calculated. RMSD represents the absolute error, while ubRMSD represents the centered error, which removes the bias component and is considered more appropriate for assessing the relative error of soil moisture dynamic range. Due to potential systematic errors arising from the different depths across datasets, more emphasis is placed on ubRMSD rather than RMSD in this study.

RMSD is calculated as (Equation 2):

$$RMSD = \sqrt{\frac{1}{N}\sum_{n=1}^{N} \left(SM_{in-situ} - SM_e\right)^2} \tag{2}$$

ubRMSD is calculated as Equation 3:

$$ubRMSD = \sqrt{(RMSD)^2 - (Bias)^2} \tag{3}$$

Bias, indicating the average direction of the deviation from observed values, is calculated as Equation 4:

$$Bias = \frac{1}{N}\sum_{n=1}^{N} \left(SM_e - SM_{in-situ}\right) \tag{4}$$

where, a positive bias indicates an overestimation of soil moisture measurements, while a negative bias implies an underestimation (Albergel et al., 2010).

Additionally, normalized standard deviation (SDV) is calculated to evaluate the relative amplitude in the pattern variations (Equation 5),

$$SDV = \frac{\sigma_e}{\sigma_{in-situ}} \tag{5}$$

where, σ_e and $\sigma_{in-situ}$ are the standard deviations for estimate product of soil moisture and *in situ* observations.

2.3.2 Triple collocation

The validation of gridded SM products is usually carried out by *in situ* data (Xu et al., 2021). *In-situ* soil moisture is measured directly and usually represents the soil moisture condition of the site being measured or homogeneous surroundings. However, the number of *in situ* sites is limited and is unable to be expanded on a large spatial scale. As a complement, the triple collocation (TC) method, which is a kind of mathematics-based error analysis approach (Yang et al., 2022), has been developed for SM evaluation when *in situ* data are not available (Xu et al., 2021; Yu et al., 2023). Recent advances in triple collocation (TC) method has facilitated the assessment of root means square error while simultaneously solving for systematic differences across collocated dataset (Scipal et al., 2008). In this study, we constructed triplets based on daily SM_{ECV}, SM_{ERA5} and $SM_{in-situ}$ data from 1 January 2013 to 31 December 2015 (Dorigo et al., 2010).

Suppose the true value of soil moisture is θ. Three sets of independent observation data are x, y, and z, which satisfy the following linear model (Equation 6):

$$\begin{cases} x = a_x + \beta_x \theta + \varepsilon_x \\ y = a_y + \beta_y \theta + \varepsilon_y \\ z = a_z + \beta_z \theta + \varepsilon_z \end{cases} \tag{6}$$

where constants αi and βi represent calibration constants and ϵi denote the residual error of the estimates.

By eliminating the truth value θ, the unbiased estimates of the error variances for the three sets of data are derived (Equations 6–9):

$$\sigma_x^2 = \langle (x-y)(x-z) \rangle \tag{7}$$

$$\sigma_y^2 = \langle (y-z)(y-x) \rangle \tag{8}$$

$$\sigma_z^2 = \langle (z-x)(z-y) \rangle \tag{9}$$

where $\langle . \rangle$ denotes the mean value in terms of time or space.

It is important to note that applying triple collocation to soil moisture anomalies provides complementary insights into dataset performance. Anomaly-based approach offers more accurate information on the product's ability to capture single events of drying and wetting (e.g., due to rain-fall). Moreover, anomalies are insensitive to systematic bias that may exist between satellite retrievals and climate model simulations (Lei et al., 2015).

In this study, each soil moisture estimate is decomposed into its climatological mean and anomaly components. Mean values of the seasonal climatology are calculated using a moving window averaging of multiyear data with a 31-day window (Crow and Van Den Berg, 2010; McColl et al., 2014). The difference between the climatology and the original data can be treated as the anomaly components. Many studies have demonstrated the effectiveness of this approach before applying Triple Collocation (Parinussa et al., 2012).

3 Results

3.1 Overall accuracy

Figure 2 shows the Taylor Diagram for daily SM_{ECV} and SM_{ERA5} data against $SM_{in-situ}$ across the three typical areas during 2013–2015. In the Taylor Diagram, the standard deviation (SDV) is normalized as the ratio of the standard deviation of the estimates relative to $SM_{in-situ}$ (Taylor 2001).

As depicted in Figure 2, the SDV of SM_{ERA5} data (ranging from 1.5 to 2.3) is consistently higher than that of SM_{ECV} data (ranging from 0.8 to 1.6) across the three regions, especially in northeast area. This indicates that SM_{ERA5} data exhibit greater magnitude variations compared to $SM_{in-situ}$ data in these areas. Systematic deviations between the SM_{ERA5} product and the *in situ* observations could not be neglected, and a better consistency is achieved when deviations are reduced in the northwest area. Similarly, the ubRMSD for SM_{ECV} (ranging from 0.8 to 1.4 m^3 m^{-3}) is lower than that for SM_{ERA5} (ranging from 1.2 to 1.6 m^3 m^{-3}). Regarding the correlation coefficient, SM_{ERA5} demonstrates a relatively higher correlation

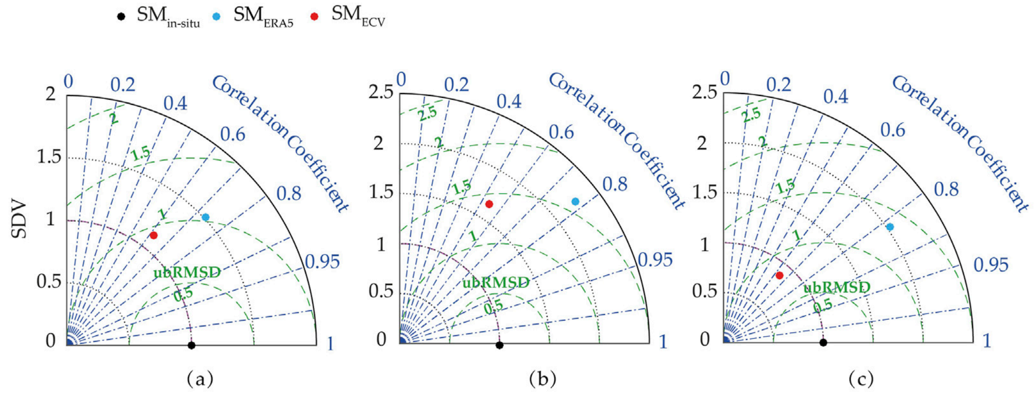

FIGURE 2
Taylor diagram showing comparison of daily soil moisture variation for three typical areas: **(a)**, **(b)**, **(c)** represent typical area NW, NE, SE respectively.

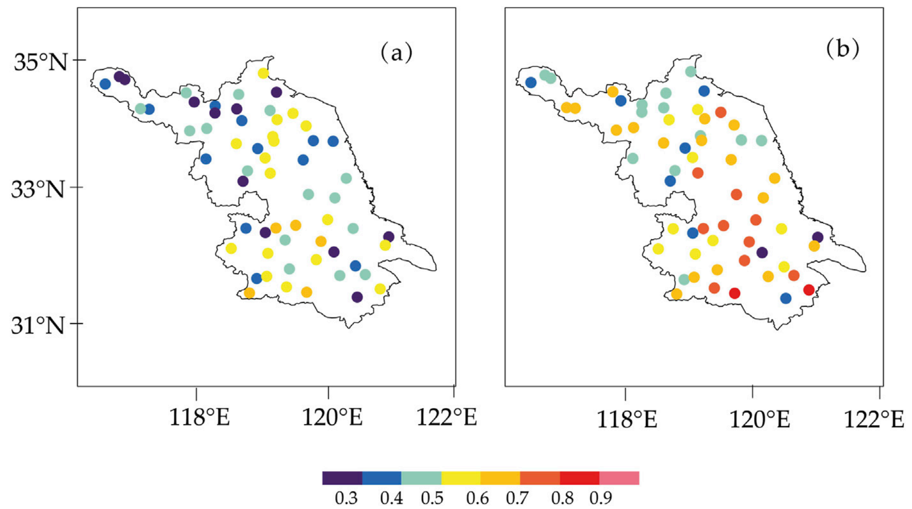

FIGURE 3
The correlation coefficients of **(a)** the SMECV and **(b)** the SMERA5 data against the SMin-situ data respectively from 2013 to 2015.

with $SM_{in\text{-}situ}$ data across the three regions, with values approximately ranging from 0.72 to 0.82, whereas SM_{ECV} data show correlation coefficients ranging from about 0.53 to 0.63.

Generally, the southern region (SE) outperforms northern regions (NW, NE) in both R and ubRMSD for both products. It is noteworthy that the regional differences among all indicators, as displayed in the Taylor Diagram, are particularly pronounced in the SE region. This performance disparity in the SE can be attributed to its unique climate; the prevailing easterly winds from the Pacific Ocean result in significant temperature fluctuations, which in turn cause substantial variations in soil moisture at that location. Additionally, the SE region receives more precipitation and solar energy flux than the northern regions, primarily influenced by the Meiyu Belt and its humid climate. Given that the mechanisms governing precipitation are well-represented in reanalysis systems and satellite retrieval algorithms (Ullah et al., 2018), precipitation is likely a key factor influencing soil moisture performance and will be further discussed in Section 4.

3.2 Spatial characteristics of accuracy

3.2.1 Daily scale

3.2.1.1 Temporal variations

In this section, we have derived Pearson's correlations coefficient (R) of the SM_{ECV} and the SM_{ERA5} data against the $SM_{in\text{-}situ}$ data respectively using daily data from 2013 to 2015 as shown in Figure 3. Since only 3 years of daily values are calculated, which is rather limited, however, we are still able to capture the dynamic variability of soil moisture due to its seasonal March from one season to another season.

The correlation coefficients between SM_{ECV} and $SM_{in\text{-}situ}$ data appear to be high with $R > 0.5$ over 1/3 of the study area (Figure 3a). Correlation coefficients over northern especially northwest area ($R < 0.4$) are relatively lower than middle and southern area. An increase in R value over middle area and a further increase over southern area are observed. This demonstrates that SM_{ECV} performs better over southern and middle area than northern area.

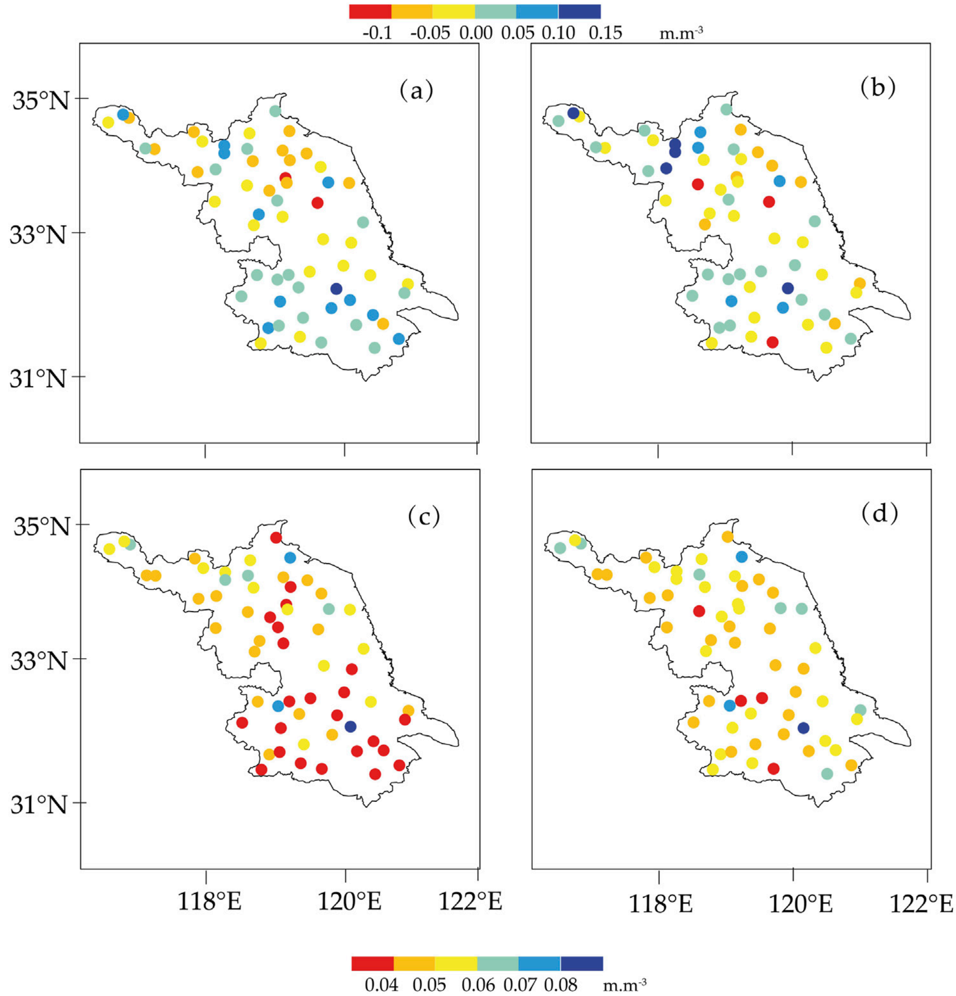

FIGURE 4
Station scale biases of **(a)** the SM_{ECV} and **(b)** the SM_{ERA5} and ubRMSD of **(c)** the SM_{ECV} and **(d)** the SM_{ERA5} against the $SM_{in\text{-}situ}$ data over Jiangsu province.

The SM_{ERA5} data (Figure 3b), are in remarkable agreement with the $SM_{in\text{-}situ}$ data in most areas of the Jiangsu province with correlation coefficients higher than 0.6, suggesting significant consistency in terms of their seasonal dynamics. This distribution is particularly strong in southern area, where they show correlation coefficients higher than 0.7 or even 0.8. Increases in R value are also observed from north to the middle part that more stations with R > 0.5 are found.

Thus, we can conclude that both SM_{ECV} product and SM_{ERA5} product over study area are able to reproduce the temporal pattern of $SMi_{n\text{-}situ}$ data and the SM_{ERA5} data performs better than the SM_{ECV} data, in terms of the day-to-day variations. In addition, the consistent spatial pattern and relatively better performance for two products over southern area than north should be paid enough attention. This phenomenon is especially strong for SM_{ERA5}, R values > 0.7 are mainly located over the southern area. As we know, the NDVI over northern area are mainly larger than southern area, which ranges from 0.75 to 1. From Hagan et al. (2020) results, we known that the performance of LSM dropped over very dense regions (NDVI>0.65), hence we can get the similar conclusion that NDVI value may influence the SM_{ECV} and the SM_{ERA5} data over northern areas where dense vegetation located. In addition, the variation in correlation from north to south is mainly because of higher temperature, together with enhanced evaporation in southern area (Hagan et al., 2020; Lou et al., 2018).

3.2.1.2 Bias and ubRMSD spatial distribution

Figures 4a,b shows the biases of the SM_{ECV} and the SM_{ERA5} data against the $SM_{in\text{-}situ}$ data, computed from the daily observations during 2013–2015. On the other hand, it has been widely acknowledged that the $SM_{in\text{-}situ}$ data is subjected to certain uncertainties that can be describe as those due to its retrieval such as depth, sensor placement, and installation, and its point scale representation of a small area, which does not depict a clear picture of large scale soil moisture variability (Ullah et al., 2018; Wu et al., 2016). To show a clear picture of soil moisture dynamics with reduced impacts of such uncertainties, the ubRMSD of the SM_{ECV} and the SM_{ERA5} data are also shown in Figures 4c,d.

In Figure 4a, it appears negative bias with value < -0.1 m^3 m^{-3} are found over northern and central area, especially over the central area, demonstrating the underestimation of SM_{ECV} over these areas. An overestimation reaching 0.15 m^3 m^{-3} is observed over the

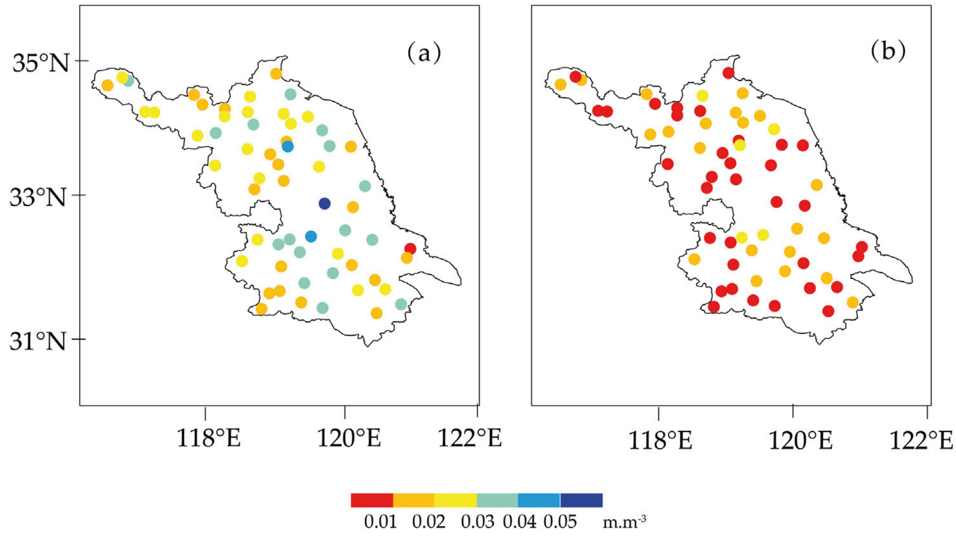

FIGURE 5
Station scale TC error **(a)** SMECV and **(b)** SMERA5 over Jiangsu.

southern area. For ubRMSD, data of SM_{ECV} (Figure 4c) shows larger ubRMSD over the northern areas, ranging from 0.05 to 0.08 m^3 m^{-3}, while the values are considerably reduced to less than 0.05 m^3 m^{-3} over the central and southern areas, reaching the minimum value in the southern area, with a regional average value of 0.045 m^3 m^{-3}.

For SM_{ERA5} data (Figure 4b), more stations with overestimation are found over northern area except for stations over the northwest region that underestimation are found (<0.1 m^3 m^{-3}). In addition, more stations with underestimation are found over southern area. Though SM_{ERA5} data ubRMSD (Figure 4d) also have similar spatial distribution, we can see a significant increase in ubRMSD value of SM_{ERA5} data. The number of stations with ubRMSD <0.05 m^3 m^{-3} largely reduced, especially over the central and southern area. The ubRMSD over the entire area ranging from 0.04 to 0.06 m^3 m^{-3}, only few stations less than 0.04 m^3 m^{-3} are located over southwest area. In average, the ubRMSD of SM_{ERA5} is about 0.052 m^3 m^{-3}.

In general, the biases of two products are higher in southern-east, north and less in eastern and central parts. In addition, both data of SM_{ECV} and SM_{ERA5} have larger ubRMSD over the northern areas; and over the southern areas the ubRMSD of both data are considerably reduced except for a few stations. In comparison to correlation, the regions where the correlation is higher, the biases and ubRMSD are also higher, and on the contrary the regions with smaller correlation have less biases and ubRMSD especially for SM_{ERA5}. We can see that the SM_{ECV} and SM_{ERA5} data have considerable discrepancies regarding their interannual variations and the associated errors; and, such discrepancies may vary with regions. This phenomenon could be explained by the relatively rough terrain, close to water bodies, or densely vegetated over southern area (Hagan et al., 2019; Holmes et al., 2009). Human induced alteration of land cover may cause this discrepancy in modelled and remotely sensed soil moisture data (Ullah et al., 2018), since southern and northern area are under different developing speed in Jiangsu. However, exploring these reasons is beyond the scope of current study. In addition, the SM_{ECV} data appears to have relatively smaller bias and ubRMSD than the SM_{ERA5} data across the Jiangsu Province. Therefore, the SM_{ECV} data can better characterize the soil moisture with smaller bias and random differences.

3.2.1.3 TC errors

The results of the error estimation suggest that both SM_{ECV} and SM_{ERA5} data are featured by a relatively low error, which are shown in Figure 5. Most stations with SM_{ECV} TC error (Figure 5a) less than 0.03 m^3 m^{-3}, and SM_{ECV} TC error larger than 0.03 m^3 m^{-3} can be frequently found over the southern area. For SM_{ERA5} TC error (Figure 5b), the magnitude is largely reduced to less than 0.02 m^3 m^{-3} and seems evenly distributed over the entire area.

Since TC error best characterizes the intrinsic disability of TC triplets' datasets to capture the soil moisture value, SM_{ERA5} data substantially lower TC bias value illustrate the superiority of SM_{ERA5} data with smallest error relative to truth. In addition, the lower SM_{ERA5} TC errors also manifest the stronger capability than the SM_{ECV} data in catching the drying and wetting events, which is found in the study of climate and model assimilation. The mean regional TC error is 0.025 m^3 m^{-3} for the SM_{ECV}, and 0.01 m^3 m^{-3} for the SM_{ERA5}. The average TC errors calculated for SM_{ERA5} in this study is reasonablyy lower than those global average TC errors of $SM_{ERA\text{-}Interim}$ (0.02 m^3 m^{-3}) obtained by Scipal et al. (2010) for a combination of the ERS-2 scatterometer (0.028 m^3 m^{-3}), the TMI radiometer (0.046 m^3 m^{-3}) and $SM_{ERA\text{-}Interim}$ (0.018 m^3 m^{-3}) calculated by Dorigo et al. (2017) for a combination of the ASCAT (0.017 m^3 m^{-3}), the AMSR-E (0.019 m^3 m^{-3}) soil moisture.

3.2.2 Seasonal scale

Figure 6 shows the spatial patterns of $SM_{in\text{-}situ}$, SM_{ECV} and SM_{ERA5} data in different seasons, namely, winter (December-February), spring (March-May), summer (June-August) and autumn (September-November) derived for 2013–2015. In winter season, the $SM_{in\text{-}situ}$ soil moisture exhibited a distinct dipole pattern with minimum soil moisture values in the north (< = 0.32 m^3 m^{-3}), that gradually reaches to maximum (< = 0.35 m^3 m^{-3} values in the central part and a slight decrease (< = 0.32 m^3 m^{-3}) afterwards in

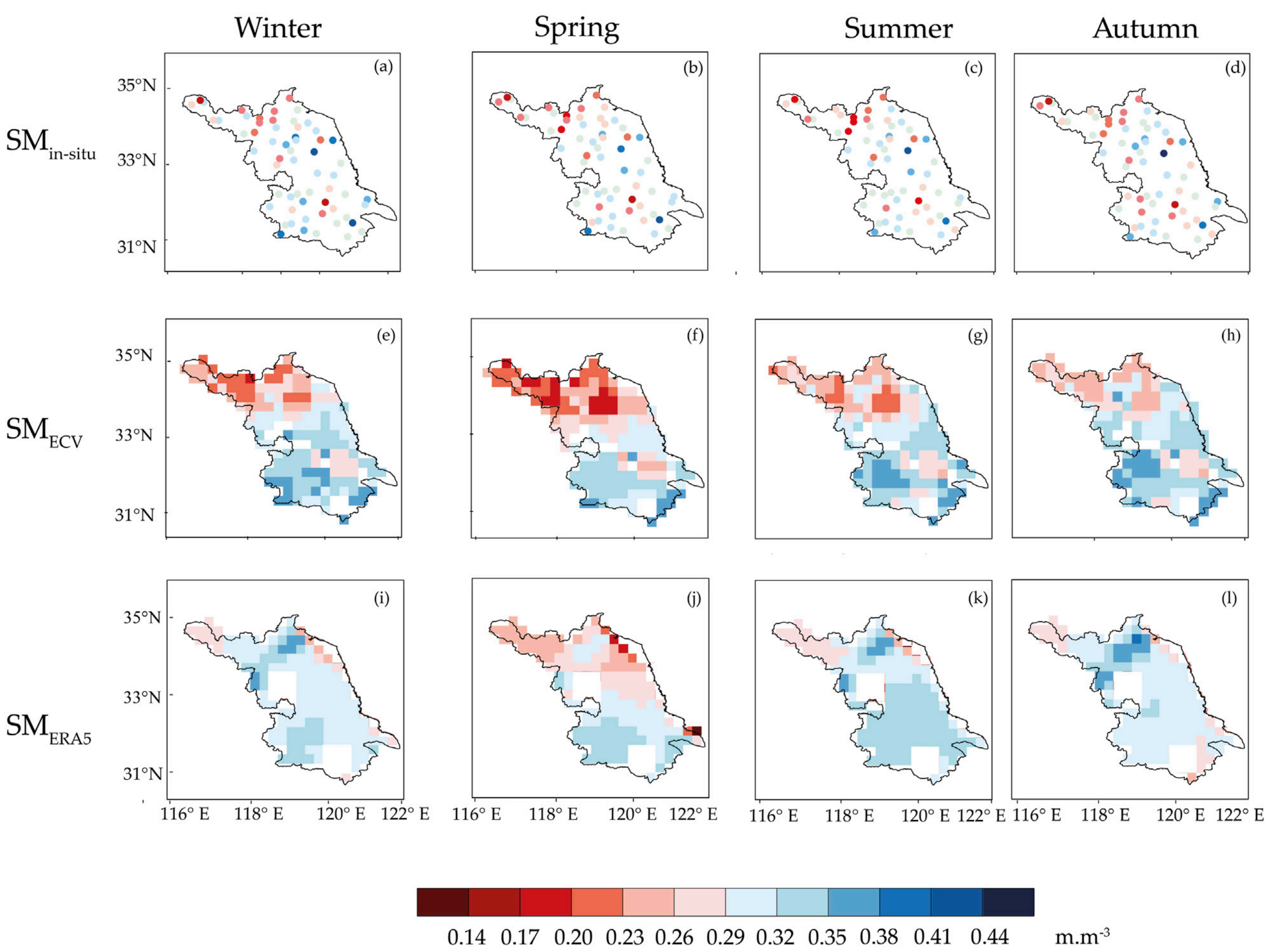

FIGURE 6
Seasonal mean SMin-situ, SMECV and SMERA5 soil moisture ($m^3.m^{-3}$) in winter, spring, summer and autumn respectively.

magnitude is obvious. Alike pattern is obvious in SM_{ECV} that is consistent with $SM_{in\text{-}situ}$ in terms of spatial soil moisture variation from north to south. The SM_{ERA5} soil moisture generally exhibited similar pattern as observed for the *in situ* and remotely sensed products, which however appeared to overestimate both observed and remotely sensed soil moisture product.

During spring season, there is an overall decrease in $SM_{in\text{-}situ}$ magnitude in most parts of the region, especially over the northern area. The $SM_{in\text{-}situ}$ data soil moisture values are less than 0.29 m^3 m^{-3} in the northern areas, with an increase of absolute magnitude to 0.32 m^3 m^{-3} towards the central area, and to around 0.38 m^3 m^{-3} in the southern area is obvious. The SM_{ECV} data in spring season also shows a reduced magnitude and similar spatial distribution as $SM_{in\text{-}situ}$ data. Less soil moisture at the northern area with slight increase towards central region and relatively enhanced soil moisture in the southwestern parts. The SM_{ERA5} appears to be consistent with those of the observed and remotely sensed soil moisture products, with less soil moisture, and a distinct increase towards south is evident.

During summer season, $SM_{in\text{-}situ}$ data have shown an obvious increase in soil moisture magnitude (< = 0.29 m^3 m^{-3}), in north with a slight increase towards central (< = 0.32 m^3 m^{-3}) and southern parts. The SM_{ECV} data exhibited slight increase and in close agreement with those of *in situ* observations depicting seasonal transition. A similar increase in the SM_{ERA5} can also be seen, which ranges from 0.29 $m^3 \cdot m^{-3}$over the southern to 0.32 m^3 m^{-3} over the northern area and consistently shows relatively higher soil moisture magnitude.

For autumn season, the $SM_{in\text{-}situ}$ magnitude decreases over most areas, which is more obvious over the southern (< = 0.23 m^3 m^{-3}) and the central area (< = 0.26 m^3 m^{-3}); however, there is increase over the northern areas. This seasonal variation is not well captured by the SM_{ECV} data, since an overall increase in magnitude are observed. Unlike SM_{ECV} data, the SM_{ERA5} show a general decrease from summer to autumn over the whole area except for the northeast part (< = 0.29 m^3 m^{-3}), though an overestimation is found.

In conclusion, both SM_{ECV} data and SM_{ERA5} data were able to show north-south variation relatively higher soil moisture magnitude over southern areas and lower magnitude over northern areas in all seasons. SM_{ECV} closely followed $SM_{in\text{-}situ}$ soil moisture in terms of absolute values, whereas SM_{ERA5} consistently overestimated observed and remotely sensed soil moisture. The distinct north-south spatial patterns could be, at least partly, due to the unevenly distributed precipitation over the Jiangsu province, that however may not be represented in SM_{ERA5} data. The regional variation of soil moisture is subjected to precipitation variation and thus both *in situ* and remotely sensed

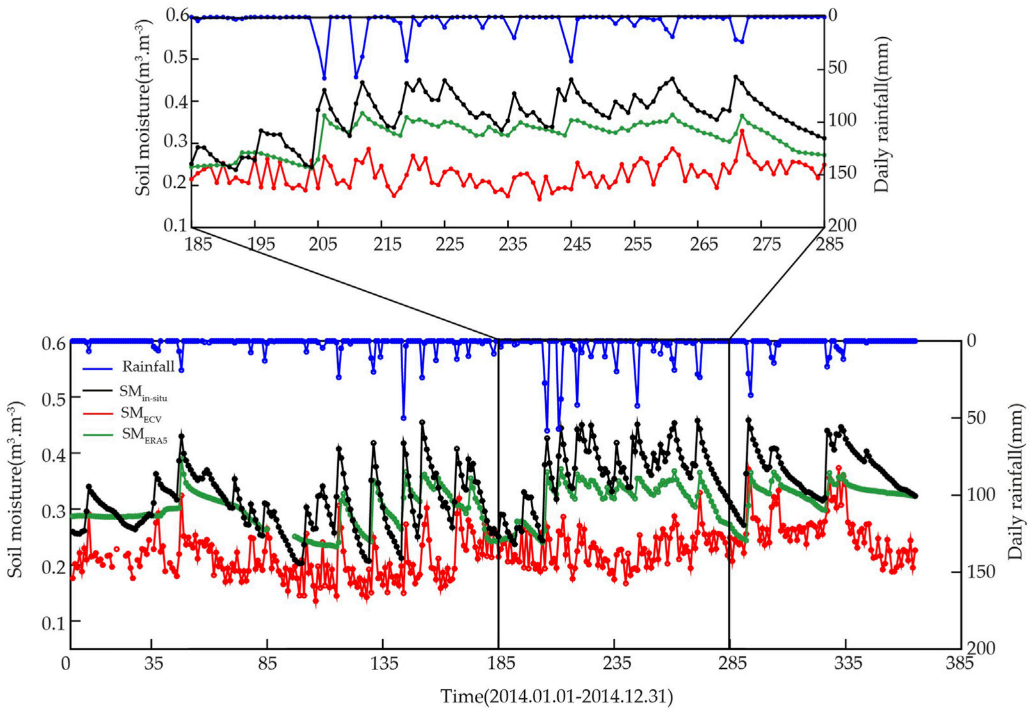

FIGURE 7
Time variations of soil moisture for SMin-situ, SMECV, SMEAR5 and precipitation from a single station (station number 58047).

soil moisture appeared to be capturing such variations much better than reanalysis products. The soil moisture dynamics may be presented and affected by different processes in both observed and reanalysis soil moisture data and thus more detailed investigation is needed in this regard.

3.3 Response to heavy precipitation events

Since soil moisture is part of the terrestrial water cycle, which is highly chaotic and shows major diversity in both space and time (Albergel et al., 2018), its value could easily be altered by a single precipitation event. Hence, the capability of soil moisture response to precipitation event should be a factor in evaluating the soil moisture data, and similar works have been done in many places including Tibetan Plateau and Southwest China (Bi et al., 2016; Peng et al., 2015b). However, their responses of the SM_{ECV} and the SM_{ERA5} products to precipitation event over Jiangsu province remain unexplored. Since we want to see the temporal evolution of soil moisture and precipitation during heavy raining events other than annual precipitation, we choose a typical station (shown as in Figure 1) among these 60 stations where has relatively more heavy precipitation events.

The time series of precipitation and soil moisture data, spanning from 2014–01–01 till 2014–12–31, are shown in Figure 7. An obvious response can be seen in the $SM_{in\text{-}situ}$ to the precipitation events. The SM_{ERA5} data also shows good responses to heavy precipitation events, indicating its considerable sensitivity to precipitation, although not as good as the $SM_{in\text{-}situ}$ data. However, the SM_{ECV} response to heavy precipitation events is with inferior performance than the SM_{ERA5} data. Although the SM_{ECV} values are also higher when there are precipitation events, their responses are not as distinct as the SM_{ERA5} data. The TRMM (Tropical Rainfall Measuring Mission satellite) precipitation data, which is one of the forcing datasets of the SM_{ERA5} product, has been extensively validated and is a very reliable quantitative precipitation estimates around the world. In addition, Albergel et al. (2018) has demonstrated ERA5 has a good global balance of precipitation and evaporation, which can also be the reason of SM_{ERA5} data better performance. On the other side, it has been proved that SMOS, which is one of the passive sensors used to generate the combined SM_{ECV} product in this study (Dorigo et al., 2015), performed not that good in response to precipitation over the southwest China due to the RFI effect (Peng et al., 2015a). Hence, this finding in Peng's (Peng et al., 2015b) study can also be the explanation in Jiangsu.

4 Discussion

Soil moisture plays a critical role in the land surface-atmosphere coupling process and is key factor in water and energy cycles. Accurate and reliable estimates of soil moisture are essential for numerical weather prediction, hydrological forecasting, and land surface data assimilation. SM_{ERA5} is the successor to the $SM_{ERA\text{-}Interim}$ reanalysis, while SM_{ECV} is a widely used soil moisture product that combines several high-quality satellites products. Both products are considered promising alternatives to *in situ* soil moisture measurements.

Both SM_{ECV} and SM_{ERA5} show similar spatial patterns as $SM_{in\text{-}situ}$ across all seasons, generally showing higher moisture in southern areas and lower values in northern areas. However, discrepancies with $SM_{in\text{-}situ}$ are observed in areas with higher precipitation and dense vegetation. All three datasets exhibit different seasonal variations in magnitudes. SM_{ERA5} and the SM_{ECV} data showed more pronounced seasonal cycles than the relatively stable $SM_{in\text{-}situ}$ data.

According to performance metrics, both SM_{ERA5} and the SM_{ECV} effectively capture the temporal dynamics of $SM_{in\text{-}situ}$, although subtle differences exist. SM_{ERA5} demonstrates superior performance with higher correlation coefficient and lower TC errors. However, SM_{ECV} shows lower random errors (ubRMSD = 0.045 m^3 m^{-3} for SM_{ECV} vs 0.052 m^3 m^{-3} for SM_{ERA5}), indicating more stable performance related to $SM_{in\text{-}situ}$. Moreover, SM_{ERA5} shows more sensitive response to heavy precipitation events compared to SM_{ECV}.

The superior performance of SM_{ERA5} aligns with findings from previous studies, which have demonstrated that $SM_{ERA\text{-}Interim}$ reanalysis products outperform remotely sensed products in capturing soil moisture variations. This advantage stems from their integration of precipitation observations (Albergel et al., 2012; Peng et al., 2015a). Further supporting this, Yu et al. (2023) evaluated multiple soil moisture products in Central Asia and found that SM_{ERA5} exhibited the closest agreement with $SM_{in\text{-}situ}$ observations, achieving an average correlation coefficient of 0.59. In comparison, GLDAS and SM_{ECV} followed with coefficients of 0.52, while FLDAS performed less favorably. Regarding error metrics, the patterns diverged: FLDAS showed the highest average ubRMSE (0.054 m^3/m^3), whereas SM_{ERA5}, SM_{ECV}, and GLDAS demonstrated comparable performance, with average ubRMSE values ranging between 0.039 m^3/m^3 and 0.044 m^3/m^3. In addition, we reveal the variability of three soil moisture products over the study period, highlighting the effects of precipitation on surface soil moisture dynamics. Since SM_{ERA5} shows good response to precipitation, it holds significant potential for improving hydrological forecasting (Hong et al., 2024).

SM_{ERA5} retains the high-quality forcing data used in $SM_{ERA\text{-}Interim}$ reanalysis, and addresses several known limitations of its predecessor ($SM_{ERA\text{-}Interim}$). The assimilation of updated satellite data and improved representation of the global water balance of precipitation and evaporation further support the improved performance of SM_{ERA5}. Additionally, it should be noted that the soil depth of each soil moisture data was inconsistent with that of the $SM_{in\text{-}situ}$, which may potentially lead to incomplete control/correction of systematic biases (Li et al., 2022; Yu et al., 2023). In this study, the depth of SM_{ERA5} (0–7 cm) is more comparable to $SM_{in\text{-}situ}$ (0–10 cm) than SM_{ECV} (0–5 cm), potentially contributing to SM_{ERA5}'s better agreement with $SM_{in\text{-}situ}$ (Luo et al., 2021).

The results also indicated that the temporal agreement of SM_{ERA5} and SM_{ECV} varies across regions. In northern regions, both SM_{ERA5} and SM_{ECV} perform relatively poorly in terms of temporal agreement and TC error, confirmed the Taylor Diagrams of three typical areas (Figure 7). By contrast, performance is generally better in the southern area (SE), where both products exhibit higher correlation coefficients with $SM_{in\text{-}situ}$ than in northern areas (NW and NE). Notably, regional differences among all indicators are also pronounced over the SE area, which can be explained by the special climate. The prevailing eastly wind from Pacific Ocean induce large fluctuations in temperature, and consequently in soil moisture. Moreover, higher precipitation and solar energy in the SE region due to the Meiyu Belt and humid climate further contribute to the spatial difference. Other influencing factors, including the distance to large water bodies, vegetation cover, and urbanization degree, may also significantly affect accuracy of soil moisture estimates (Hagan et al., 2019; Hagan et al., 2020).

Since soil moisture climatology is the reflection of temporal variations and spatial patterns of long-term meteorological forcing data, whereas soil moisture anomalies are the reflection of short-term forcing dynamics. These findings can provide a valuable reference for improving land surface modes and hydrological forecasting. SM_{ERA5}'s sensitivity to precipitation and depth compatibility with *in situ* data make it a robust candidate for enhancing land surface model initialization and flood forecasting. However, the rapid evolution of soil moisture products necessitates continuous evaluation of emerging datasets. With the recent release of Era-land, a next-generation product integrating advanced satellite observations and machine learning techniques, future research should focus on comparative assessments to determine whether it demonstrates improved performance in regions with complex climate conditions (e.g., high precipitation or dense vegetation) and whether its spatial resolution enhances the monitoring of localized soil moisture dynamics. Such studies would further guide the selection of optimal products for specific hydrological and meteorological applications. However, the rapid evolution of soil moisture products necessitates continuous evaluation of emerging datasets. With the recent release of ERA5-land, a next-generation product integrating advanced satellite observations and machine learning techniques, future research should focus on comparative assessments to determine whether it demonstrates improved performance in regions with complex climate conditions (e.g., high precipitation or dense vegetation) and whether its spatial resolution enhances the monitoring of localized soil moisture dynamics (Muñoz-Sabater et al., 2021; Wu et al., 2021; Zhang et al., 2021). Such studies would further guide the selection of optimal products for specific hydrological and meteorological applications.

5 Conclusion

In this study, we have validated both SM_{ECV} and SM_{ERA5} against *in situ* observations across Jiangsu province, China. The results show that while both SM_{ECV} and SM_{ERA5} have their own strengths and weaknesses in capturing soil moisture dynamics compared to $SM_{in\text{-}situ}$.

SM_{ERA5} generally outperforms SM_{ECV} in terms of correlation coefficient and response to heavy precipitation, which is in line with previous research and can be attributed to its high - quality data sources and improved assimilation techniques. However, SM_{ECV} has lower random errors, indicating more stable performance.

The temporal agreement of the two products with $SM_{in\text{-}situ}$ also varies regionally, with better performance in the southern area and relatively poor performance in the northern area. This regional variation is influenced by climate factors such as wind, precipitation, and solar energy, as well as other factors like distance to water bodies, vegetation cover, and urbanization.

Overall, this study provides valuable insights into the performance of SM_{ECV} and SM_{ERA5} in different regions and seasons, which can help in the selection and application of these soil moisture products for various purposes such as numerical weather prediction and hydrological forecasting. Future research could further explore the impact of different soil depths and other influencing factors on soil moisture estimates to improve their accuracy and reliability.

Data availability statement

The datasets presented in this article are not readily available because confidentiality of meteorological observation data. Requests to access the datasets should be directed to the corresponding author.

Author contributions

XS: Writing – original draft, Writing – review and editing. RY: Writing – original draft, Validation, Visualization. WU: Conceptualization, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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