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Evaluation of a multi-satellite soil moisture product and the Community Land Model 4.5 simulation in China

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Abstract

Twenty years of in situ soil moisture data from more than 300 stations located in China are used to perform an evaluation of two surface soil moisture datasets: a microwave-based multi-satellite product (ECV-SM) and the land surface model simulation from the Community Land Model 4.5 (CLM4.5). Both soil moisture products generally show a good agreement with in situ observations. The ECV-SM product has a low bias, with a root mean square difference (RMSD) of 0.075 $m^3 m^{-3}$, but shows a weak correlation with in situ observations ($R = 0.41$). In contrast, the CLM4.5 simulation, forced by an observation-based atmospheric forcing data, produces better temporal variation of surface soil moisture ($R = 0.52$), but shows a clear overestimation (bias = 0.05 $m^3 m^{-3}$) and larger RMSD (0.09 $m^3 m^{-3}$), especially in eastern China, caused by inaccurate descriptions of soil characteristics. The ECV-SM product is more likely to be superior in semi-arid regions, mainly because of the accurate retrievals and high observation density, but inferior over areas covered by dense vegetation. Furthermore, it shows a stable to slightly increasing performance in China, except for a decrease during the 2007–2010 blending period. Results from this study can provide comprehensive insight into the performances of the two soil moisture datasets in China, which will be useful for their improvements in merging algorithms or model simulations and for applications in soil moisture data assimilation.

1 Introduction

Soil moisture is a key variable in hydrological, climatological, biological and ecological processes. It is central to land–atmosphere interactions because of its control on the partitioning of water and energy fluxes at the Earth's surface (Dai et al., 2004). Soil moisture also affects the seasonal and inter-annual dynamics of vegetation, which is an essential component of the coupled hydrological and carbon cycles (Ciais et al., 2005). A significant number of studies have been conducted to obtain estimates of soil moisture using remote sensing techniques (Njoku et al., 2003; Owe et al., 2008; Kerr et al., 2012) and land surface modeling (Dirmeyer et al., 2006; Wang et al., 2011; Liu and Xie, 2013).

Spaceborne microwave instruments are able to provide quantitative information about surface soil water content (Schmugge, 1983), particularly in the low-frequency microwave region from 1 to 10 GHz (Albergel et al., 2012). Several microwave-based soil moisture datasets have been generated using satellite retrievals from active microwave sensors, e.g. the European Remote Sensing Satellites 1 and 2 Active Microwave Instrument Wind Scatterometer (AMI-WS; Scipal et al., 2002) and Advanced SCATterometer (ASCAT) onboard the Meteorological Operational satellite program (MetOp; Bartalis et al., 2007), and from passive microwave sensors, including the Scanning Multichannel Microwave Radiometer (SMMR; Owe et al., 2008), the Special Sensor Microwave Imager (SSM/I) of the Defense Meteorological Satellite Program (DMSP; Owe et al., 2008), the Tropical Rainfall Measuring Mission microwave imager (TMI; Jackson and Hsu, 2001; Gao et al., 2006; Owe et al., 2008), and more recently the Advanced Microwave Scanning Radiometer–Earth observing system (AMSR-E) onboard the Aqua satellite (Njoku et al., 2003; Owe et al., 2008). The AMSR-E radiometer was switched off in October 2011 because of rotation problems with its antenna; however, the AMSR2, launched in May 2012 onboard the Global Change Observation Mission 1–Water (GCOM–W1), was intended to extend the valuable heritage of AMSR-E and provide improved spatial resolution because of its larger reflector (Parinussa et al., 2015). Even though none of these sensors were specifically designed for measuring soil moisture, good correspondences have been found between the individual datasets and ground-based observations taken over a large variety of environmental conditions (Albergel et al., 2009, 2012; Draper et al., 2009; Gruhier et al., 2010; Brocca et al., 2011).

However, none of the individual microwave products cover the decadal timescales required to be considered for the climate applications. Recently, a multi-satellite Essential Climate Variable soil moisture dataset (ECV-SM) with over thirty years was constructed by merging two active and six passive microwave products (Liu et al., 2011, 2012). This product, which was initially developed under the European Space Agency (ESA) Water Cycle Multi-Mission Observation Strategy (WACMOS) project, is now being extended and improved within the Climate Change Initiative (CCI) (http://www.esa-soilmoisture-cci.org/; Wagner et al., 2012). A few studies have considered the evaluation of the ECV-SM using in situ observations. Liu et al. (2011, 2012) indicated that the merged dataset had a similar accuracy to that of the best input product but with an increased temporal sampling density. Albergel et al. (2013a) found that the ECV-SM agreed well with in situ measurements between 2007 and 2010 for 196 sites from five networks across the world, but that its performance over most networks remained poorer than that of the reanalysis soil moisture products. Dorigo et al. (2014) provided a more in-depth evaluation; they used 596 stations from 28 historical and active monitoring networks worldwide. Whilst the performance of the ECV-SM appeared to be relatively stable over time, large discrepancies were observed among different networks. In addition, the ECV-SM can also capture long-term systematic changes in trends of ground-based observations (Dorigo et al., 2012; Albergel et al., 2013b), which suggests that it has a large potential for climate trend assessments (Loew et al., 2013).

China has the third largest land area and diverse climates and biomes. Previous studies have used only 34 sites for the period 1981–2000 across China and only 20 sites for the period 2008–2010 from the Maqu network in northwest China to investigate the performance of the ECV-SM (Albergel et al., 2013a; Drigo et al., 2014). Such sparse observations will clearly affect the evaluation results, leading to large uncertainties. Recently, Chinese soil moisture observations for 778 sites from 1993 were updated by the China Meteorological Administration (CMA) National Meteorological Information Center (NMIC). These data have been extensively used to investigate the variations of soil moisture and evaluate the land surface modeling (Li et al., 2005; Wang and Zeng, 2011; Liu and Xie, 2013).

Land surface modeling is another strategy to produce large-scale surface and root zone soil moisture estimations. When forced with high quality atmospheric forcing data, this strategy has proved to be an effective tool for the evaluation of satellite retrievals at both the regional and global scales (Albergel et al., 2010, 2012). The ECV-SM product has also shown a demonstrated potential for evaluating climate model performances (Loew et al., 2013; Szczypta et al., 2014). As one of the state-of-art land surface models, the Community Land Model version 4.5 (CLM4.5) from National Center for Atmospheric Research (NCAR) was released in 2013 (Oleson et al., 2013). To our knowledge, few studies focus on the performance of CLM4.5 soil moisture simulations in China.

In this study, we will provide an in-depth evaluation of the ECV-SM product and CLM4.5 simulation in China using ground-based observations from 778 sites. We will also investigate their performances over the sub-regions under different climate conditions, including bias characteristics and temporal variations. This in-depth evaluation is expected to provide a better understanding of the quality of both soil moisture products and their potential problems, which can be used to improve their accuracy. The soil moisture datasets used in this study and the methodology for their evaluation are described in Sect. 2. The results and discussion are then presented in Sects. 3 and 4, respectively. Finally, the conclusion is given in Sect. 5.

2 Material and methods

2.1 Community Land Model (CLM4.5)

The NCAR/CLM is a community-developed model for simulating land surface processes, such as water, energy, and carbon fluxes. CLM4.5 is the latest version of the CLM family of models (Oleson et al., 2013). It contains several notable improvements over previous releases, including the decrease of biases associated with the modelled terrestrial carbon cycle and modifications of canopy and hydrology processes (Oleson et al., 2013). In CLM4.5, spatial land surface heterogeneity is represented as a nested subgrid hierarchy in which grid cells are composed of multiple land units, snow/soil columns, and plant functional types (PFTs). CLM4.5 has one vegetation layer, fifteen layers for soil and up to five layers for snow, depending on snow depth. The soil depths for top five layers are 1.75, 4.51, 9.06, 16.55 and 28.91 cm. For soil points, temperature calculations are performed over all layers, while hydrology calculations are performed over the top ten layers only; the bottom five layers being classified as bedrock. A detailed description of the physical processes included within CLM4.5 can be found in Oleson et al. (2013). It should be noted that although CLM4.5 includes the option to be run with a dynamical vegetation or prognostic carbon-nitrogen model, in our study CLM4.5 was run using prescribed satellite-based phenology (Lawrence and Chase, 2007), taken from the Moderate Resolution Imaging Spectroradiometer (MODIS).

In this study, CLM4.5 was forced by a 34-year (1979–2012) observation-based atmospheric forcing dataset from the Institute of Tibetan Plateau Research, Chinese Academy of Sciences (hereafter ITP), with a spatial resolution of $0.1^{\circ} \times 0.1^{\circ}$ at a three-hourly temporal resolution over China (15–55° N, 70–140° E). This dataset was constructed by merging the observations from 740 operational stations of the CMA with the corresponding meteorological forcing dataset from the Global Land Data Assimilation System (Rodell et al., 2004) to produce near-surface air temperature, pressure, wind speed and specific humidity fields. It combined three precipitation datasets, including ground-based observations and two satellite retrieval products (Chen et al., 2011), to determine the precipitation field. It also corrected the Global Energy and Water Cycle Experiment–Surface Radiation Budget (Pinker and Laszlo, 1992) with reference to radiation estimates (Yang et al., 2010) to ascertain the incident shortwave radiation fields. Chen et al. (2011) demonstrated that simulations driven by the ITP forcing improve land surface temperature modeling for dry land in China. Liu and Xie (2013) found that over most regions of China, the soil moisture estimations of the CLM3.5 forced by the ITP forcing dataset have closer correlations with ground-based observations than three other studied atmospheric forcing datasets.

2.2 ECV soil moisture data

In response to the Global Climate Observing System endorsement of soil moisture as an ECV, the ESA-WACMOS and CCI projects have supported the generation of the ECV-SM product by merging multiple microwave-based soil moisture products (Wagner et al., 2012), including passive data derived from SMMR, SSM/I, TMI, and AMSR-E and active data from the ERS and ASCAT (Liu et al., 2011, 2012). In July 2014, the ECV-SM version 2 was released by The Vienna University of Technology with improved merging schemes and procedures compared to previous versions. Furthermore, it was extended to the year 2013 by including the WindSat and AMSR2 data (Parinussa et al., 2012, 2015). Initially, the ECV-SM data were separated into two homogenized products: one for active and one for passive data; then they were merged into a single active-passive product according to their relative sensitivity to vegetation density (Liu et al., 2011, 2012; Wagner et al., 2012). ECV-SM has a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ and a daily time stamp centered at 00:00 UTC, although the actual observation time corresponds to that of the input product at a specific time (Liu et al., 2012). These data are in volumetric ($m^3\,m^{-3}$) units and quality flags (snow coverage or temperature below 0 °C and dense vegetation) are also provided.

2.3 In situ measurements in China

This study makes use of in situ soil moisture measurements from agricultural meteorological stations across mainland China, collected by the CMA-NMIC, to evaluate the ECV-SM and CLM4.5. The original data for 20 years (1993–2012) from 778 stations were obtained every 10 days (i.e., on the 8th, 18th and 28th day of every month) at soil depths of 10, 20, 50, 70 and 100 cm, respectively. No measurements were recorded in frozen soil. Soil water content was measured using the gravimetric

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technique and originally recorded as mass percentage. It was converted to volumetric soil moisture using field capacity and soil bulk density observations (Liu and Xie, 2013). This soil moisture observation dataset has been widely used to study temporal variations in soil moisture and evaluate land surface model simulations in China (Li et al., 2005; Wang and Zeng, 2011; Liu and Xie, 2013), and is constantly updated. However, not all datasets are suitable for the evaluation of remote sensing product and model simulation. Here, we selected a simple quality control procedure (Wang and Zeng, 2011; Liu and Xie, 2013) on the updated soil moisture observations in terms of observation frequency: the ratio of valid measurements during the period from March to October (1993–2012) is over 50 %. Finally, the monthly soil water content values at depths of 0–10 cm at 308 stations were used in this study to evaluate the remotely sensed and simulated values at those depths. These stations were grouped into eight sub-regions on the basis of the spatial patterns of the centers of dryness and wetness throughout China, based on Zhu (2003) and Liu and Xie (2013), and are defined in Table 1. Figure 1 shows the eight sub-regions and the location of all 308 in situ measurement sites, 291 of which were located in the eight sub-regions in this study.

2.4 Evaluation strategy

For the CLM4.5 simulation, we first spin-up 300 years by repeating 30-year (1979–2009) ITP meteorological forcing data to achieve an equilibrium state and initial conditions. The 1979–2012 atmospheric forcing data were then used to force CLM4.5 and the simulated results will be used in this study. To be consistent with the ECV-SM, these simulations were all run at spatial resolution of $0.25^\circ \times 0.25^\circ$ at 30 min time steps. Given the low temporal frequency of in situ datasets, the validation of ECV-SM and CLM4.5 was conducted at the monthly scale (Wang and Zeng, 2011; Liu and Xie, 2013). The "nearest neighbor" approach was retained to match the grid point location from ECV-SM or CLM4.5 with that of the in situ measurements.

In this study, the following five statistical indicators (Eqs. 1–5) are used to quantitatively evaluate the accuracy of the ECV-SM product and CLM4.5 simulation:

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mean bias (BIAS), root-mean-squared difference (RMSD), correlation coefficient (R), the normalized standard deviation (SDV), and the centered normalized RMSD (E). They are defined as follows:

$$\mathrm{BIAS} = \frac{1}{n}\sum_{i=1}^{n}(S_i - O_i), \tag{1}$$

$$\mathrm{RMSD} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2}, \tag{2}$$

$$R = \frac{\frac{1}{n}\sum_{i=1}^{n}(S_i - \overline{S})(O_i - \overline{O})}{\sigma_S \sigma_O}, \tag{3}$$

$$\mathrm{SDV} = \sigma_S / \sigma_O, \tag{4}$$

$$E = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[(S_i - \overline{S}) - (O_i - \overline{O})\right]^2}, \tag{5}$$

where S represents soil moisture from either the ECV-SM or CLM4.5 dataset, O is the in situ measurement and σ_S and σ_O are the corresponding SDs related to S and O, respectively. SDV gives the relative amplitude of SDs while E quantifies errors in the pattern variations ($E = 0$ represents the in situ measurement value). Both SDV and E do not include any information on biases since the means of the fields are subtracted before computing second order errors. However, R, SDV, and E are not independent as they are related by Eq. (6):

$$E^2 = 1 + \mathrm{SDV}^2 - 2 \cdot \mathrm{SDV} \cdot R. \tag{6}$$

Taylor diagrams are used to represent these three statistics using two-dimensional plots (Taylor, 2001).

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In the following section, we first investigate the performances of both the remotely sensed product and the model simulation for the whole time period (1993–2012). As the different products used to develop ECV-SM vary over space and time, the differences in the microwave observation channels and sampling densities are expected to influence the quality of the different periods for the new merging satellite product (Liu et al., 2012; Dorigo et al., 2014). The following describes the eight sub-periods used to construct the ECV-SM (Albergel et al., 2013a; Dorigo et al., 2014):

- blend 1: January 1979–August 1987, based SMMR observations only,
- blend 2: September 1987–June 1991, based on SSM/I only,
- blend 3: July 1991–December 1997, based on a combination of SSM/I and ERS AMI,
- blend 4: January 1998–June 2002: based on a combination of TMI and AMI between 40° N and 40° S, and a combination of SSM/I and ERS AMI elsewhere,
- blend 5: July 2002–December 2006: based on a combination of AMSR-E and ERS AMI,
- blend 6: January 2007–September 2011: based on a combination of AMSR-E and ASCAT,
- blend 7: October 2011–June 2012: based on a combination of WindSat and ASCAT,
- blend 8: July 2012–December 2013: based on a combination of AMSR2 and ASCAT.

To illustrate their potential effects on the quality of the ECV-SM, its evaluation was repeated for the last five time periods during which in situ observations were available.

3 Results

3.1 Availability of the ECV-SM data in China

Previous studies (Dorigo et al., 2014; Loew, 2014) showed that the performance of the ECV-SM product may be strongly affected by any data gaps and the period of observation. Therefore, we first analyzed the data availability of the ECV-SM product in China for the entire period (1979–2013) as well as for the eight individual time periods (Sect. 2.4). A clear increase of observation density can be observed over time (Fig. 2), which is mainly due to the growing number of satellites available for soil moisture retrieval (Liu et al., 2012; Dorigo et al., 2014). The improved instrument design and sensor performance also contributes to this effect. They have led to a convergence of active and passive remote sensing products, especially over areas with intermediate vegetation cover (Liu et al., 2012), and an increase over time of areas where both products are used in a synergistic way.

For example, for the second period (1 September 1987–30 June 1991), the ECV-SM product was generated using the SSM/I Ku-band (19.3 GHz) data alone, which was strongly attenuated by the vegetation canopy; and it then led to large masked areas with moderate to dense vegetation, such as northeast and southern China (Fig. 2b). The introduction of the ERS AMI *C* band (5.3 GHz) scatterometer during the subsequent period (1 July 1991–31 December 1997) was able to partly fill these gaps (Fig. 2c), e.g. a clear increase of the number of observations over southern China. With the introduction of the high quality AMSR-E *C* band (6.9 GHz) data in July 2002, a large increase of the observation density can be found over most areas of China, except the Tibetan Plateau (Fig. 2e). As a result of the unavailability of the AMSR-E data in October 2011, the observation density decreased over large parts of northwest China and Inner Mongolia, which are mainly arid or semiarid areas, despite the inclusion of the high quality WindSat data for this period (Fig. 2g). In addition, the introduction of the AMSR2 product clearly increases the fractions of valid observations over most areas of China, except central and southern China (Fig. 2h).

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3.2 Evaluation using in situ data

Figure 3 presents the biases and RMSDs of the ECV-SM product and CLM4.5 simulation with in situ measurements, in which their values are ranked using the same intervals. The data gaps for the ECV-SM product (Fig. 2) lead to only 301 stations available; about 54 % of the stations (139) have negative biases (Fig. 3a), with a mean of −0.01 (SD is ±0.065) $m^3 m^{-3}$ (Table 2), suggesting a slight underestimation. For the CLM4.5 simulation, there are 241 stations (78 % of total) with positive values (Fig. 3b) and the average bias at all sites is 0.05 (±0.074) $m^3 m^{-3}$, which indicates a clear tendency to overestimate soil moisture. The ECV-SM product shows an improved RMSD, of which about 85 % (257) of the stations have a value less than 0.01 $m^3 m^{-3}$ (Fig. 3c), compared to 65 % using the CLM4.5 simulation (Fig. 3d). Table 2 shows that averaged RMSD values are 0.075 and 0.09 $m^3 m^{-3}$ for the ECV-SM and CLM4.5, respectively, which suggests that the ECV-SM product is closer to in situ measurements in China than the CLM4.5 simulation.

For the ECV-SM product, over 68 % of the stations have correlation values between 0.2 and 0.6 (Fig. 4a), with a mean of 0.35 (± 0.02; Table 2). In contrast, the CLM4.5 simulation has superior skill in capturing surface soil moisture temporal variability (averaged R value is 0.49, Table 2); about 31 % of the stations have R values greater than 0.6 (orange and blue circles, Fig. 4b) but only 10 % for the ECV-SM (Fig. 4a). When only the configurations associated to significant correlation values ($p = 0.05$) are considered, averaged R values of the ECV-SM and CLM4.5 are 0.41 and 0.52, respectively. Since the centered normalized RMS difference (E) is a comprehensive statistical metric of the R and SDV (Eq. 6) and can quantify errors in the pattern variations, it is also presented in Fig. 4 (bottom) to illustrate the statistics of the comparison between the ECV-SM, CLM4.5 and in situ measurements. Most of the stations (71 %) for the CLM4.5 (Fig. 4d) have E values less than 1.0 (orange and blue circles) and only 36 % for the ECV-SM (Fig. 4c); and their mean values are 0.93 and 1.13, respectively. These comparisons suggest that, compared to the ECV-SM, the CLM4.5 shows superior soil moisture temporal dynamics; however, it has a large systematic bias.

3.3 Performances over eight sub-regions

To evaluate the performance of the satellite-based product and process-based model simulation over eight sub-regions of China (Table 1 and Fig. 1), their statistical metrics with in situ measurements are presented in Fig. 5. It should be noted that we first generated the time series of soil moisture by averaging available observations at all stations of each region, only considering those grid cells closest to the relevant observation stations for the ECV-SM product and CLM4.5 simulation; and then used them to calculate their statistical performances. Over most regions, the ECV-SM product underestimates soil moisture (negative values) except for southwest China (China VII and VIII, Fig. 5a). Conversely, the CLM4.5 simulation shows clearly positive biases over all sub-regions except for China VI and VIII, which suggests a systematic overestimation for model simulation. Larger RMSDs for the CLM4.5 can be observed in eastern China (China I–IV), which may be due to the deficiencies in CLM4.5; for example, scaling of canopy interception (Lawrence et al., 2007), soil texture and model structure (Liu and Xie, 2013). The ECV-SM product shows lower RMSD values than the CLM4.5 simulation, with the exception of China VI (Fig. 5b), which is consistent with the results from Fig. 2 and Table 2. However, Fig. 5c shows that the CLM4.5 simulation correlates better with in situ data ranging from 0.51 (China VI) to 0.81 (China III), compared to the ECV-SM, which ranges from 0.34 (China VI) to 0.71 (China VIII). A negative R value of the ECV-SM for China II is also observed in Fig. 5c. This is because the ECV-SM product overestimates soil moisture over northern parts of China II while the main underestimations occur over southern parts; and the averaging at all stations of this region leads to a weak temporal variation with in situ measurements.

Figure 6 compares the annual soil moisture cycle (March–October) of the ECV-SM product and CLM4.5 simulation against in situ measurements, averaged over the eight sub-regions. Both the ECV-SM and CLM4.5 generally capture the annual cycle in most sub-regions, but soil moisture simulated by the CLM4.5 is usually wetter than the observations, showing clearly systematic overestimation over all sub-regions except for China VI and VIII. However, compared to the ECV-SM, CLM4.5 correlates better with the observations. The ECV-SM is drier than the observations in spring over most parts of China, except China VIII.

3.4 Comparison of the anomaly time series

The results presented above are based on comparisons of the multi-year observation dataset and the ECV-SM or CLM4.5 datasets on a monthly timescale, which may be somewhat affected by the seasonal cycle of soil moisture. The time series of the soil moisture anomaly from the three datasets (ECV-SM, CLM4.5, and in situ observations) for the eight sub-regions (Table 1), computed by removing the multi-year annual cycle (only March–October available), are presented in Fig. 7. In general, both the ECV-SM product and the CLM4.5 simulation capture the temporal evolution of the observed soil moisture anomalies reasonably well for most of the regions. However, the ECV-SM product (red line) slightly overestimates the amplitude of fluctuations over China I, VII, and VIII. In contrast, CLM4.5 simulation tends to reproduce the temporal variation of surface soil moisture anomalies better because it is sensitive to precipitation (Gao and Dirmeyer, 2006; Liu and Xie, 2013). The precipitation data in the ITP atmospheric forcing data were generated by merging ground-based observations and two satellite retrieval products (Chen et al., 2011). Due to strong attenuation by the vegetation canopy on the microwave retrievals, the soil moisture anomalies of the ECV-SM product tends to be considerably stronger than in situ observations and generates spurious temporal variations over northeast (China I) and southwest China (China VII and VIII). These areas are mainly covered with moderate to dense vegetation, including mixed evergreen coniferous and broadleaf deciduous forests, and broadleaf deciduous forest. Table 3 presents the RMSDs of soil moisture anomalies, henceforth termed the unbiased root mean square difference (ubRMSD; Albergel et al., 2013b), for the ECV-SM and CLM4.5 over eight sub-regions. Unlike the RMSD, the ubRMSD corrects

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the biases in the mean. From Table 3, it is clear that the CLM4.5 has lower ubRMSD values over all eight sub-regions than the ECV-SM, which suggests that the CLM4.5 simulation is closer to in situ observations than the ECV-SM product after removing their systematic biases.

As a further quantitative illustration of the effects of seasonal cycle on the evaluation results, Fig. 8 shows two Taylor diagrams for the original and anomaly data comparing the two datasets with in situ measurements over the eight sub-regions. In general, the seasonal cycle in soil moisture has a large effect on the comparison of R values over China VI and VIII for both the ECV-SM and CLM4.5. It is also clear that both the ECV-SM and CLM4.5 have very weak correlations with in situ data over the China VI sub-region. This is consistent with the result from Fig. 4, which showed that the R values at most stations within this area are relatively low, being less than 0.4 for the CLM4.5 simulation (Fig. 4b) and less than 0.2 for the ECV-SM product. In some cases there were even some negative R values (Fig. 4a). However, both the ECV-SM product and CLM4.5 simulation show good agreement, with ubRMSD = $0.01\,\mathrm{m^3\,m^{-3}}$ and $R = 0.5$. In situ observations are from agricultural meteorological stations while the China VI sub-region is mainly covered by bare soil or sparse vegetation for the ECV-SM product and CLM4.5 simulation. The mismatch in surface types suggests that many sites over this region may not be representative of the coarse satellite footprint or model grid. In addition, the low observation intensity of the ECV-SM (Fig. 2) over this region may also contribute to its lower correlation.

3.5 Evolution of the ECV-SM over time

Since different products to generate the ECV-SM dataset vary over space and time, the microwave observation channels and sampling densities are expected to affect the quality for different periods (Liu et al., 2012; Albergel et al., 2013a). Figure 9 presents the averaged RMSDs and correlation coefficients of the ECV-SM product for the five individual time periods defined in Sect. 2.4. Due to limited time length and sparse sample for the last two blended periods (blends 7 and 8), they were combined into one

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period. Considering the sites which have significant R values ($p = 0.05$) for all periods (red), averaged correlations range from 0.46 to 0.69 while RMSD values from 0.068 to 0.074 $m^3 m^{-3}$. A similar pattern is obtained when considering the sites for which the correlation is significant for each blended period with averaged R values ranging from 0.54 to 0.91.

For the fourth period (January 1998–June 2002), a higher correlation is observed (Fig. 9b) compared to the previous period (January 1993–December 1997), which may be related to the introduction of the circular non-polar orbiting TMI data in 1998 (Doirgo et al., 2014). In July 2002, a high quality soil moisture dataset from C band AMSR-E retrievals was introduced instead of the SSM/I and TMI, which increased the correlations of the ECV-SM with in situ measurements and reduced its RMSD values for the fifth period (July 2002–December 2006). This is consistent with the results of the comparison between the ECV-SM and the ERA-Land, an update of the land surface component of the ERA-Interim reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF) (Albergel et al., 2013a), and in situ measurements from other soil moisture networks (Dorigo et al., 2014). Unexpectedly, we see a drop in quality for the sixth period (January 2007–September 2007), with weaker correlations and higher RMSD, also found by Dorigo et al. (2014). This may be because a new active input product from ASCAT (Dorigo et al., 2014) expanded the ECV-SM data (increasing observation intensity) in areas that are less favorable to soil moisture, such as central and north China (Fig. 2f). The best performance for all metrics was obtained for the last two periods (October 2011 2011–December 2012), which is expected, given the higher quality satellite instrumentation and improved retrieval algorithms. However, the shorter length of time within the two periods may have a slight effect on the statistical metrics and therefore more in situ measurements would be needed to confirm our results.

4 Discussion

During the past twenty years, huge efforts have been made to make more in situ soil moisture observations available in China. These measurements are important for the evaluation of both remotely sensed and modeled soil moisture. In this study, we evaluated the performances of the ECV-SM and CLM4.5 in China using 20 years of in situ observations from more than 300 sites. However, some limitations to the evaluation should be noted. The spatial representativity, temporal mismatch, instrumental errors, and installation depth of in situ observations may lead to a negative effect on the evaluation results. Such limitations have been extensively reported in previous studies (Brocca et al., 2010; Crow et al., 2012). Therefore, future work is expected to reduce these uncertainties through the enhancement of ground-based measurements and the improvement of the evaluation strategy.

Land surface models can capture the temporal dynamics of soil moisture well when forced with high quality atmospheric forcing data (Albergel et al., 2010, 2012) and are usually used to upscale in situ surface soil moisture observations or complete the evaluation of satellite derived products (Albergel et al., 2013a). In this study, the CLM4.5 was forced by an atmospheric forcing data generated using lots of ground-based observations and showed better correlation with in situ observations than the ECV-SM. However, there are still many unrealistic representations in model parameterizations (soil water and temperature, for example) and large uncertainties in land surface datasets (such as soil texture and PFTs), which will affect its accuracy in soil moisture simulation. An example of this is the high RMSDs found in eastern China between the observations and the CLM4.5 (Fig. 5). To improve soil moisture estimations, many studies incorporated remotely sensed brightness temperatures (Jia et al., 2013) or soil moisture retrievals (Draper et al., 2012) into land surface models using various modern data assimilation systems. However, data assimilation is beyond the scope of the present study. Nonetheless, our study provides an in-depth evaluation of both the ECV-SM product and CLM4.5 simulations in China including

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their performances over different sub-regions. This is expected to be useful for the assimilation of the ECV-SM into land surface models, especially the CLM4.5, since the observation and model errors have been estimated approximately.

For the ECV-SM product, only soil moisture retrievals acquired by night time overpasses (occurring between 19:00 and 08:00 LT) were used (Liu et al., 2012) since all input products had varying local observation times (Dorigo et al., 2014). However, the original in situ soil moisture observations are available every 10 days (three times each month) and the time step of CLM4.5 is 30 min. To reduce the effect caused by the mismatch in actual observation or model time, we compared the three datasets at a coarser time scale using their monthly values, similarly to previous studies (Li et al., 2005; Wang and Zeng, 2011; Liu and Xie, 2013). It should be noted that the effect of temporal mismatch among different soil moisture datasets is not considered in this study.

5 Conclusion

In this study, the performances of a microwave-based merging satellite product (ECV-SM) and the CLM4.5 simulation in China were investigated using 20 years of in situ observations from 308 stations. In general, both two soil moisture products show a good agreement with observations. The ECV-SM product has a lower bias, with RMSD = 0.075 $m^3 m^{-3}$ but with weak correlations ($R = 0.41$). In contrast, the CLM4.5 simulation produces better temporal variation of surface soil moisture ($R = 0.52$), but shows clear overestimation (bias = 0.05 $m^3 m^{-3}$) and larger RMSD values (0.09 $m^3 m^{-3}$).

Both the satellite product and model simulation show large discrepancies over eight sub-regions in China. The CLM4.5 simulation is mainly affected by the accuracy of precipitation and land surface datasets; for example, larger RMSDs in eastern China caused by inaccurate description of soil characteristics (Liu and Xie, 2013). The performance of the ECV-SM product is likely to be best in semi-arid regions (China III and V), mainly because of accurate retrievals and high observation density (Albergel et al., 2013a), and worst over areas covered by dense vegetation (China IV, VII and VIII). In addition, the statistical scores of the ECV-SM product in China confirm the findings of Albergel et al. (2013a) and Dorigo et al. (2014) of a stable to slightly improving performance over time in China, with the exception of a decrease during the 2007–2010 blending period, which may be related to the incorporation of the ASCAT product.

In response to the sparse observation temporal frequency (three times each month), all analyses were performed on a monthly timescale. Future efforts are expected to make more in situ soil moisture observations available in China for the evaluation of either remote sensing retrievals or modeled simulation. Furthermore, the differences in observation timescales and spatial scales can affect the evaluation to some extent. Therefore, the definition of a more suitable measure of accuracy to characterize the quality of soil moisture data is needed in future studies (Albergel et al., 2013a). Data assimilation has been an effective tool to incorporate remotely sensed soil moisture into land surface models to improve soil moisture simulation (Draper et al., 2012). The in-depth evaluation of the ECV-SM and CLM4.5 in China in this study will be useful for its application in soil moisture data assimilation, which is expected to provide further information regarding observation and model errors.

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Table 1. Locations of the eight sub-regions in China.

Identification	Region name	Location	Number of observational stations
China I	northeast China	120–135° E, 40–50° N	62
China II	northern North China	110–120° E, 40–45° N	15
China III	southern North China	110–120° E, 34–40° N	58
China IV	central and lower Yangtze River Basin	110–122° E, 30–34° N	28
China V	eastern northwest China	95–110° E, 34–42° N	77
China VI	western northwest China	80–95° E, 34–50° N	20
China VII	northern southwest China	100–110° E, 28–34° N	22
China VIII	southern southwest China	100–110° E, 20–28° N	9

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Table 2. Averaged performance metrics and SDs of the ECV-SM and CLM4.5 over all available in situ sites (Stations: Number of stations; *N*: Number of valid measurements; Bias: EVC-SM or CLM4.5 minus measurements; RMSD: root mean square difference; *R*: correlation coefficient; *E*: centered normalized root mean square difference).

	ECV-SM	CLM4.5
Stations	301	308
N	37 373	38 957
BIAS ($m^3 m^{-3}$)	-0.010 ± 0.065	0.050 ± 0.074
RMSD ($m^3 m^{-3}$)	0.075 ± 0.034	0.090 ± 0.041
R	$0.35 \pm 0.20^*$ (0.41 ± 0.15)	0.49 ± 0.19 (0.52 ± 0.15)
E	1.13 ± 0.32	0.93 ± 0.20

* The correlation coefficients in the brackets represent the average values from the sites with significant correlations ($p = 0.05$).

Table 3. The root mean square differences of soil moisture anomalies for the ECV-SM and CLM4.5 against in situ measurements over eight sub-regions (Table 1). Unit is $m^3 m^{-3}$.

	ECV-SM	CLM4.5
China I	0.020	0.015
China II	0.032	0.019
China III	0.018	0.011
China IV	0.027	0.017
China V	0.013	0.012
China VI	0.020	0.019
China VII	0.032	0.018
China VIII	0.031	0.022

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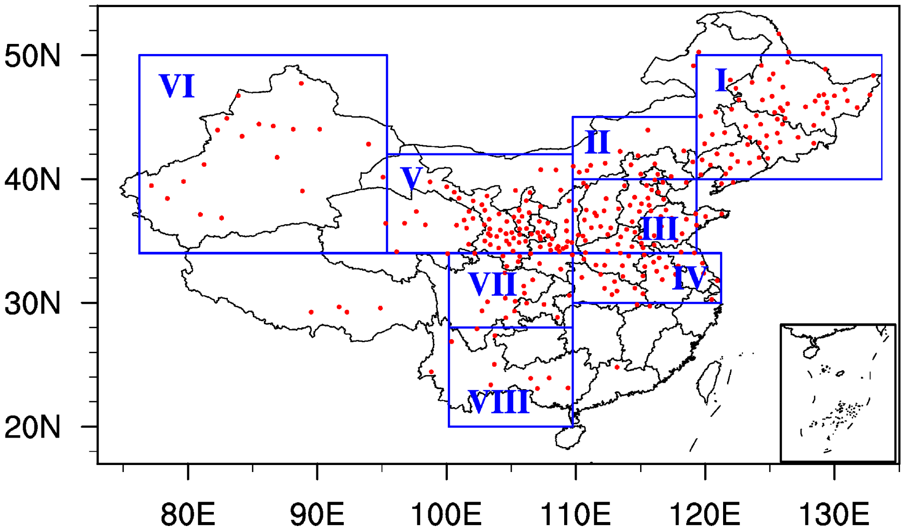

Figure 1. Locations of the 308 in situ soil moisture measurement sites (red dots). Also shown (blue boxes) are the eight sub-regions defined in Table 1.

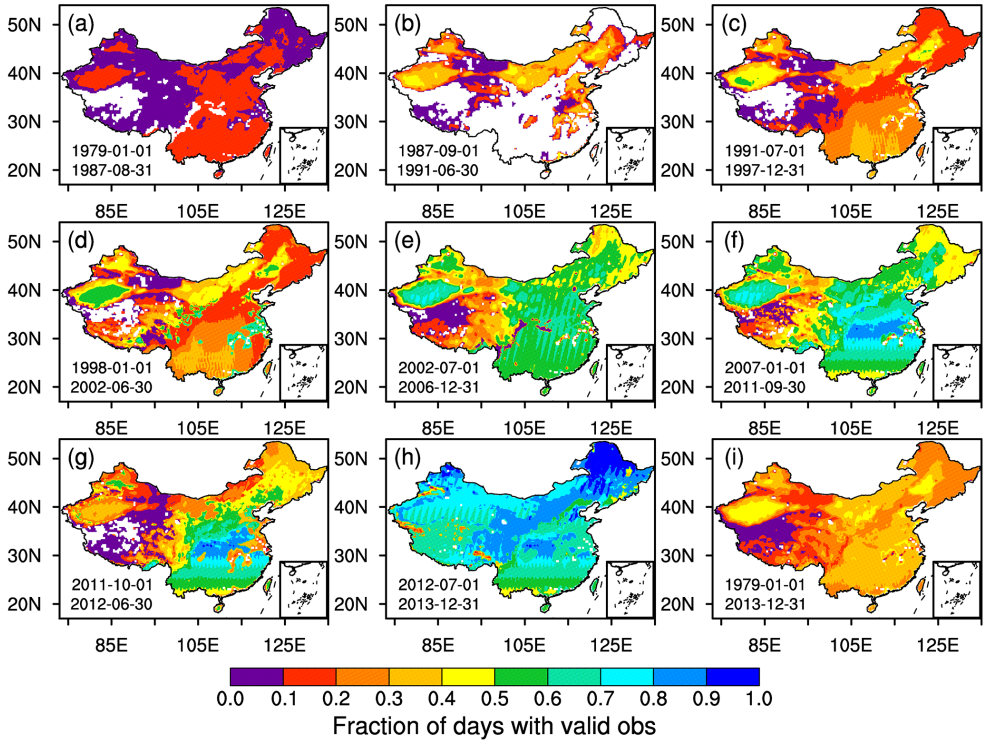

Figure 2. Fraction of days with valid observations, expressed as the number of days with observations divided by the total number days per period, split up according to six different merging periods: **(a)** 1 January 1979–31 August 1987, **(b)** 1 September 1987–30 June 1991, **(c)** 1 July 1991–31 December 1997, **(d)** 1 January 1998–30 June 2002, **(e)** 1 July 2002–31 December 2006, **(f)** 1 January 2007–30 September 2011, **(g)** 1 October 2011–30 June 2012, **(h)** 1 July 2012–31 December 2013; and **(i)** for the total period 1 January 1979–31 December 2013.

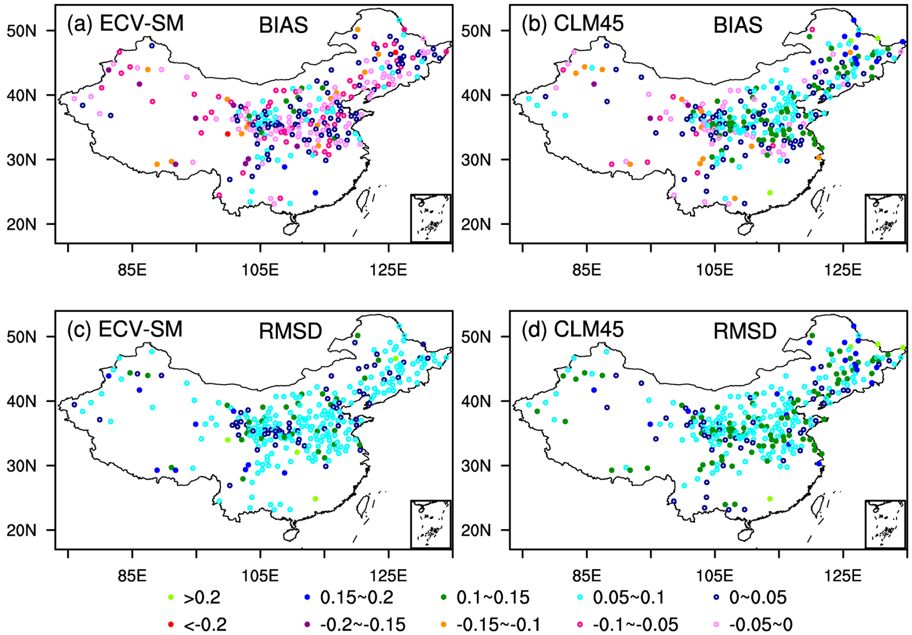

Figure 3. The biases (top, the EVC-SM or CLM4.5 minus in situ measurements) and root mean square differences (RMSDs, bottom) between the ECV-SM product or CLM4.5 simulation and ground-based measurements from 1993 to 2012 at 308 sites in China.

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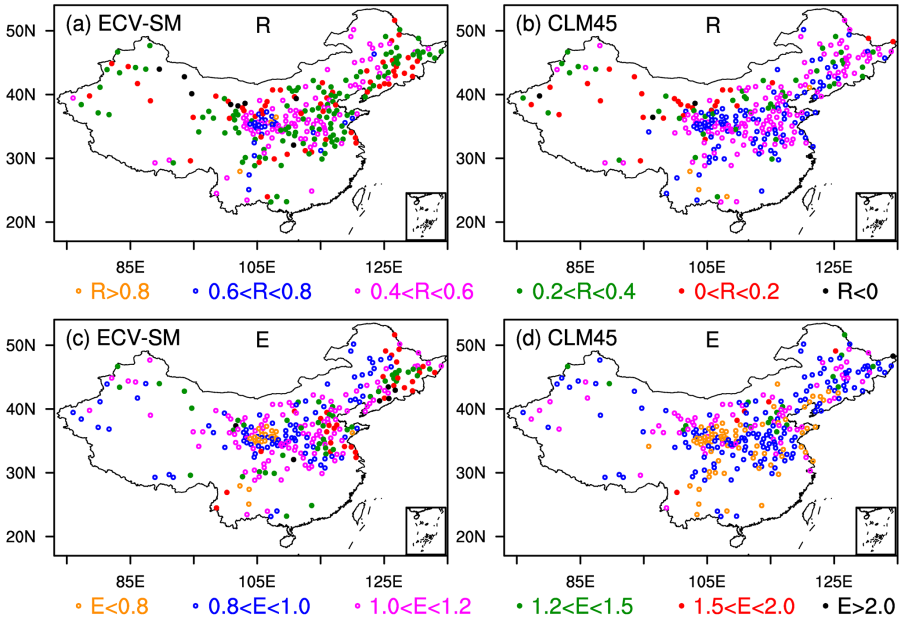

Figure 4. The same as Fig. 4 but for the correlation coefficients R (top) and the centered normalized root mean square difference E (bottom).

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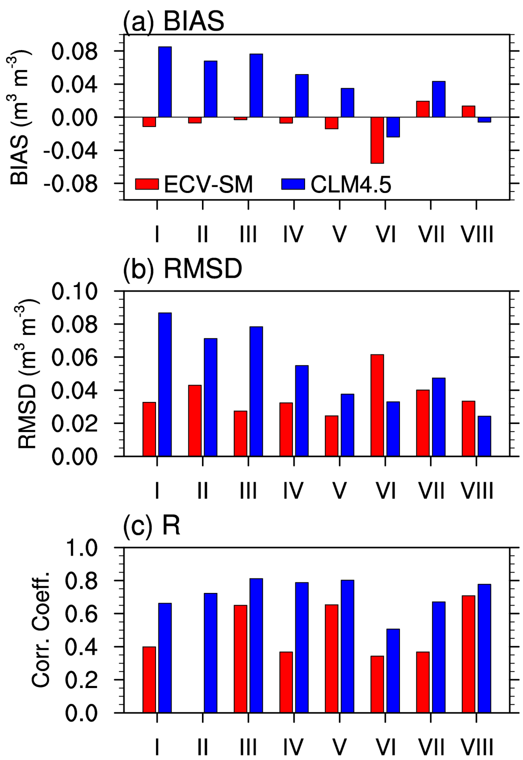

Figure 5. Statistical scores for the ECV-SM product and CLM4.5 simulation between 1993 and 2012 in the eight sub-regions of China defined in Table 1: **(a)** BIAS; **(b)** RMSD; **(c)** correlation coefficients (*R*).

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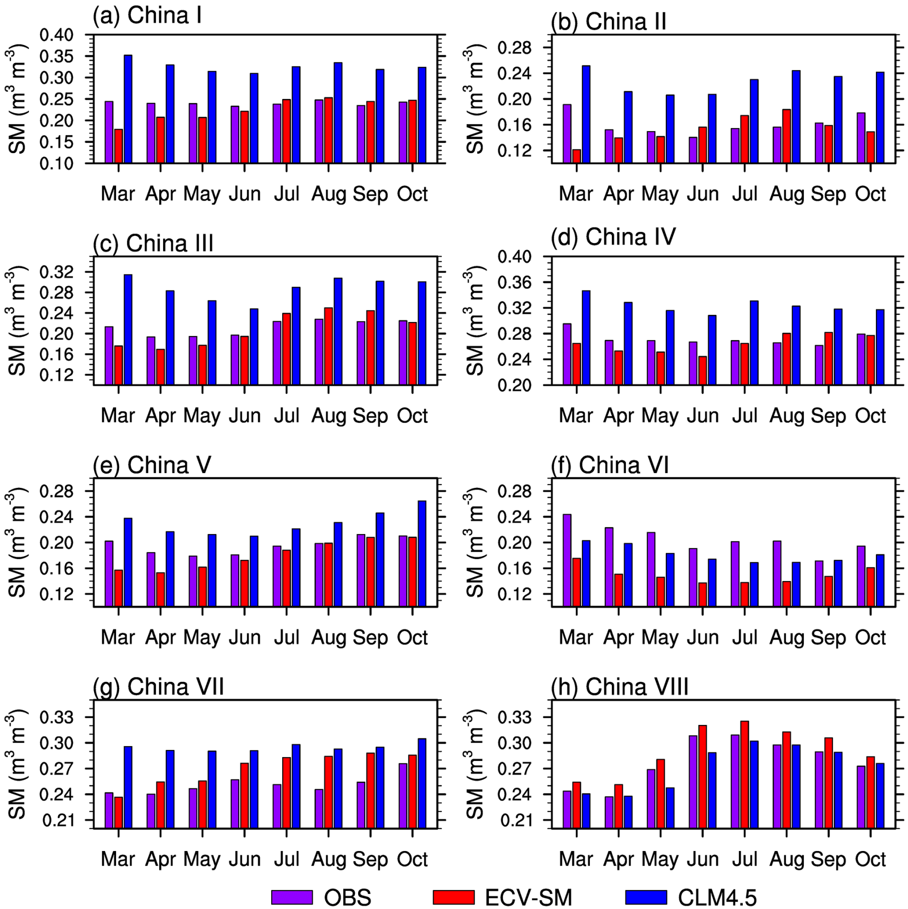

Figure 6. Multi-year (1993–2012) mean monthly volumetric soil moisture (SM, m^3 m^{-3}) for the period between March and October from in situ observations, ECV-SM product and CLM4.5 simulation in the eight sub-regions of China defined in Table 1.

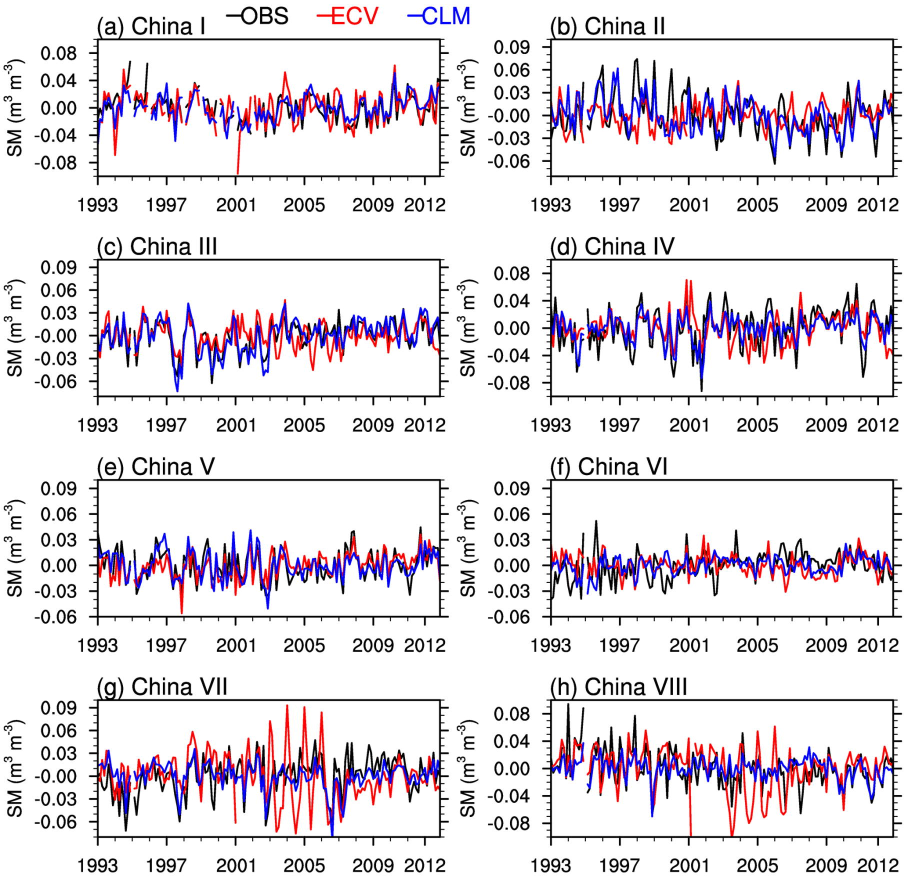

Figure 7. Comparison of the anomaly time series of monthly soil moisture derived from the ECV-SM product, CLM4.5 simulation and in situ observations between 1993 and 2012 for the eight sub-regions of China (Table 1).

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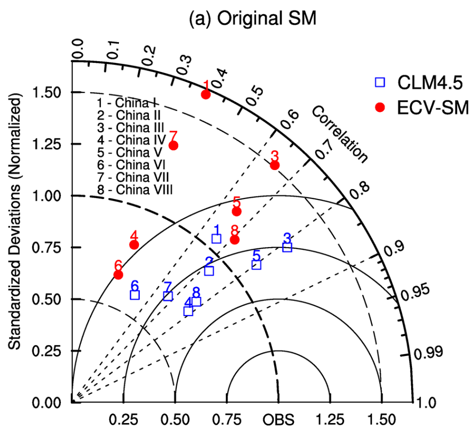

Figure 8. Taylor diagram summarizing the comparison results of **(a)** the original soil moisture values and **(b)** soil moisture anomalies between the ECV-SM, CLM4.5 and in situ measurements in the eight sub-regions of China defined in Table 1 between 1993 and 2012.

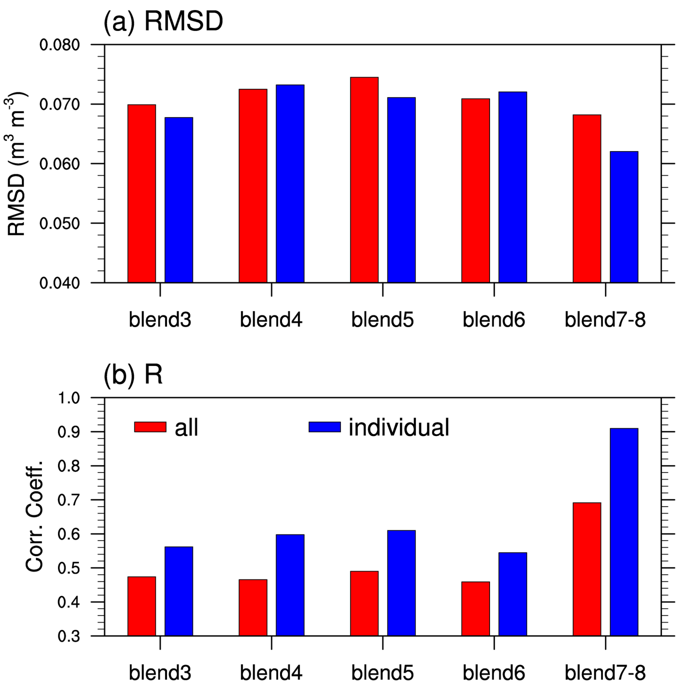

Figure 9. Averaged correlation coefficients of the ECV-SM product with in situ data for the five blended periods defined in Sect. 2.2. Red bars represent the sites with significant R values ($p = 0.05$) for all periods (1993–2012) while blue bars consider sites with significant R values ($p = 0.05$) for each blended period.

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