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Intercomparison of microwave remote-sensing soil moisture data sets based on distributed eco-hydrological model simulation and in situ measurements over the North China Plain

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Intercomparisons of microwave-based soil moisture products from active ASCAT (Advanced Scatterometer) and passive AMSR-E (Advanced Microwave Scanning Radiometer for the Earth Observing System) is conducted based on surface soil moisture (SSM) simulations from the eco-hydrological model, Vegetation Interface Processes (VIP), after it is carefully validated with in situ measurements over the North China Plain. Correlations with VIP SSM simulation are generally satisfactory with average values of 0.71 for ASCAT and 0.47 for AMSR-E during 2007–2009. ASCAT and AMSR-E present unbiased errors of 0.044 and 0.053 m$^3$m$^{-3}$ on average, with respect to model simulation. The empirical orthogonal functions (EOF) analysis results illustrate that AMSR-E provides more consistent SSM spatial structure with VIP than ASCAT; while ASCAT is more capable of capturing SSM temporal dynamics. This is supported by the facts that ASCAT has more consistent expansion coefficients corresponding to primary EOF mode with VIP ($R = 0.825, p < 0.1$). However, comparison based on SSM anomaly demonstrates that AMSR-E and ASCAT have similar skill in capturing SSM short-term variability. Temporal analysis of SSM anomaly time series shows that AMSR-E provides best performance in autumn, while ASCAT provides lower anomaly bias during highly-vegetated summer with vegetation optical depth of 0.61. Moreover, ASCAT retrieval accuracy is less influenced by vegetation cover, as it is in relatively better agreement with VIP simulation in forest than in other land-use types and exhibits smaller interannual fluctuation than AMSR-E. Identification of the error characteristics of these two microwave soil moisture data sets will be helpful for correctly interpreting the data products and also facilitate optimal specification of the error matrix in data assimilation at a regional scale.

1. Introduction

As a crucial component in the hydrological cycle, soil moisture plays an important role in governing the water and energy balance between land surface and atmosphere. Soil

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moisture has considerable influence on the partitioning of precipitation between runoff and infiltration, as well as the partitioning of incoming radiation between latent and sensible heat fluxes; the quantities of soil moisture in the root zone also influence vegetation growth and restoration in semiarid environments (Western et al. 2002; Ahmad, Kalra, and Stephen 2010). Therefore, the spatio-temporal pattern of soil moisture is of great importance to many applications such as crop yield estimation (Jaynes, Colvin, and James 2003; Green and Erskine 2004), geological disaster prediction, e.g. landslide susceptibility mapping (Ray et al. 2010), and early warning of drought and flood (Brocca et al. 2010; Koster et al. 2010).

Diverse sources of data depicting soil wetness conditions at various scales are available to explore the spatio-temporal patterns of soil moisture. In situ observations, as the most direct way of obtaining soil moisture, can be interpreted as ‘ground truth’ within a certain spatial scope. However, spatial estimation of soil moisture acquired by this method is challenged by lack of extensive in situ observation network, short coverage of observation period, and representative sampling (Seneviratne et al. 2010; Brocca et al. 2011). Recently, the accessibility to global in situ soil moisture observations has improved, e.g. through the International Soil Moisture Network (Dorigo et al. 2011) website available at: http://www.ipf.tuwien.ac.at/insitu/. Nevertheless, data coverage is very limited in most parts of the world.

Physical modelling of soil–vegetation–atmosphere transfer (SVAT) processes is another approach to retrieve information on soil moisture dynamics (Eitzinger et al. 2004; Vano et al. 2006; Ju et al. 2010). Systematic investigations have revealed that inter-model variability of estimated soil moisture is partly determined by different land-surface parameterization schemes (Liang and Guo 2003). In fact, under the framework of PILPS (Project for Intercomparison of Land-surface Parameterization Schemes) (Henderson-Sellers, Yang, and Dickinson 1993) and GSWP (Global Soil Wetness Project) (Dirmeyer et al. 2006), it has been confirmed that SVAT models are capable of reproducing soil moisture seasonal cycles and interannual variations, yet absolute quantities of modelled soil moisture vary greatly among models. Moreover, the accuracy of SVAT models is further constrained by the large horizontal and vertical heterogeneity of soil properties that are not readily observable (Hain et al. 2011). All these factors have given rise to remarkable uncertainty in the predicted soil moisture by SVAT models.

Spaceborne remote sensors are able to provide quantitative information about the water content of a shallow near-surface layer at global scale. Among them, the soil moisture retrievals from microwave instruments operating at low electromagnetic frequencies are of particular interest to hydrological communities, on account of the relatively short revisit time and the ability to retrieve through cloud cover. The reliability and application of global soil moisture products from the Advanced Scatterometer (ASCAT), Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), as well as from the Soil Moisture and Ocean Salinity mission (SMOS) and other satellites have been studied extensively (Ceballos et al. 2005; Wagner et al. 2007; Al-Jassar and Rao 2010; Jackson et al. 2010; Juglea et al. 2010; Chaurasia et al. 2011; Cheema, Bastiaanssen, and Rutten 2011; Mo et al. 2011; Su et al. 2011; Albergel et al. 2012; Choi 2012; Rebel et al. 2012). The operational microwave-based soil moisture products are derived from polarimetric radiance using different retrieval algorithms, and in some cases rely on ancillary data to estimate vegetation water content and land-surface temperature. The accuracy of the microwave-based soil moisture products varies in regions with different vegetation density, topographic effect, snow cover, radio frequency interference, etc. (Owe, de Jeu, and Holmes 2008; Sahoo et al. 2008; Draper et al. 2009; Liu et al. 2009; Rüdiger et al. 2009; Gruhier et al. 2010; Champagne et al. 2010; Liu et al. 2011). Brocca et al. (2011) reported that orographic
effects are one of the potential factors hampering the performance of AMSR-E and ASCAT observations in Europe, with obvious higher retrieval noise in those products from mountainous areas. A global investigation carried out by de Jeu et al. (2008) showed that in regions where vegetation optical depth is within the range of 0.1–0.5, AMSR-E data are in highest correlation with the other operational satellite (European Remote Sensing Satellites (ERS))-retrieved surface soil moisture (SSM). Over the continental USA and Canada, it is also shown that AMSR-E soil moisture data are more reliable in areas with less vegetation impact, based on the comparison with in situ network and land-surface model (Champagne et al. 2010; Hain et al. 2011).

Since the accuracy of soil moisture data sets are affected by the aforementioned various factors, it is crucial to quantitatively identify the product characteristics before correctly interpreting and applying them in local areas. Traditional methods for error identification have usually relied on in situ observations, and are thus constrained by sparsity of the long-term and large-scale observations. Intercomparison with model simulation can improve the knowledge of errors in space and time, and is therefore of great value to soil moisture applications such as data assimilation (Balsamo et al. 2007; Champagne et al. 2010). Therefore, there have been increasing investigations focusing on the intercomparisons of microwave-based soil moisture products based on model simulation and reanalysis data sets in different hydroclimatic regions (Rüdiger et al. 2009; Albergel et al. 2010; Dorigo et al. 2010; Parrens et al. 2011).

The main objectives of this study are: (1) to integrate the eco-hydrological model, Vegetation Interface Processes (VIP), with a remotely sensed vegetation index for soil moisture monitoring in the study basin; (2) to identify the spatial-temporal characteristic of error structures from AMSR-E and ASCAT microwave remote-sensing data sets, taking the model simulation as reference; and (3) following this, to discuss the factors that underlie such error characteristics of two microwave data sets across the study basin.

2. Study area

Baiyang Lake basin is located in north China, where elevation steps down from the Taihang Mountain (approximately 2765 m a.m.s.l.) in the north-west to the piedmont alluvial plain in the southeast (Figure 1). Accordingly, grassland, shrub, and forest dominate the mountainous area, while cropland is the principal land use in the plain area. The prevailing cropping system is the rotation of winter wheat and summer maize. Soil texture mainly includes loam and sandy and clay loam. Meteorological records in the last 50 years show annual mean temperatures of 6.8–12.7°C and precipitation of 548 mm year⁻¹. The study area is about 200 km west of the Bohai Sea of China, and its climate is greatly influenced by the East Asian monsoon. The southeast monsoon leads to the rainy season (from June to August) and up to 80% of the annual precipitation in the study basin. Within Baiyang Lake basin, there are ten major sub-catchments, whose sizes range between 500 and 4420 km². The coefficient of variation for annual precipitation is approximately 20%. Extensive monitoring of soil moisture is conducted in the Chongling experimental basin (115° 21′ E, 39° 23′ N), which locates in northern Taihang mountainous region, and lies in the upper catchment of Baiyang Lake.

3. Materials and methods

3.1. Passive microwave satellite-based retrievals of AMSR-E

AMSR-E is on-board the National Aeronautics and Space Administration (NASA) Aqua platform and has provided soil moisture data since 2002. There are several versions of
AMSR-E products, which use different algorithms to solve the radiative transfer equations. Investigation on the performances of these AMSR-E products has been made by Draper et al. (2009). It is noted that the AMSR-E soil moisture data set, generated based on the Land Parameter Retrieval Model (LPRM) (Owe, de Jeu, and Holmes 2008), matches in situ soil moisture better than other AMSR-E soil moisture products in Australia. The comparatively better performance of the LPRM AMSR-E data set has also been documented in other investigations conducted around the world using both in situ observations (Wagner et al. 2007; Gruhier et al. 2010; Champagne et al. 2010) and modelled soil moisture (Crow, Miralles, and Cosh 2010; Rüdiger et al. 2009), when compared with the NSIDC AMSR-E soil moisture. In addition, the LPRM AMSR-E data set has been frequently seen in passive microwave remote-sensing applications. Therefore, in this study, we choose the LPRM AMSR-E product to conduct intercomparison. LPRM uses dual-polarized C- and X-band (6.925 and 10.65 GHz) brightness temperature for simultaneous retrieval of SSM and vegetation water content. The default retrieval band of the LPRM data set is the C-band, and it is substituted by the X-band when the signal at the C-band frequency is contaminated by radio frequency interference (RFI). In this study, we use version 5 of the product obtained from http://www.falw.vu/~jeur/lprm/. In the LPRM soil moisture data set, retrievals are screened under dense canopy (vegetation optical depth greater than 0.8). The rain flag data set along with the v5 product is also applied to screen the gridded soil moisture data in order to avoid active rain effect (7.2% of the total data are eliminated from AMSR-E product).

3.2. Active microwave satellite-based retrievals of ASCAT
ASCAT is a real aperture backscatter radar operating at the C-band (5.255 GHz), and it orbits on EUMETSAT’s Meteorological Operational (MetOp) satellite. The active
microwave-based soil moisture product used in this study is derived using the empirical change-detection approach developed at the Vienna University of Technology (TU-Wien) by Wagner, Lemoine, and Rott (1999). Time series of soil moisture based on the change-detection method permit the discrimination of scattering processes at various time scales, and thus separate the highly variable soil moisture process and seasonal vegetation patterns. The final product is the relative measure of SSM ranging from 0 (dry condition reference) to 100 (wet condition reference) obtained by scaling normalized backscatter between the historically lowest and highest values. In this study, the ASCAT product we used is the updated version based on 2 years (2007–2008) of ASCAT observations. The ASCAT soil moisture product is discussed in more detail by Bartalis et al. (2007) and Naeimi et al. (2009).

### 3.3. In situ measurements

Two sources of *in situ* soil moisture data from Chongling experimental basin and agro-meteorological network with different temporal resolutions are used in this study. In the Chongling experimental basin, soil moisture is measured by the SWR3 sensor at an accuracy of ±0.02 m$^3$ m$^{-3}$ when soil moisture is within the range of 0~0.50 m$^3$ m$^{-3}$. The sensors are installed at depths of 10, 20, 30, and 50 cm in two runoff plots, namely a Chinese pine plot and a grass plot. Each plot has two measurement sites on its upper and lower areas, and the soil moisture of each plot is taken as the mean of measurements from the two sites. The volumetric soil moisture is recorded during April to November of 2007–2009 in 1 minute steps. For each site, recorded soil moisture quality is checked to remove exceptional values due to unstable voltage. A summary of the soil physical properties within each plot is provided in Table 1.

The second source of *in situ* measurements is the more temporally sparse soil moisture measurements collected from 28 agro-meteorological stations across the study basin during

<table>
<thead>
<tr>
<th>Plot</th>
<th>Depth (cm)</th>
<th>Bulk density (g cm$^{-3}$)</th>
<th>Water content at saturation (%)</th>
<th>Field capacity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chinese pine plot</td>
<td>0–5</td>
<td>1.39</td>
<td>25.87</td>
<td>18.93</td>
</tr>
<tr>
<td></td>
<td>5–10</td>
<td>1.40</td>
<td>30.25</td>
<td>20.81</td>
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<tr>
<td></td>
<td>10–15</td>
<td>1.31</td>
<td>33.69</td>
<td>27.50</td>
</tr>
<tr>
<td></td>
<td>15–20</td>
<td>1.32</td>
<td>32.22</td>
<td>25.36</td>
</tr>
<tr>
<td></td>
<td>20–25</td>
<td>1.38</td>
<td>30.68</td>
<td>24.32</td>
</tr>
<tr>
<td></td>
<td>30–35</td>
<td>1.47</td>
<td>23.30</td>
<td>20.12</td>
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<td></td>
<td>40–45</td>
<td>1.66</td>
<td>24.37</td>
<td>21.55</td>
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<tr>
<td></td>
<td>50–55</td>
<td>1.82</td>
<td>26.71</td>
<td>24.41</td>
</tr>
<tr>
<td></td>
<td>60–65</td>
<td>1.84</td>
<td>21.08</td>
<td>19.16</td>
</tr>
<tr>
<td>Grass plot</td>
<td>0–5</td>
<td>1.09</td>
<td>44.53</td>
<td>30.11</td>
</tr>
<tr>
<td></td>
<td>5–10</td>
<td>1.26</td>
<td>44.83</td>
<td>30.75</td>
</tr>
<tr>
<td></td>
<td>10–15</td>
<td>1.33</td>
<td>33.01</td>
<td>22.99</td>
</tr>
<tr>
<td></td>
<td>20–25</td>
<td>1.36</td>
<td>28.79</td>
<td>21.01</td>
</tr>
<tr>
<td></td>
<td>30–35</td>
<td>1.43</td>
<td>30.58</td>
<td>23.02</td>
</tr>
<tr>
<td></td>
<td>40–45</td>
<td>1.49</td>
<td>25.66</td>
<td>23.50</td>
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<td>50–55</td>
<td>1.45</td>
<td>26.22</td>
<td>21.16</td>
</tr>
<tr>
<td></td>
<td>60–65</td>
<td>1.53</td>
<td>20.12</td>
<td>15.88</td>
</tr>
</tbody>
</table>
2002–2009. For the purpose of monitoring the soil water stress in the cropland, measurements are taken on 8th, 18th, and 28th days of each month, at depths of 10, 20, 30, 50, 70, and 100 cm. Soil moisture is measured by the gravimetric method and recorded as a relative ratio to the field capacity (http://cdc.cma.gov.cn/).

3.4. VIP model simulation

The process-based eco-hydrological model VIP is used to simulate the soil water movement in Baiyang Lake basin.

3.4.1. VIP model structure

The VIP model simulates water, energy, and CO₂ transfer processes by coupling (1) an improved multi-layer canopy radiative transfer submodel; (2) a new canopy conductance/photosynthesis submodel that distinguishes sunlit and shaded leaves; (3) a two-source soil–canopy energy balance submodel; and (4) a multi-layer soil water and heat transfer submodel (Mo and Liu 2001). VIP has been validated and applied extensively in North China regions (Mo and Liu 2001; Mo et al. 2004, 2005; Liu et al. 2009; Mo, Liu, and Lin 2012). Details about the model can be referred to Mo and Liu (2001) and Mo et al. (2004, 2005). Here, the scheme for soil moisture estimation is briefly introduced.

In the model, soil water movement is simulated with the discrete Richards equation in a three-layer scheme (2, 100, and 60 cm) in which plant roots only take up water from the second layer. The governing equations are expressed as follows:

\[
\frac{\partial \theta_i}{\partial t} = \frac{1}{L_i} (P' - Q_{i,i+1} - E_s),
\]

\[
\frac{\partial \theta_2}{\partial t} = \frac{1}{L_2} (Q_{12} - Q_{23} - E_c),
\]

\[
\frac{\partial \theta_3}{\partial t} = \frac{1}{L_3} (Q_{23} - Q_3),
\]

where \( \theta_i \) (\( i = 1, 2, 3 \)) is the soil moisture in the \( i \)th soil layer with thickness \( L_i \); \( P' \) is the residual amount of precipitation minus canopy interception and overland runoff. \( E_s \) and \( E_c \) are soil evaporation and canopy transpiration, respectively. \( Q_{i,i+1} \) is the flow between the \( i \) and \( i+1 \) layers, \( Q_3 \) is the gravitational drainage from the bottom layer. Fluxes \( Q_{i,i+1} \) and \( Q_3 \) are estimated according to Darcy’s law following Sellers et al. (1986).

\( E_s, E_c, \) and canopy intercepted evaporation, \( E_i \), which constitute the total above-canopy evapotranspiration (\( ET \)), are expressed in forms similar to the Penman–Monteith equation.

3.4.2. VIP model input

The climatic data, which include daily maximum and minimum air temperature, humidity, wind speed, and sunshine duration, were collected from eight stations in and around Baiyang Lake basin to drive the VIP model (http://cdc.cma.gov.cn/). Precipitation data were obtained from 149 rain-gauge stations of Baiyang Lake basin from the hydrological yearbook. All of these daily observations were interpolated to the whole basin using the inverse distance square method.
The land-surface characterization information required for model input can be categorized as topography, soil texture, land use, and vegetation type/density. Topography information was obtained from the digital elevation model from the topographic contour map at 1:250,000 scale. The soil property database, which consists of fractions of sand, silt, and clay, was used to determine the soil hydraulic parameters, and the database was established based on the second national soil survey taken during the 1980s at 1:1,000,000 scales. Land-use information was obtained from TM images in 2000, at the scale of 1:100,000 (http://www.resdc.cn/). The dynamics of vegetation were retrieved from Terra MODIS (Moderate Resolution Imaging Spectroradiometer) 16-day composite NDVI (normalized difference vegetation index) with 1 km resolution (http://modis.gsfc.nasa.gov). The NDVI time series had been smoothed by a Savitzky-Golay (S-G) filter for noise reduction (to remove deviations from the vegetation cycle) (Savitzky and Golay 1964; Chen et al. 2004).

The VIP model was run from year 2002–2009 to simulate profile soil moisture at hourly time steps, with one year spin-up. The irrigation amount per hectare was determined by the provincial-level records of annual irrigation consumption and effective irrigation area from the Rural Statistical Annual of Hebei Province from 2002–2009. Temporal distribution of irrigation was assumed to be evenly assigned among seedling, recovering, heading, and maturity stages of winter wheat, as well as seedling stage of summer maize (50 mm for each stage), if soil water content at these critical growth stages was below 60% of the field capacity. For simulation of soil moisture at Chongling experimental site, the VIP model used the measured soil parameters presented in Table 1 and the MODIS NDVI data extracted from the pixel nearest to measurement sites.

### 3.5. Data preprocessing and metrics used

In order to exclude all of the measurements affected by snow or frost from the analysis, we employed the MODIS daily global snow cover map (MOD10C1) (http://modis-snow-ice.gsfc.nasa.gov/), and masked the grids with mean snow cover fraction greater than 50% (1.46% and 0.83% of total data are eliminated from AMSR-E and ASCAT products). Additionally, for the purpose of removing the systematic bias from the satellite remote-sensing data, both the AMSR-E and ASCAT data sets ($\theta_{RS}$) were linearly rescaled to the VIP range (Liu et al. 2009):

$$\theta_{rescaled} = \frac{\theta_{RS} - \min(\theta_{RS})}{\text{range}(\theta_{RS})} \text{range}(\theta_{VIP}) + \min(\theta_{VIP}).$$

For the purpose of capturing the short-term variability of SSM, anomalies were calculated relative to seasonally varying soil moisture climatology by using a sliding window of 5 weeks (if there were at least five measurements during this period), and the difference was scaled to the standard deviation (Albergel et al. 2009). For each SSM estimate at day ($i$), a period $F$ was defined, with $F = [i-17, i + 17]$ corresponding to the 5 week window. The anomaly $\theta$ is dimensionless and is given by

$$\theta(i) = \frac{\text{SSM}(i) - \text{SSM}(F)}{\text{stdev}(\text{SSM}(F))}.$$  

Equation (5) is used to compute SSM anomalies for VIP and in situ observations in Section 4.1, and also for AMSR-E, ASCAT in Sections 4.3 and 4.4.
Performance metrics in this study include the Pearson correlation coefficient ($R$) and unbiased root mean square error (ubRMSE) (Dara Entekhabi et al. 2010):

$$ubRMSE = \sqrt{\left( (\theta_{RS} - \theta_{RS}) - (\theta_{VIP} - \theta_{VIP}) \right)^2},$$  \hspace{1cm} (6)

$$R = \frac{(\theta_{RS} - \theta_{RS}) - (\theta_{VIP} - \theta_{VIP})}{\sigma_{RS} \cdot \sigma_{VIP}},$$  \hspace{1cm} (7)

Normalized by the standard deviations of reference VIP, the standard deviation and the ubRMSE of remote-sensing data are written as NSDV and NubRMSE, respectively. The three complementary statistics $R$, NSDV and NubRMSE are presented on two-dimensional plots of Taylor diagrams (Taylor 2001), as, for example, recently used by Albergel et al. (2012). The NSDV is displayed as a radial distance and the $R$ as an angle in the polar plot. VIP simulations are represented by a point located on the x-axis at $R = 1$ and NSDV = 1. The distance to this point represents the NubRMSE of remote-sensing data.

### 3.6. EOF method

The empirical orthogonal functions (EOF) method is employed to compare the space–time variability of VIP SSM simulation and remote-sensing data. EOF analysis determines a set of time-invariant orthogonal spatial patterns (EOFs) and temporal varying expansion coefficients (ECs, in some literature, also called principal components), in order to characterize the variability of time series for a set of sampling location measurements. Each EC has an associated spatial pattern (EOF) that represents the projections of the original data onto the transformed axes (Jawson and Niemann 2007). One advantage of using the EOF method is the ability to identify and quantify the spatial structures of the correlated variability (Mu, Jackson, and Stoffa 2004), and it has been applied in comparison of different data sets (Crossley et al. 2012; Liu et al. 2012).

### 4. Results

#### 4.1. Validation of VIP simulation with in situ measurements

The validation results of VIP SSM simulation against 10 cm in situ measurements from agro-meteorological stations are presented in Table 2. Averaged over all of the stations, the Pearson correlation coefficient between VIP SSM simulation and 10 cm in situ measurements ranged between 0.48 and 0.70 (significant at $p < 0.01$), and ubRMSE was in the range of 0.032–0.054 m$^3$ m$^{-3}$ during 2002–2009.

The VIP SSM also shows good agreement with high temporal resolution in situ measurements from the Chongling experimental site, as can be seen from the temporal evolution of the two data sets, both of which correspond rapidly to rainfall stimulation (Figure 2). The Pearson correlation coefficient between model prediction and in situ sensor measurements during 2007–2009 were 0.78 and 0.74 for grass and Chinese pine plot, respectively, with similar ubRMSE in both plots (0.030 and 0.025 m$^3$ m$^{-3}$). The short-term scale SSM variations were also examined by computing the anomaly from the 35-day sampling window. The correlation between the VIP SSM anomaly and the observation anomaly varied between 0.627 and 0.774 for the grass plot during 2007–2009, and the value ranged between 0.594 and 0.752 for the Chinese pine plot. The ubRMSEs for both plots...
Table 2. Validation statistic of VIP SSM against observation at 10 cm in Chongling experimental basin and agro-meteorological network.

<table>
<thead>
<tr>
<th>Year</th>
<th>Year</th>
<th>R</th>
<th>ubRMSE (m$^3$ m$^{-3}$)</th>
<th>R</th>
<th>ubRMSE (m$^3$ m$^{-3}$)</th>
<th>R</th>
<th>ubRMSE (m$^3$ m$^{-3}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>10 cm</td>
<td></td>
<td>10 cm</td>
<td></td>
<td>10 cm</td>
</tr>
<tr>
<td>2002</td>
<td></td>
<td></td>
<td>−</td>
<td>0.70</td>
<td>0.03</td>
<td>0.70</td>
<td>0.03</td>
</tr>
<tr>
<td>2003</td>
<td></td>
<td></td>
<td>−</td>
<td>0.50</td>
<td>0.04</td>
<td>0.50</td>
<td>0.04</td>
</tr>
<tr>
<td>2004</td>
<td></td>
<td></td>
<td>−</td>
<td>0.54</td>
<td>0.04</td>
<td>0.54</td>
<td>0.04</td>
</tr>
<tr>
<td>2005</td>
<td></td>
<td></td>
<td>−</td>
<td>0.48</td>
<td>0.05</td>
<td>0.48</td>
<td>0.05</td>
</tr>
<tr>
<td>2006</td>
<td></td>
<td></td>
<td>−</td>
<td>0.51</td>
<td>0.05</td>
<td>0.51</td>
<td>0.05</td>
</tr>
<tr>
<td>2007</td>
<td></td>
<td></td>
<td>0.74</td>
<td>0.03</td>
<td>0.70</td>
<td>0.03</td>
<td>0.70</td>
</tr>
<tr>
<td>2008</td>
<td></td>
<td></td>
<td>0.66</td>
<td>0.05</td>
<td>0.63</td>
<td>0.02</td>
<td>0.63</td>
</tr>
<tr>
<td>2009</td>
<td></td>
<td></td>
<td>0.81</td>
<td>0.03</td>
<td>0.82</td>
<td>0.02</td>
<td>0.82</td>
</tr>
<tr>
<td>All years</td>
<td>0.78</td>
<td>0.03</td>
<td>0.74</td>
<td>0.025</td>
<td>0.39</td>
<td>0.059</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2. The temporal evolution of precipitation, VIP SSM simulation, and observation at 10 cm depth for grass plot (left panel) and Chinese pine plot (right panel): (a), (b) 2007; (c), (d) 2008; (e), (f) 2009. (g) and (h) are scatter plots of VIP and observation in grass and Chinese pine plots, respectively.

were within the range of 0.640–0.878, which are comparable to validation results of the European Centre for Medium-Range Weather Forecasts (ECMWF) soil moisture analysis using global ground-based in situ observations (Albergel et al. 2012). This result is particularly good, as VIP is not calibrated to the conditions at the study area, but rather uses the
default parameter set and vegetation dynamics obtained from the MODIS sensor. For total water storage of the 0–50 cm soil profile, the coefficients of correlation between VIP model prediction and \textit{in situ} measurement were 0.70 and 0.77 in both grass and Chinese pine plots, respectively, during 2007–2009. The difference in model accuracy between the two plots can be attributed to the physical properties of the soil profile. The homogeneity of soil hydrological properties in the two plots are quite distinctive (Table 1), the continuous loess layer in the Chinese pine plot better satisfies the assumption of a vertically uniform soil profile in the VIP simulation; while the gravel structure and abrupt change of field capacity in the profile of the grass plot result in slightly decreased model prediction accuracy.

The change in soil water storage is small at the annual scale, and is usually estimated as approximately 2% of annual precipitation in the simulation; hence, it is treated as a negligible term in the water balance component (Mo et al. 2009). In this study, the VIP-estimated annual ET is validated with the observed annual ET, which is the difference between the water input (precipitation, irrigation) and observed discharge collected from the hydrological yearbook. Figure 3 shows the validation results from 10 sub-catchments of Baiyang Lake basin during 2006–2009, with R being 0.94. Since irrigation from underground water is a pivotal part in the hydrological cycle in this region, the validation considering irrigation achieved better results than otherwise (figure not shown here), and it gives reasonable explanation for the slight excess of ET over precipitation in some sub-catchments.

Although the point-scale validation of the VIP model has achieved reasonably good agreement with observations at both daily and annual scales, deviations exist in some periods, which are related to errors of both observation and the model. In this section, the Monte Carlo method is used for evaluation of the impact of parameter uncertainty on the model outputs. The key parameters directly related to soil moisture movement and photosynthesis

![Figure 3](image-url)

\[ y = 0.99x + 15.24 \]
\[ R = 0.940 \]

**Figure 3.** Comparison of the simulated annual mean ET and the observed annual ET based on water balance in sub-catchments of the Baiyang Lake basin during 2006–2009.
Table 3. Model parameters sampled for Monte Carlo simulations.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{cmax}$</td>
<td>Carboxylation rate limited by Rubisco activity ($\mu$mol C m$^{-2}$ s$^{-1}$)</td>
<td>35.0</td>
</tr>
<tr>
<td>$m$</td>
<td>Coefficient of stomatal conductance/photosynthesis relationship</td>
<td>9.0</td>
</tr>
<tr>
<td>$K_{wsat}$</td>
<td>Saturated hydraulic conductivity (cm s$^{-1}$)</td>
<td>5.36e$^{-4}$</td>
</tr>
<tr>
<td>$\theta_{fc}$</td>
<td>Soil water content at field capacity (m$^3$ m$^{-3}$)</td>
<td>0.189</td>
</tr>
<tr>
<td>$\theta_{sat}$</td>
<td>Soil water content at saturation (m$^3$ m$^{-3}$)</td>
<td>0.259</td>
</tr>
<tr>
<td>$\theta_{wp}$</td>
<td>Soil water content at wilting point (m$^3$ m$^{-3}$)</td>
<td>0.095</td>
</tr>
<tr>
<td>$a_1$</td>
<td>Coefficient of the soil resistance for water vapour diffusion</td>
<td>8.2</td>
</tr>
<tr>
<td>$b_1$</td>
<td>Coefficient of the soil resistance for water vapour diffusion</td>
<td>4.255</td>
</tr>
</tbody>
</table>

processes are selected, and normalized distribution is set for the parameter values around the references in Table 3. The model is run with 10,000 randomly sampled parameter sets within 10% of the references. It is shown that the uncertainty caused by the parameter approximates 0.05 m$^3$ m$^{-3}$ and the uncertainty envelope includes 90.9% of the observation. The width between upper and lower bound increases in July to August, when the eastern monsoon has brought frequent precipitation events and increases average soil moisture.

4.2. The choice of the descending orbit retrievals from AMSR-E and ASCAT

Preliminary investigations are conducted on the comparison of ascending and descending orbit retrieval performances from AMSR-E and ASCAT in this section. First, the consistency of ascending and descending orbit retrievals with in situ measurement of high temporal resolution is examined. Evaluated against 10 cm soil moisture measurements extracted during the satellite pass time in year 2007, the Pearson correlation $R$ is 0.54 and 0.20 for AMSR-E descending and ascending orbits, respectively. Comparison of both orbit retrievals from AMSR-E with measurements in year 2008 and 2009 also show similar results, which is in consensus with earlier research (Ceballos et al. 2005; Wagner et al. 2007; Draper et al. 2009; Rüdiger et al. 2009; Champagne et al. 2010; Gruhier et al. 2010; Liu et al. 2011). During night-time, the difference between canopy temperature and soil temperature as well as the temperature gradient of the soil profile is reduced. The combined effect of vertically and horizontally more homogenous soil temperature is probably the main reason why the descending retrievals are better in the study area. The accuracy differences between separate orbit retrievals are much less distinctive for ASCAT, as both satellite passes from ASCAT are correlated with ground measurements in a similar degree.

Further, the statistics of the comparison between both ascending and descending orbit retrievals of AMSR-E, ASCAT, and VIP daily soil moisture simulation during 2007 to 2009 are shown in the Taylor diagram (Figure 4). Overall, the LPRM estimation from descending orbit AMSR-E has obvious higher $R$ with VIP simulation than its ascending pass does. The median $R$ are 0.47 and 0.16 for descending and ascending orbits, respectively, and the median ubRMSE are 0.053 and 0.064 m$^3$ m$^{-3}$ for both passes. The normalized standard deviations of both AMSR-E orbits are mostly below 1.0, which indicates the narrower spread of this product than the VIP simulation. In respect of ASCAT, the consistency of both orbit retrievals and model predication are much more similar, with the descending and ascending orbit $R$ being 0.71 and 0.70, and ubRMSE being 0.043 and 0.044 m$^3$ m$^{-3}$, respectively. Moreover, the normalized standard deviations of descending
orbit retrievals from ASCAT is slightly more centred around 1.0 than those of the ascending orbit (Figure 4), indicating the variation ranges of the former are more similar to VIP than are the latter. Therefore, it could be safely concluded that AMSR-E descending orbit retrievals are more representative of daily average soil moisture in the basin under investigation. Therefore, the descending orbit retrievals from both AMSR-E and ASCAT are chosen for detailed analysis in the following sections.

4.3. Spatial characteristic of the agreement between the two data sets and VIP simulation

In Section 4.1, it is shown that there is strong agreement between the SSM from VIP forecasts and point-scale observations. After the credibility of the model predicted SSM is established at simulation resolution (1 km), VIP simulations that fall in each microwave data grid are aggregated and compared with microwave remote-sensing products in this section.

The right panel of Figure 5(a) shows the correlation between the VIP SSM and ASCAT time series ($R_{\text{VIPASCAT}}$) at each grid during 2007–2009. The highest $R_{\text{VIPASCAT}}$ is observed in the west mountain of the study basin, and the strong agreement between the VIP and ASCAT SSM is repeated across Baiyang Lake basin. The mean $R_{\text{VIPASCAT}}$ across the whole basin is 0.71, and 50.6% of all grids have a correlation coefficient greater than 0.71. The correlation between the VIP and AMSR-E retrievals ($R_{\text{VIPAMSR-E}}$) during 2007–2009 is displayed in the left panel of Figure 5(a). It is quite obvious that most of $R_{\text{VIPASCAT}}$ is generally higher than $R_{\text{VIPAMSR-E}}$ across the basin. The mean $R_{\text{VIPAMSR-E}}$ is 0.47, and 54.2% of the basin grids have a value greater than 0.47. The estimated correlations are significant at a 1% level at all except one grid, which is associated with infrequent AMSR-E observations. In terms of $\text{ubRMSE}$, the averages are 0.053 and 0.044 m$^3$ m$^{-3}$ for AMSR-E and ASCAT respectively.

While using original soil moisture products provides information on the absolute SSM quantity, using the anomaly-based approach gives us more accurate information on the ability of the different data sets to capture short-term variability, excluding the seasonal cycle. From the perspective of SSM anomaly, slightly higher consistency is found between
Figure 5. Comparison between VIP SSM simulation and microwave data set time series at each grid over Baiyang Lake basin during 2007–2009: (a) correlation coefficient and (b) ubRMSE. Left panel is VIP/AMSR-E pair and right panel is VIP/ASCAT pair.

AMSR-E and VIP than that between ASCAT and VIP across the basin, with $R_{VIPAMSR-E}$ ranging from 0.27 to 0.63 and $R_{VIPASCAT}$ ranging from 0.14 to 0.52. This is in consensus with previous evaluation of AMSR-E and ASCAT data sets (Draper et al. 2009; Champagne et al. 2010) and comparable to other satellite-retrieved soil moisture product accuracy such as SMOS (Brocca et al. 2011; Albergel et al. 2012). Moreover, it is particularly noteworthy that similar to analysis results using original data sets (Figure 5), the SSM anomaly also shows that active and passive remote-sensing data sets have different sensitivity to vegetation fraction; the AMSR-E data accuracy is easily affected by the dominated forest cover.
in the north of the study area (to the north of Taihang Mountain), while ASCAT retrievals show more stable performance in the same region. This feature of two data sets will be further examined in Section 4.5.

Secondly, we employ the EOF method, which can present data in an inherent incompatible and efficient manner, to conduct intercomparison between three data sets. In this study, EOF analysis uses monthly SSM during 2008–2009 to ensure all three data sets have identical temporal length, and the winter period is excluded to avoid a data void. We show the cumulative variance as a function of the number of eigenmodes for all data sets in Figure 6(a). It is shown that ASCAT has larger explained variances for the first EOF than AMSR-E and VIP (approximately 69% against 51%), and converges faster than the other two data sets. On the other hand, variances explained by the first three EOF modes of AMSR-E are in high accordance with VIP. This implies that the ASCAT data set tends to simulate a more uniform spatial distribution for SSM in the study region, while the spatial structure extracted by the AMSR-E data set highly resembles that by VIP simulation. The temporal varying EC corresponding to primary EOF mode (refer to as EC1) of three data sets are also shown in Figure 6(b). It is noted that compared to AMSR-E, EC1 of ASCAT is in much higher consistency with VIP in both magnitude and phase, especially in summer. R is 0.825 between EC1 of VIP and ASCAT (p < 0.01), while the value is 0.210 between VIP and AMSR-E (p > 0.1).

Figure 6. Comparison of the variance explained by three data sets and EC corresponding to the primary EOF mode of three data sets in EOF analysis.
4.4. Temporal characteristic of the agreement between the two data sets and VIP simulation

The temporal agreement is also examined using the SSM anomaly described in Section 3.5. \( R_{\text{VIPAMSR-E}}, R_{\text{VIPASCAT}}, \) and vegetation optical depth (also obtained from the AMSR-E product), which is highly related to vegetation water content are shown at seasonal scale in Figure 7. Statistics of seasonally varying agreement between VIP and two microwave data sets over the study area are presented in Table 4. It is seen from Figure 7 that both microwave data sets exhibit lowest performances in winter. For the ASCAT data set, depending on the wetness of snow cover, the backscatter signal changes sporadically, and makes it very difficult to predict the behaviour of backscatter from a surface covered with snow and frozen soil (Albergel et al. 2009). There is no obvious difference in the performance provided by the AMSR-E data set in seasons other than autumn, while statistic results show that it provides relatively best performance during autumn, with highest R

![Figure 7. Comparison of VIP SSM simulation with AMSR-E and ASCAT data sets in four seasons (the quantities of \( R_{\text{VIPAMSR-E}} \) and \( R_{\text{VIPASCAT}} \) are presented in the left y-axis, \( \text{ubRMSE}_{\text{VIPAMSR-E}}, \text{ubRMSE}_{\text{VIPASCAT}} \), and vegetation optical depth of different land uses are presented in the right y-axis).](image)

<table>
<thead>
<tr>
<th></th>
<th>VIP/AMSR-E</th>
<th>VIP/ASCAT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correlation</td>
<td>ubRMSE</td>
</tr>
<tr>
<td>Spring</td>
<td>0.50</td>
<td>0.969</td>
</tr>
<tr>
<td>Summer</td>
<td>0.47</td>
<td>0.967</td>
</tr>
<tr>
<td>Autumn</td>
<td>0.51</td>
<td>0.889</td>
</tr>
<tr>
<td>Winter</td>
<td>0.31</td>
<td>0.970</td>
</tr>
</tbody>
</table>

Note: Winter (January, February, and December); spring (March to May); summer (June to August); and autumn (September to November).
of 0.51 and ubRMSE of 0.889. As the observation time of AMSR-E descending pass is when dew is most likely to form, and earlier studies have found that dew has a significant effect on passive microwave observations by increasing the horizontal brightness (Jackson and Moy 1999; de Jeu et al. 2005; Du et al. 2012), therefore we investigate the potential effect of dew on the quality of AMSR-E descending observations on a seasonal scale. Daily meteorological data were used for the estimation of potential dewfall following Jacobs, Bert, and Simon (2002). Estimation results indicate that dewfall is most significant during summertime (0.22 mm d$^{-1}$) due to the considerable diurnal temperature range over highly-vegetated cropland. This value is followed by 0.10 mm d$^{-1}$ (in spring) and 0.06 mm d$^{-1}$ (in autumn). This distinctive seasonal difference on dewfall amount provides another explanation for the relative different performance of AMSR-E in summer and autumn. On the other hand, it is apparent that the ASCAT SSM anomaly has the highest accordance with VIP in summer, with normally distributed bias centred at 0. The correlation $R$ peaked at 0.57 and ubRMSE is 0.873 for VIP/ASCAT during summer (Table 4). The fact that ASCAT can achieve better agreement with VIP than AMSR-E during the highly-vegetated (spatial average vegetation optical depth of 0.61) summer period has demonstrated that the accuracy of the former is less influenced by vegetation cover.

The temporal evolution of VIP simulated SSM at Chongling Chinese pine plot with 5% and 95% quantiles (using the parameter sampling method introduced in Section 4.1), observed daily SSM, AMSR-E, and ASCAT time series in the pixel nearest to Chongling site are presented in Figure 8, taken 2008 as an example. It is seen from Figure 8 that both AMSR-E and ASCAT tend to overestimate soil moisture during winter; ASCAT shows strong response to rainfall in summer, while this response is more profound for AMSR-E during autumn.

4.5. Consistency between the two data sets and VIP simulation in different land-use types

The general agreement between model simulation and two microwave products under various underlying surface conditions are examined across the study basin. In this section, we further investigate the consistency between these three data sets specific to land-cover type. For this purpose, the land-use map at 1 km resolution is first re-projected and the zonal statistic is conducted to figure out the majority land-use type within each 0.25° pixel. A pixel is assumed to be a certain land-use type when occurrence frequency of this certain type exceeds 70% (Adegoke and Carleton 2002).

![Figure 8](image)

Figure 8. Time series of VIP simulated daily SSM at Chongling Chinese pine plot with 5% and 95% quantiles, as well as observed daily SSM, AMSR-E, and ASCAT in 2008.
The correlation and ubRMSE for VIP/AMSR-E and VIP/ASCAT pairs based on the aggregated land cover are displayed in Figure 9. Generally, both VIP/AMSR-E and VIP/ASCAT consistency are higher in grassland than in cropland. For the VIP/AMSR-E pair, the average correlation coefficient during 2003–2009 in grassland is 0.51, with mean ubRMSE of 0.050 m$^3$ m$^{-3}$; while for cropland R and ubRMSE they are 0.46 and 0.051 m$^3$ m$^{-3}$. Similarly, R for grassland and cropland are 0.71 and 0.65 in the VIP/ASCAT pair, respectively. The most possible factor attributing to this phenomenon is associated with irrigation setup in the model. Unlike the rain-fed area in Taihang Mountain in the northeast of the study basin, irrigation is the dominant agricultural practice in the southeast cultivated area (Han et al. 2008), which adds uncertainty to VIP modelling of soil water movement.

Furthermore, the VIP/AMSR-E pair has lower correlation and higher ubRMSE in forest cover compared to other herbaceous vegetation covers, which implies a major impact of vegetation on AMSR-E data quality. Specifically, vegetation density is one of the most influential factors for accuracy of passive remote-sensing-retrieved soil moisture, since it affects received radiometer signals by absorbing/scattering the radiation emanating from the soil and emitting its own radiation (de Jeu et al. 2008). It is interesting to see that the VIP/ASCAT pair exhibits highest accordance in forests which have consistently higher vegetation fractions throughout the year (Figure 7). Also, the fluctuation of $R_{\text{VIPASCAT}}$ and ubRMSE$_{\text{VIPASCAT}}$ is much smaller between three major land uses and different years than those of $R_{\text{VIPAMSR-E}}$ and ubRMSE$_{\text{VIPAMSR-E}}$. To examine the longer-term agreement between VIP and active microwave product, R and ubRMES between VIP simulation and the ERS data set (similar sensor with same TUW retrieval algorithm but different parameters, the predecessor of ASCAT) are also plotted in Figure 9. As can be seen from Figure 9, correlations are almost the same for grassland and forest in VIP/ASCAT and VIP/ERS pairs, while ubRMSE is slightly lower in forest (0.039 m$^3$ m$^{-3}$), followed by grassland (0.043 m$^3$ m$^{-3}$) and cropland (0.046 m$^3$ m$^{-3}$).

5. Discussion

From the above analysis, the ASCAT soil moisture products appear to conserve good agreement with VIP in different hydrological years. Also, R and ubRMSE in VIP/ASCAT and VIP/ERS pairs are much less variable than those in VIP/AMSR-E pairs among different land-use types. Three effects are underlying this characteristic of ASCAT and ERS products. First, the change-detection algorithm used for ASCAT and ERS is capable of accounting for heterogeneous land cover, since it can separate the seasonal vegetation cycle process from shorter time scale soil moisture variation contained in the backscattered signal time series (Ceballos et al. 2005). Thus, the dynamics of SSM can be more readily detected. Secondly, the change-detection model parameters are recently updated based on two years (2007–2008) of ASCAT observations to generate the latest version of ASCAT product (Wagner et al. 2010). This update avoids small-scale artefacts associated with strong backscatter gradients in the ASCAT retrievals, as well as a strong incidence angle dependent bias associated with a swath-location-based instrument error, all caused by the difference in resolution and radiometric calibration of two instruments (Wagner et al. 2010; Matgen et al. 2011). Thirdly, according to the ASCAT product guide, (http://oiswww.eumetsat.org/WEBOPS/eps-pg/ASCAT/ASCAT-PG-4ProdOverview.htm), the radiometric accuracy of ASCAT is expected to be less than 0.5 dB peak-to-peak. In other documents, it is recorded as having a radiometric accuracy better than about 0.3 dB (Verspeek et al. 2010). Additionally, the maximum of ASCAT ESME (estimated soil moisture error), which
Figure 9. The comparison of VIP SSM simulation in different land-use types with (a) AMSR-E, (b) ASCAT, and (c) ERS.
is provided along with the ASCAT data set as a measure of the performance of the change-detection model in extracting the soil moisture from the backscatter observations, is less than 6.5% (equivalent to approximately 0.03 m$^3$ m$^{-3}$) during 2007–2009 in the study basin. The fact that ERS and on-going ASCAT product qualities are less sensitive to vegetation cover is valuable since it allows estimation of soil moisture even in areas where abundant forest cover reduces the effective sensitivity of backscatter to soil moisture.

Recently, there are increasing investigations that focus on the quantification of satellite soil moisture error characteristics. Comparison of our results with others which use different methods will provide insights into the observation uncertainty of satellite soil moisture products and evaluation approaches. In all, evaluation results for ASCAT and AMSR-E in our study are in agreement with previous research based on in situ observation and model simulation. Generally, the ASCAT data set exhibits comparatively higher skill in capturing the soil moisture dynamic than AMSR-E in more heavily vegetated regions, which can be indicated by both higher correlation coefficient and lower anomaly bias (Wanders et al. 2012; Brocca et al. 2011). Rüdiger et al. (2009) demonstrated that over France, ERS scatterometer soil moisture data is less prone to error than AMSR-E for forested regions, which is in consensus with our findings. Recently, several research groups have applied different error techniques including the triple collocation (TC) method and R metric data assimilation approach to quantify the error characteristics of ASCAT and AMSR-E (Crow 2007; Dorigo et al. 2010; Miralles, Crow, and Cosh 2010; Parinussa et al. 2011). Using the TC method, Dorigo et al. (2010) assessed the relative quality of ASCAT and AMSR-E data sets on a global scale, using reanalysis soil moisture as an independent reference. Overall, the spatial error for ASCAT and AMSR-E identified in our study are similar to their error patterns expressed in climatology of the reanalysis soil moisture data. The error for ASCAT in Baiyang Lake basin also shows smaller magnitude than AMSR-E in their study. Also by applying the TC method, Hain et al. (2011) came to the similar conclusion that large information gaps exist in AMSR-E over moderate to dense vegetation in the continental USA. Recently, Crow (2007) introduced an evaluation strategy for remotely sensed soil moisture products by evaluating the correlation coefficient (R metric) between antecedent rainfall errors and analysis increments realized when the soil moisture product is assimilated into a simple water balance model. It is interesting to note that similar conclusions were drawn using this data-assimilation-based approach and its improved version. It is confirmed that AMSR-E have clearly higher added value in regard to anomaly detection in sparsely vegetated areas than in densely vegetated areas over the USA (Crow, Miralles, and Cosh 2010). It is also noted by this method that relative to the AMSRE-based products, the ERS scatterometer product shows less spatial variability in response to variations in vegetation water content (which is similar to our EOF analysis result), and the latter provide slightly better performance than the former product in heavily vegetated areas (Crow and Zhan 2007).

6. Conclusion

Intercomparison of microwave-based soil moisture products have been conducted based on in situ measurements in different hydroclimatic regions at various scales, but few reports are seen in China. In this study, the eco-hydrological model VIP, which accurately discerns canopy and soil surface energy fluxes with the assistance of MODIS NDVI information, is used to simulate the SSM and serves as a reference for soil moisture intercomparison in Baiyang Lake basin of North China.
Microwave-based soil moisture products show good agreements with VIP and in situ measured SSM. The correlation coefficient, with the mean values being 0.71, between VIP simulation and the ASCAT data set is generally higher than the correlation coefficient, with the mean value being 0.46, between VIP simulated data and AMSR-E across the study basin during 2007–2009. ASCAT and AMSR-E present an estimated ubRMSE of 0.044 and 0.054 m$^3$ m$^{-3}$ on average. The comparison statistics are in overall consensus with previous investigations conducted in contrasted biomes and climate conditions. Through EOF analysis of the monthly SSM, it is found that AMSR-E provides more consistent SSM spatial structure with VIP, yet ASCAT is better at capturing SSM temporal dynamics, as EC1 of ASCAT is in much higher consistency with VIP than that of AMSR-E is. However, comparison using the SSM anomaly shows that AMSR-E is in slightly higher accordance with VIP than ASCAT is. Unbiased errors of these two data sets in four seasons and major land-use types of the study area are also identified. It is found that the accuracy of the ASCAT data set exhibits smaller interannual fluctuation and lower variability among different land-use types. This is most likely attributed to the advantage of the product retrieval algorithm, advanced feature of the sensor, and the improvement of this product by updating the change-detection model parameter from the analysis of ASCAT time series of the 2007–2008 periods. Research results highlight the potential of monitoring the SSM condition with microwave soil moisture products, and further lay the foundation for assimilating the microwave retrievals into model simulation for improved regional soil moisture estimation.

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References


