Evaluation of remotely sensed and reanalysis soil moisture products over the Tibetan Plateau using in-situ observations

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\section*{Abstract}
Long-term and large-scale remotely sensed and reanalysis soil moisture products of the Tibetan Plateau are very important for understanding the land–atmosphere interactions in this area and their impacts on the weather and climate in the Asian continent. However, it is of great importance to assess the reliability of these products before using them. In the study, in-situ soil moisture measurements from three networks which represent different climatic and vegetation conditions over the Tibetan Plateau are used to evaluate the skill of seven remotely sensed soil moisture products and one reanalysis soil moisture product in the period of 2002–2012. The remotely sensed soil moisture products include three widely used products derived from the Advanced Microwave Scanning Radiometer — Earth Observing System (AMSR-E); the National Aeronautics and Space Administration (NASA) soil moisture product, the Land Parameter Retrieval Model (LPRM) soil moisture product, and the Japan Aerospace Exploration Agency (JAXA) soil moisture product; the remaining products are the JAXA AMSR2 soil moisture product, the Soil Moisture and Ocean Salinity (SMOS) soil moisture product, the Advanced Scatterometer (ASCAT) soil moisture product, and the Essential Climate Variable (ECV) soil moisture product which is a new merged product using both active and passive soil moisture products. The reanalysis product is the latest ERA-Interim product produced by the European Centre for Medium Range Weather Forecasts (ECMWF). The results show that all these products can generally capture the soil moisture dynamics well except for the NASA product which significantly underestimates the soil moisture and also lacks temporal dynamics. The JAXA AMSR-E and AMSR2 products underestimate the ground measurements at most of the time, whereas the LPRM product gives much larger seasonal amplitude than the in-situ observations with a large positive bias. It seems that the SMOS observations are severely affected by the well-known radio-frequency interference (RFI) which leads to a big noise and bias in the SMOS product. The ASCAT product overestimates the ground measurements, but it correlates with in-situ soil moisture very well and is also less influenced by vegetation cover. In general, the ECV and ERA products outperform other products. Though the ECV product underestimates the soil moisture, it shows the best correlation with ground measurements and captures the variation of in-situ soil moisture very well while the ERA product is closest to the absolute values of soil moisture observations. Overall, most of the products give reasonable results in terms of correlation in sparsely vegetated areas. We expect that the validation results can be used as a feedback to the algorithm developers to further enhance the accuracy of soil moisture retrievals over the Tibetan Plateau.

\section*{1. Introduction}
Soil moisture is not only an important part of the earth ecosystem, but also a critical link between the land surface and atmosphere. It has been widely used as a key variable in numerous environmental applications, including the hydrological modeling (Brocca et al., 2012), the numerical weather forecasting (Dharssi, Bovis, Macpherson, & Jones, 2011), the modeling of land surface evaporation (Miralles et al., 2011), and the prediction of surface runoff (Brocca et al., 2010). Global or continental scale soil moisture information is often needed for such applications. In-situ measurements are able to provide accurate information of soil moisture. However, they are only representative over a very small spatial scale due to the strong heterogeneity of the land surface. It is also impractical to deploy dense stations all over the world. Therefore, in-situ observations cannot fully characterize the spatial and temporal variability of soil moisture at large scales. An alternative way is to obtain soil moisture from satellite microwave remote sensing. It has been considered the best way to monitor soil moisture both temporally and spatially since it is the only technology that provides a direct measure of the absolute soil moisture contents which are already spatially averaged.
Microwave remote sensing has been effectively applied to measure soil moisture since the late 1970s (Schmugge, Jackson, & McKim, 1980). Over the past decades, researchers have exerted great efforts on development of soil moisture retrieval algorithms for various microwave remote sensing satellites/sensors, including the Advanced Scatterometer (ASCAT) (Naeimi, Scipal, Bartalis, Hasenauer, & Wagner, 2009; Wagner, Lemoine, & Rott, 1999; Wen & Su, 2003a, 2003b), the Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) (Jackson, 1993; Jones, Jones, Kimball, & McDonald, 2011; Koike et al., 2004; Njoku & Chan, 2006; Njoku, Jackson, Lakshmi, Chan, & Nghiem, 2003; Owe et al., 2008; Paloscia, Macelloni, & Santi, 2006; Pan, Sahoo, & Wood, 2014; Santi et al., 2012; Zeng, Li, Chen, & Bi, 2015), the Advanced Microwave Scanning Radiometer–2 (AMSR2) (Koike et al., 2004), the Windsat (Li et al., 2010; Parinussa, Holmes, & Nghiem, 2004), the Japan Aerospace Exploration Agency (JAXA) AMSR-E and AMSR2 soil moisture products (Koike et al., 2004), the SMOS soil moisture product (Kerr et al., 2012), and the ASCAT soil moisture product (Naeimi et al., 2009; Wagner et al., 1999). However, it is very important to assess the accuracy and reliability of these products before using them. The purpose of verification includes two aspects: one is that the validation results can be used as a feedback to algorithm developers to help them further improve the algorithms, and the other is to facilitate the potential users to understand the status of the products and thus can better use them for practical applications. Some studies have assessed the AMSR-E, SMOS and ASCAT soil moisture products using model simulations (Al-Yaari, Wigneron, Ducharme, Kerr, de Rosnay, et al., 2014; Al-Yaari, Wigneron, Ducharme, Kerr, Wagner, et al., 2014; Dorigo et al., 2010; Draper et al., 2013; Qiu et al., 2013; Rötzer et al., 2014; Rüdiger et al., 2009; Wanders et al., 2012) or in-situ measurements (Albergel et al., 2012; Jackson et al., 2010, 2012; Leroux et al., 2014; Pan et al., 2012; Sahoo et al., 2008; Su et al., 2011; Wagner, Naieimi, Scipal, de Jeu, & Martínez-Fernández, 2007), while less evaluation work has been done for the latest AMSR2, and the Essential Climate Variable (ECV) soil moisture products (Albergel et al., 2013; Dorigo et al., 2015). The latter is a new merged product using both active and passive soil moisture products (Liu et al., 2011, 2012; Wagner et al., 2012), which urgently needs to be validated using more “ground truth”. In addition, most validation work was performed in Europe (Albergel et al., 2011; Brocca et al., 2011; Lacava et al., 2012; Parinussa, Yilmaz, Anderson, Hain, & de Jeu, 2014; Wagner et al., 2007; Wigneron et al., 2012), the United States (Al-Bitar et al., 2012; Jackson et al., 2010, 2012; Leroux et al., 2014; Pan et al., 2012; Sahoo et al., 2008), and Australia (Draper, Walker, Steinle, de Jeu, & Holmes, 2009; Rüdiger et al., 2011; Su, Ryu, Young, Western, & Wagner, 2013), while less verification activities were conducted in Asia, especially over the Tibetan Plateau which is one of the most special and least explored areas on earth, but yet of great importance for understanding the global change (Su et al., 2011).

The Tibetan Plateau, which is often called the “Third Pole” or the “Roof of the World”, is the highest and most extensive plateau in the world (Yang et al., 2013). It is also the most prominent and complicated terrain on the earth as well as one of the most sensitive areas to global change (Su et al., 2011; Xie, Ye, Liu, & Chongyi, 2010). Many studies have demonstrated that the Tibetan Plateau directly impacts its surrounding climate and environment through atmospheric and hydrological processes, thus greatly influencing circulations over China, Asia and even the globe (Ma et al., 2003; Yang et al., 2011). Soil moisture is one of the most important parameters, which plays a key role in the water cycle and the climate of the plateau, as a result, affecting the monsoon system and precipitation patterns. Consequently, reliable long-term and large-scale remotely sensed soil moisture products of the Tibetan Plateau are very crucial for understanding the land–atmosphere interactions of this region and their effects on the climate of Eastern and South-East Asia. However, due to the special geographical environment and harsh climate conditions, the Tibetan Plateau was rarely explored, and thus there has been a lack of measurements of the key surface parameter soil moisture in the region for a long time. As a result, very few evaluation activities have been performed in this region so far. Until recent years, Su et al. (2011) and Chen et al. (2013) evaluated several satellite soil moisture products in this area.

In the study, a detailed evaluation of seven remotely sensed soil moisture products, including the NASA AMSR-E soil moisture product, the LPRM AMSR-E soil moisture product, the JAXA AMSR-E and AMSR2 soil moisture products, the SMOS soil moisture product, the ASCAT soil moisture product, and the ECV soil moisture product, as well as one soil moisture reanalysis product (ERA-Interim), is conducted over three networks established in the Tibetan Plateau in the period of 2002–2012. Dense sites have been deployed in these networks which represent different climatic and vegetation conditions that can ensure a robust validation of the soil moisture products. In the following section, the networks and the soil moisture products used for this study are briefly introduced. Section 3 describes the method for the evaluation of the products. The results are then presented in Section 4. Section 5 discusses the possible explanations for the results and also gives some suggestions. Finally, some conclusions of the study are summarized in Section 6.

2. Materials

Due to the special geographical environment, extreme climate conditions and the high cost of conducting experimental work in the Tibetan Plateau, this region has been a lack of soil moisture and temperature measurements for a long time. Fortunately, great efforts have been made in the last decade to establish long-term observation networks in various biomes and climate conditions over the Tibetan Plateau. These measurements provide a lot of valuable experimental data for validation of various soil moisture products in the Tibetan Plateau. The following is a brief introduction of the existing soil moisture and temperature networks of the Tibetan Plateau and the soil moisture products used in the study.

2.1. In-situ measurements

2.1.1. CAMP/Tibet

The soil moisture and temperature measurement system (SMTMS) network of the CEOP (Coordinated Enhanced Observing Period) Asia–Australia Monsoon Project (CAMP) on the Tibetan Plateau (CAMP/Tibet) is a meso-scale observational network set up over the central Tibetan Plateau (Ma et al., 2003). The objective of this network is to monitor soil moisture and temperature to develop the land surface process models and satellite-based soil moisture retrieval methods. The network consists of eight stations, including Amdo, Bj, D66, D105, D110, M53608, M53637 and Tuotuohe. The ground surface of all stations is sparsely covered with short grasses (Wen, Su, & Ma, 2003). The location and distribution of the stations are shown in Fig. 1. Each site recorded soil moisture and temperature from 1 October 2002 to 31 March 2004 at different depths (from 4 to 250 cm below surface) with a temporal resolution of 1 h, and soil moisture and temperature are measured by using a Time-Domain Reflectometry (TDR) system and a platinum resistance thermometer (Pt100 sensor), respectively. The CAMP/Tibet network is in a cold semiarid climate, and soil thawing and freezing begin in May and November respectively owing to the cold environment. In the study, the daily averaged soil moisture measured by the sensors at 4 cm of all sites of CAMP/Tibet network was used. For more
In the study, the daily averaged soil moisture measured by the sensors at 0–5 cm from 38 stations of the Naqu large-scale network was used. Table 1 summarizes the main characteristics of each network. For more details about Naqu network, readers are kindly referred to Yang et al. (2013).

Furthermore, in order to investigate the vegetation cover conditions of the three network regions, the Normalized Difference Vegetation Index (NDVI) was used in the study. The NDVI data were obtained from the Free Vegetation Products (www.vito-eodata.be), resulting from 10 days of SPOT-4/vegetation acquisitions with a resolution of 1 km. The averaged NDVI of the three network regions from 1 January 2002 to 31 December 2012 is shown in Fig. 2. It can be seen that there is a clear vegetation cover distinction between the three network regions. The Maqu network region has the highest NDVI during the entire period while the CAMP/Tibet network region has the lowest NDVI, which indicates the densest and sparsest vegetation cover in the two regions respectively. Thus, these networks supply a representative coverage of different climate and vegetation cover conditions on the Tibetan Plateau, which will contribute to a more robust validation of the soil moisture products in this region.

### 2.2. Soil moisture products

#### 2.2.1. AMSR-E

AMSR-E was the first satellite sensor to incorporate soil moisture as a standard product with an expectant accuracy of less than 0.06 m$^3$ m$^{-3}$ (Njoku & Chan, 2006; Njoku et al., 2003). It measures brightness temperatures at six dual-polarized frequencies in the range of 6.5–89 GHz and scans the Earth’s surface in an ascending (13:30 local solar time) and descending (01:30 local solar time) mode. Several algorithms are routinely applied to estimate soil moisture from AMSR-E observations. In the study, three most widely used soil moisture products derived from AMSR-E: the NASA soil moisture product (version 6, hereafter called NASA product) (Njoku & Chan, 2006), the JAXA soil moisture product (version 700, hereafter called JAXA product) (Koike et al., 2004) and the LPRM soil moisture product (version 2, hereafter called LPRM product) (Owe et al., 2008) were used. The original algorithm of NASA is a multifrequency-polarization iterative algorithm, which performs an iterative minimization of the root mean square error (RMSE) between model simulations and satellite observations for three parameters (soil moisture, vegetation water content and soil temperature) retrievals (Njoku et al., 2003). NASA modified its earlier version by using a global regressive method (Njoku & Chan, 2006). The algorithm uses microwave polarization difference index (MPDI) (Becker & Choudhury, 1988) of AMSR-E brightness temperatures at 10.65 and 18.7 GHz to account for the effects of vegetation and roughness, and soil moisture is estimated using the deviation of MPDI at 10.65 GHz from a baseline value. In the JAXA algorithm, the method of look-up tables is used to estimate soil moisture and vegetation water content simultaneously (Koike et al., 2004). At first, a forward radiative transfer scheme is used to generate brightness temperatures for a wide range of parameter values (soils and vegetation) for multiple frequencies and polarizations. Then, the data sets of brightness temperatures are used to create look-up tables. Finally, soil moisture and vegetation water contents are estimated by utilizing MPDI at 10.65 GHz and the index of soil wetness (ISW) (Koike, Tsukamoto, Kumakura, & Lu, 1996) at 36.5 GHz and 10.65 GHz horizontal channels. The LPRM is a three-parameter (soil moisture, vegetation optical depth, and surface temperature) retrieval method.

#### 2.2.2. Satellite-based and model-simulated soil moisture products

In the study, three most widely used soil moisture products derived from AMSR-E: the NASA soil moisture product (version 6, hereafter called NASA product) (Njoku & Chan, 2006), the JAXA soil moisture product (version 700, hereafter called JAXA product) (Koike et al., 2004) and the LPRM soil moisture product (version 2, hereafter called LPRM product) (Owe et al., 2008) were used. The original algorithm of NASA is a multifrequency-polarization iterative algorithm, which performs an iterative minimization of the root mean square error (RMSE) between model simulations and satellite observations for three parameters (soil moisture, vegetation water content and soil temperature) retrievals (Njoku et al., 2003). NASA modified its earlier version by using a global regressive method (Njoku & Chan, 2006). The algorithm uses microwave polarization difference index (MPDI) (Becker & Choudhury, 1988) of AMSR-E brightness temperatures at 10.65 and 18.7 GHz to account for the effects of vegetation and roughness, and soil moisture is estimated using the deviation of MPDI at 10.65 GHz from a baseline value. In the JAXA algorithm, the method of look-up tables is used to estimate soil moisture and vegetation water content simultaneously (Koike et al., 2004). At first, a forward radiative transfer scheme is used to generate brightness temperatures for a wide range of parameter values (soils and vegetation) for multiple frequencies and polarizations. Then, the data sets of brightness temperatures are used to create look-up tables. Finally, soil moisture and vegetation water contents are estimated by utilizing MPDI at 10.65 GHz and the index of soil wetness (ISW) (Koike, Tsukamoto, Kumakura, & Lu, 1996) at 36.5 GHz and 10.65 GHz horizontal channels. The LPRM is a three-parameter (soil moisture, vegetation optical depth, and surface temperature) retrieval method.

### 2.2.3. Model-simulated soil moisture products

In the study, three most widely used soil moisture products derived from AMSR-E: the NASA soil moisture product (version 6, hereafter called NASA product) (Njoku & Chan, 2006), the JAXA soil moisture product (version 700, hereafter called JAXA product) (Koike et al., 2004) and the LPRM soil moisture product (version 2, hereafter called LPRM product) (Owe et al., 2008) were used. The original algorithm of NASA is a multifrequency-polarization iterative algorithm, which performs an iterative minimization of the root mean square error (RMSE) between model simulations and satellite observations for three parameters (soil moisture, vegetation water content and soil temperature) retrievals (Njoku et al., 2003). NASA modified its earlier version by using a global regressive method (Njoku & Chan, 2006). The algorithm uses microwave polarization difference index (MPDI) (Becker & Choudhury, 1988) of AMSR-E brightness temperatures at 10.65 and 18.7 GHz to account for the effects of vegetation and roughness, and soil moisture is estimated using the deviation of MPDI at 10.65 GHz from a baseline value. In the JAXA algorithm, the method of look-up tables is used to estimate soil moisture and vegetation water content simultaneously (Koike et al., 2004). At first, a forward radiative transfer scheme is used to generate brightness temperatures for a wide range of parameter values (soils and vegetation) for multiple frequencies and polarizations. Then, the data sets of brightness temperatures are used to create look-up tables. Finally, soil moisture and vegetation water contents are estimated by utilizing MPDI at 10.65 GHz and the index of soil wetness (ISW) (Koike, Tsukamoto, Kumakura, & Lu, 1996) at 36.5 GHz and 10.65 GHz horizontal channels. The LPRM is a three-parameter (soil moisture, vegetation optical depth, and surface temperature) retrieval method.

### Table 1

<table>
<thead>
<tr>
<th>Networks</th>
<th>Sites</th>
<th>Climate</th>
<th>Measuring depth of surface soil moisture (cm)</th>
<th>Time step (min)</th>
<th>Land use</th>
<th>Date period</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAMP/Tibet</td>
<td>8</td>
<td>Cold semiarid</td>
<td>4</td>
<td>60</td>
<td>Grassland</td>
<td>2002.01.03–2004.03.31</td>
</tr>
<tr>
<td>Maqu</td>
<td>20</td>
<td>Cold humid</td>
<td>5</td>
<td>15</td>
<td>Grassland</td>
<td>2008.07.01–2010.07.31</td>
</tr>
<tr>
<td>Naqu</td>
<td>56</td>
<td>Cold semiard</td>
<td>0–5</td>
<td>30</td>
<td>Grassland</td>
<td>2010.08.01–2012.12.31</td>
</tr>
</tbody>
</table>

Fig. 1. Location of the three networks and distribution of the corresponding sites in each network. Yellow, blue and black rectangles represent the CAMP/Tibet, Naqu, and Maqu network regions respectively, and the stars, triangles, and circles in each rectangle represent the sites in each network. The legend of the color map indicates the altitude above mean sea level in meters.
model. In the algorithm, the vegetation optical depth is expressed as a function of the soil dielectric constant and the MPDI to avoid a reliance on additional vegetation data sets (Meesters, de Jeu, & Owe, 2005). The land surface temperature is derived independently from the vertically polarized Ka-band observations of AMSR-E by using an empirical regression model (Holmes, de Jeu, Owe, & Dolman, 2009). Thus, soil moisture is the only unknown parameter in the radiative transfer equation and can be finally obtained through a nonlinear iterative procedure. In addition, it should be noted that the LPRM releases two products which use C-band and X-band brightness temperature observations for soil moisture retrieval, respectively. Since there is no apparent radio-frequency interference (RFI) at C-band over the Tibetan Plateau as well as less signal attenuation from vegetation and atmosphere at C-band than at X-band (Njoku, Ashcroft, Chan, & Li, 2005; Zeng, Li, Chen, & Bi, 2014), we use the LPRM soil moisture product derived from C-band observations in the study.

2.2.2. AMSR2

AMSR2 boarded on Global Change Observation Mission (GCOM)-W1 satellite was launched by JAXA on 18 May 2012, and has started its scientific observation since 3 July 2012 (Imaoka et al., 2010). It is a successor of AMSR-E on the NASA's Aqua satellite, and continues the observations of AMSR-E and constructs the long-term data accumulation (Imaoka et al., 2012). The ascending and descending overpasses of AMSR2 are the same as those of AMSR-E and the basic instrument concept of AMSR2 is almost identical to that of AMSR-E as well. However, it has several improvements over AMSR-E, including larger main reflector (2.0 m), additional channels at the C-band frequency band (7.3 GHz), improved calibration system, and increased reliability (Imaoka et al., 2012). The soil moisture retrieval algorithm of AMSR2 is the same as that of JAXA AMSR-E. In the study, the AMSR2 Level 3 soil moisture product (version 1.11, hereafter called AMSR2 product) was used, which can be obtained through GCOM-W1 Data Providing Service (https://gcom-w1.jaxa.jp/auth.html).

2.2.3. ASCAT

The ASCAT is a real aperture backscatter radar and was launched in October 2006 on the Meteorological Operation-A (MetOp-A) satellite (Wagner et al., 2013). It operates in C-band (5.255 GHz) at VV polarization and scans the Earth's surface in a descending (9:30 local solar time) and ascending (21:30 local solar time) mode. Soil moisture is retrieved from the ASCAT backscatter measurements using a time series-based change detection method developed at the Vienna University of Technology (TU-Wien) by Wagner et al. (1999) and Naeimi et al. (2009). In the study, the ASCAT soil moisture product we used is the updated version based on 2 years (2007–2008) of ASCAT observations (version TU-Wien-WARP 5.5, hereafter called ASCAT product) from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) (Wagner et al., 2010). This product is the relative measure of surface soil moisture ranging from 0 (dry) to 100% (wet) obtained by scaling normalized backscatter between the historically lowest and highest values. In order to be compatible with other soil moisture products as well as the in-situ measurements, this product is rescaled to volumetric soil moisture by using the soil database from the Food and Agriculture Organization (FAO) (Reynolds, Jackson, & Rawls, 2000). For more details about the ASCAT product, readers are kindly referred to a comprehensive review written by Wagner et al. (2013).

2.2.4. ECV

The ECV soil moisture product is the first purely multi-decadal satellite-based soil moisture product that spans over 35 years (from November 1978 to December 2013) on a daily basis and at a spatial resolution of 0.25°. It was developed as part of the European Space Agency's (ESA) Water Cycle Multimission Observation Strategy (WACMOS) and Soil Moisture Climate Change Initiative (CCI) projects (Dorigo et al., 2014; Liu et al., 2012; Wagner et al., 2012). The ECV soil moisture product was generated using active and passive soil moisture products, which were derived from the Scanning Multichannel Microwave Radiometer (SMMR) onboard Nimbus-7, the Special Sensor Microwave Imager (SSMI) of the Defense Meteorological Satellite Program, the Tropical Rainfall Measuring Mission Microwave Imager (TMI), the AMSR-E onboard the Aqua satellite, the WindSat satellite, and the AMSR2 boarded on the GCOM-W1 satellite for the passive data sets, and the scatterometers (SCAT) onboard the European Remote Sensing satellites (ERS-1/2) and the ASCAT onboard the MetOp-A satellite for the active data sets (Liu et al., 2012). The soil moisture was estimated by using the LPRM (Owe et al., 2008) for passive sensors and using the change detection algorithm (Naeimi et al., 2009; Wagner et al., 1999) for active sensors. The first version of ECV product is ECV SM 01.0 which is released in June 2012 and covers the 32 year period from 1978 to 2010. Recently, ESA released the new version of ECV product that is the ECV SM 02.0. The ECV SM 02.0 has been extended to the year 2013 by including Windsat and AMSR-2 data. Besides three more years of data, the revised product (ECV SM 02.0) includes improved gap filling, new data attributes, and a revision of processing algorithms
and merging procedures (http://www.esa-soilmoisture-cci.org/node/185). The new ECM SM 0.20 product consists of three surface soil moisture data sets: the “active product” created by fusing scatterometer soil moisture products, the “passive product” created by fusing passive soil moisture products, and the “combined product” blended based on the “active product” and the “passive product”. In the study, the “combined product” (version 0.20, hereafter called ECMV product) was used. For more details about the data harmonization procedure, readers are kindly referred to Liu et al. (2011, 2012) and Wagner et al. (2012).

2.2.5. SMOS

As the first mission specifically designed for soil moisture monitoring, the SMOS satellite was successfully launched in 2 November 2009 and it has become a useful tool for monitoring key elements of the global water cycle (Jacquette et al., 2010; Kerr et al., 2010). SMOS provides global coverage at the equator every three days with a morning ascending orbit at 06:00 local solar time and an afternoon descending orbit at 18:00 local solar time (Kerr et al., 2012). The forward model used for SMOS soil moisture retrieval is the L-band microwave emission of the biosphere (L-MEB) model (Wigneron et al., 2007), which is based on a zero-order radiative transfer equation (Mo, Choudhury, Schmugge, Wang, & Jackson, 1982). Soil moisture and vegetation optical depths are retrieved simultaneously from multangular observations of SMOS by minimizing a cost function using a generalized least-squares iterative algorithm (Wigneron et al., 2007). In the study, the SMOS Level 3 daily soil moisture product (version 2.45, hereafter called SMOS product) from CATDS (Centre Aval de Traitement des Données SMOS) (Jacquette et al., 2010) was used.

2.2.6. ERA-Interim

ERA-Interim is the latest global atmospheric reanalysis product, which was produced by the European Centre for Medium Range Weather Forecasts (ECMWF) (Dee et al., 2011). It covers the period from 1 January 1979 to present and continues in near real time. It is based on a variational data assimilation system which assimilates various types of observations including satellite and ground-based measurements in a consistent framework (Dee et al., 2011). Soil moisture is a prognostic variable in ERA-Interim and is provided at 00:00, 06:00, 12:00 and 18:00 UTC. ERA-Interim considers four layers of soil (0–7, 7–28, 28–100, and 100–289 cm). Additionally, it should be noted that another new reanalysis product, the ERA-Interim/Land, offers several parameterization improvements in the land surface scheme with respect to the ERA-Interim dataset (Balsamo et al., 2013). However, the ERA-Interim/Land product only covers the period from 1979 to 2010 which cannot cover the observation period of Naqu network, while the ERA-Interim product can be provided in near real time. In order to make full use of the valuable measurements in the Tibetan Plateau to draw more reliable conclusions, we used 0.25° daily averaged ERA-Interim soil moisture simulations of the upper layer (0–7 cm) (version 2.0, hereafter called ERA product) for inter-comparison and evaluation in the study.

3. Methods

First, the NASA, SMOS and ASCAT soil moisture products were resampled to the spatial resolution of 0.25° to match with other products. Additionally, in order to reduce the inherent uncertainties in the scale difference between in-situ points and satellite pixels, the average surface soil moisture measurements of all sites of each network were compared with the soil moisture products which were also averaged over all grids within each network. The same technique has been used by many previous studies for validation purpose (Jackson et al., 2010, 2012; Leroux et al., 2014; Su, de Rosnay, et al., 2013; Su et al., 2011). Besides, for the purpose of evaluating the performance of soil moisture retrieval algorithms at different satellite overpasses, we classified the soil moisture products according to their acquisition time that is divided into nighttime and daytime. The nighttime corresponds to the descending overpass of AMSRE and AMSR2, and the ascending overpass of SMOS and ASCAT. The daytime corresponds to the ascending overpass of AMSRE and AMSR2, and the descending overpass of SMOS and ASCAT. It should be noted that the ECM and ERA products used in the study are on a daily basis, and they were classified into the nighttime group in order to facilitate the comparison. The satellite-based products are expected to have better accuracy during nighttime because the near-surface soil moisture and temperature profiles are more uniform during nighttime than during daytime, which is more consistent with the basic assumption made in the algorithms. Four commonly used error metrics, the RMSE, the mean bias (Bias), the correlation coefficient (R), and the unbiased RMSE (ubRMSE) as defined by Entekhabi, Reichl, Koster, and Crow (2010) were computed to quantify the level of agreement between the remotely sensed and reanalysis soil moisture products and the in-situ measurements. The p-value was also used to determine the significance level. If the p-value is small (e.g. less than 0.05), it means that the correlation is not a coincidence (Albergel et al., 2011). Moreover, the Taylor diagram offers a good way of graphically describing how closely a set of patterns matches observations (Taylor, 2001). Since it gives a good view of the performance of different products in a single diagram by considering three statistics including correlation coefficient, centered (unbiased) RMSE and standard deviation, we also added the Taylor diagrams for analysis. In theory, the satellite soil moisture retrieval algorithms cannot estimate soil moisture accurately under frozen soil conditions (Wigneron et al., 2007), because soil freezing can lead to significant changes in the soil dielectric constant which would further result in the inapplicability of the soil dielectric model in this case (Dobson, Ulaby, Hallikainen, & El-Rayes, 1985).

Therefore, the conclusions are mainly derived from the evaluation during unfrozen season in this study, although we still evaluate the products during frozen season. Besides, it should be noted that though the remotely sensed datasets are associated with flags that can be used to filter out the soil moisture products, we evaluated the complete datasets in order to make a fair comparison of them and the results can also be compared with previous similar work (Chen et al., 2013; Su, de Rosnay, et al., 2013; Su et al., 2011). Moreover, for the frozen period, the ERA-Interim soil moisture product provides both liquid and solid water while the sensor only measures liquid water. Therefore, the ERA-Interim soil moisture product is not assessed during the frozen season.

4. Results

In this section, we will analyze the results of each network respectively. For each network, firstly, we examined the temporal behavior of observed and estimated soil moisture during the entire period, which can reveal how the soil moisture products perform seasonally and annually. The complementary information (precipitation data) was also added to each time series, shown in Fig. 3. Four error metrics (RMSE, Bias, ubRMSE and R) used to quantify the accuracy of the eight soil moisture products were computed separately for nighttime and daytime, summarized in Tables 2, 3 and 4. To further investigate the true skill of each satellite algorithm, we examined the scatter plots of observed and estimated soil moisture only during the unfrozen season to make a clearer view of the consistency between them, shown in Fig. 4. The Taylor diagrams during the unfrozen season were also shown in Fig. 5. Moreover, the abovementioned four error metrics of each network during the unfrozen period were also displayed in Figs. 6 to 9, respectively.

4.1. CAMP/Tibet network results

The precipitation varies significantly in the CAMP/Tibet network region, and most of the precipitation occurs during the monsoon season (from May to October). As can be seen in Fig. 3(a) and (b), the in-situ
Fig. 3. Time series of the station-averaged and estimated soil moisture for nighttime (a) CAMP/Tibet, (c) Maqu, and (e) Naqu, and for daytime (b) CAMP/Tibet, (d) Maqu, and (f) Naqu during the entire period.

Precipitation In-Situ ECV ASCAT LPRM NASA JAXA AMSR2 SMOS ERA
Fig. 3 (continued).
soil moisture responds to variation in the precipitation well and there is a good agreement between them. Overall, the NASA product cannot capture the soil moisture dynamics, and it almost maintains a constant value around 0.1 m$^3$ m$^{-3}$ during the entire period. The other products can well reflect the soil moisture dynamic range during the unfrozen period but show different seasonal amplitudes. As mentioned above, the satellite soil moisture algorithms cannot accurately estimate soil moisture under frozen soil conditions due to the great changes in the soil dielectric constant. Thus, these algorithms use different criteria (land use or temperature) to exclude unreliable values in this case. The LPRM uses an empirical regression model to estimate the land surface temperature, which is used to distinguish the unfrozen and frozen conditions (Holmes et al., 2009). However, Zeng et al. (2015) recently found that the surface temperature derived from LPRM is not very

Table 2
Error metrics of soil moisture for CAMP/Tibet network. RMSE (root mean square error), Bias (mean bias) and ubRMSE (unbiased RMSE) are both in m$^3$ m$^{-3}$. R is the correlation coefficient, p-value is used to determine the significance level and NS means no significance for p-value greater than 0.05, N is the number of samples. Bold data in the table represent the best results concerning each error metric.

<table>
<thead>
<tr>
<th>Period</th>
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<th>Daytime</th>
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<td>Bias</td>
<td>ubRMSE</td>
</tr>
<tr>
<td>Unfrozen</td>
<td>ECV</td>
<td>0.060</td>
<td>-0.054</td>
</tr>
<tr>
<td></td>
<td>LPRM</td>
<td>0.152</td>
<td>0.127</td>
</tr>
<tr>
<td></td>
<td>NASA</td>
<td>0.121</td>
<td>-0.116</td>
</tr>
<tr>
<td></td>
<td>JAXA</td>
<td>0.123</td>
<td>-0.114</td>
</tr>
<tr>
<td></td>
<td>ERA</td>
<td>0.090</td>
<td>0.085</td>
</tr>
<tr>
<td>Frozen</td>
<td>ECV</td>
<td>0.040</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>LPRM</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>NASA</td>
<td>0.026</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>JAXA</td>
<td>0.058</td>
<td>-0.053</td>
</tr>
<tr>
<td></td>
<td>ERA</td>
<td>-</td>
<td>-</td>
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</tbody>
</table>
accurate in the Tibetan Plateau. Specifically, the LPRM underestimates the surface temperature at AMSR-E descending overpass while it overestimates the surface temperature at AMSR-E ascending overpass in the Tibetan Plateau. As a result, the LPRM cannot exclude the unreliable retrievals during frozen season at daytime that corresponds to AMSR-E ascending overpass, shown in Fig. 3(b). The NASA and JAXA algorithms perform more accurate during nighttime since near-surface soil moisture and temperature profiles are more uniform and the temperature difference between the ground surface and the canopy is smaller during nighttime than during daytime, which are supposed to be basic assumptions made in the soil moisture retrieval algorithms. Some previous work also yielded similar results (Brocca et al., 2011; Chen et al., 2013), and Brocca et al. (2011) argued the reason may be that the higher temperature during daytime makes the vegetation more transparent, resulting in less effect of vegetation on emission attenuation from soils.

Table 3
Error metrics of soil moisture for Naqu network. RMSE (root mean square error), Bias (mean bias) and ubRMSE (unbiased RMSE) are both in m$^3$ m$^{-2}$. R is the correlation coefficient, p-value is used to determine the significance level and NS means no significance for p-value greater than 0.05, N is the number of samples. Bold data in the table represent the best results concerning each error metric.

<table>
<thead>
<tr>
<th>Period</th>
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<th>ubRMSE</th>
<th>R</th>
<th>p-Value</th>
<th>N</th>
<th>RMSE</th>
<th>Bias</th>
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<th>p-Value</th>
<th>N</th>
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<td>−0.177</td>
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<td>0.695</td>
<td>0.000</td>
<td>458</td>
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</tr>
<tr>
<td></td>
<td>ASCAT</td>
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<td>0.100</td>
<td>0.055</td>
<td>0.704</td>
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<td>0.072</td>
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<td>0.000</td>
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<td>−0.233</td>
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Table 4
Error metrics of soil moisture for Naqu network. RMSE (root mean square error), Bias (mean bias) and ubRMSE (unbiased RMSE) are both in m$^3$ m$^{-2}$. R is the correlation coefficient, p-value is used to determine the significance level and NS means no significance for p-value greater than 0.05, N is the number of samples. Bold data in the table represent the best results concerning each error metric.

<table>
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<tr>
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<td>0.810</td>
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<td>182</td>
<td>0.160</td>
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<td>0.047</td>
<td>0.683</td>
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<tr>
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<td>167</td>
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<td>0.000</td>
<td>231</td>
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<td>0.049</td>
<td>0.618</td>
<td>0.000</td>
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<td>0.000</td>
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<td>0.044</td>
<td>0.417</td>
<td>0.000</td>
<td>76</td>
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<td>−0.018</td>
<td>0.026</td>
<td>0.159</td>
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<tr>
<td></td>
<td>ERA</td>
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</tr>
</tbody>
</table>
4.2. Maqu network results

As mentioned above, the Maqu network region has the densest vegetation cover, and the NDVI ranges from 0.2 to 0.8 for the unfrozen season. Therefore, it can be expected that this network would involve maximal vegetation effects. Though the ECV product still underestimates the ground measurements with a relatively large negative Bias value for the unfrozen period, it is highly correlated with the ground measurements which is consistent with previous studies that the merged product can preserve the correlation coefficient very well (Dorigo et al., 2015; Liu et al., 2012). Moreover, it is particularly noteworthy that the number of observations of the ECV product is significantly improved compared with other microwave remotely sensed soil moisture products, which benefited from merging both the active and passive datasets. This will be more beneficial to practical applications since many of them require frequent soil moisture measurements. Due to the predictable vegetation effects in Maqu network region, all passive microwave remotely sensed soil moisture products except for the LPRM at daytime have a large RMSE value more than 0.1 m$^3$ m$^{-3}$ and a low correlation coefficient during the unfrozen season. In contrast, though the active microwave satellite-based ASCAT product overestimates the in-situ data, it shows much higher correlation (greater than 0.7) with the ground measurements than the passive microwave remotely sensed soil moisture products. It is in consensus

Fig. 4. Scatter plots of the station-averaged and estimated soil moisture for nighttime (a) CAMP/Tibet, (c) Maqu, and (e) Naqu, and for daytime (b) CAMP/Tibet, (d) Maqu, and (f) Naqu during the unfrozen period.
with previous studies that the ASCAT product is less sensitive to the vegetation cover (Matgen et al., 2012; Qiu et al., 2013). The main reason may be that the change detection algorithm used for ASCAT can separate the seasonal vegetation cycle process from shorter time scale soil moisture variation contained in the backscattered signal time series which leads to more readily detection of the dynamics of the surface soil moisture (Qiu et al., 2013). In terms of the absolute accuracy, the ERA product outperforms other six soil moisture products with the lowest RMSE value of $0.077 \text{ m}^3 \text{ m}^{-3}$ and a relatively higher R value of 0.602, even though it underestimates the ground measurements with a negative Bias. This can be explained by the fact that the accuracy of model-based product is mainly influenced by atmospheric forcing data and model parameters rather than by vegetation (Bi, Ma, & Wang, 2014; Moradkhani, Hsu, Gupta, & Sorooshian, 2005), but it still shows lower variation than in-situ data which can be clearly seen from the Taylor diagram shown in Fig. 5(c). The LPRM, NASA, JAXA and ASCAT products perform still somewhat better during daytime than during nighttime for the unfrozen period. While the SMOS product performs much better during nighttime with much lower RMSE, Bias and ubRMSE values, which can be clearly seen from Figs. 6 to 8 and Table 3. But the results still fall out of the acceptable range. In theory, the SMOS satellite can provide the most reliable soil moisture, since the effects of vegetation and atmosphere can be minimized by using L-band frequency. Unfortunately, the SMOS brightness temperature measurements have been severely affected by the well-known RFI in some parts of the world, including large parts of Europe, China, Southern Asia, and the Middle
East (Oliva et al., 2012). The RFI disturbs the natural microwave emission received by SMOS, thus resulting in unreliable soil moisture estimations. The phenomenon that the SMOS observations have been affected by RFI at the Tibetan Plateau has also been found by Dente, Su, and Wen (2012) recently. Moreover, it seems that the occurrence probabilities of RFI are higher at SMOS descending overpass than at ascending overpass in Maqu network region because of the highly undesirable results obtained during daytime. It is consistent with Leroux et al.’s (2014) work who also found that the SMOS observations at descending overpass are more likely to be contaminated by RFI. The JAXA and NASA products perform the worst with a RMSE value greater than 0.2 m$^3$ m$^{-3}$ and they obviously underestimate the soil moisture for the unfrozen period. Additionally, it is unexpected that the LPRM product performs somewhat better at Maqu network region than at other two network regions in terms of RMSE value for the unfrozen period, while other remotely sensed soil moisture products perform the worst at Maqu network region. It may indicate that the LPRM can provide more accurate absolute volumetric soil moisture in cold humid climate area than in cold semiarid climate area. For the frozen period, the LPRM product unexpectedly shows the best conformity with the ground data during nighttime. But on average, the NASA product is still closest to the in-situ data while the JAXA product displays the best correlation with the observations.

4.3. Naqu network results

The Naqu network is the latest network established in the Tibetan Plateau, so its observation period covers the latest AMSR2 mission. It has moderately low aboveground biomass with NDVI ranging from 0.1 to 0.55 for the unfrozen period. As mentioned above, the skill of all remotely sensed soil moisture products is improved at Naqu network region than at Maqu network region with a lower RMSE value and a higher R value except for the LPRM product. The ERA product is still closest to the absolute ground measurements with the lowest RMSE value for the unfrozen period. Moreover, compared with the results of other two network regions, it seems that the ERA product appears to overestimate the soil moisture in cold semiarid climate area corresponding to the CAMP/Tibet and Naqu network regions, whereas it underestimates the soil moisture in cold humid climate area corresponding to Maqu network region. The ECV product can capture the soil moisture dynamics very well and exhibits similar variation with in-situ data. It has a high correlation coefficient of 0.852 and a small ubRMSE value of 0.034 m$^3$ m$^{-3}$ indicating that it is highly related to in-situ observations. The ASCAT product still overestimates the ground measurements but performs very well in terms of the correlation, and it even shows the highest R value of 0.890 during daytime. The performance of LPRM product is comparable with the ASCAT product. It also systematically overestimates soil moisture with a large positive Bias value, but it is highly correlated with ground measurements in the unfrozen period, which can be obviously seen from Table 4, Figs. 7 and 9.

The NASA product performs the worst with the highest RMSE and Bias value. It evidently underestimates soil moisture and still shows very low variation compared with the ground measurements in the unfrozen period. Although their absolute accuracy is still not very satisfactory and they exhibit higher variation than in-situ measurements, they show favorable correlation with ground data. The AMSR2 product even gives an R value up to 0.885 during daytime, indicating that the AMSR2 sensor has the potential to continue the long-term and large-scale soil moisture accumulation. The SMOS product is still very likely to be contaminated by RFI with the lowest R value, and it performs slightly better during nighttime than during daytime. In contrast, the results of other remotely sensed soil moisture products (NASA, LPRM, JAXA, AMSR2 and ASCAT) all perform slightly better during daytime than during nighttime, which is consistent with the results found at CAMP/Tibet and Maqu network regions. For the frozen season, the ECV product misjudged the unfrozen and frozen soil conditions, but unexpectedly shows the best correlation with the ground measurements. The NASA, JAXA and AMSR2 products perform almost at the same level but better than the SMOS product in terms of RMSE value. However, the NASA product gives unrealistic R value whereas that of JAXA and AMSR2 products is favorable.

Fig. 4 (continued).
4.4. Summary performance

Based upon the results from the three networks in the period of 2002–2012, the inferences for the soil moisture products used in the study are summarized. Moreover, since the satellite soil moisture algorithms cannot accurately retrieval soil moisture under frozen soil conditions due to the great changes in the soil dielectric constant, the following conclusions are only made for the unfrozen period.

(1) With the exception of LPRM, all of the other remotely sensed soil moisture products give better results at CAMP/Tibet and Naqu network regions than at Maqu network region which has the densest vegetation cover, resulting in heavy emission attenuation from soils.

(2) The ECV product systematically underestimates the soil moisture at all network regions, but it shows very high correlation with ground observations and can reflect the seasonal variation of soil moisture. The ASCAT product is highly correlated with ground measurements with an average R value of 0.751 and 0.850 at Maqu and Naqu network regions respectively and is also less affected by the vegetation, though it overestimates the soil moisture with a positive Bias. The LPRM can give relatively reasonable estimations in terms of R value, but it always routinely estimates very high soil moisture that produces large positive Bias. In contrast, the NASA algorithm significantly underestimates soil moisture and also cannot capture the soil moisture dynamics. The JAXA and AMSR2 products perform better than the NASA product but still have an underestimation Bias at most of the time. The ERA product can achieve the lowest average RMSE value of 0.079 m$^3$m$^{-3}$ at the three network regions, but it shows lower variation than in-situ data and it seems to overestimate soil moisture at CAMP/Tibet and Naqu network regions.

Fig. 5. Taylor diagram illustrating the statistics of the comparison between station-averaged and estimated soil moisture for nighttime (a) CAMP/Tibet, (c) Maqu, and (e) Naqu, and for daytime (b) CAMP/Tibet, (d) Maqu, and (f) Naqu during the unfrozen period.
which both are in a cold semi-arid climate, while it underestimates soil moisture at Maqu network which is in a cold humid climate.

(3) The results of ASCAT, LPRM, NASA, JAXA and AMSR2 products are slightly better during daytime than during nighttime, indicating that the daytime overpass may have a positive effect over the Tibetan Plateau. The SMOS observations are very likely to be contaminated by the RFI at the Tibetan Plateau which leads to unfavorable results, and the occurrence probabilities of RFI are higher at SMOS descending overpass than at ascending overpass.

(4) Overall, both ECV and ERA products have better performance against ground observations than other soil moisture products. Specifically, the ECV product is highly related to in-situ data with the highest R value and the smallest uRMSE value. It shows similar variation with in-situ data and the number of observations is also greatly improved. The ERA product is closest to the absolute ground measurements with the lowest RMSE value. The NASA product performs the worst with the largest underestimation Bias and also lacks temporal dynamics.

5. Discussion

As the results shown above, although most of the remotely sensed soil moisture products can well reflect the seasonal variation of ground soil moisture, some of them do not provide expectant accuracy. It is very necessary to investigate the error source of the soil moisture retrievals, and the errors may be the results of combined effects of many factors, especially in the Tibetan Plateau with very complex underlying surface. Possible explanations for the errors are as follows: 1) different spatial observation scales between in-situ points and satellite pixels. Although ground measurements from dense stations are used to minimize the effect of this well-known issue, the differences in spatial resolution still introduce some deviation, especially for the CAMP/Tibet network with less stations and larger area than the other two networks. Since nowadays there are no ground soil moisture observations which can exactly represent the same scale as that of the satellite observations, we have to use the average point-based measurements as the “ground truth”.

However, some studies pointed out that spatial soil moisture patterns are difficult to characterize using in-situ measurements and few point measurements are only able to reproduce the temporal dynamic of soil moisture, but not the absolute values (Koster et al., 2009; Wagner et al., 2013). Therefore, the readers should not only focus on the RMSE or Bias value, but also pay more attention to the correlation. Moreover, to further relieve the scale-related issue, the point soil moisture measurements can be up-scaled to a coarse scale using some spatial up-scaling methods proposed recently (Loew & Schlenz, 2011; Qin et al., 2013). 2) A mismatch between in-situ soil moisture measuring depth and the microwave penetration depth. In the study, the surface ground measurements used for validation are at 4 cm, 5 cm and 0–5 cm for CAMP/Tibet, Maqu and Naqu networks respectively. While the effective soil moisture sampling depth at L-band and C-band is 0–3 cm and 0–1 cm respectively (Al-Yaari, Wigneron, Ducharne, Kerr, de Rosnay, et al., 2014), and it also varies according to the soil moisture content (Escorihuela, Chanzy, Wigneron, & Kerr, 2010; Owe et al., 2008). A recent study also found that the effective soil moisture sampling depth even at L-band is shallower than provided by widely used in-situ moisture sensors (Escorihuela et al., 2010). Thus, compared with ground observations, satellite-based retrievals are more sensitive to atmospheric forcings such as precipitation, radiation and wind, which will lead to the phenomenon that the remotely sensed products usually exhibit higher temporal variability than the in-situ measurements (Wagner et al., 2007). 3) Errors in the in-situ data caused by measurement accuracy of sensors (Dorigo et al., 2013). 4) Inaccuracies in the retrieval algorithm (making some assumptions for simplicity) and related inputs (such as the soil texture and land surface temperature data).

Among them, the fourth point is the main reason that leads to different performances of the soil moisture algorithms. The passive microwave satellite-based soil moisture (NASA, LPRM, JAXA, and SMOS) algorithms are based on the same principles and radiative transfer equation. Specifically, they all use a zero-order radiative transfer model that is the so called $\tau$-$\omega$ model (Mo et al., 1982) as the forward model to represent the electromagnetic radiation from the Earth’s surface. However, except for soil moisture, the radiative transfer equation demands estimation of many other parameters including vegetation properties (vegetation optical depth and single scattering albedo), surface roughness and temperature. The difference between each
The JAXA algorithm assumes that the vegetation optical depth is linearly related to vegetation water content which can be determined by the NDVI from optical data. However, optical observations are often influenced by clouds and atmospheric conditions, which sometimes hamper the use of the algorithm. In contrast, the LPRM does not need any ancillary data, thus is considered to have the greatest potential to estimate soil moisture on a global scale. However, the estimation of surface temperature parameter in LPRM is from a global empirical regression model, which is developed based on the physical basis that the Ka-band (36.5 GHz) vertical brightness temperature is highly sensitive to the surface temperature (de Jeu & Owe, 2003; Holmes et al., 2009; Owe & Van de Griend, 2001; Salama et al., 2012; Zeng et al., 2015). But the ground measurements that used to establish the empirical model are mainly from the United States and some European countries. Therefore, it may have regional dependence and be inapplicable outside these regions, especially in the Tibetan Plateau with its quite different geographical environment and climate conditions. A recent study also validated the accuracy of the land surface temperature derived from LPRM at the CAMP/Tibet, Maqu and Naqu network regions (Zeng et al., 2015). The results showed that the LPRM temperature retrievals are not very accurate in the Tibetan Plateau and sometimes even bring large errors. Moreover, only land skin temperature information can be obtained from the Ka-band vertical brightness temperature observations, while the effective soil temperature is more important for the retrieval of soil moisture information (Chanzy, Raju, & Wigneron, 1997). The effective soil temperature, which is a superposition of the intensities emitted at various depths within the soil (Choudhury, Schmugge, & Mo, 1982), is heavily dependent on soil moisture and soil temperature information from deeper layers (Lv, Wen, Zeng, Tian, & Su, 2014). Some researchers have developed two-layer algorithms to calculate the effective soil temperature which can eliminate the influence of temperature more effectively (Holmes et al., 2006; Lv et al., 2014; Wigneron, Chanzy, de Rosnay, Rüdiger, & Calvet, 2008; Wigneron, Laguerre, & Kerr, 2001). Consequently, the inaccurate...
estimation of land surface temperature must be one factor that leads to the deviation of LPRM product in the Tibetan Plateau.

Besides, the surface roughness is also a very important parameter that influences the accuracy of soil moisture retrieval. Surface roughness is considered to increase the soil emissivity due to the increase in surface area of the emitting surface (Schmugge, 1985). At present, the Q/H model (Wang & Choudhury, 1981) is the most widely used roughness model in the soil moisture algorithms. The “Q” and “H” are two parameters in the Q/H model used to parameterize the effects of surface roughness. Theoretically, the two roughness parameters can be characterized by the surface root mean square (RMS) height and horizontal roughness correlation length (Wang & Choudhury, 1981; Wen et al., 2003; Wigneron et al., 2011). However, there are very few data available to quantify these two parameters globally, especially in some special areas such as the Tibetan Plateau. Moreover, the effects of incidence angle and frequency on the roughness parameters have not been studied thoroughly (Holmes, 2003; Owe, de Jeu, & Walker, 2001), either. As a result, the “Q” and “H” are usually determined empirically. Due to the lack of auxiliary data to quantify “Q” and “H”, some algorithms such as the JAXA algorithm, the LPRM, and the SMOS algorithm have to assume the two parameters as global constant values. However, the global constant roughness assumption made in the algorithms is inconsistent with the actual surface, and thus may introduce retrieval errors sometimes. Su et al. (2011) pointed out that the variability of roughness in the Tibetan Plateau is quite large. Therefore, the constant roughness parameter assumption is not valid in this area, which can be one reason for the deviation of JAXA, LPRM and SMOS products. Though some methods have been developed to correct the effects of surface roughness on surface reflectivity recently (Chen, Shi, Wigneron, & Chen, 2010; Guo, Shi, Liu, & Du, 2013; Shi et al., 2006), none of these methods can be applied to vegetation coverage area directly since they are developed for bare ground surface.

Furthermore, in the study, the validation results show that the NASA and JAXA algorithms seem to have relatively poorer performance in terms of RMSE values. The reason may be that the two algorithms calibrated some key parameters and coefficients in the algorithms in specific regions. The JAXA algorithm calibrated the surface roughness and

Fig. 8. ubRMSE regarding comparison between station-averaged measurements and soil moisture products in each network for (a) nighttime and (b) daytime during the unfrozen period.

Fig. 9. R regarding comparison between station-averaged measurements and soil moisture products in each network for (a) nighttime and (b) daytime during the unfrozen period.
some vegetation parameters in Mongolia, while the NASA algorithm is a global empirical regression algorithm and some key coefficients in the algorithm are mainly calibrated in the United States. Since these parameters/coefficients which are calibrated in specific regions exert an important role in the soil moisture algorithms, these algorithms may have regional dependence and be unsuitable for other regions. Thus, though some previous studies have shown that the JAXA and NASA algorithms can achieve relatively favorable results in Mongolia (Kaihatsu et al., 2009) and the United States (Jackson et al., 2010) respectively, they still cannot provide accurate soil moisture estimations at the Tibetan Plateau. It is suggested that these parameters/coefficients should be recalibrated at the Tibetan Plateau to improve the estimation accuracy of soil moisture in this region.

Besides, the well-known RFI is also a very important factor that influences the accuracy of soil moisture retrievals. Since AMSR-E is a multifrequency-polarization sensor, the algorithms developed for AMSR-E can switch between C-band and X-band observations to avoid the RFI. However, it is still a big problem for the SMOS satellite which can only provide single band observations. A recent study demonstrated that the RFI had the largest influence over Asia, especially in the central Asia and East Asia (Leroux, Kerr, Richaume, & Fieuzal, 2013). Therefore, though some exciting results of SMOS have been found in the United Sates (Jackson et al., 2012; Leroux et al., 2014) and Australia (Albergel et al., 2012; Su, Ryu, et al., 2013) where observations are rarely contaminated by RFI at L-band, it cannot get favorable results at the Tibetan Plateau. Additionally, the results in the study show that the ASCAT product is better or comparable with the AMSR-E products which is consistent with Brocca et al.’s (2011) work. The ASCAT product is highly correlated with in-situ data but still overestimates the ground measurements. Wagner et al. (2013) pointed out that the deviation of the ASCAT retrievals may be caused by some imperfections of the ASCAT data processing over the high-elevation areas. Moreover, in the study, the texture data derived from FAO is used to convert the ASCAT product from degree of saturation (\%) into volumetric soil moisture content (m$^3$-m$^{-3}$). However, recent studies found that the soil texture information from FAO cannot be representative for the Tibetan Plateau. Thus, the inaccurate soil texture information should be one factor that leads to the deviation of ASCAT product in the Tibetan Plateau as well as other remotely sensed soil moisture products. The ECV product is the first purely multi-decadal satellite-based soil moisture dataset. Its harmonization procedure is based on a rescaling of the microwave soil moisture data using the soil moisture statistics from the Noah land surface model (Liu et al., 2012; Loew et al., 2013). Although this procedure affects the absolute soil moisture values, temporal variations and trends of the original datasets are well preserved (Dorigo et al., 2015; Liu et al., 2012). Some studies also demonstrated that most of applications require the information on soil moisture dynamic rather than its absolute value (Koster et al., 2009; Miralles, Crow, & Cosh, 2010). In the study, the results show that ECV product can capture the soil moisture dynamics in the Tibetan Plateau very well. The results also show that the number of observations of the merged product is significantly improved than the individual microwave satellite-based soil moisture product which will be of great benefit to practical applications since many of them require frequent soil moisture measurements. It is expected that the ECV product can be extended with additional observations from SMOS and the ongoing Soil Moisture Active Passive (SMAP) mission (Entekhabi, Njoku, et al., 2010) to constitute a more comprehensive product.

6. Conclusions

Validation of different remotely sensed and real-analysis soil moisture products is very important for the data application and the improvement of the retrieval algorithms. In this study, a detailed evaluation of seven remotely sensed and one reanalysis soil moisture products was performed in the period of 2002–2012 over the Tibetan Plateau which is one of the most sensitive areas to global climate change and is also very crucial for understanding the climate system. The ground soil moisture measurements used for validation are from three dense networks named CAMP/Tibet, Maqu and Naqu established in various locations over the Tibetan Plateau. Both the CAMP/Tibet and Naqu networks are in a cold semiarid climate, and the Maqu network is in a cold humid climate. Moreover, each network was located in regions of different vegetation covers. The Maqu network region has the highest biomass, followed by Naqu and CAMP/Tibet network regions. Therefore, the three networks are under different biomes and climate conditions that can provide a more robust validation of the soil moisture products over the Tibetan Plateau.

Overall, except for the NASA product, the seasonal variation of other products is generally in good agreement with the ground measurements over the three network regions. It seems that the NASA product cannot capture the soil moisture dynamics and evidently underestimates the soil moisture during the entire period. The JAXA AMSR-E and AMSR2 products perform somewhat better, but still underestimate the ground measurements at most of the time. The reason for the deviation of these three products may be that the key parameters and coefficients in the algorithms are calibrated in specific regions which may be unsuitable for the Tibetan Plateau. The LPRM product can get reasonable results in terms of correlation, but gives much larger seasonal amplitude than in-situ observations, and it routinely overestimates the soil moisture with a very large positive bias. The errors of LPRM are supposed to be mainly caused by the inaccurate surface temperature estimation in the algorithm. The empirical surface temperature model of LPRM is not very accurate at the Tibetan Plateau and thus more accurate surface temperature estimates should be provided to improve the LPRM. The presence of RFI is probably the most important factor that causes biases in the SMOS product. Moreover, the occurrence probabilities of RFI are higher at SMOS descending overpass than at the ascending overpass. Thus, it seems better to use other sensors such as AMSR2 to monitor soil moisture at Asia which is the most contaminated region by RFI at L-band. The ASCAT can correlate with in-situ data very well with an average correlation value of 0.751 and 0.850 at Maqu and Naqu network regions respectively and is also less influenced by the vegetation, but it still overestimates the ground measurements which may be caused by the defects of the ASCAT data processing over the high-elevation areas as well as the uncertainties in available soil texture data. Therefore, with further improvements in processing techniques and obtaining more accurate soil texture data, it can be expected to achieve more high-quality ASCAT retrievals. In general, the ERA and ECV products perform the best compared with other products used in the study. The ERA product shows the highest absolute accuracy with the lowest RMSE value, while the ECV product best correlates with ground measurements with the highest correlation value. Though it still underestimates the soil moisture, it exhibits similar variation with ground measurements and the number of observations is also greatly improved. The results confirm the effectiveness of merging active and passive soil moisture products over the Tibetan Plateau, which is very beneficial to understanding the land–atmosphere interactions of the plateau since the ECV product can provide information on soil moisture dynamics over a period of more than 35 years. It also reveals great potential for extending the merged product with additional observations from SMOS and the ongoing SMAP mission to form a more comprehensive product.

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