remote sensing

MDPI

Article

# Validation Analysis of SMAP and AMSR2 Soil Moisture Products over the United States Using Ground-Based Measurements

**Xuefei Zhang [1,2], Tingting Zhang [1,*], Ping Zhou [2], Yun Shao [1] and Shan Gao [3]**

1 Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100101, China; nbzhangxuefei@163.com (X.Z.); shaoyun@radi.ac.cn (Y.S.)
2 School of Earth Science and Resource, China University of Geosciences, Beijing 100083, China; zhoupx@cugb.edu.cn
3 School of Land Science and Technology, China University of Geosciences, Beijing 100083, China; gaoshan920827@163.com
* Correspondence: zhangtt@radi.ac.cn; Tel.: +86-136-8152-6498

Academic Editors: José A.M. Demattê, Nicolas Baghdadi and Prasad S. Thenkabail
Received: 10 November 2016; Accepted: 23 January 2017; Published: 25 January 2017

**Abstract:** Soil moisture products acquired from passive satellite missions have been widely applied in environmental processes. A primary challenge for the use of soil moisture products from passive sensors is their reliability. It is crucial to evaluate the reliability of those products before they can be routinely used at a global scale. In this paper, we evaluated the Soil Moisture Active/Passive (SMAP) and the Advanced Microwave Scanning Radiometer (AMSR2) radiometer soil moisture products against in situ measurements collected from American networks with four statistics, including the mean difference (MD), the root mean squared difference (RMSD), the unbiased root mean square error (ubRMSE) and the correlation coefficient (R). The evaluation results of SMAP and AMSR2 soil moisture products were compared. Moreover, the triple collocation (TC) error model was used to assess the error among AMSR2, SMAP and in situ data. The monthly average and daily AMSR2 and SMAP soil moisture data were analyzed. Different spatial series, temporal series and combined spatial-temporal analysis were carried out. The results reveal that SMAP soil moisture retrievals are generally better than AMSR2 soil moisture data. The remotely sensed retrievals show the best agreement with in situ measurements over the central Great Plains and cultivated crops throughout the year. In particular, SMAP soil moisture data shows a stable pattern for capturing the spatial distribution of surface soil moisture. Further studies are required for better understanding the SMAP soil moisture product.

**Keywords:** soil moisture; SMAP; in situ; AMSR2; triple collocation (TC); statistics

## 1. Introduction

Soil moisture is a critical environmental variable in the energy and water cycles on a global scale. With remotely sensed observations of surface soil moisture increasingly available from a number of satellite missions, soil moisture satellite observations play a key role in environmental applications, including meteorology, hydrology, water resource management and climatology.

In the past two decades, various studies have demonstrated that soil moisture can be retrieved by passive satellite missions, such as the Soil Moisture and Ocean Salinity (SMOS) mission [1,2], the Soil Moisture Active/Passive (SMAP) mission [3], the Special Sensor Microwave/Imager (SSM/I) mission, the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E)and Advanced Microwave Scanning Radiometer 2 (AMSR2) mission [4–8]. Soil moisture data sets acquired from all of these passive missions are widely used. However, as a result of the different algorithms used for different satellite data, the quality and continuity of passive microwave soil moisture products varies in space and time [9–11]. The evaluation of satellite soil moisture products is needed to guide their correct use and to improve our understanding of their advantages and disadvantages under different conditions across the world and at different times. Several studies have evaluated soil moisture products based on passive microwave sensors against in situ measurements over different regions [12–15]. SMOS data have large deviations that are influenced by radio-frequency interference (RFI) [1]. Essential Climate Variable (EVC) data underestimates in situ values in some cases, but it shows good correlation with in situ observations. In addition, quality evaluations for other soil moisture products, such as the AMSR-E, Aquarius, European Space Agency Climate Change Initiative (ESA CCI), and ERA-Interim soil moisture products produced by the Centre for Medium-Range Weather Forecasts (ECMWF), have yielded promising results [16–19].

Previous studies have also focused on the comparison of several soil moisture products [2,16,20]. Leroux et al. [21] conducted comparisons among the SMOS, ASCAT, and ECMWF soil moisture products. Al-Yaari et al. [22] performed a comparison between the SMOS and AMSR-E products using long time series. The validity of the SMOS and Aquarius soil moisture products in agricultural areas was also discussed [23]. An et al. [17] exploited the performance of the correlation coefficient, residual error and root mean squared error in evaluating correlations between meteorological station data and ESA CCI data for crop belts and urban areas.

Recently, many studies have assessed the potential of the AMSR2 soil moisture product for climate applications by evaluating its temporal dynamics and absolute deviations using in situ observations [14,24]. Zeng et al. [25] compared the AMSRE, AMSR2 and ASCAT products using annual and seasonal sequences, and the results revealed that the AMSR-E and AMSR2 products were underestimated in most cases. To generate a consistent spatial series of soil moisture data, the performance of AMSR2 soil moisture observations was assessed for different land cover types, because the analysis of soil moisture data in spatial series is helpful for identifying trends in soil moisture in different land cover types or ecoregions [15].

Due to the absence of long-term SMAP data, there is a lack of adequate research in comparison with other soil moisture products. The SMAP soil moisture product has been evaluated by comparing the uncertainty of downscaled brightness temperature acquired from airborne and ground observations simultaneously [26,27]. Yee et al. [28] investigated the representativeness of soil moisture monitoring stations within the Yanco study area for the validation of SMAP data products at a spatial resolution of 3 km for radar measurements, 9 km for radar–radiometer measurements and 36 km for radiometer measurements. Zeng et al. [29] carried out a preliminary evaluation of the SMAP radiometer soil moisture product against in situ measurements collected from different networks that cover different climatic and land surface conditions, and the results show that the SMAP soil moisture product is in good agreement with the in situ measurements, although it exhibits dry or wet bias at different network regions. Chen et al. [30] proposed and validated SMAP soil moisture data and existing sparse soil moisture networks with a TC-based strategy, and the result suggests that unbiased estimates of correlation between the satellite product and the true footprint average can be obtained.

In previous studies, several conventional statistics, such as the correlation coefficient, the mean difference (MD; also called the bias), the root mean square difference (RMSD), ubRMSE and the mean relative error (MRE), were computed to describe the level of agreement between the in situ data and the evaluated satellite soil moisture products [12,13,15,17,22,31]. The triple collocation (TC) method was first used in oceanography to evaluate wind and wave height observations [32] and subsequently introduced to validate satellite-based soil moisture data [9,33–36]. The results suggest that the TC method provides realistic error estimation.

In this paper, we attempt to compare the descending AMSR2 soil moisture products (Japan Aerospace Exploration Agency (JAXA)algorithm) with SMAP soil moisture products at daily and monthly average time scales over the contiguous U.S. by using in situ data from monitoring stations from two different networks for a 1-year period (April 2015–March 2016). We conducted the evaluation of AMSR2 and SMAP soil moisture products in terms of four statistical indicators: the mean difference (MD), the root mean squared difference (RMSD), ubRMSE and the correlation coefficient (R). Meanwhile, triple collocation was applied to error estimation. We carried out the evaluation of AMSR2 soil moisture products and SMAP data in terms of different spatial series, temporal series and combined spatial-temporal analysis to provide a more useful guideline for the suitability and reliability of AMSR2 and SMAP soil moisture products for different applications.

## 2. Datasets

### 2.1. Passive Microwave Soil Moisture Products

AMSR2 is a single-mission instrument onboard the Global Change Observation Mission 1—Water (GCOM-W1) satellite that was launched by the Japan Aerospace Exploration Agency (JAXA) in May 2012. The data are available beginning in August 2012 [4,15]. The available soil moisture product was provided by the JAXA Earth Observation Research Center (EORC) from both the ascending (13:30 local time) and descending (01:30 local time) overpasses. The spatial resolution of the soil moisture products is 0.1 degree (10 km) and 0.25 degree (25 km), and the data are provided on daily and monthly time scales. These data are available from https://gcom-w1.jaxa.jp/. The AMSR2 soil moisture product was derived using the radiative transfer model (RTM) of the soil surface vegetation layer [37,38]. Since the nighttime (descending) microwave satellite data is generally expected to obtain more accurate soil moisture estimates than the daytime (ascending) overpass [19,39–41], the following discussions will focus on the descending overpass. The AMSR2 level 3 (L3) monthly and daily soil moisture (SM) products collected during descending overpasses at 10 km resolution were used for evaluation.

SMAP satellite was launched on January 2015 by the National Aeronautics and Space Administration (NASA) [29]. SMAP provides a soil moisture product that covers the top 5 cm of the soil column with an accuracy of 0.04 $m^3 \cdot m^{-3}$ and a spatial resolution of 9 km, and covers the globe every three days [3,27,42,43]. SMAP level 4 soil moisture (L4 SM) data were derived using NASA's Catchment Land Surface Model using brightness temperatures observed by SMAP. Moreover, the SMAP L4 SM product provides observations and analysis update data containing relevant geophysical fields reported as 3-hourly time averages, distributed over a 9-km grid [44]. These data are available from https://nsidc.org/. SMAP L4 SM was chosen to be evaluated in this paper. To evaluate the SMAP L4 soil moisture products with AMSR2 L3 soil moisture products at same scale, SMAP L4 SM data were resampled to 10 km resolution to match the spatial characteristics of AMSR2 L3 SM data.

### 2.2. In Situ Soil Moisture Data

In situ soil moisture data were acquired from 164 monitoring stations of two networks in this paper (Figure 1). 97 of the samples were from the U.S. Department of Agriculture Soil Climate Analysis Network (SCAN, http://www.wcc.nrcs.usda.gov/scan/) [45], and 67 samples were from the U.S. Climate Reference Network (USCRN; http://www.ncdc.noaa.gov/crn/). The data selected from the SCAN and USCRN indicate soil moisture data depth of 5 cm. Data acquired from April 2015 to March 2016 were selected. The soil moisture observation sites acquired data every day and every month respectively; however, some stations have no reported values on some days and months. Soil moisture data which are temporally discontinuous were excluded from the analysis. To obtain enough samples for analysis, stations without continuous daily value were retained.

### 2.3. Land Cover Data

The National Land Cover Dataset (NLCD) is classified according to the 2011 Landsat satellite data with a spatial resolution of 30 m and was constructed by the Multi-Resolution Land Characteristics (MRLC) Consortium (http://www.mrlc.gov) [46]. The NLCD of the United States was used to analyze the performance of SMAP and AMSR2 soil moisture products for different terrain types across the contiguous U.S. The NLCD 2011 map covering SCAN and USCRN stations is shown in Figure 1. The number of stations distributed in different spatial regions and land cover types is shown in Table 1. Due to insufficient sample numbers, woody wetlands and open water were excluded in the following analysis. Total of 103 soil moisture monitoring stations were selected for monthly analysis and Total of 156 soil moisture monitoring stations were selected for daily analysis (Table 1).

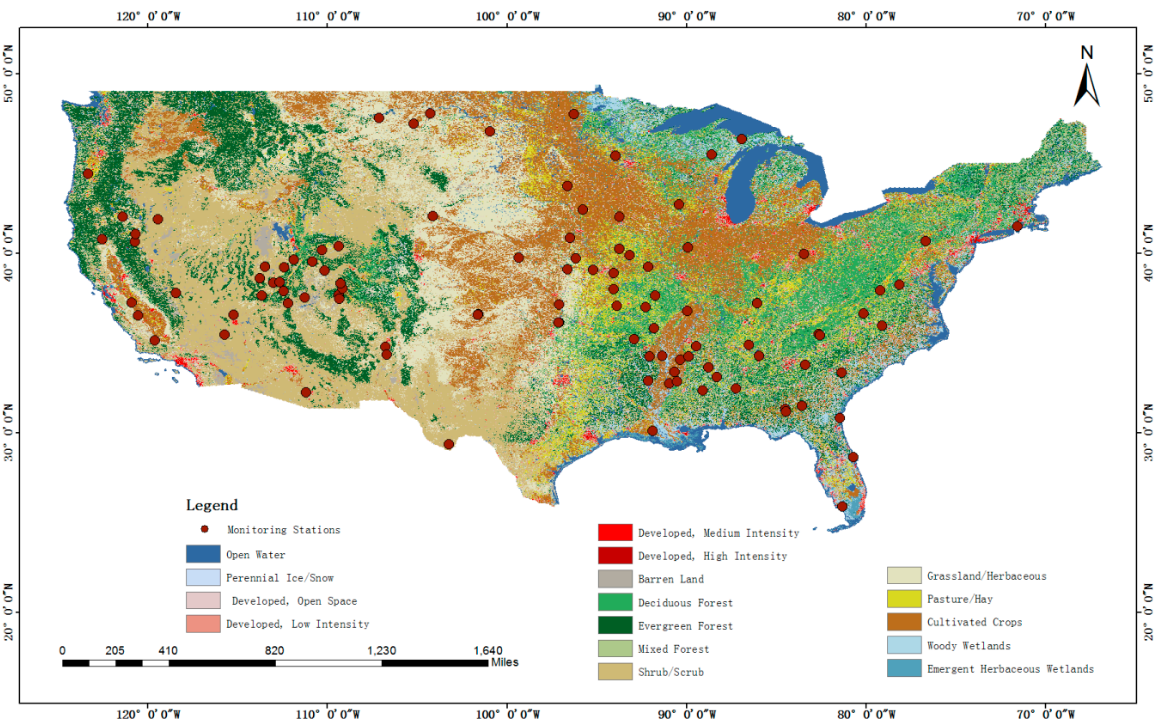



**Figure 1.** The 2011 National Land Cover Dataset (NLCD) land cover map and in-situ soil moisture observations sites.

**Table 1.** The number of soil moisture sampling sites located in different spatial region and land cover types across the contiguous U.S. for acquiring monthly and daily average soil moisture data.

| Spatial Distribution | No. of Soil Moisture Sampling Stations | |
|---|---|---|
| | Monthly Average | Daily Average |
| Overall | 105 | 162 |
| West | 32 | 61 |
| Central | 28 | 37 |
| East | 45 | 64 |
| Open Water Ice/Snow | 0 | 3 |
| Deciduous/Evergreen Forest | 13 | 29 |
| Shrub/Scrub | 14 | 33 |
| Grassland/Herbaceous | 12 | 24 |
| Pasture/Hay | 35 | 33 |
| Cultivated Crops | 29 | 37 |
| Woody Wetlands | 2 | 3 |

## *2.4. Ancillary Data*

Normalized difference vegetation index (NDVI) products acquired with MODIS can provide information about global green vegetation conditions and processes. In this study the monthly NDVI products MOD13A3 with 1 km resolution was used as an indication for the vegetation condition in different regions and vegetation cover types.

The precipitation product obtained by AMSR2 from JAXA (https://gcom-w1.jaxa.jp/) providing amount of rain was used as ancillary data to evaluate the influence of precipitation to SMAP L4 and AMSR2 L3 products. The precipitation product is of global coverage with unit of mm/h. The monthly average NDVI and rainfall data at every sampling stations (Table 1) were extracted.

## 3. Methods

Previous studies have adopted different approaches to compare satellite-based soil moisture products with in situ observations [3,15,18,36]. In this paper, the quality of AMSR2 L3 and SMAP L4 surface soil moisture products were assessed by comparing them to the in situ soil moisture observation from ground stations of the monitoring networks. Four statistics were used, including the mean difference (MD), the root mean squared difference (RMSD), the unbiased root mean square error (ubRMSE) and the correlation coefficient (R). Triple collocation (TC) method was also used for analyzing the uncertainty of the two satellite-based soil moisture products and the in situ data sets [9,32,35].

### 3.1. Four Statistics

The accuracy of AMSR2 L3, SMAP L4 soil moisture data are evaluated in terms of the MD, the RMSD, and the R. The MD represents the bias, namely the systematic difference between satellite soil moisture retrievals and in situ soil moisture measurements. The MD can be calculated using the following formula:

$$\mathrm{MD} = \frac{\sum_{i=1}^{N}(\Theta_s(i) - \Theta_m(i))}{N} \quad (1)$$

The RMSD represents the absolute difference or accuracy of AMSR2 and SMAP L4 soil moisture retrievals relative to in situ soil moisture measurements. The RMSD is calculated as:

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{N}(\Theta_s(i) - \Theta_m(i))^2}{N}} \quad (2)$$

where $\Theta_s$ represents a satellite soil moisture retrieval ($m^3 \cdot m^{-3}$), and $\Theta_m$ is the in situ soil moisture measurement ($m^3 \cdot m^{-3}$). For temporal analysis, N represents the total number of samples, and i represents a specific sample. On the basis of spatial series analysis, N is the total number of time steps, and i represents a specific daily or monthly time step.

In order to get a better reliable estimation of RMSD, the bias can be easily removed by defining the ubRMSE that characterizes random error. The ubRMSE is calculated using the following equation [47].

$$\mathrm{ubRMSE} = \sqrt{(\mathrm{RMSD})^2 - (\mathrm{MD})^2} \quad (3)$$

The R shows the relative accuracy between AMSR2 L3 or SMAP L4 soil moisture data and in situ soil moisture measurements. The correlation coefficient R for the evaluation of the AMSR2 and SMAP soil moisture data against in situ soil moisture is calculated as:

$$R = \frac{\sum_{i=1}^{N}(\theta_S\ (i) - \mu_s\ )(\theta_m\ (i) - \mu_m)}{(N-1)б_s б_m} \quad (4)$$

where $\mu_s$ is the average AMSR2 L3 or SMAP L4 soil moisture during the entire evaluation period for a footprint ($m^3 \cdot m^{-3}$), and $\mu_m$ represents the average of in situ soil moisture measurements ($m^3 \cdot m^{-3}$). $б_s$ and $б_m$ are the standard deviation of satellite and in situ soil moisture ($m^3 \cdot m^{-3}$), respectively.

### 3.2. The Triple Collocation Error Model

In addition to MD, RMSE, and R (four statistics for the evaluation of AMSR2 and SMAP data), the triple collocation error model (TC) was also introduced to estimate the error and uncertainty of AMSR2 L3 and SMAP L4 soil moisture products.

The TC method provided an effective technique to perform the satellite-based soil moisture validation [9,35]. The TC model was introduced by [31] to calibrate scatterometer-derived ocean winds and estimate errors. Subsequently, the method was used to evaluate the error and uncertainty of LAI soil water content, snow depth and other remote sensing data products [48]. Assuming three independent soil moisture data sets in situ, AMSR2 L3 and SMAP L4 exhibit the following linear relationship:

$$\begin{cases} \mathrm{SM_x} = \alpha_x + \beta_x\,\mathrm{SM_t} + \varepsilon_x \\ \mathrm{SM_y} = \alpha_y + \beta_y\,\mathrm{SM_t} + \varepsilon_y \\ \mathrm{SM_z} = \alpha_z + \beta_z\,\mathrm{SM_t} + \varepsilon_z \end{cases} \tag{5}$$

where $\mathrm{SM_t}$ represents the true soil moisture; $\mathrm{SM_x}$, $\mathrm{SM_y}$, and $\mathrm{SM_z}$ represent in situ and AMSR2 L3 and SMAP L4 soil moisture, respectively; $\alpha$i and $\beta$i represent the calibration constants, with subscript i standing for x, y, and z; and $\varepsilon$x, $\varepsilon$y, and $\varepsilon$z, denote the residual errors in the estimates of $\mathrm{SM_x}$, $\mathrm{SM_y}$, and $\mathrm{SM_z}$.

The main objective of the study is to estimate $\varepsilon$x, $\varepsilon$y, and $\varepsilon$z. Dividing both sides of formula (1) by $\beta$i (i =x, y, z) and introducing new variables SMi* = (SMi-$\alpha$i)/$\beta$i and $\varepsilon$i* = $\varepsilon$i/$\beta$i, we obtain:

$$\begin{cases} \mathrm{SM_x^*} = \mathrm{SM_t} + \varepsilon_x^* \\ \mathrm{SM_y^*} = \mathrm{SM_t} + \varepsilon_y^* \\ \mathrm{SM_z^*} = \mathrm{SM_t} + \varepsilon_z^* \end{cases} \tag{6}$$

The unknown true $\mathrm{SM_t}$ can then be eliminated through cross subtraction:

$$\begin{cases} \mathrm{SM_x^*} - \mathrm{SM_y^*} = \varepsilon_x^* - \varepsilon_y^* \\ \mathrm{SM_x^*} - \mathrm{SM_z^*} = \varepsilon_x^* - \varepsilon_z^* \\ \mathrm{SM_y^*} - \mathrm{SM_z^*} = \varepsilon_y^* - \varepsilon_z^* \end{cases} \tag{7}$$

By pairwise multiplication of the lines of Equation (7) and taking the average of the estimates. Assuming that the residual errors $\varepsilon_x$, $\varepsilon_y$, $\varepsilon_z$ are independent, the residual covariances then become 0; hence, the error variances are fully determined by the three independent calibrated soil moistures datasets. The variance of the residual errors can be estimated by

$$\begin{cases} \sigma_x^{*2} = < \left(\mathrm{SM_x^*} - \mathrm{SM_y^*}\right)(\mathrm{SM_x^*} - \mathrm{SM_z^*}) > \\ \sigma_y^{*2} = < \left(\mathrm{SM_y^*} - \mathrm{SM_x^*}\right)\left(\mathrm{SM_y^*} - \mathrm{SM_z^*}\right) > \\ \sigma_z^{*2} = < (\mathrm{SM_z^*} - \mathrm{SM_x^*})\left(\mathrm{SM_z^*} - \mathrm{SM_y^*}\right) > \end{cases} \tag{8}$$

where $< \cdot >$ indicate the calculation of mean values.

To calculate the residual covariance of different soil moisture data, the calibration constants, $\alpha$i and $\beta$i (i = x, y, z) should be computed. The true values are unknown, and thus we choose the in situ data as a reference and set $\alpha$x = 0, $\beta$x = 1. Considering the symmetry of Equation (5), the estimations of $\varepsilon_x^{*2}$, $\varepsilon_y^{*2}$, $\varepsilon_z^{*2}$are independent of this choice. Equation (5) can then be written as:

$$\begin{cases} \mathrm{SM_x} = \mathrm{SM_t} + \varepsilon_x \\ \mathrm{SM_y} = \alpha_y + \beta_y\,\mathrm{SM_t} + \varepsilon_y \\ \mathrm{SM_z} = \alpha_z + \beta_z\,\mathrm{SM_t} + \varepsilon_z \end{cases} \tag{9}$$

The calibration constants $\alpha$i and $\beta$i (i = y, z) can be calculated using a simple linear least squares approximation that considers the errors in both variables.

We adopt an iterative scheme because the calibration of the SMy and SMz constants will affect the estimation of errors in SMx, SMy and SMz. We make an initial guess for the calibration parameters by assuming $< (\varepsilon_x)^2 > = < (\varepsilon_y)^2 > = < (\varepsilon_z)^2 >$ and subsequently solve the calibration and error equations until convergence is achieved [9,35,49].

## 4. Results

The quality of the AMSR2 L3 descending soil moisture product and the SMAP L4 soil moisture product was assessed by comparing with in situ data using four statistics (MD, RMSD, ubRMSE, R) and the TC method. The significance test of R was queried through Table of Critical Values for Person's r (http://www.life.illinois.edu). The daily and monthly averaged soil moisture data acquired from in situ and satellite measurements during April 2015 to March 2016 were used to analyze the temporal variation of passive microwave soil moisture products. Land cover type and regional differences were considered.

### *4.1. Temporal Analysis*

The results of MD, RMSD ubRMSE and R were calculated for SMAP L4 and AMSR2 L3 soil moisture products with in situ soil moisture data. As shown in Figure 2, negative MD was obtained for AMSR2 L3 SM for the twelve months evaluated. The MD for SMAP L4 SM had positive values of 0.02–0.10 during the period August 2015 to December 2015, while in the other months, MD had negative values of $-0.014$ m$^3$·m$^{-3}$ to $-0.06$ m$^3$·m$^{-3}$.

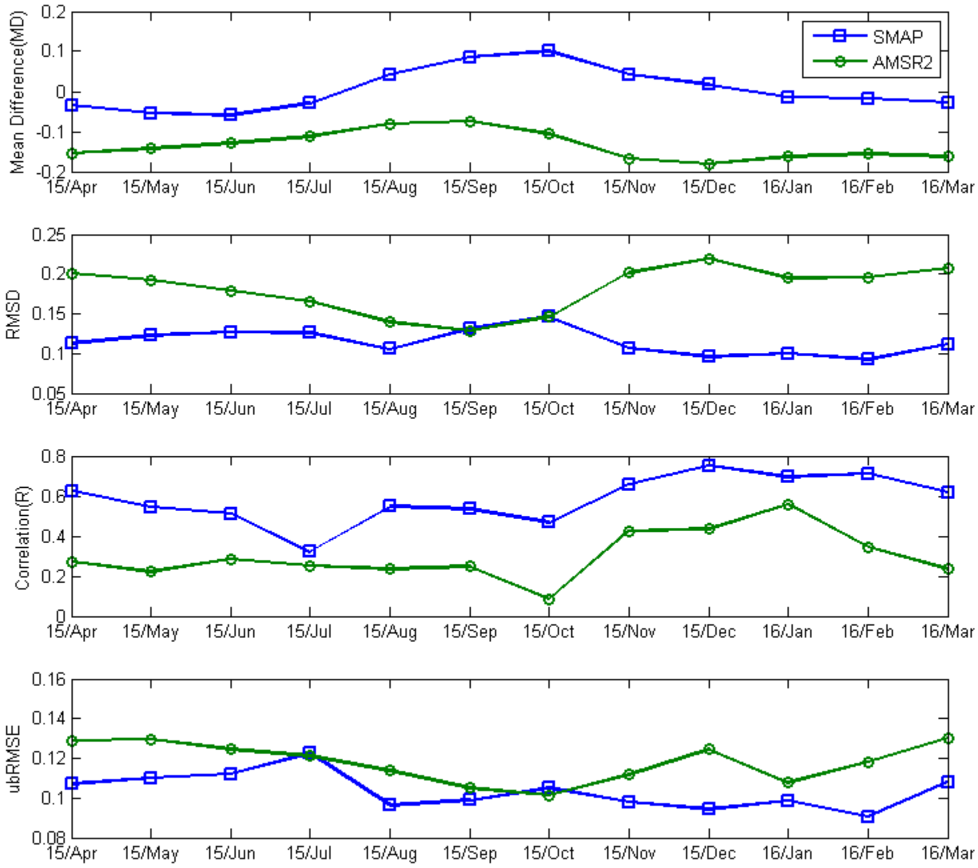
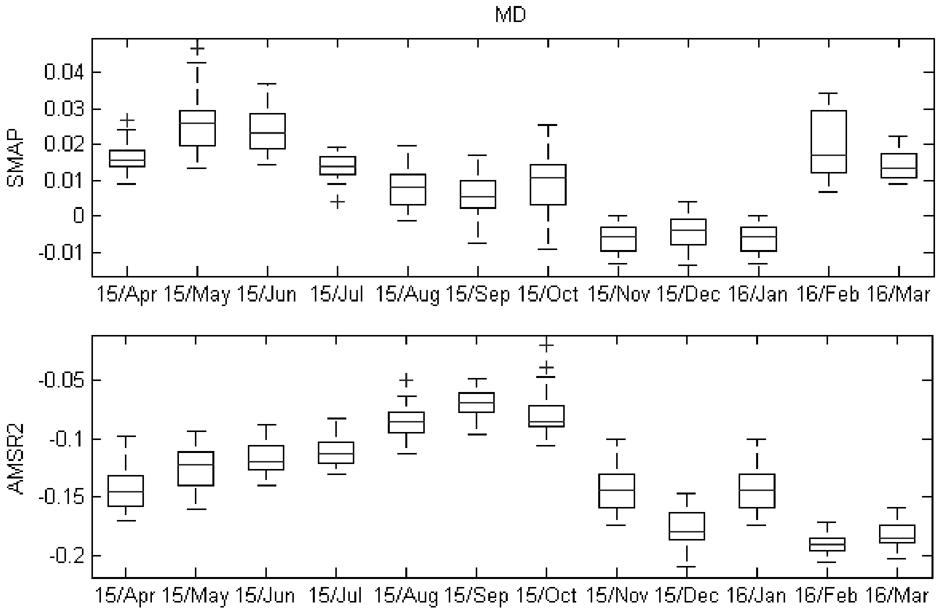



**Figure 2.** Temporal evolution of four statistics results for Soil Moisture Active/Passive (SMAP) L4 SM and Advanced Microwave Scanning Radiometer (AMSR2) L3 SM monthly data.

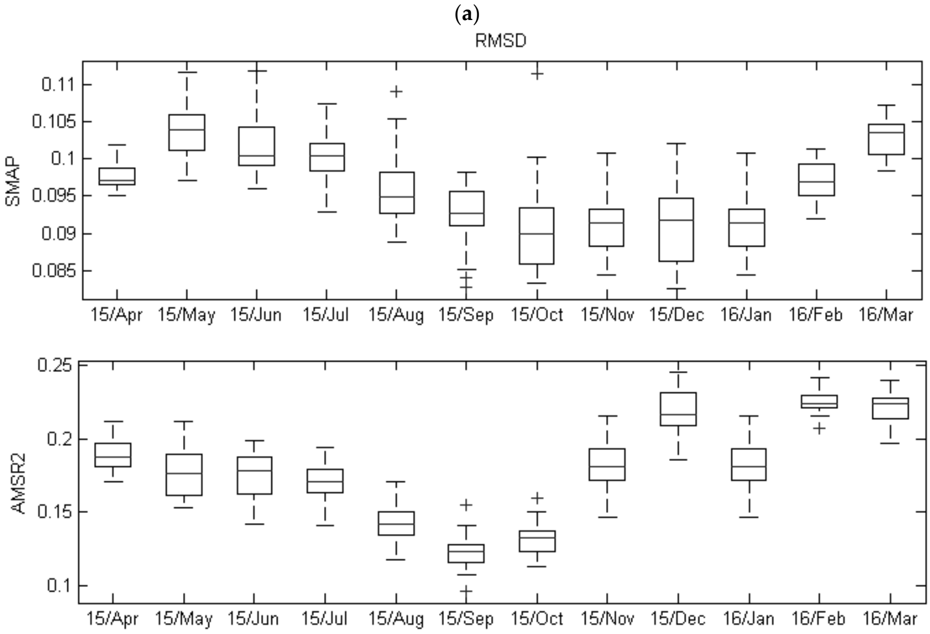
The SMAP L4 SM demonstrates better performance than that of AMSR2 L3 SM with RMSD values ranging from 0.09 m$^3$·m$^{-3}$ to 0.15 m$^3$·m$^{-3}$ and ubRMSE values from 0.09 m$^3$·m$^{-3}$ to 0.12 m$^3$·m$^{-3}$, which do not exceed the SMAP mission requirement of 0.04 m$^3$·m$^{-3}$. The 1 km change in spatial resolution for the SMAP L4 SM product has little effect on the results from these four statistics.

Figure 2 demonstrates that, compared to the AMSR2 L3 SM product, the SMAP L4 SM product is more strongly correlated with in situ measurements, with $R > 0.54$ ($p < 0.0005$) at most times during the 12-month period. The AMSR2 L3 SM product got the poorest R result of 0.09 ($p > 0.05$) in October, when the SMAP L4 SM product also performed poorly. The SMAP L4 and AMSR2 L3 soil moisture products displayed the best correlation with in situ measurements in December, respectively.

The results of the four statistics using daily time series for the SMAP L4 SM and AMSR2 L3 SM products are shown as box plots in Figure 3. The box plots present the median (the horizontal line inside each box), the 1st quantile Q1 and 3rd quantile Q3 (as indicated by the bottom and top of the box) for every month. As with the daily average data, AMSR2 L3 SM daily data also show a negative bias (Figure 3). However, the MD results of the SMAP L4 SM daily data are slightly different from those obtained using monthly average data (Figure 3 MD). No negative bias for SMAP L4 SM occurred in any of the time series. Small MD values occurred in November 2015, December 2015, and January 2016, meaning that more accurate soil moisture estimates were obtained for SMAP L4 SM.

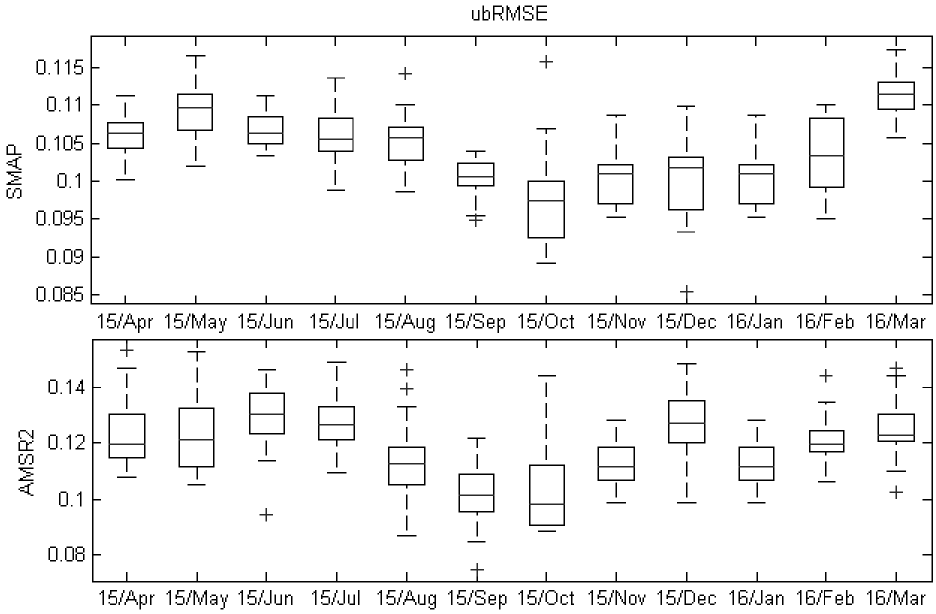



(**a**)

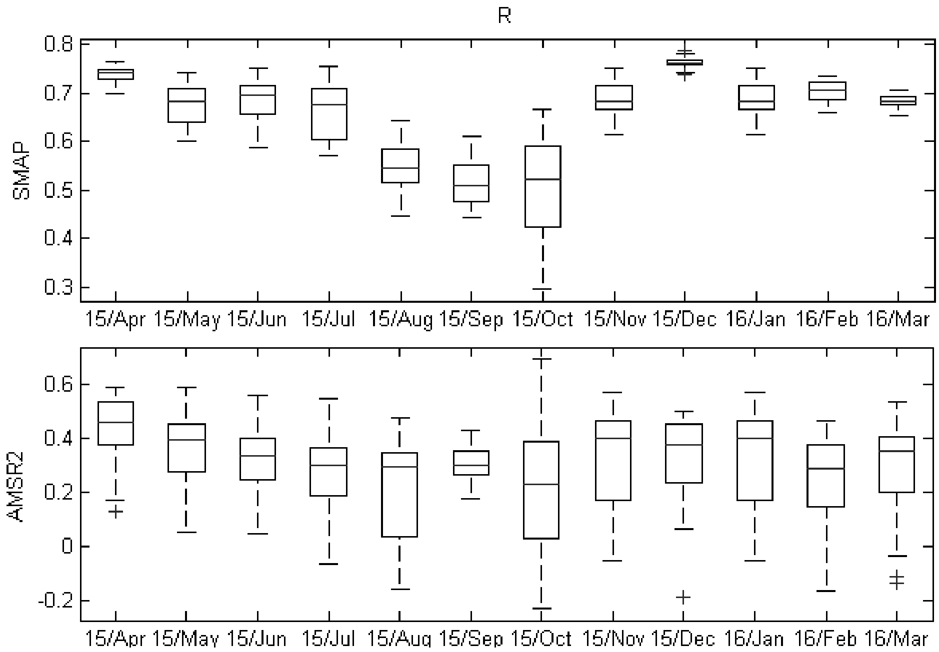



(**b**)

**Figure 3.** *Cont.*




**(c)**




**(d)**

**Figure 3.** (**a**–**d**) Temporal evolution of four statistics results for SMAP L4 SM and AMSR2 L3 SM daily data (mean difference (MD), the root mean squared difference (RMSD), the unbiased root mean square error (RMSE) and correlation coefficient (R)). Presented are the median, the 1st quantile Q1 and 3rd quantile Q 3 (as indicated by the box), and the Q1 − 1.5 (Q3 − Q1) and Q3 + 1.5 (Q3 − Q1) values (whiskers).

Daily RMSD values (Figure 3 RMSD) show that the SMAP L4 SM performance is in reality stable, while the AMSR2 L3 SM obtained opposite results in August, September, and October 2015. However, if the bias is removed, it can achieve lower discrepancy between AMSR2 L3 and SMAP L4 (Figure 3 RMSD and ubRMSE). Similarly, this situation also appeared in the monthly average data (Figure 2 RMSD and ubRMSE). As seen from box plots of the correlation coefficients (Figure 3 R), for the daily data, as assessed using the correlation coefficient, the SMAP L4 SM data is generally better than the AMSR2 L3 SM data. Both SMAP L4 SM data and AMSR2 L3 SM data show great variation; the standard deviations of the two data products were 0.11 and 0.18, respectively. Meanwhile, both SMAP L3 SM and AMSR2 L3 SM data presented weak correlation coefficient distributions, which is consistent with the monthly average data analysis.

### 4.2. Spatial Analysis

The correlation between SMAP L4 and AMSR2 L3 products in different regions and land covers were shown in Figures 4 and 5. Both Central region and Cultivated Crops region with R = 0.33 and R = 0.49 respectively show better agreement with each other. In West, East and Deciduous/Evergreen regions, the correlation between SMAP L4 and AMSR2 data was poor with R results of 0.14, 0.24 and 0.1, respectively.

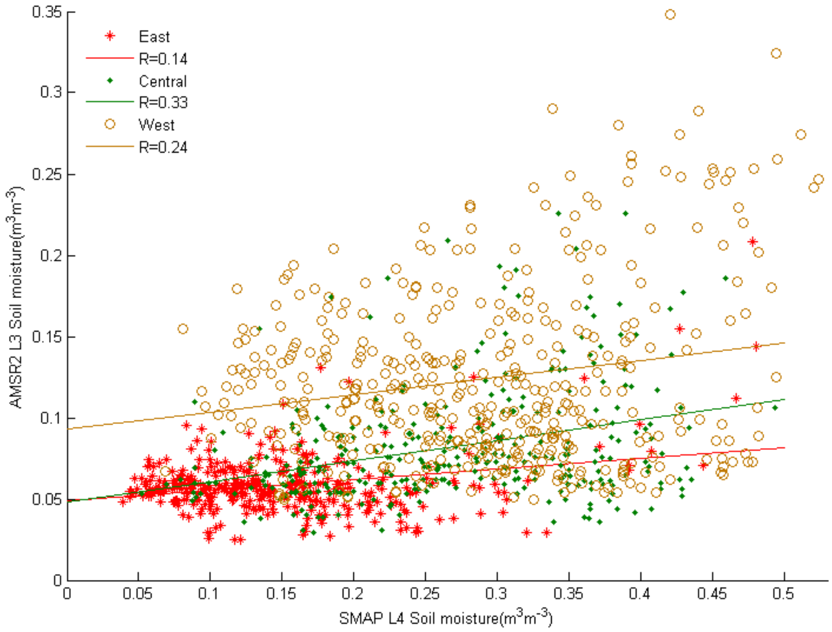



**Figure 4.** Comparison Soil moisture in different regions between SMAP L4 and AMSR2 L3 data.

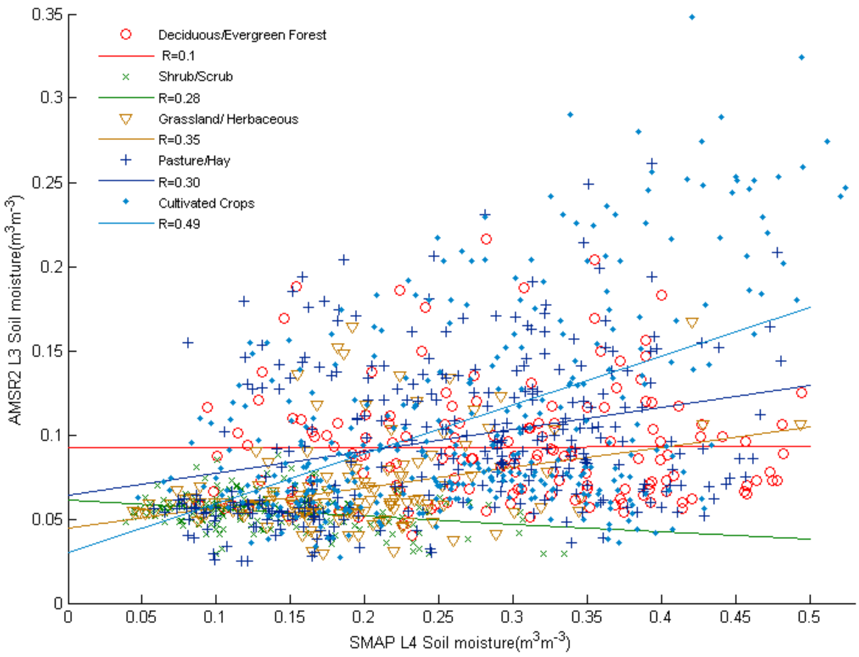



**Figure 5.** Comparison Soil moisture in different land covers between SMAP L4 and AMSR2 L3 data.

The performance of the AMSR2 L3 and SMAP L4 soil moisture products retrieved from different regions of the United States with different land covers were analyzed. Monthly and daily averaged AMSR2 L3 and SMAP L4 soil moisture data were compared with in situ data (Figure 6). Daily and monthly averaged AMSR2 L3 soil moisture data had negative MD values in the western, central and eastern regions of the United States, which means that the products are underestimates. SMAP L4 soil moisture data got low positive MD values for the western, central and eastern parts of the United States. The lowest MD values associated with SMAP L4 soil moisture data were obtained in the central part (Figure 6). The RMSD and ubRMSE got the best results for SMAP soil moisture data in the central part. The AMSR2 L3 soil moisture data product showed poor RMSD (0.22 $m^3 \cdot m^{-3}$) results in the central part and poor ubRMSE (0.14 $m^3 \cdot m^{-3}$) results in the eastern parts (Figure 6). SMAP L4 SM data performed better than AMSR2 L3 SM, as reflected by higher R values (Figure 6), in the eastern, central and western United States. SMAP L3 SM had the best results in terms of R values ($R > 0.50$ with $p < 0.0005$) in the central part. The AMSR2 L3 SM had the poorest correlation with in situ soil moisture data in the western region compared to the central and eastern parts.

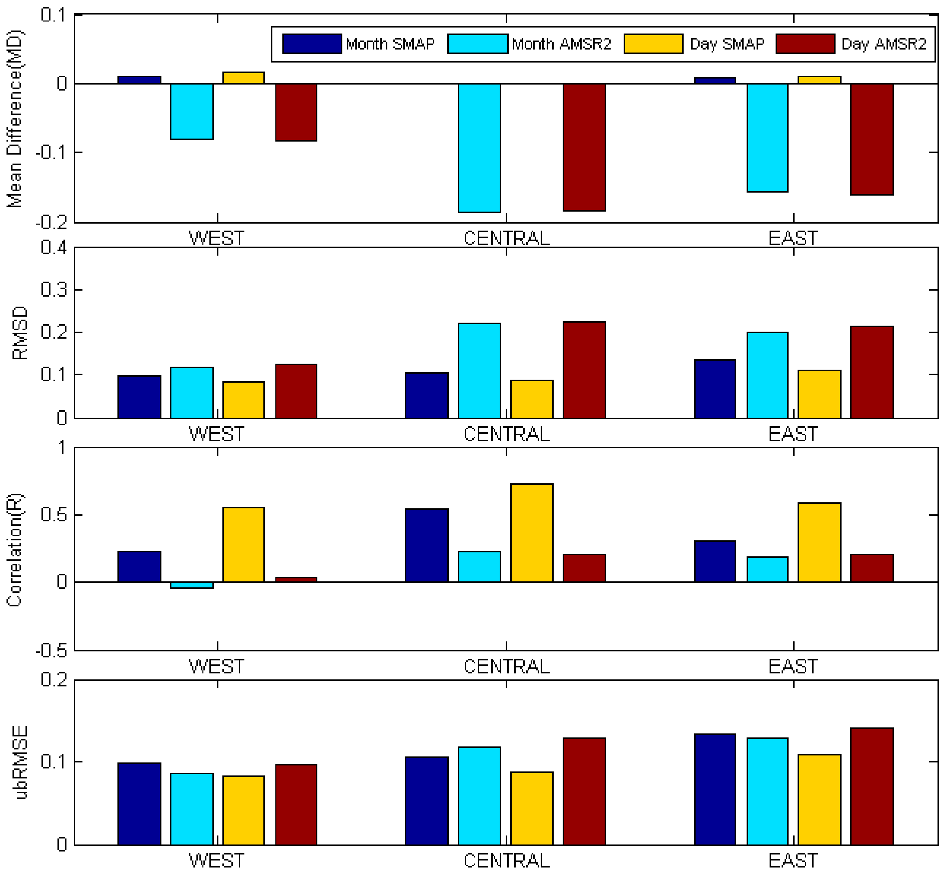



**Figure 6.** Four statistics results for SMAP L4 SM and AMSR2 L3 SM monthly and daily data in different region of U.S.

The accuracy of soil moisture products is affected by the type of vegetation cover. The MD, RMSD, ubRMSE and R were calculated for the AMSR2 L3 and SMAP L4 soil moisture products with different vegetation cover (Figure 7). Monthly and daily data were used to analyze the effect of temporal scale on soil moisture observations. For the AMSR2 L3 soil moisture product, the best performance was obtained for the Shrub/Scrub vegetation type, where the MD was −0.06, the RMSD was 0.09 and the ubRMSE was 0.07. AMSR2 L3 SM monthly data got better R results than AMSR2 L3 SM daily data for most vegetation types. SMAP L4 SM data have similar features as AMSR2 L3 SM.

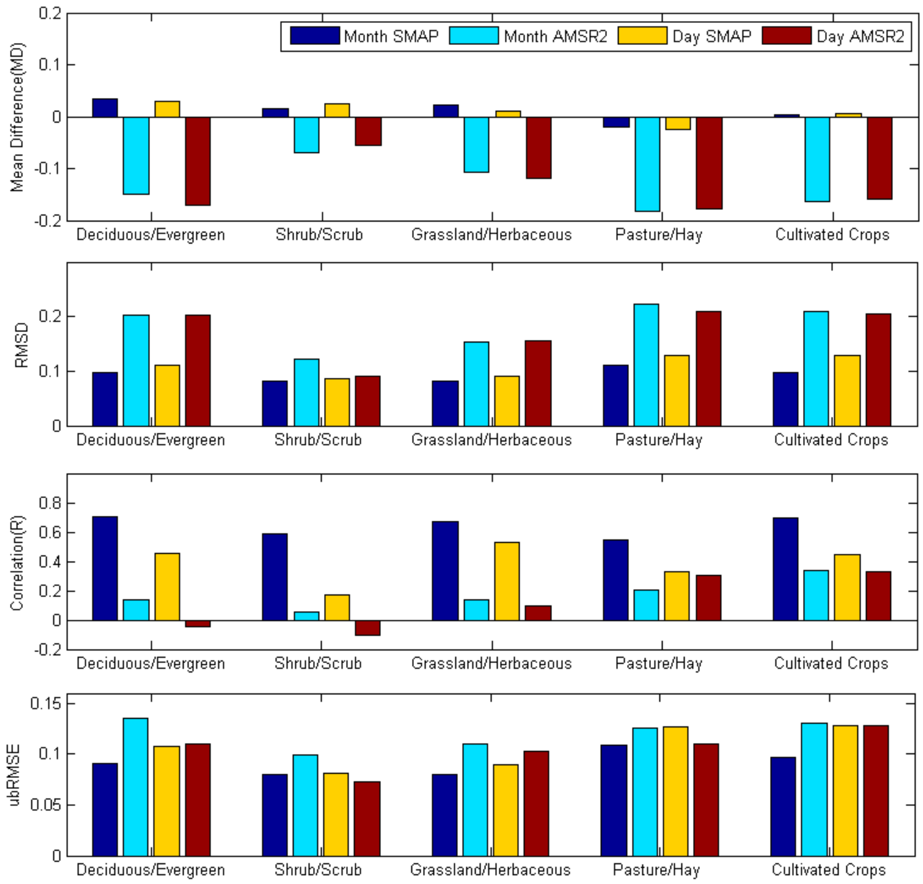



**Figure 7.** Four statistics results for SMAP L4 SM and AMSR2 L3 SM monthly and daily data with different vegetation cover types.

The low range and variation of soil moisture in desert regions partly contributed to the low RMSD and ubRMSE of Shrub/Scrub, however, as reflected in the correlation coefficients (Figure 7). The correlation coefficients for monthly and daily data for the Shrub/Scrub vegetation type were 0.057 and −0.10 ($p > 0.05$), respectively. For regions of Deciduous/Evergreen Forest, the AMSR2 L3 SM data exhibit negative correlations, with a correlation coefficient of −0.05 ($p > 0.05$) for daily averaged data. Compared with other vegetation cover types, the Cultivated Crops region showed the best R values for AMSR2 L3 SM data (0.34 $m^3 \cdot m^{-3}$) ($p < 0.005$) for monthly averaged data and 0.33 $m^3 \cdot m^{-3}$ ($p < 0.005$) for daily averaged data). AMSR2 L3 SM data in all vegetation cover types has generally much poorer performance compared to SMAP L4 SM data, with poor results for MD, RMSD and R. SMAP L4 SM data obtained in regions covered by Pasture/Hay showed negative bias, a slightly high RMSD (0.13 $m^3 \cdot m^{-3}$) and a low R compared with in situ soil moisture data. The lowest MD and the best R results were obtained in regions covered by Cultivated Crops for SMAP L4 SM daily and monthly average data. Daily SMAP L4 SM data showed the poorest R value for shrub/scrub cover, with an R value of 0.17 ($p < 0.005$). However, monthly SMAP L4 SM data showed the lowest R value for regions covered by Pasture/Hay.

### *4.3. Temporal- Spatial Analysis*

The daily SMAP L4 and AMSR2 L3 soil moisture data were compared with in situ soil moisture data month by month during April 2015–March 2016 respectively. Different regions and different vegetation cover types were considered.

Figure 8 presents the temporal-spatial characteristic of SMAP L4 and AMSR2 L3 SM data. SMAP L4 soil moisture data got much higher R results ($R > 0.60$) in the central region of the United

States than in the western and eastern regions. AMSR2 L3 SM shows similar patterns as those of SMAP L4 SM from May to November, except in October. AMSR2 L3 SM has the poorest correlation with in situ data in October. For the eastern region, SMAP L4 SM obtained negative R values of −0.19 ($p > 0.05$) in June and −0.16 ($p > 0.05$) in July, and showed the best R values around December and February. SMAP L4 SM have similar temporal pattern in the western region as in the eastern region. In the western region, SMAP L4 SM got better R results from December to March through a single year.

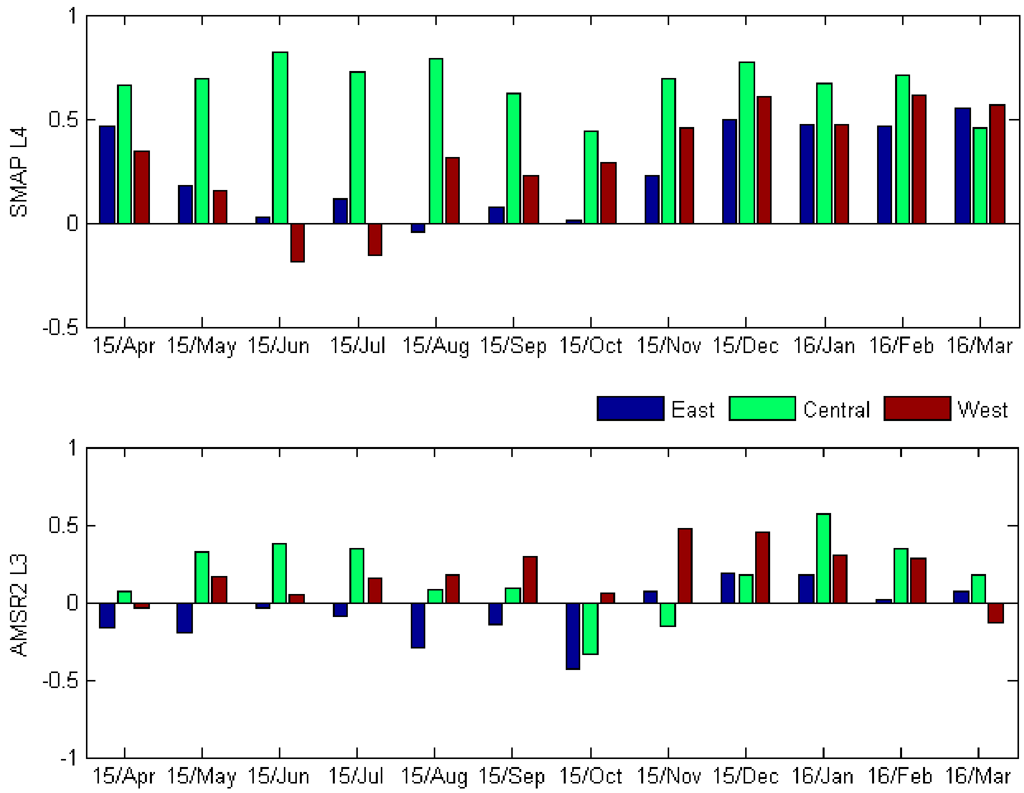



**Figure 8.** Temporal evolution of correlation between SMAP L4 or AMSR2 L3 monthly average data and in situ soil moisture data in west, central and east region of U.S.

For AMSR2 L3 SM data, the best performance occurred in the central region in January. However, the poorest R, including negative values were obtained in October and November for the AMSR2 L3 SM product in the central region. Compared with the central and eastern regions, AMSR2 L3 SM data exhibited weak correlation with in situ data in the western region. The best correlation in the eastern part was found in November.

AMSR2 L3 SM and SMAP L4 SM data were assessed with the R statistic for five types of vegetation cover throughout one year. The results showed that the correlation of SMAP L4 SM data with in situ soil moisture data for all investigated land cover types, except Grass/Herbaceous, were generally bad over the period from July to October. It can be seen that the accuracy of SMAP L4 SM for Deciduous/Evergreen Forest, Pasture/Hay and Cultivated Crops was significantly influenced by seasonal variation. At most times, SMAP L4 SM data showed good results for Grass/Herbaceous land cover. SMAP L4 SM data showed good results for all vegetation types in December ($R > 0.65$ with $p < 0.0005$).

It can be seen from Figure 9 that the SMAP L4 SM data are better correlated with in situ data compared to the AMSR2 L3 SM data for most types of vegetation cover, particularly the Grassland/Herbaceous cover. The results of evaluating the daily averaged AMSR2 L3 SM and SMAP L4 SM retrievals with in situ observations are exhibited with box plots, which macroscopically express the temporal variation characteristics of land cover types in terms of symmetry, the degree of dispersion and aggregation, and outliers. As seen from (Figure 10, Figure 11 and Table 2), the correlation coefficients computed from the SMAP L4 SM data are consistently higher than those computed from the AMSR2 L3 data. In terms of the SMAP L4 SM daily averaged data, there is lower variability in the SMAP L4 SM data than in the AMSR2 L3 data for each month and land cover type. This observation can be tested using the standard deviations shown in Table 2 and the box heights shown in Figure 11. Both the SMAP L4 SM data and the AMSR2 data L3 SM data show greater correlations each month in the central region than in the western and eastern regions (Figure 10). A similar pattern for standard deviation is also found in the SMAP L4 SM data (Table 2), while a high standard deviation and a weak correlation coefficient can be found in the AMSR2 L3 SM data, indicating that most of the days in the month show weak correlation.

Large variations in October 2015 are shown by the standard deviation shown in Table 2 and the box heights shown in Figures 10 and 11. The AMSR2 L3 SM data show very weak or even negative correspondence and large standard deviation with in situ data from December 2015 to March 2016. This situation is also seen in the Shrub/Scrub region (Figure 11). It is evident that satellite-based soil moisture data better represent the true level of soil moisture in regions covered by Cultivated Crops. In addition, a trend of seasonal fluctuations in SMAP L4 SM data can be seen among all land cover types, whereas weak correlations can be seen clearly in summer and autumn. However, compared with the SMAP L4 SM data, the AMSR2 L3 SM data cannot show seasonal fluctuations except in regions of Cultivated Crops. We picked out the optimal average correlation coefficient and standard deviation of each spatial region through the year, and the degree of aggregation demonstrates that the best estimation mainly occurs from December to April.

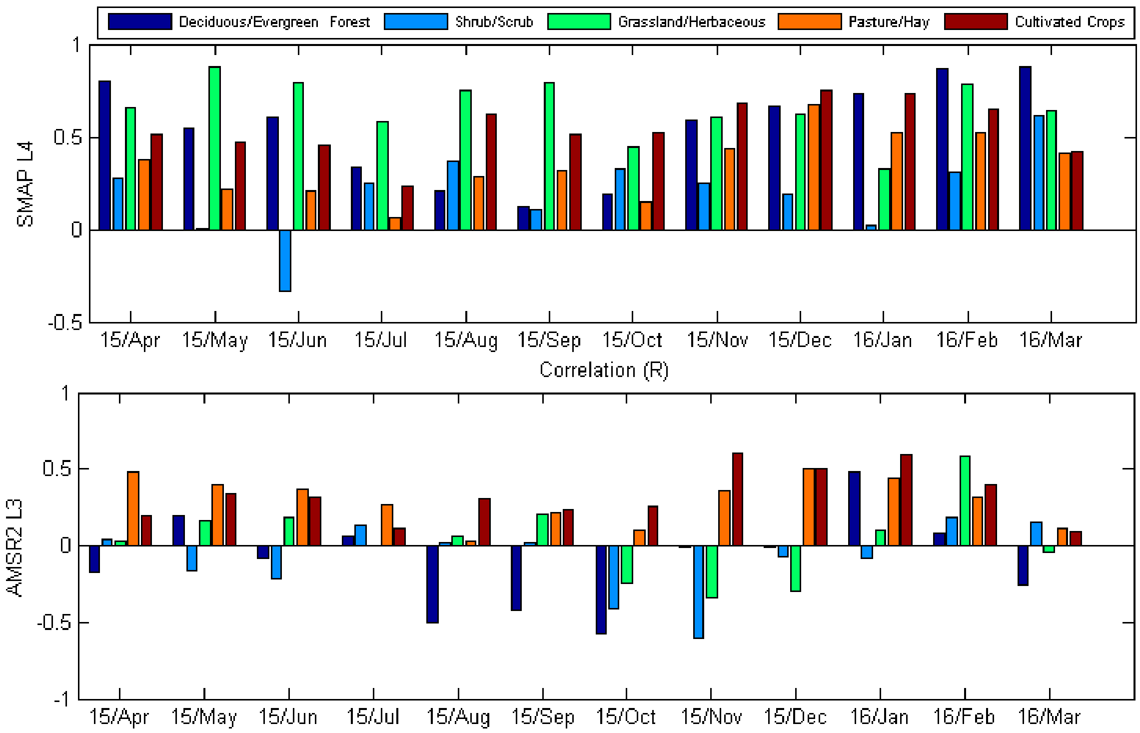



**Figure 9.** Temporal evolution of correlation between SMAP L4 or AMSR2 L3 monthly average data and in situ soil moisture data in the regions with different vegetation cover types of U.S.

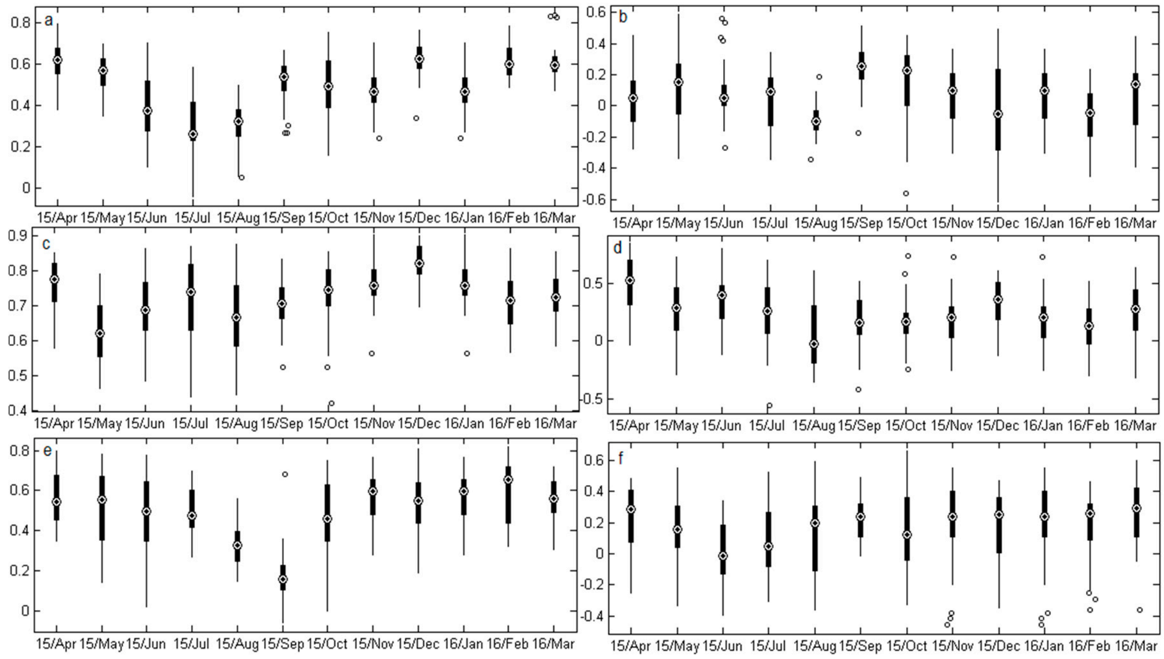


**Figure 10.** Temporal evolution of correlation between SMAP L4 (**a**,**c**,**e**) or AMSR2 L3 (**b**,**d**,**f**) daily average data and in situ soil moisture data in the western (**a**,**b**), central (**c**,**d**), and eastern (**e**,**f**) regions of U.S.

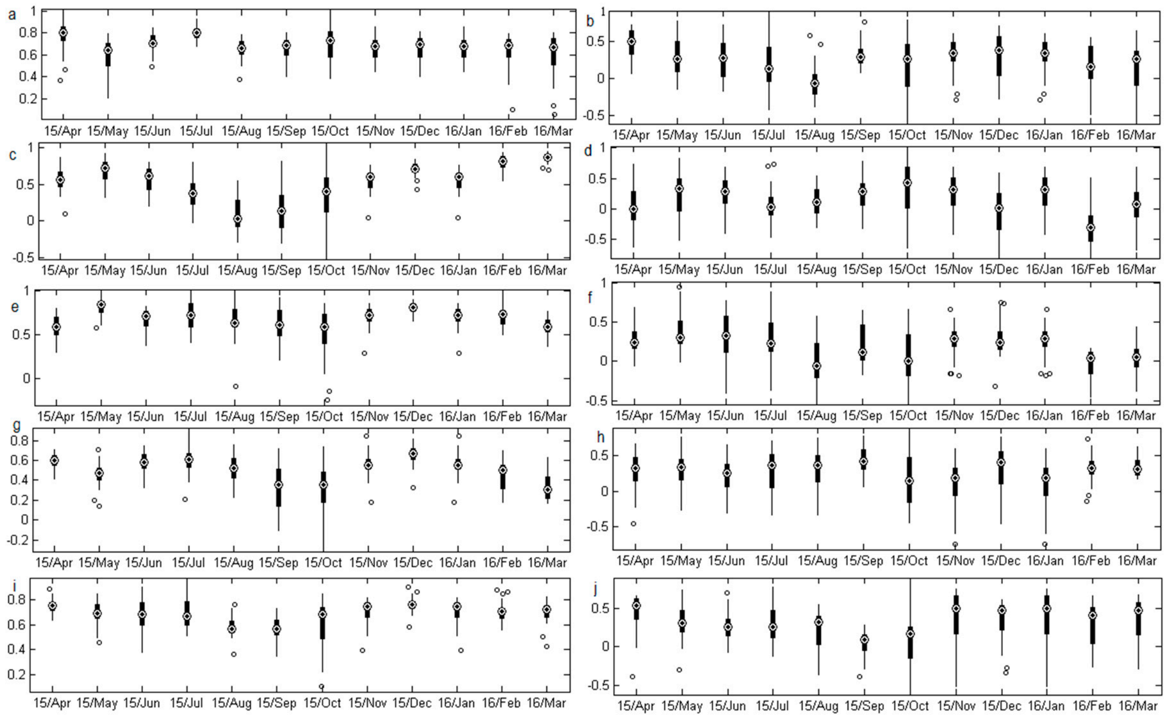


**Figure 11.** Temporal evolution of correlation between SMAP L4 (**a**,**c**,**e**,**g**,**i**) or AMSR2 L3 (**b**,**d**,**f**,**h**,**j**) daily average data and in situ soil moisture data with the Deciduous/Evergreen Forest (**a**,**b**), Shrub/Scrub (**c**,**d**), Grassland/Herbaceous (**e**,**f**), Pasture/Hay (**g**,**h**) and Cultivated Crops (**i**,**j**) land cover types in U.S.

**Table 2.** Average correlation and standard deviation of correlation for SMAP L4and AMSR2 L3 daily average soil moisture retrievals against in situ observations (R) (The highlight blue data are the largest Mean value of R and the highlight gray data are the lowest Standard Deviation value of R).

| | | | | 15/Apr | 15/May | 15/Jun | 15/Jul | 15/Aug | 15/Sep | 15/Oct | 15/Nov | 15/Dec | 16/Jan | 16/Feb | 16/Mar |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Average(R) | Region | SMAP | West | 0.5 | 0.55 | 0.39 | 0.31 | 0.31 | 0.51 | 0.48 | 0.46 | 0.63 | 0.57 | 0.61 | 0.61 |
| | | | Central | 0.73 | 0.64 | 0.7 | 0.7 | 0.68 | 0.71 | 0.73 | 0.77 | 0.83 | 0.81 | 0.72 | 0.73 |
| | | | East | 0.48 | 0.52 | 0.47 | 0.48 | 0.31 | 0.2 | 0.47 | 0.56 | 0.52 | 0.51 | 0.59 | 0.55 |
| | | AMSR2 | West | 0.05 | 0.13 | 0.1 | 0.05 | −0.07 | 0.25 | 0.13 | 0.01 | −0.02 | −0.05 | −0.06 | 0.06 |
| | | | Central | 0.24 | 0.28 | 0.37 | 0.2 | 0.07 | 0.18 | 0.16 | 0.21 | 0.32 | 0.27 | 0.11 | 0.25 |
| | | | East | 0.16 | 0.17 | 0.01 | 0.09 | 0.16 | 0.22 | 0.16 | 0.2 | 0.17 | 0.09 | 0.18 | 0.25 |
| | Land Cover Type | SMAP | Deciduous/Evergreen Forest | 0.77 | 0.59 | 0.72 | 0.78 | 0.65 | 0.68 | 0.7 | 0.66 | 0.66 | 0.6 | 0.63 | 0.59 |
| | | | Shrub/Scrub | 0.56 | 0.68 | 0.57 | 0.34 | 0.09 | 0.16 | 0.36 | 0.57 | 0.72 | 0.77 | 0.8 | 0.85 |
| | | | Grassland/Herbaceous | 0.59 | 0.81 | 0.68 | 0.69 | 0.65 | 0.63 | 0.52 | 0.72 | 0.81 | 0.84 | 0.71 | 0.59 |
| | | | Pasture/Hay | 0.59 | 0.47 | 0.58 | 0.59 | 0.51 | 0.33 | 0.31 | 0.56 | 0.66 | 0.57 | 0.45 | 0.33 |
| | | | Cultivated Crops | 0.75 | 0.7 | 0.68 | 0.67 | 0.59 | 0.58 | 0.61 | 0.72 | 0.76 | 0.77 | 0.71 | 0.7 |
| | | AMSR2 | Deciduous/Evergreen Forest | 0.46 | 0.29 | 0.25 | 0.15 | 0.02 | 0.31 | 0.2 | 0.35 | 0.29 | 0.09 | 0.16 | 0.18 |
| | | | Shrub/Scrub | 0.03 | 0.26 | 0.25 | 0.05 | 0.12 | 0.23 | 0.29 | 0.21 | −0.07 | −0.21 | −0.27 | 0.09 |
| | | | Grassland/Herbaceous | 0.26 | 0.39 | 0.34 | 0.28 | −0.01 | 0.23 | 0.09 | 0.25 | 0.26 | 0.23 | −0.04 | 0.03 |
| | | | Pasture/Hay | 0.27 | 0.3 | 0.22 | 0.28 | 0.31 | 0.44 | 0.12 | 0.14 | 0.35 | 0.37 | 0.33 | 0.24 |
| | | | Cultivated Crops | 0.47 | 0.33 | 0.28 | 0.24 | 0.21 | 0.07 | 0.1 | 0.4 | 0.36 | 0.35 | 0.27 | 0.37 |
| Standard Deviation(R) | Region | SMAP | West | 0.16 | 0.09 | 0.16 | 0.15 | 0.1 | 0.1 | 0.15 | 0.1 | 0.07 | 0.11 | 0.08 | 0.08 |
| | | | Central | 0.1 | 0.1 | 0.09 | 0.12 | 0.11 | 0.07 | 0.1 | 0.07 | 0.05 | 0.07 | 0.08 | 0.08 |
| | | | East | 0.19 | 0.18 | 0.21 | 0.13 | 0.1 | 0.17 | 0.19 | 0.14 | 0.15 | 0.16 | 0.15 | 0.11 |
| | | AMSR2 | West | 0.23 | 0.23 | 0.19 | 0.19 | 0.12 | 0.16 | 0.24 | 0.21 | 0.29 | 0.24 | 0.19 | 0.21 |
| | | | Central | 0.26 | 0.24 | 0.26 | 0.28 | 0.29 | 0.21 | 0.21 | 0.23 | 0.21 | 0.23 | 0.23 | 0.25 |
| | | | East | 0.23 | 0.18 | 0.19 | 0.22 | 0.25 | 0.15 | 0.26 | 0.27 | 0.24 | 0.26 | 0.22 | 0.2 |
| | Land Cover Type | SMAP | Deciduous/Evergreen Forest | 0.13 | 0.15 | 0.09 | 0.06 | 0.09 | 0.11 | 0.14 | 0.1 | 0.11 | 0.14 | 0.15 | 0.2 |
| | | | Shrub/Scrub | 0.15 | 0.15 | 0.17 | 0.21 | 0.22 | 0.24 | 0.34 | 0.11 | 0.08 | 0.07 | 0.1 | 0.06 |
| | | | Grassland/Herbaceous | 0.12 | 0.1 | 0.11 | 0.16 | 0.19 | 0.19 | 0.29 | 0.07 | 0.06 | 0.08 | 0.12 | 0.11 |
| | | | Pasture/Hay | 0.07 | 0.13 | 0.1 | 0.12 | 0.14 | 0.2 | 0.25 | 0.12 | 0.09 | 0.1 | 0.15 | 0.13 |
| | | | Cultivated Crops | 0.06 | 0.1 | 0.13 | 0.12 | 0.09 | 0.08 | 0.19 | 0.09 | 0.06 | 0.09 | 0.08 | 0.08 |
| | | AMSR2 | Deciduous/Evergreen Forest | 0.2 | 0.25 | 0.27 | 0.3 | 0.27 | 0.17 | 0.35 | 0.24 | 0.27 | 0.29 | 0.3 | 0.29 |
| | | | Shrub/Scrub | 0.29 | 0.35 | 0.3 | 0.24 | 0.23 | 0.27 | 0.42 | 0.31 | 0.37 | 0.29 | 0.28 | 0.31 |
| | | | Grassland/Herbaceous | 0.15 | 0.26 | 0.29 | 0.31 | 0.25 | 0.24 | 0.33 | 0.21 | 0.21 | 0.22 | 0.21 | 0.19 |
| | | | Pasture/Hay | 0.26 | 0.21 | 0.25 | 0.27 | 0.27 | 0.18 | 0.37 | 0.31 | 0.29 | 0.16 | 0.19 | 0.17 |
| | | | Cultivated Crops | 0.22 | 0.22 | 0.21 | 0.22 | 0.26 | 0.14 | 0.29 | 0.32 | 0.26 | 0.26 | 0.3 | 0.26 |

### 4.4. TC Analysis

Triple collocation errors were calculated using in situ soil moisture data, AMSR2 L3 soil moisture data and SMAP L4 soil moisture data to investigate the accuracy of passive microwave satellite-based soil moisture data (Table 3 and Figure 12). A total of 366 days soil moisture measurements acquired daily from April 2015 to March 2016 were used to build the model. The monthly mean values of the daily soil moisture data were also used to build the TC model.

**Table 3.** Estimated errors of the in situ, SMAP, AMSR2 soil moisture dataset for different spatial distribute with the triple collocation (TC) method.

| Spatial Distribution | Daily Average | | | Monthly Average | | |
|---|---|---|---|---|---|---|
| | In Situ | SMAP | AMSR2 | In Situ | SMAP | AMSR2 |
| Overall | 0.102 | 0.007 | 0.207 | 0.02 | 0.019 | 0.087 |
| Deciduous/Evergreen Forest | 0.004 | 0.012 | 0.995 | 0.014 | 0.066 | 5.049 |
| Shrub/Scrub | 0.023 | 0.004 | 2.434 | 0.065 | 0.03 | 0.393 |
| Grassland/Herbaceous | 0.033 | 0.019 | 0.674 | 0.052 | 0.025 | 1.004 |
| Pasture/Hay | 0.015 | 0.021 | 0.598 | 0.034 | 0.079 | 0.099 |
| Cultivated Crops | 0.009 | 0.01 | 0.115 | 0.038 | 0.03 | 0.097 |
| West | 0.07 | 0.051 | 8.71 | 0.03 | 0.076 | 1.055 |
| Central | 0.011 | 0.003 | 0.363 | 0.023 | 0.012 | 0.249 |
| East | 0.01 | 0.023 | 0.437 | 0.037 | 0.141 | 0.397 |

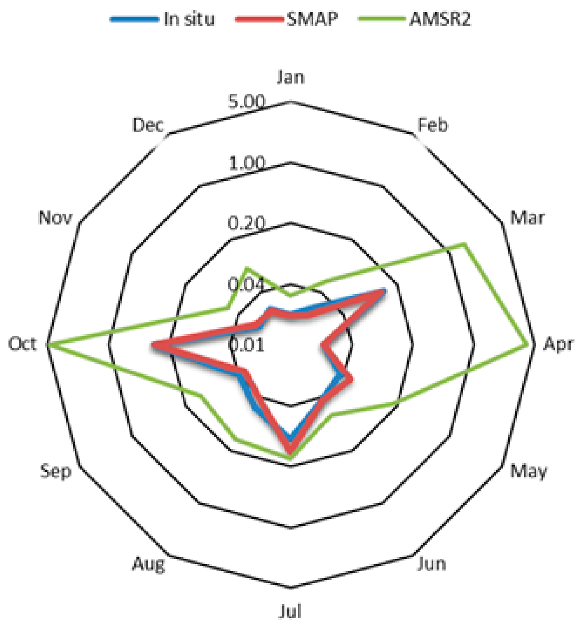



**Figure 12.** Estimated errors of soil moisture dataset for monthly average with the TC method.

As shown in Table 3 for the overall data calculation result, the mean errors in the above three daily datasets were 0.10, 0.01 and 0.21, respectively, and the corresponding values for the monthly datasets were 0.02, 0.019 and 0.087, respectively. The error in the AMSR2 L3 soil moisture data was greater than that of the SMAP L4 SM product, regardless of whether it was based on daily or monthly average values. Thus, the SMAP L4 soil moisture product better detected the soil moisture.

Table 3 shows the estimated errors of the in situ, AMSR2 L3, and SMAP L4 soil moisture with the measured soil moisture at each spatial location. In general, the error of the AMSR2 L3 SM was found to be greater than those of the other two soil moisture data sets. This similar tendency is consistent with the results from previous studies that targeted the assessment of AMSR2 L3 SM data [50].

The results of the error estimation for daily averaged data over the western region and the Shrub/Scrub land cover type, and for monthly averaged data over Deciduous/Evergreen Forest, suggest that the AMSR2 L3 SM datasets are characterized by a relatively high error. The mean error is 8.71 for the western region, 2.43 for Shrub/Scrub land cover types, and 5.05 for Deciduous/Evergreen Forest land cover types. The Shrub/Scrub land cover type is mainly distributed in the western region (Figure 1). Therefore, the consistency of the results is proved. The results of the error estimation in land cover suggest that regions covered by Cultivated Crops were characterized by a relatively low error (daily average 0.01 and monthly average 0.03) compared with the AMSR2 L3 SM datasets. The Shrub/Scrub land cover type also shows low error estimates for the SMAP L4 SM data.

The TC model was also applied to the temporal analysis for monthly average data. In this way, estimated errors were computed monthly to analysis the temporal variability. The results are shown in Table 4 and Figure 12. It can be seen briefly from Figure 12 that both SMAP L4 and AMSR2 L3 characterized by a relatively high estimated errors in March, July and October, with estimated value 0.126, 0.137 and 0.297 in SMAP L4 data and 1.635, 0.161 and 4.661 in AMSR2 L3 respectively. The poor values in October were consistent with Figures 2c and 3. It can be also observed from Table 4 that AMSR L3 provide poor performance with estimated error 4.18. In addition, both SMAP L4 and AMSR2 L3 data are characterized by slightly smaller error in January, February, November and December with respect to in situ probes (Figure 12). Surprisingly, both SMAP L4 and AMSR2 L3 in June are characterized by small error (0.04 and 0.07).

**Table 4.** Estimated errors of the in situ, SMAP, AMSR2 soil moisture dataset for monthly average with the TC method.

| Month | In Situ | SMAP | AMSR2 |
|---|---|---|---|
| January | 0.018 | 0.017 | 0.029 |
| February | 0.025 | 0.019 | 0.055 |
| March | 0.137 | 0.126 | 1.635 |
| April | 0.019 | 0.019 | 4.183 |
| May | 0.037 | 0.050 | 0.185 |
| June | 0.043 | 0.044 | 0.070 |
| July | 0.099 | 0.137 | 0.161 |
| August | 0.053 | 0.042 | 0.147 |
| September | 0.039 | 0.033 | 0.125 |
| October | 0.295 | 0.297 | 4.661 |
| November | 0.021 | 0.023 | 0.055 |
| December | 0.024 | 0.022 | 0.082 |

## 5. Discussion

This study investigated the estimated error of two remotely sensed soil moisture products (SMAP L4 and AMSR2 L3) with respect to reference in situ soil moisture measurements for different spatial distribution, monthly and daily time using TC method. The method successfully captured the spatial and temporal variations. For instance, cultivated crops performed well with daily and monthly averaged data both for SMAP and AMSR2, Poor performances with large estimation error were found for western region and Deciduous/Evergreen Forest both for SMAP and AMSR2. The combination of TC model and the four statistical indicators (MD, RMSE and R) is helpful for estimating the quality of regional soil moisture distribution of SMAP and AMSR2. Results showed that the trends of estimation error agreed with four statistics to some extent. For monthly averaged temporal analysis, both SMAP and AMSR2 got the poor error in October (Table 4), R results show similarly trend in Figure 3c. The low errors from November 2015 to February 2016 (Table 4) also consist with good monthly average R shown in Figures 2, 6 and 13. Moreover, as shown from Table 3 and Figure 12, poor estimated error with TC and low R with statistic indicator were fairly unanimous especially for AMSR2 L3 data. However, discrepancies also exist, for instance, poor quality in April with TC was not significantly displayed in temporal correlation analysis with four statistics.

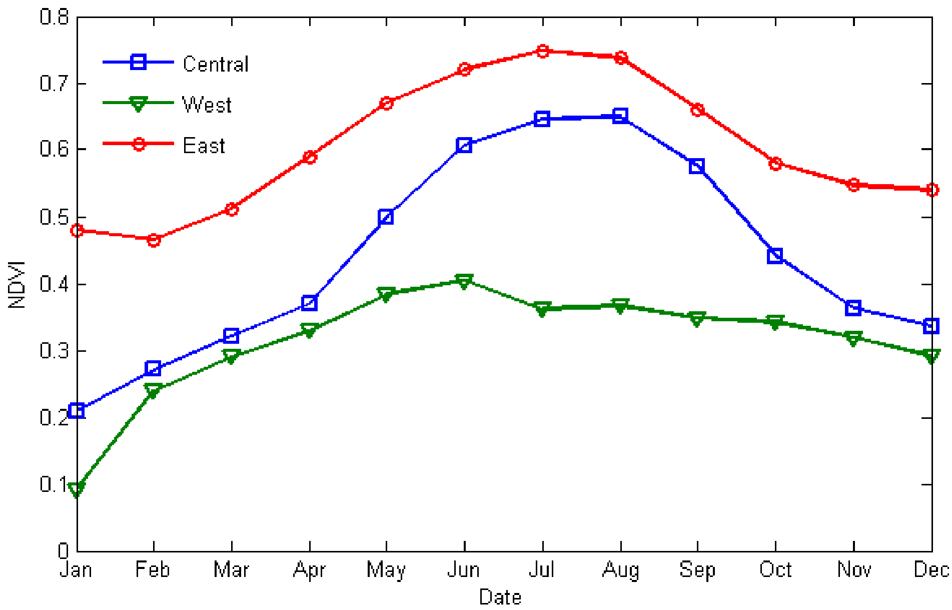



**Figure 13.** The temporal variation of averaged normalized difference vegetation index (NDVI) for sample sites in different spatial regions.

In our analysis, the in situ soil moisture observations from monitoring stations were used as ground truth to evaluate AMSR2 L3 and SMAP L4 soil moisture retrievals. Due to the coarse resolution and the spatial heterogeneity of AMSR2 L3 and SMAP L4 soil moisture data, point-based in situ measurements may not represent the spatially averaged soil moisture field well [51]. In addition, due to the disparity in spatial cover and the depth at which soil moisture is measured, in situ observations cannot exactly match the soil moisture retrievals of AMSR2 and SMAP, even under ideal land cover conditions [52,53].

The diversity of vegetation coverage, precipitation and climate characteristics are the key factors that influence the evaluation results. In addition, there is always substantial spatial heterogeneity in different land cover types and temporal and dynamic variation in their characteristics, which lead to different levels of performance in spatial-temporal analysis.

Examining the evaluated results, AMSR2 L3 SM data exhibited weak performance, no matter whether one of the four statistical indicators (MD, R, ubRMSE and RMSD) or the triple collocation method was used.

When evaluated at a global scale, the correlations and estimated error among the products highlight differences in their representations of the spatial and temporal series of soil moisture, with negative correlations found for several regions. This result was also obtained by previous studies [24]. The weak results from this evaluation may be explained by several reasons. First, uncertainties result from a number of complex factors that affect the radiative transfer model [15]. Second, there is a disparity in the vertical depth examined by the remotely sensed AMSR2 L3 SM data and the in situ data. The soil moisture content of the shallow layer (~1 cm) observed by AMSR2 L3 SM will differ from that of the deeper layer measured by the in situ monitoring stations (5 cm for SCANand USCRN). The soil moisture in the shallower remotely sensed layer (∼1 cm) tends to respond more rapidly to atmospheric forcing than the deeper soil layer (5 cm) observed by in situ soil sensors.

The SMAP L4 algorithm uses an ensemble Kalman filter (EnKF)to merge SMAP observations with soil moisture estimates from the NASA Catchment land surface model [43], while AMSR2 L3 use brightness temperature correction on the soil moisture content algorithm [15], Different retrieval algorithms and brightness temperature observations were used by AMSR2 and SMAP [26,42], which contributes to the differences between the two evaluation results. Conventional in situ measurements of soil moisture are made at a point, whereas satellite sensors provide results for an integrated area or volume covering a much larger spatial extent. The enormous heterogeneity in each pixel relative to the in situ measurement negatively influenced the accuracy of the assessment [40].

The factors presented above may also apply to the SMAP L4 SM data. The SMAP L4 SM data generally showed good agreement with the reference dataset and successfully captured the spatial and temporal variations present in Figures 6–11 and Tables 3 and 4. For instance, SMAP L4 SM performed well in the central region and in areas covered by Cultivated Crops. In particular, the two remotely sensed soil moisture products being compared give consistent and correct results in these areas, where soil moisture has been recognized to exert a strong influence on the spatial distribution. Conversely, both SMAP L4 SM and AMSR2 L3 SM exhibited weak correlations with the reference data in dry regions (e.g., for the Shrub/Scrub land cover type in the western region) (Figures 7 and 9), since that region is mainly desert with low vegetation cover (Figures 13 and 14). These results could be related to the low range of variation in soil moisture in these regions, which roughly corresponds to the expected retrieval accuracy of the remotely sensed products [22]. Meanwhile, both SMAP L4 SM and AMSR2 L3 SM also exhibited weak correlations with the reference data and large TC estimate error in evergreen forest regions. As shown in Figure 1, the eastern coastal area was found to mainly consist of Evergreen Forests. The results confirmed that vegetation plays a key role in the evaluated performance of the SMAP L4 and AMSR2 L3 soil moisture products. It can be seen from Figure 14 the NDVI were large through the year for Evergreen Forest. The correlation between the SMAP L4 computed R with in situ and NDVI is relative high with R = 0.78 (Figure 15), which demonstrated the vegetation influence to soil moisture products. The quality of soil moisture retrieval decreases with increasing vegetation intensity in Deciduous/Evergreen Forest, Pasture/Hay and Cultivated Crops (Figure 15). These findings were consistent with previous studies [8]. While Shrub/Scrub and Grassland/Herbaceous regions did not show similar correlation pattern with other land cover types, this can be partly explained by the low vegetation in Shrub/Scrub and high grass density in Grassland/Herbaceous (Figure 14).

Examining the temporal trends more closely, SMAP L4 SM tends to overestimate soil moisture from August to October and performs better during the winter dry season (e.g., November 2015–January 2016) than during the rest of the year. The reasons can be related to several aspects. At first, central region has low frequency of rainfall events in winter than other time periods (Figure 16), which partly demonstrated the better performance of SMAP soil moisture products in winter. Meanwhile, the August-October period also has abundant vegetation, which further exacerbates the inconsistency with in situ data (Figures 13 and 14). It can be demonstrated that the influence of vegetation could be captured by using a time series-based approach to soil moisture assessment [54]. In this paper, with NDVI of different regions and different land cover types from April 2015 to March 2016 (Figures 13 and 14) and the correlation between SAMP L4 evaluation R against in situ and NDVI (Figure 15), influence of vegetation for soil moisture products can be quantitative explained.

Furthermore, some aspects of the spatiotemporal data should be emphasized. From Figure 8, we found that the central region outperforms the western and eastern regions during almost the entire time series. As shown from Figure 13, higher NDVI in East region contributed to the weak performance. Although in West region the NDVI show little influence on the evaluation of SMAP L4 and AMSR2 L3 data, simultaneously, compare with East part lower rainfall occurs in West (Figure 16), which means that some other factors such as large spatial complexity of topography and surface feature may mainly influence the evaluation results. Through the compare analysis of precipitation in different regions (Figure 16), we can found that more rainfall occurs in the eastern region, which influenced the evaluation quality. Nevertheless, the AMSR L3 SM data exhibit opposite results for correlation from August to October. A similar phenomenon is also found in the land cover spatial-temporal analysis, as shown in Figure 9. Deciduous and Evergreen forest show negative correlation in the monthly average data. This result may be due to a number of factors, including greater vegetation coverage or changes in rainfall.

The time series analysis reveals weak performance in October, which can be clearly shown by the height and outline of box plots for daily averaged data (Figure 3). The same performance is also obtained in different spatial regions and land cover types. We speculate that some parts of each region lead to this situation. Analyzing the standard deviation of the correlation coefficients from Table 3, all of the standard deviation values in this month are relatively bigger than those of other months, which demonstrated the consistency of analysis result. we tried to find out the reasons for the weak performance in October through the Monthly NDVI and rainfall, as shown in Figures 13, 14 and 16, no singular value occurred in October, further embedded verification in daily scale are needed to be conducted.

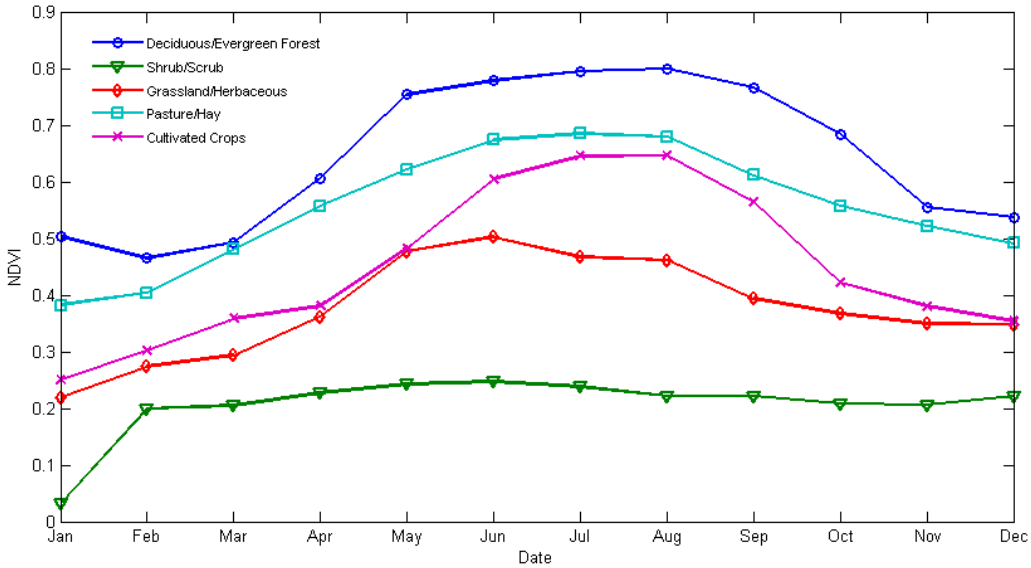



**Figure 14.** The temporal variation of averaged NDVI for sampling sites in different land covers.

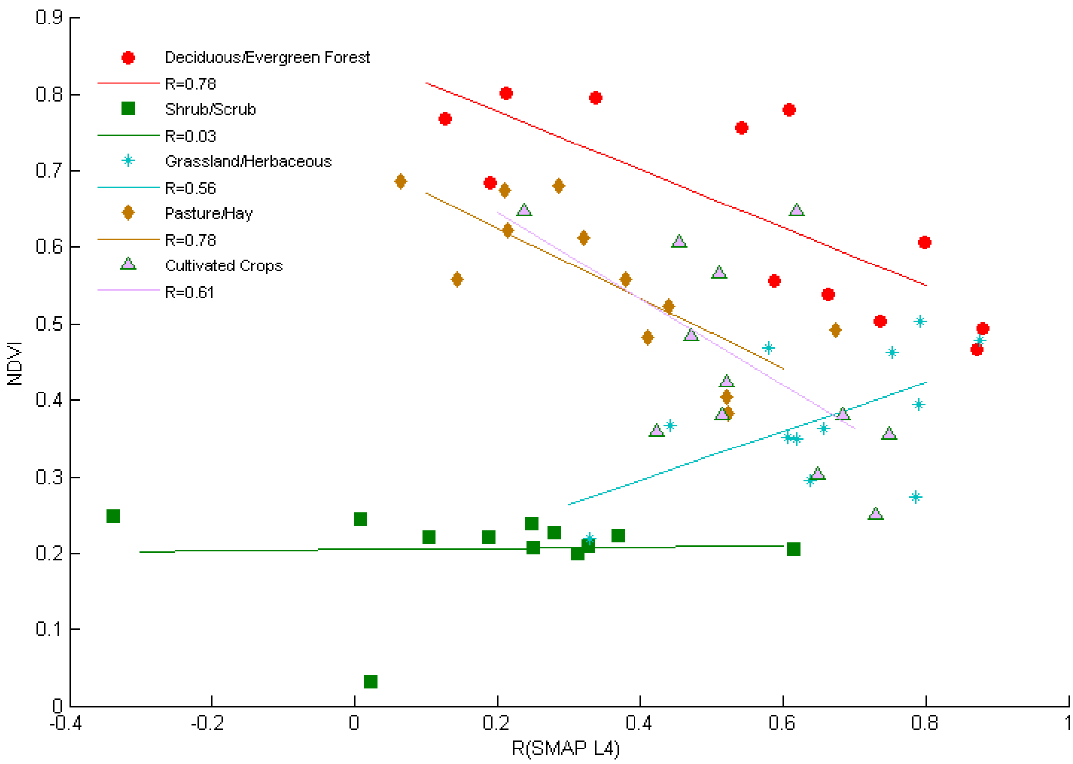



**Figure 15.** The comparison between NDVI and SMAP L4 evaluation results against in situ (R).

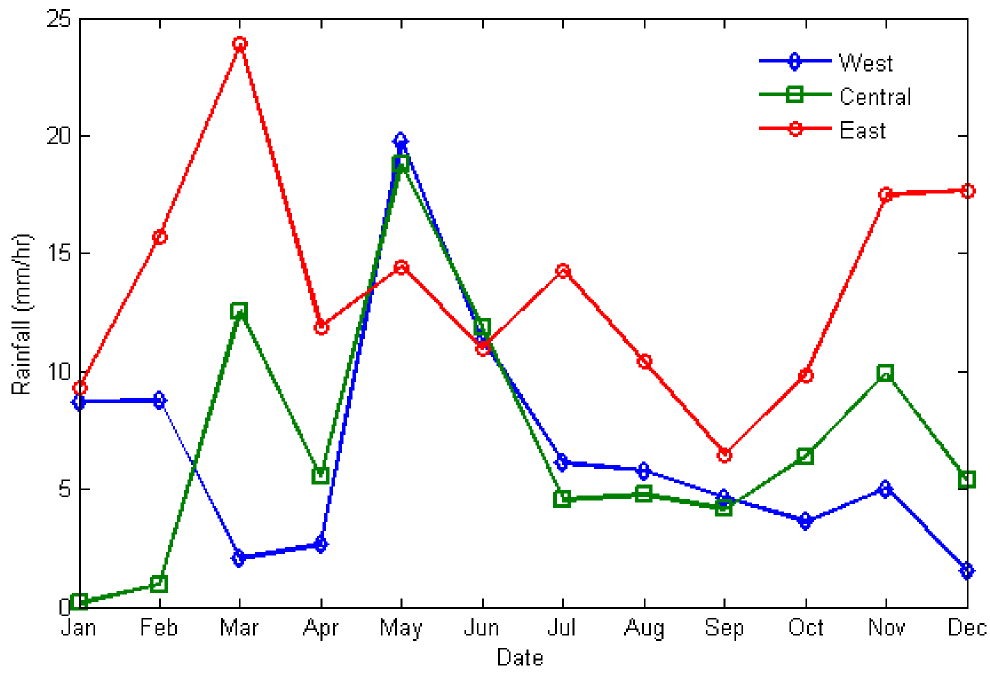



**Figure 16.** The monthly average rainfall in different regions.

Considering the absolute difference between remotely sensed soil moisture retrievals and in situ soil moisture observations, SMAP L4 SM data displayed relatively small average RMSD and ubRMSE (Figure 2). In Figure 6 RMSD and Figure 7 RMSD, the western region shows lower RMSD for both the SMAP L4 SM and AMSR2 L3 SM data. Meanwhile, the Shrub/Scrub land cover type shows comparatively lower RMSD and ubRMSE throughout the time series. It is generally seen from Figure 1 that the Shrub/Scrub land cover type is mainly found in the western region, in this region the NDVI was low through the year (Figure 13). The low range and variation of soil moisture in those regions partly contribute to the low RMSD and ubRMSE. For validation of satellite-based soil moisture products, the most challenging issue is the representativeness of the in situ measurements, both in situ sensor errors and the under sampling of the true field mean soil moisture based on a finite number of point samples can cause bias and amplitude errors in the estimates [47]. Although SMAP L4 soil moisture products show good agreement with in situ observations in R, however the ubRMSE value of SMAP L4 and AMSR2 L3 in different spatial and time series can't meet the design criteria. According to the previous research [15], the ubRMSE and RMSD with original data were higher than anomaly data, in this study the statistics indicators are based on original data, the lower ubRMSE may exhibit in anomaly data based analysis. Moreover, lower ubRMSE, which meet the product criteria always displayed in density samples with smaller ranges [29], while relatively higher ranges with sparse samples and Terrain complexity, which further lead to the high ubRMSE.

In previous studies, anomalous in situ data were retained for evaluation [13]. In this study, in situ observations near water were excluded. Hence, discrepancies may appear to some extent. Theoretical uncertainties are good indicators of existing uncertainties among different products.

## 6. Conclusions

Based on the results obtained, the following conclusions can be drawn:

The satellite soil moisture estimates derived from AMSR2 L3 soil moisture data products and SMAP L4 soil moisture data products were assessed. The SMAP L4 SM data showed relatively better agreement than AMSR2 L3 SM data with in situ observed data located in different spatial regions and arranged in a time series covering a whole year. This conclusion can be supported fairly well by triple collocation (TC) and the four statistics used (MD, RMSD, ubRMSE and R).

Our analysis suggests that the performance of the AMSR2 L3 SM and SMAP L4 SM data varies depending upon their spatial distribution and time series distribution. In terms of spatial series analysis, both SMAP L4 SM and AMER2 L3 SM data in the central region and land covered by Cultivated Crops show good agreement with in situ observations, considering both monthly average and daily average time scales.

In terms of time series analysis, the accuracy and reliability of the two remotely sensed soil moisture estimates varies over time. With a weak correlation coefficient from May to October 2015 and a good correlation coefficient from November 2015 to January 2016. The SMAP L4 SM data performed better in capturing surface soil moisture over time.

It should be noted that even though the evaluated SMAP L4products used in this study were found to be very reliable according to the spatial series analysis and time series analysis. Focus on the influence of spatial-temporal characteristics, the land covers with Cultivated Crops, Deciduous/Evergreen Forest, Pasture/Hay and were significantly influenced by seasonal variation, while the AMSR2 L3 SM data cannot show seasonal fluctuations except in regions of Cultivated Crops.

Overall, the conducted validation analysis allowed determination of the reliability of AMSR2 L3 SM and SMAP L4 SM soil moisture products through a robust and standardized comparison with ground observations for analysis of spatial series, time series and spatiotemporal series on both daily and monthly time scales across the contiguous United States.

**Acknowledgments:** This work was supported by the NSFC Project Fund (41671353, 41301394, 41431174, 61471358). The authors wish to thank JAXA, NSDIC, NRCS, NCDC and MRLC for making soil moisture data available online.

**Author Contributions:** Xuefei Zhang and Tingting Zhang designed the research; Xuefei Zhang, Tingting Zhang and ShanGao performed data analysis; Yun Shao and Ping Zhou contributed ideas.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Kang, C.S.; Kanniah, K.D.; Kerr, Y.H.; Cracknell, A.P. Analysis of in-situ soil moisture data and validation of SMOS soil moisture products at selected agricultural sites over a tropical region. *Int. J. Remote Sens.* **2016**, *37*, 3636–3654. [CrossRef]
2. Kerr, Y.H.; Waldteufel, P.; Richaume, P.; Wigneron, J.P.; Ferrazzoli, P.; Mahmoodi, A.; Al Bitar, A.; Cabot, F.; Gruhier, C.; Juglea, S.E.; et al. The SMOS soil moisture retrieval algorithm. *IEEE Trans. Geosci. Remote Sens.* **2012**, *50*, 1384–1403. [CrossRef]
3. Entekhabi, D.; Njoku, E.G.; O'Neill, P.E.; Kellogg, K.H.; Crow, W.T.; Edelstein, W.N.; Entin, J.K.; Goodman, S.D.; Jackson, T.J.; Johnson, J.; et al. The Soil Moisture Active Passive (SMAP) mission. *Proc. IEEE* **2010**, *98*, 704–716. [CrossRef]
4. Imaoka, K.; Kachi, M.; Kasahara, M.; Ito, N.; Nakagawa, K.; Oki, T. Instrument performance and calibration of AMSR-E and AMSR2. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2010**, *38*, 13–16.
5. Kawanishi, T.; Sezai, T.; Ito, Y.; Imaoka, K.; Takeshima, T.; Ishido, Y.; Shibata, A.; Miura, M.; Inahata, H.; Spencer, R.W. The advanced microwave scanning radiometer for the earth observing system (AMSR-E), NASDA'S contribution to the EOS for global energy and water cycle studies. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 184–194. [CrossRef]
6. Njoku, E.G.; Jackson, T.J.; Lakshmi, V.; Chan, T.K.; Nghiem, S.V. Soil moisture retrieval from AMSR-E. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 215–229. [CrossRef]
7. Lu, H.; Koike, T.; Fujii, H.; Ohta, T.; Tamagawa, K. Development of a physically-based soil moisture retrieval algorithm for spaceborne passive microwave radiometers and its application to AMSR-E. *J. Remote Sens. Soc. Jpn.* **2009**, *29*, 253–262.
8. Brocca, L.; Tarpanelli, A.; Moramarco, T.; Melone, F.; Ratto, S.M.; Cauduro, M.; Ferraris, S.; Berni, N.; Ponziani, F.; Wagner, W.; et al. Soil moisture estimation in alpine catchments through modeling and satellite observations. *Vadose Zone J.* **2013**. [CrossRef]
9. Dorigo, W.A.; Scipal, K.; Parinussa, R.M.; Liu, Y.Y.; Wagner, W.; de Jeu, R.A.M.; Naeimi, V. Error characterisation of global active and passive microwave soil moisture datasets. *Hydrol. Earth Syst. Sci.* **2010**, *14*, 2605–2616. [CrossRef]

10. Owe, M.; de Jeu, R.; Van de Griend, A. *Estimating Long Term Surface Soil Moisture from Satellite Microwave Observations in Illinois, USA*; IAHS Publication: Wallingford, UK, 2001.
11. Parinussa, R.; Meesters, A.; Liu, Y.; Dorigo, W.; Wagner, W.; De Jeu, R. An analytical solution to estimate the error structure of a global soil moisture data set. *IEEE Geosci. Remote Sens. Lett.* **2011**, *8*, 779–783. [CrossRef]
12. Albergel, C.; de Rosnay, P.; Gruhier, C.; Munoz-Sabater, J.; Hasenauer, S.; Isaksen, L.; Kerr, Y.; Wagner, W. Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations. *Remote Sens. Environ.* **2012**, *118*, 215–226. [CrossRef]
13. Brocca, L.; Hasenauer, S.; Lacava, T.; Melone, F.; Moramarco, T.; Wagner, W.; Dorigo, W.; Matgen, P.; Martinez-Fernandez, J.; Llorens, P.; et al. Soil moisture estimation through ascat and AMSR-E sensors: An intercomparison and validation study across Europe. *Remote Sens. Environ.* **2011**, *115*, 3390–3408. [CrossRef]
14. Parinussa, R.M.; Holmes, T.R.H.; Wanders, N.; Dorigo, W.A.; de Jeu, R.A.M. A preliminary study toward consistent soil moisture from AMSR2. *J. Hydrometeorol.* **2015**, *16*, 932–947. [CrossRef]
15. Wu, Q.S.; Liu, H.X.; Wang, L.; Deng, C.B. Evaluation of AMSR2 soil moisture products over the contiguous united states using in situ data from the international soil moisture network. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *45*, 187–199. [CrossRef]
16. Albergel, C.; Calvet, J.C.; de Rosnay, P.; Balsamo, G.; Wagner, W.; Hasenauer, S.; Naeimi, V.; Martin, E.; Bazile, E.; Bouyssel, F.; et al. Cross-evaluation of modelled and remotely sensed surface soil moisture with in situ data in Southwestern France. *Hydrol. Earth Syst. Sci.* **2010**, *14*, 2177–2191. [CrossRef]
17. An, R.; Zhang, L.; Wang, Z.; Quaye-Ballard, J.A.; You, J.; Shen, X.; Gao, W.; Huang, L.; Zhao, Y.; Ke, Z. Validation of the esa cci soil moisture product in China. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *48*, 28–36. [CrossRef]
18. Crow, W.T.; Berg, A.A.; Cosh, M.H.; Loew, A.; Mohanty, B.P.; Panciera, R.; de Rosnay, P.; Ryu, D.; Walker, J.P. Upscaling sparse ground-based soil moisture observations for the validation of coarse-resolution satellite soil moisture products. *Rev. Geophys.* **2012**. [CrossRef]
19. Draper, C.S.; Walker, J.P.; Steinle, P.J.; de Jeu, R.A.M.; Holmes, T.R.H. An evaluation of AMSR-E derived soil moisture over Australia. *Remote Sens. Environ.* **2009**, *113*, 703–710. [CrossRef]
20. Dorigo, W.A.; Gruber, A.; De Jeu, R.A.M.; Wagner, W.; Stacke, T.; Loew, A.; Albergel, C.; Brocca, L.; Chung, D.; Parinussa, R.M.; et al. Evaluation of the ESA CCI soil moisture product using ground-based observations. *Remote Sens. Environ.* **2015**, *162*, 380–395. [CrossRef]
21. Leroux, D.J.; Kerr, Y.H.; Al Bitar, A.; Bindlish, R.; Jackson, T.J.; Berthelot, B.; Portet, G. Comparison between SMOS, VUA, ASCAT, and ECMWF soil moisture products over four watersheds in US. *IEEE Trans. Geosci. Remote Sens.* **2014**, *52*, 1562–1571. [CrossRef]
22. Al-Yaari, A.; Wigneron, J.P.; Ducharne, A.; Kerr, Y.; de Rosnay, P.; de Jeu, R.; Govind, A.; Al Bitar, A.; Albergel, C.; Muñoz-Sabater, J.; et al. Global-scale evaluation of two satellite-based passive microwave soil moisture datasets (SMOS and AMSR-E) with respect to land data assimilation system estimates. *Remote Sens. Environ.* **2014**, *149*, 181–195. [CrossRef]
23. Champagne, C.; Rowlandson, T.; Berg, A.; Burns, T.; L'Heureux, J.; Tetlock, E.; Adams, J.R.; McNairn, H.; Toth, B.; Itenfisu, D. Satellite surface soil moisture from SMOS and aquarius: Assessment for applications in agricultural landscapes. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *45*, 143–154. [CrossRef]
24. Kim, S.; Liu, Y.Y.; Johnson, F.M.; Parinussa, R.M.; Sharma, A. A global comparison of alternate AMSR2 soil moisture products: Why do they differ? *Remote Sens. Environ.* **2015**, *161*, 43–62. [CrossRef]
25. Zeng, J.; Li, Z.; Chen, Q.; Bi, H.; Qiu, J.; Zou, P. Evaluation of remotely sensed and reanalysis soil moisture products over the Tibetan Plateau using in-situ observations. *Remote Sens. Environ.* **2015**, *163*, 91–110. [CrossRef]
26. Das, N.N.; Entekhabi, D.; Dunbar, R.S.; Njoku, E.G.; Yueh, S.H. Uncertainty estimates in the SMAP combined active-passive downscaled brightness temperature. *IEEE Trans. Geosci. Remote Sens.* **2016**, *54*, 640–650. [CrossRef]
27. Leroux, D.J.; Das, N.N.; Entekhabi, D.; Colliander, A.; Njoku, E.; Jackson, T.J.; Yueh, S. Active-passive soil moisture retrievals during the SMAP Validation Experiment 2012. *IEEE Geosci. Remote Sens. Lett.* **2016**, *13*, 475–479. [CrossRef]
28. Yee, M.S.; Walker, J.P.; Monerris, A.; Rudiger, C.; Jackson, T.J. On the identification of representative in situ soil moisture monitoring stations for the validation of SMAP soil moisture products in Australia. *J. Hydrol.* **2016**, *537*, 367–381. [CrossRef]

29. Zeng, J.Y.; Chen, K.S.; Bi, H.Y.; Chen, Q. A preliminary evaluation of the SMAP radiometer soil moisture product over united states and europe using ground-based measurements. *IEEE Trans. Geosci. Remote Sens.* **2016**, *54*, 4929–4940. [CrossRef]
30. Chen, F.; Crow, W.T.; Colliander, A.; Cosh, M.H.; Jackson, T.J.; Bindlish, R.; Reichle, R.H.; Chan, S.K.; Bosch, D.D.; Starks, P.J. Application of triple collocation in ground-based validation of Soil Moisture Active/Passive (SMAP) level 2 data products. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2016**, *99*, 1–14. [CrossRef]
31. Al-Yaari, A.; Wigneron, J.P.; Kerr, Y.; de Jeu, R.; Rodriguez-Fernandez, N.; van der Schalie, R.; Al Bitar, A.; Mialon, A.; Richaume, P.; Dolman, A.; et al. Testing regression equations to derive long-term global soil moisture datasets from passive microwave observations. *Remote Sens. Environ.* **2016**, *180*, 453–464. [CrossRef]
32. Stoffelen, A. Toward the true near-surface wind speed: Error modeling and calibration using triple collocation. *J. Geophys. Res. Oceans* **1998**, *103*, 7755–7766. [CrossRef]
33. Miralles, D.G.; Crow, W.T.; Cosh, M.H. Estimating spatial sampling errors in coarse-scale soil moisture estimates derived from point-scale observations. *J. Hydrometeorol.* **2010**, *11*, 1423–1429. [CrossRef]
34. Pierdicca, N.; Fascetti, F.; Pulvirenti, L.; Crapolicchio, R.; Munoz-Sabater, J. Analysis of ASCAT, SMOS, in-situ and land model soil moisture as a regionalized variable over Europe and North Africa. *Remote Sens. Environ.* **2015**, *170*, 280–289. [CrossRef]
35. Scipal, K.; Holmes, T.; de Jeu, R.; Naeimi, V.; Wagner, W. A possible solution for the problem of estimating the error structure of global soil moisture data sets. *Geophys. Res. Lett.* **2008**. [CrossRef]
36. Wang, S.; Mo, X.; Liu, S.; Lin, Z.; Hu, S. Validation and trend analysis of ECV soil moisture data on cropland in North China plain during 1981–2010. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *48*, 110–121. [CrossRef]
37. Koike, T.; Nakamura, Y.; Kaihotsu, I.; Davaa, G.; Matsuura, N.; Tamagawa, K.; Fujii, H. Development of an Advanced Microwave Scanning Radiometer (AMSR-E) algorithm for soil moisture and vegetation water content. *Proc. Hydraul. Eng.* **2004**, *48*, 217–222. [CrossRef]
38. Maeda, T.; Taniguchi, Y. *Descriptions of GCOM-W1 AMSR2 Level 1r and Level 2 Algorithms*; Japan Aerospace Exploration Agency Earth Observation Research Center: Ibaraki, Japan, 2013.
39. Cho, E.; Moon, H.; Choi, M. First assessment of the Advanced Microwave Scanning Radiometer 2 (AMSR2) soil moisture contents in Northeast Asia. *J. Meteorol. Soc. Jpn.* **2015**, *93*, 117–129. [CrossRef]
40. Jackson, T.J.; Cosh, M.H.; Bindlish, R.; Starks, P.J.; Bosch, D.D.; Seyfried, M.; Goodrich, D.C.; Moran, M.S.; Du, J.Y. Validation of advanced microwave scanning radiometer soil moisture products. *IEEE Trans. Geosci. Remote Sens.* **2010**, *48*, 4256–4272. [CrossRef]
41. Owe, M.; de Jeu, R.; Holmes, T. Multisensor historical climatology of satellite-derived global land surface moisture. *J. Geophys. Res. Earth Surf.* **2008**. [CrossRef]
42. Das, N.N.; Entekhabi, D.; Njoku, E.G. An algorithm for merging SMAP radiometer and radar data for high-resolution soil-moisture retrieval. *IEEE Trans. Geosci. Remote Sens.* **2011**, *49*, 1504–1512. [CrossRef]
43. Reichle, R.; Koster, R.; De Lannoy, G.; Crow, W.; Kimball, J. Level 4 Surface and Root Zone Soil Moisture (L4_SM) Data Product. Available online: http://nsidc.org/sites/nsidc.org/files/files/272_L4_SM_RevA_web.pdf (accessed on 10 November 2016).
44. Reichle, R.H.; De Lannoy, G.J.; Liu, Q.; Colliander, A.; Conaty, A.; Jackson, T.; Kimball, J.; Koster, R.D. *Soil Moisture Active Passive (SMAP) Project Assessment Report for The Beta-Release L4_SM Data Product*; NASA Technical Report Series on Global Modeling and Data Assimilation, NASA/TM-2015; NASA: Houston, TX, USA, 2015.
45. Schaefer, G.L.; Cosh, M.H.; Jackson, T.J. The usda natural resources conservation service soil climate analysis network (scan). *J. Atmos. Ocean. Technol.* **2007**, *24*, 2073–2077. [CrossRef]
46. Jin, S.M.; Yang, L.M.; Danielson, P.; Homer, C.; Fry, J.; Xian, G. A comprehensive change detection method for updating the national land cover database to CIRCA 2011. *Remote Sens. Environ.* **2013**, *132*, 159–175. [CrossRef]
47. Entekhabi, D.; Yueh, S.; O'Neill, P.E.; Kellogg, K.H.; Allen, A.; Bindlish, R.; Brown, M.; Chan, S.; Colliander, A.; Crow, W.T. *SMAP Handbook–Soil Moisture Active Passive: Mapping Soil Moisture and Freeze/Thaw From Space*; Jet Propulsion Laboratory: Pasadena, CA, USA, 2014.
48. Fang, H.; Wei, S.; Jiang, C.; Scipal, K. Theoretical uncertainty analysis of global MODIS, Cyclopes, and Globcarbon Lai products using a triple collocation method. *Remote Sens. Environ.* **2012**, *124*, 610–621. [CrossRef]

49. Barber, M.; Grings, F.; Bruscantini, C.; Karszenbaum, H. Rationale behind an optimal field experiment to assess the suitability of soil moisture retrieval algorithms for SAR data. *IEEE Geosci. Remote Sens. Lett.* **2015**, *12*, 791–795. [CrossRef]
50. Cho, E.; Choi, M. Regional scale spatio-temporal variability of soil moisture and its relationship with meteorological factors over the Korean Peninsula. *J. Hydrol.* **2014**, *516*, 317–329. [CrossRef]
51. Dorigo, W.; Wagner, W.; Hohensinn, R.; Hahn, S.; Paulik, C.; Xaver, A.; Gruber, A.; Drusch, M.; Mecklenburg, S.; Oevelen, P.V. The international soil moisture network: A data hosting facility for global in situ soil moisture measurements. *Hydrol. Earth Syst. Sci.* **2011**, *15*, 1675–1698. [CrossRef]
52. Hollinger, S.E.; Isard, S.A. A soil-moisture climatology of illinois. *J. Clim.* **1994**, *7*, 822–833. [CrossRef]
53. Vivoni, E.R.; Gebremichael, M.; Watts, C.J.; Bindlish, R.; Jackson, T.J. Comparison of ground-based and remotely-sensed surface soil moisture estimates over complex terrain during SMEX04. *Remote Sens. Environ.* **2008**, *112*, 314–325. [CrossRef]
54. Wagner, W.; Lemoine, G.; Rott, H. A method for estimating soil moisture from ERS scatterometer and soil data. *Remote Sens. Environ.* **1999**, *70*, 191–207. [CrossRef]