Spatial Evaluation and Assimilation of SMAP, SMOS, and ASCAT Satellite Soil Moisture Products Over Africa Using Statistical Techniques

B. G. Mousa1,2,3 and Hong Shu1,2

1State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China, 2Collaborative Innovation Center of Geospatial Technology, Wuhan, China, 3Faculty of Engineering, Al-Azhar University, Cairo, Egypt

Abstract The limited number of in situ stations of surface soil moisture (SM) in Africa creates a shortage in the validation of SM satellite products. Therefore, this study investigates the performance of Soil Moisture Active Passive (SMAP), Soil Moisture and Ocean Salinity (SMOS), and the H113 product from the Advanced Scatterometer (ASCAT) on the regional scale over Africa through these goals: (1) validate of satellite SM products against in situ stations and SM data from the ERA-Interim atmospheric reanalysis product, (2) study the spatiotemporal variability of satellite SM products on the regional scale, and (3) evaluate the regional scale error patterns and investigate regions where the assimilation of satellites SM data may add improvement to ERA-Interim. Standard statistical metrics, hovmöller diagrams, and the Triple Collocation (TC) model were used to achieve these goals. Land cover data, Normalized Difference Vegetation Index, and precipitation data were used to interpret results. The validation results based on statistical metrics and TC indicate that over the desert and shrub, passive products showed better performance than ASCAT, while over moderate vegetation areas (grassland), SMAP had the best among SM products. Over high densely vegetated regions, ASCAT showed a high comparatively performance than passive products. The potential regions for assimilation of satellite data sets were selected to be over savannas and grassland regions for ASCAT, and over shrub and grassland regions for SMAP. In particular, SMAP and ASCAT SM data sets are considered more stable than SMOS for data assimilation and capturing the spatial distribution of SM on the regional scale over Africa.

1. Introduction

Surface soil moisture (SM) has a clear impact on the energy partition and water on the land surface and also acts as a critical control on the interaction between land and atmosphere, biogeochemical cycles, and hydrology (Brocca et al., 2016; Paloscia et al., 2012). Therefore, surface SM is essential in many studies, such as flood forecasting, climate simulation, and land surface modeling (Brocca et al., 2017; Vittucci et al., 2013).

In satellites, the most common method for measuring SM is by using active and passive microwave remote sensing instruments that operate in the range from 1 to 10 GHz (Wagner et al., 2012). Passive remote sensing is more sensitive to surface SM content and therefore the most widely used way to map global or regional SM (Jackson et al., 1999). Over the past few decades, passive remote sensing at different frequencies including the X, C, and L bands has been widely used to evaluate soil moisture (Kolassa et al., 2016; Schmugge et al., 1974; Vittucci et al., 2013).

Two satellite missions specified for measuring global SM including the Soil Moisture Active Passive (SMAP) mission of National Aeronautics and Space Administration (NASA) launched in 2015 and the Soil Moisture and Ocean Salinity (SMOS) mission launched in 2009 and operated by the European Space Agency (ESA) (Entekhabi et al., 2010; Kerr et al., 2010). At present, both SMAP and SMOS operate on L-band microwave radiometers (1–2 GHz), where the L-band observation can penetrate to a deeper depth than other bands (e.g., X and C bands), which makes it more reliable for SM retrieval. The soil moisture retrieved from the SMOS and SMAP observations on a global scale is released freely to users, supporting many applications and associated soil moisture research (Anam et al., 2017; Shellito et al., 2016). In addition to the capabilities of these two satellite missions, there are many operational sensors (active and passive), which provide surface SM observations at C band and X band. These instruments include the Advanced Scatterometer

© 2019 The Authors. This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.
ASCAT), the Microwave Radiation Imager, and the Advanced Microwave Scanning Radiometer 2. ASCAT is an active microwave sensor on board Metop-A and Metop-B and works at frequency 5.255 GHz (Albergel et al., 2009; Y. Cui et al., 2016; Dorigo et al., 2010; Parinussa et al., 2015; Wagner et al., 2013).

The near-real-time ASCAT SM service launched in 2008 supports many applications. One of these applications is a numerical weather prediction (NWP). Motivated by some successful experiments for NWP assimilation, many centers for meteorological forecasts were used ASCAT SM data for verification and assimilation. For instance, based on a simplified extended Kalman filter, the European Center for Medium-range Weather Forecasts (ECMWF) applied an assimilation system in 2010, which showed improvements over the SM forecasts (De Rosnay et al., 2012). In addition, in 2010 the Met office in the U.K. implemented an assimilation system based on a nudging scheme. In this system, the screen-level parameters were improved over North America, Australia, and the tropics (Dharssi et al., 2011).

Understanding the spatial error patterns of different satellite SM products is essential for many operational applications. The most common way to validate satellite SM products is through relative comparison with ground data considered as truth (Brocca et al., 2010; Draper et al., 2011). However, mismatches between ground measurements and the footprints of satellite observations on the large-scale lead to increasing error, often exceeding the actual value of retrieval errors for the data set under validation (Gruber et al., 2013; Miralles et al., 2010). Moreover, the ground measurements cover only small regions of the land surface and are, therefore, not enough for comprehensive validation of satellite SM products for different land surface covers and under all climate conditions (Dorigo et al., 2011).

The other common way to assess satellite products is to compare satellite retrievals to land surface model outputs (Leroux et al., 2014). These models are available in the global range and have similarity in their spatial resolution but contain significant errors in the modeling itself and their quality is often not finely characterized (Albergel et al., 2012). In addition, the Triple Collocation (TC) method is a statistical model that can evaluate the satellite SM products without the need for an additional reference data set as in the case of conventional metrics. In TC, the random error variances and signal to noise ratios (SNR) of three independent data sets for the same geophysical variable can be estimated without considering any of them as a hypothetically error-free references (Gruber et al., 2016).

The objective of this study therefore is to investigate the performance of the ASCAT, SMAP, and SMOS, products on the regional scale over Africa. There were four goals:

1. Assess SM retrievals from SMAP, SMOS, and the H113 product from the ASCAT products through a comparison with available ground stations and an ERA-Interim reanalysis.
2. Calculate hovmöller diagrams to investigate spatiotemporally SM dynamic between SM products on the regional scale.
3. Estimate error patterns and SNR for soil moisture products on the regional scale by using TC analysis, considering different land surface covers.
4. Investigate the potential of SMAP, SMOS, and ASCAT SM products for improving the ERA-Interim model.

The rest of this paper is organized as follows: section 2 includes a short introduction about soil moisture products from satellites, in situ data, and ancillary data. The methodologies used in this study are covered in section 3 including, error statistics metrics, hovmöller diagram, and triple collocation error model. Results are presented and discussed in section 4, and conclusions are drawn in section 5.

2. Data Sets

2.1. Radiometric Data Sets

In our work, the SMAP L3 Radiometer Daily SM with a 36 km resolution (Version 5, https://search.earthdata.nasa.gov) was used. SMAP satellite was developed by NASA as the first Earth observation satellite and launched on 31 January 2015 (Colliander et al., 2017; Zeng, 2016). SMAP carries both an L-band radiometer with frequency 1.41 GHz and L-band radar with 1.26 GHz nonimaging SAR. Due to an irrecoverable hardware failure a few months after the launch, the radar instrument stopped working. Currently, the working radiometer can provide passive observations with a 36 km spatial resolution every two to three days (Reichle, 2015). SMAP covers the globe every three days and overpasses the equator at 06:00 (descending orbit) and 18:00 (ascending orbits) local solar time. The SMAP mission was designed to retrieve SM at an
The SMAP SM data set was filtered for soil moisture values lower than 0.02 m$^3$m$^{-3}$ and higher than 0.50 m$^3$m$^{-3}$ and based on the SM retrieval quality flag when set as “recommended for retrieval” (Chan et al., 2016). The daily average ascending and descending SM SMAP retrievals were calculated and resampled using the nearest neighbor method to 25 km resolution to match the spatial characteristics of other SM data sets.

In this study, the SMOS L3 SM product projected on EASE Grid with a spatial resolution of 25 km from the Centre Aval de Traitement des Données SMOS (CATDS) (https://www.catds.fr/Products/Available-products-from-CPDC) were evaluated (Jacquette et al., 2010). The SMOS satellite was launched in November 2009 as a second explorer Opportunity mission for the earth by the ESA. SMOS carries a 2-D interferometric microwave radiometer that can provide both dual polarization and multimodal measurements. It was the first L-band (1.4 GHz) microwave satellite that was specified for near-surface SM observations on a global scale. This satellite can revisit one region within 2–3 days at 6:00 (ascending orbit) and 18:00 (descending orbit) local solar time. SMOS SM was retrieved by using the L-band Microwave Emission of the Biosphere (L-MEB) algorithm. The algorithm of the L-MEB model retrieves the parameters of both vegetation optical depth and surface SM simultaneously with utilizing the advantage of the SMOS multiangular data (Wigneron et al., 2007). Two filters were used to exclude unreliable SMOS retrieval data with the probability of radio frequency interference (RFI) larger than 0.2 (RFI_Prob>0.2) and Data Quality Index exceeding 0.1 (Soil_Moisture_Dqx < 0.1). Moreover, we excluded the values of SM retrieval out of the range 0–0.6 m$^3$m$^{-3}$ (C. Cui et al., 2018; Lievens et al., 2015; Ma et al., 2019). More information about the used algorithm for SMOS L3 retrieval can be found in Kerr et al. (2012). The daily average SM data retrievals of SMOS for descending and ascending were calculated to match other data sets.

2.2. Scatterometric Data

In our work, the ASCAT SM data record that available through the product H113 collected from May 2015 to December 2016 as provided by the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) Satellite Application Facility to support to hydrology and water management (H-SAF) (http://hsaf.meteoam.it) was used. The ASCAT is an active microwave radar system operated by the European Organization for the EUMETSAT and working at C-band with a frequency of 5.255 GHz by using the TU Wien algorithm. At the current time, ASCAT on board on the several Meteorological Operational Platforms (Metop satellites) includes Metop-A (launched in Oct 2006), Metop-B (launched in Sep 2012), and Metop-C (launched in Nov 2018) satellites (Wagner et al., 2013). The H113 product is generated with 12.5 km spatial sampling based on Metop-A and Metop-B Level 1b backscatter products (Product User Manual, 2018). More information about the SM retrieval algorithm used to produce H113 can be found in European Organization for the Exploitation of Meteorological Satellites (2018). The unit of the relative surface SM for H113 product was translated from the degree of saturation to absolute units (m$^3$m$^{-3}$) by using global soil porosity derived from the consistent world soil database for the top layer (0–0.40 m) (ESA-CCI, http://www.esa-soilmoisture-cci.org). The ASCAT soil moisture data set was masked using surface state flag information if the probability of frozen or snow cover and estimated retrieval error >50% (Al-Yaari et al., 2019; Chen et al., 2018; Paulik et al., 2014). In addition, the data set was resampled using the nearest neighboring algorithm to 25 km to match the spatial resolution of other SM data sets.

2.3. Reanalysis Data

In the present study, we used the first layer (topmost) of daily averaged ERA-Interim SM product with a spatial resolution of 0.25° × 0.25° to validate satellite SM products over Africa. ECMWF produced the ERA-Interim atmospheric reanalysis on a global scale, which covers the period from 1979 to the present. The data assimilation system used in this product includes a 4-D vibrational system with a 12-hr analysis window. The ERA-Interim product uses four soil depths (0–7, 7–28, 28–100, and 100–289 cm) (Albergel et al., 2013; Balsamo et al., 2015; Dee et al., 2011). This data can be downloaded from ECMWF (http://apps.ecmwf.int/datasets/data/interim-full-daily). Several studies present evaluation and validation of satellite SM products based on reanalysis SM products (Al Bitar et al., 2012; Griesfeller et al., 2016; Kędzior & Zawadzki, 2017). The results show that the ERA-Interim not only captures the spatial variation of surface SM but also provides absolute values closer to the SM measurements of surface soil (Fang et al., 2016; Peng et al., 2015; Zeng et al., 2015).
2.4. In Situ Soil Moisture Data

To evaluate satellite SM products, we used all available in situ measurements from the International Soil Moisture Network (ISMN) in Africa. ISMN is a website center for SM data that stores and organizes the measurements of in situ SM from several operational global networks and makes these data available for users freely through a web (https://ismn.geo.tuwien.ac.at). The ISMN data are important for validating SM retrievals from land surface models and different satellites for studying the climate system (Dorigo et al., 2011; Fang et al., 2016; Peng et al., 2015). At present, the ISMN has several SM data sets collected from 1,400 ground stations and operated by different agencies and used in several studies for evaluation of satellite SM products (Albergel et al., 2013; Balsamo et al., 2015; Dee et al., 2011; Zeng et al., 2015). In this study, the in situ SM data acquired in the temporal period from May 2015 to December 2016 where more stations of ISMN (13 stations) contain continuous temporal measurements as shown in Figure 1. These stations from three networks and distributed in two land covers (shrub and grasslands), seven of ground stations obtained from the University of Arizona (Friedl et al., 2002), five ground stations obtained from the University of Colorado (Friedl et al., 2010), and the last ground station from Copenhagen University (Schneider et al., 2018). The in situ SM observations data are recorded every day, which allows for the evaluation of SM products.

2.5. Ancillary Data Sets

In this study, Version 6 MCD12Q1 product with a spatial resolution of 500 m was acquired from 2015 to 2016 as shown in Figure 1a to evaluate the performance of SM products for different terrain types across Africa. The Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover (MCD12Q1) is a yearly product that provides a global map for land cover with spatial resolution 500 m from 2001 to the present (https://search.earthdata.nasa.gov/; accessed on 15 January 2019). This product was created using supervised classification of MODIS reflectance data (Friedl et al., 2002, 2010). The in situ stations were distributed over two land covers (see Figure 1a).

In addition, in this work, the monthly Version 6 MOD13C2 0.05-Deg product from MODIS, the NDVI (Figure 1b) was used as an indication of the green vegetation condition for different land cover types, which helps in analyzing the performance of SM products. This product can be downloaded free from this website.
The land cover and NDVI data sets were rescaled by using the nearest neighboring interpolation method to 25 km to match the resolution of SM products before analysis.

The Global Precipitation Climatology Centre (GPCC) monthly precipitation product version 2018 at a spatial resolution of 0.25° from the GPCC was used to assess the influence of precipitation on SM products (Schneider et al., 2018). This product provides the amount of rain with a unit of the mm/month and can access freely from (https://opendata.dwd.de/climate_environment/GPCC/html/). The average precipitation value was calculated for Africa in the temporal period from May 2015 to December 2016 (Figure 2).

3. Methods

3.1. Standard Statistical Metrics

The satellite soil moisture products were estimated against in situ observations and the ERA-Interim reanalysis SM data by using standard statistical metrics include the bias, the unbiased root-mean-square error (ubRMSE), and the correlation coefficients ($R$) (Entekhabi et al., 2010). The bias represents the mean difference, namely, the systematic difference between satellite SM retrievals and the measurements of reference SM data set. The bias can be calculated using the following formula:

\[
\text{Bias} = E[SM_s(t)] - E[SM_r(t)]
\]  

To obtain a better reliable estimation for root-mean-square error, the bias can be removed by defining the unbiased ubRMSE that characterizes random error or anomaly. The ubRMSE can be calculated using the following equation:

\[
\text{ubRMSE} = \sqrt{E[\{SM_s(t) - E[SM_s(t)]\} - \{SM_r(t) - E[SM_r(t)]\}]^2}
\]  

where $E[\cdot]$ represents the calculation of the average values, $t$ is the measurement time, $SM_s(t)$ represents a satellite soil moisture retrieval at time $t$, and $SM_r(t)$ represents the reference soil moisture data set (in situ or ERA-Interim) at time $t$.

The correlation coefficient ($R$) is a statistic metric was used to measure the strength of the linear correlation between retrieved soil moisture data and reference SM data. The range of values for this metric is from $-1.0$ to $1.0$. With decreasing $R \geq 0$ meaning, the correlation between satellite retrieval data and reference data decreases, which refers to a decrease in the quality of satellite retrieval data. While with increasing $R < 0$, the correlation between retrieval data and the measurements of reference data set increases, which reflects positively on satellite data quality. The correlation coefficient ($R$) was calculated using the following formula:

\[
R = \frac{E[\{SM_s(t) - E[SM_s(t)]\} - \{SM_r(t) - E[SM_r(t)]\}]}{\sigma_s \sigma_r}
\]  

where $\sigma_s$ and $\sigma_r$ are the standard deviation of reference data and satellite SM retrieval data, respectively. The correlation coefficient was calculated at the $p$ value ($<0.05$), a high significance level.

3.2. Hovmöller Diagram

A Hovmöller diagram represents the time evolution of spatial data. The $x$ axis shows the time, and the $y$ axis displays data set average values either overall longitudes or overall latitudes (Hovmöller, 1949). In this study, the longitudinal averages were used for evaluating the reliability between SM data sets in capturing the mean seasonal dynamics of SM in Africa (Blunden et al., 2016).
3.3. TC Error Model

In addition to evaluating satellite SM products using standard statistical metrics, the TC method was also used to estimate these products on a regional scale. The TC method considers a promising technique to validate satellite-based SM (Dorigo et al., 2010; Scipal et al., 2008). In the TC analysis method, satellite SM products can be estimated without the need to use additional reference data sets as traditional metrics. More information about TC technique has been presented in (Draper et al., 2013; Gruber et al., 2016; Scipal et al., 2008; Su et al., 2014b, 2014a). The estimation of SM products using TC is based on a linear error model represented in the following formula:

$$SM_{si} = \alpha_{SM_{si}} + \beta_{SM_{si}} SM_t + \varepsilon_{SM_{si}}$$

(4)

where $SM_t$ represents the unknown true soil moisture, $SM_{si} \in \{SM_{s1}, SM_{s2}, SM_{s3}\}$ are three spatiotemporally collocated data sets, $\beta_{SM_{si}}$ and $\alpha_{SM_{si}}$ represent multiplicative biases and systematic additive of $SM_{si}$ data set with respect to the true value, and $\varepsilon_{SM_{si}}$ represents additive zero-mean random noise (Draper et al., 2013; Gruber et al., 2016; McColl et al., 2014). Based on the error model in equation (4), we used the equations of covariance notation (see equations (5)–(11)), which are proposed by Gruber et al. (2016), to calculate the error variance and SNR of soil moisture products taking in consideration the assumptions of TC. Triple collocation assumes independent errors. Therefore, we selected SM products with different in derivation as possible because similarly in derivation between data sets may be caused by partially correlated errors (Kim et al., 2018). For example, this may happen for SMAP and SMOS because both of them have used radiometers. For these reasons, we calculated TC twice: once with SMAP, ASCAT, and ERA-Interim and once with SMOS, ASCAT, and ERA-Interim. We used the TC statistics metrics for ASCAT from the SMOS triplet because ASCAT is not close in frequency to SMOS than SMAP. However, as we expected, there is an agreement between our TC estimates for each product with different triplets as will be discussed later.

$$Var_{(SM_{si})} = Var_{(SM_{si})} - \frac{COV_{(SM_{s1}, SM_{s2})} \cdot COV_{(SM_{s1}, SM_{s3})}}{COV_{(SM_{s2}, SM_{s1})}}$$

(5)

$$Var_{(SM_{si})} = Var_{(SM_{si})} - \frac{COV_{(SM_{s2}, SM_{s1})} \cdot COV_{(SM_{s2}, SM_{s3})}}{COV_{(SM_{s3}, SM_{s2})}}$$

(6)

$$Var_{(SM_{si})} = Var_{(SM_{si})} - \frac{COV_{(SM_{s3}, SM_{s2})} \cdot COV_{(SM_{s3}, SM_{s1})}}{COV_{(SM_{s1}, SM_{s3})}}$$

(7)

where $Var_{(SM_{si})}$, $Var_{(SM_{s1})}$, and $Var_{(SM_{s3})}$ represent random error variance of satellite SM products and $SM_{s1}$, $SM_{s2}$, and $SM_{s3}$ represent the independent soil moisture data sets in a triplet.

$$SNR_{(SM_{si})} = \frac{COV_{(SM_{s2}, SM_{s1})} \cdot COV_{(SM_{s3}, SM_{s1})}}{Var_{(SM_{si})}}$$

(8)

$$SNR_{(SM_{s1})} = \frac{COV_{(SM_{s2}, SM_{s1})} \cdot COV_{(SM_{s3}, SM_{s1})}}{Var_{(SM_{s2})}}$$

(9)

$$SNR_{(SM_{s3})} = \frac{COV_{(SM_{s2}, SM_{s1})} \cdot COV_{(SM_{s3}, SM_{s1})}}{Var_{(SM_{s3})}}$$

(10)

where $SNR_{(SM_{si})}$, $SNR_{(SM_{s1})}$, and $SNR_{(SM_{s3})}$ represent SNR of SM products, COV is the covariance of the two independent SM data sets, and Var is a variance of the satellite data error. The SNR was expressed in decibel [dB] by taking the decadic logarithm for SNR where the value of SNR will be distributed regularly around 0, which helps in interpretation the value of SNR easily and clearly (Gruber et al., 2016).

$$SNR[\text{dB}] = 10\log(SNR_{(SM_{si})})$$

(11)

where the value of SNR[dB] equal to 0 means that both the signal variance and the noise variance are equal. Moreover, every (±3) dB interval indicates an additional halving/doubling of the ratio between signal and
noise. Where +3 (+6) dB refers to the signal is twice (4 times) higher than the noise, the value −3 (−6) dB indicates that the signal is half (one fourth) of the noise and so on (Gruber et al., 2016; Kim et al., 2018).

4. Results and Discussion

4.1. Validation of SM Products against In Situ Measurements

The results of an analysis of the statistical metrics for the validation of SMAP, ASCAT, and SMOS SM products against in situ over shrub and grassland land covers are listed in Table 1 for the temporal period from May 2015 to December 2016. SMAP showed a high comparatively performance than SMOS and ASCAT products with a high overall average correlation \( R \) value, less overall average bias value, and with the lowest average overall ubRMSE value, which did not exceed the SMAP mission requirement of 0.04 m\(^3\) m\(^{-3}\).

| Land cover class | SMAP | ASCAT | SMOS |
|------------------|------|-------|------|
|                  |  \( R \) | Bias (m\(^3\) m\(^{-3}\)) | ubRMSE (m\(^3\) m\(^{-3}\)) |  \( R \) | Bias (m\(^3\) m\(^{-3}\)) | ubRMSE (m\(^3\) m\(^{-3}\)) |  \( R \) | Bias (m\(^3\) m\(^{-3}\)) | ubRMSE (m\(^3\) m\(^{-3}\)) |
| Shrub            | 0.56 | −0.0384 | 0.0360 | 0.44 | −0.0907 | 0.0390 | 0.48 | −0.0459 | 0.0469 |
| Grassland        | 0.72 | −0.009 | 0.0513 | 0.66 | −0.0174 | 0.0627 | 0.54 | −0.0479 | 0.0663 |
| Average          | 0.64 | −0.0237 | 0.0437 | 0.55 | −0.0541 | 0.0509 | 0.51 | −0.0496 | 0.0566 |

Note. Correlations were calculated at the significance level \( P < 0.05 \).

Figure 3. The statistical comparisons maps for satellite SM products with ER-Interim model over Africa, where the SMAP (a, d, and g), ASCAT (b, e, and h), and SMOS (c, f, and i): (a–c) for \( R \) estimates \( (P < 0.05) \), (d–f) for Bias estimates, and (g–i) for ubRMSE estimates for the period May 2015 to December 2016. The white regions indicate insignificant results between satellite data and the ERA-Interim (i.e., \( p \gtrsim 0.05 \)).
4.2. Comparison of Satellite SM Products with Reanalysis

The results and the summary of the statistical metrics for the comparison of SMAP, SMOS, and ASCAT satellite SM products with the ERA-Interim are shown in Figure 3 and listed in Table 2, respectively. The regions at which the results between satellite data and ERA-Interim insignificance (i.e., P < 0.05) were excluded. The SMOS showed the biggest excluded regions (over the desert area of eastern North Africa) among the soil moisture products due to the high intensity of RFI contamination.

Box plots for correlation and bias statistical metrics of SMAP, SMOS, and ASCAT with ERA-Interim over different land surface covers are shown in Figure 4. Taking into consideration the consistency between land surface covers, precipitation, and NDVI parameters (see Figures 1 and 2), for example, our results in the regions of high precipitation showed more green vegetation, this appears in the average NDVI value. This relationship between the parameters was exploited to assess the error metrics for satellites at different land cover types. Over the desert and shrub areas, with lower average NDVI, the SMAP and SMOS showed less bias, as indicated in the box plots found in Figures 4d–4f and higher correlation, seen in the box plots in Figures 4a–4c with ERA-Interim than the ASCAT product. The increase in vegetation resulted from an increase in precipitation where the grassland is the major of cover surface; SMAP and ASCAT showed less bias, as shown in the box plots in Figures 4d–4f and a higher correlation with ERA-Interim as in the box plots in Figures 4a–4c than the SMOS. Over the regions of more densely vegetation including crops, savannas, and forests, the ASCAT showed a high correlation with the ERA-Interim, shown in the box plots in Figures 4a–4c and less bias, indicated by the box plots in Figures 4d–4f than passive soil moisture products.

In terms of average correlations values taking into consideration land surface covers, all SM products showed a high correlation to the ERA-Interim over the whole of Africa except in the desert and tropical forests where it is difficult for satellites to retrieve SM values. In terms of the average bias, passive SM products showed a slight performance improvement over the active SM product in the desert. This is because the active sensors can produce a wet bias from the unexpected volume of scattering from subsurface

Table 2

| Overall Average metrics | SMAP  | ASCAT | SMOS  |
|-------------------------|-------|-------|-------|
| R                       | 0.59  | 0.57  | 0.42  |
| Bias                    | −0.053| −0.071| −0.075|
| ubRMSE                  | 0.044 | 0.061 | 0.090 |

Figure 4. Box plots of averages values of correlations and bias for the SMAP (a, d), ASCAT (b, e), and SMOS (c, f) soil moisture data sets with the ERA-Interim over different land surface covers: (a–c) for R estimates (d–f) for Bias estimates.
heterogeneity or scattering from deeper soil layers. These results are consistent with previous research, which found that the amount of backscatter decreased in desert environments (Wagner et al., 2013). A precipitation map (see Figure 2) indicates the sensitivity of passive sensors over active sensors. This map shows that the distribution of bias for passive sensors changed symmetrically in the desert of North Africa from high to low according to an increase in precipitation. ASCAT higher performance in more densely vegetation areas than other passive SM products, as the active sensor can penetrate through to deeper layers than passive sensors. This is clearly represented in hovmöller diagrams shown in section 4.3. However, these results are consistent with other studies which found that C-band active SM retrievals outperform on L-band passive retrievals in the regions with dense vegetation (Al-Yaari et al., 2014; Dorigo et al., 2010; Jackson et al., 1999; Kim et al., 2018). In terms of average ubRMSE value over all of Africa, SMAP showed higher performance than SMOS and ASCAT with the lowest overall average ubRMSE value (see Table 2), and not exceeding the SMAP mission requirement of 0.04 m³ m⁻³.

4.3. Hovmöller Diagram Analysis

Hovmöller diagrams for SM products over Africa in the period from May 2015 to December 2016, where (a) ERA-Interim, (b) SMAP, (c) ASCAT, and (d) SMOS. Note that the time displayed on the x axis every four months.

Figure 5. Hovmöller diagrams for SM products over Africa in the period from May 2015 to December 2016, where (a) ERA-Interim, (b) SMAP, (c) ASCAT, and (d) SMOS. Note that the time displayed on the x axis every four months.

Over the desert regions of North Africa, which are represented in the upper parts of hovmöller diagrams, all satellites showed low variability where the values of soil moisture change are close zero. Also in these regions, all satellites showed low frequency where the sensitivity of satellites for daily change of soil moisture is very low. Therefore, these reasons can explain the wet bias of satellites with ERA-Interim over the desert, as indicated in the box plots found in Figures 4d-4f.
4.4. TC Analysis

The results of in situ-based statistical provide satellite SM performance only at limited regional and might have scale mismatch issues. These shortages can be eliminated by using TC analysis. In this section, active and passive SM products were estimated using TC metrics. Moreover, the results were interpreted by using spatial distribution of precipitation and NDVI data sets at different land surface covers to provide the advantages and shortage of using certain satellite SM products for practical applications on the regional scale.

The TC metrics results indicate that there are consistent estimates of ASCAT and ERA-Interim with the two different triplets, which indicates that TC assumptions were not violated (Gruber et al., 2016). The results of the error variance and SNR for SMAP calculated from the first triplet and for SMOS and ASCAT from the second triplet are shown in Figure 6. Figures 7 and 8 show bar graphs for average error variance and average SNR[dB] considering different land surface covers for three satellite SM products.

The regions in one of the triplet data soil moisture sets showing a significantly different SM behavior than the two other data sets (i.e., $P \leq 0.05$) were excluded. The regions in one of the triplet data sets not containing observations were also excluded. These areas covered almost all of the desert regions in the north as well as the tropical forests in the center of Africa where the TC method cannot be applied (Scipal et al., 2008).
All satellites have limitations when retrieving SM in the north and southwestern part of Africa where these areas are classified as desert (Figure 1a) with very low precipitation (Figure 2) and very small average NDVI value (0.10) (Figure 1b). This is because in desert areas, all satellites have low SM variation, as inferred from the hovmöller diagrams (Figures 5). Changes in the SM signal were too small and did not therefore exceed the background noise of the instrument. This adds to difficulties when retrieving SM information by using microwave frequency observations. However, SMAP and SMOS showed slightly improved performance in the desert than ASCAT, which shows a high relative error variance and a negative SNR [dB] (green bars in Figures 7 and 8). Extremely dry soil contributes to the high systematic retrieval error, so microwave-based SM retrieval suffers some difficulties when providing a reading (Dorigo et al., 2010). One of these difficulties is related to the problems in estimating the effective temperature and the thickness of the emitting layer (Holmes et al., 2006).

Over low vegetated regions (shrub) (Figure 1a) with low amounts of precipitation (Figure 2) and less overall average NDVI values (0.21) (Figure 1b), SMAP and SMOS showed improved performance with a lower average error variance and higher average SNR[dB] than an active product. Gradually increasing precipitation lead to an average NDVI value of 0.37 in moderate vegetation regions where the grassland is the major surface cover (Figure 1a), SMAP showed the lowest average error and highest average SNR[dB] (red bars in Figures 7 and 8) among all SM products.

Over highly vegetated areas with highest precipitation amount (Figure 2) the average NDVI values were 0.50, 0.66, and 0.70 for three land surface covers include crops, savanna, and forests (Figure 1). The ASCAT values for these areas showed a lowest error variance and highest SNR (green bars in Figures 7 and 8) among all the SM products. These results indicate that ASCAT had better performance than passive SM products over densely vegetated regions. Moreover, the apparent contrast between passive and active SNR products is shown in the black boxes in Figures 3d–3f. The areas with high-temperature conditions above and below the equator are indicated by green arrows (Figure 6). Over widely varying temperature regions, the active sensors were less sensitive to surface temperature than passive sensors. Therefore,
Figure 9. SNR[dB] differences: (a) SMAP—ERA-Interim, (b) ASCAT—ERA-Interim, and (c) SMOS—ERA-Interim. The red boxes in (a) and (b) indicate the high differences of SNR between SM products and the ERA-Interim. The white regions indicate insignificant results between triplet data sets ($p \geq 0.05$).
ASCAT displayed less susceptibility to daylight surface temperature change over more dense vegetation areas (Al-Yaari et al., 2014; Dorigo et al., 2010; Scipal et al., 2008). However, taking into consideration alternative technologies, soil moisture retrievals of passive microwave systems could be improved if the effective temperature evaluations were parameterized (Kim et al., 2018; Parinussa et al., 2011). In the retrieval algorithms of SMAP and SMOS, the surface temperature is derived from the Goddard Earth Observing System, version 5 and ECMWF simulation models, respectively. Theoretically, the underestimation of surface temperature will lead to an overestimation of soil emissivity, which leads to an underestimation of SM (C. Cui et al., 2018).

4.4.1. Data Assimilation Analysis

The SNR differences between satellite SM products and reanalysis data provide important information about the possibility of using the satellite SM data sets for data assimilation. Data assimilation aims to improve the quality of model estimates when observations are available. The weight is specified to an observation and a model estimate through an update step and directly calculated by their respective random error variance, while systematic errors are usually adjusted by rescaling the observations into the model space. Figure 9 shows the SNR differences between satellite SM products and the ERA-Interim. ASCAT shows higher SNR (>3.0 dB) than the ERA-Interim over savannas and grassland regions. SMAP outperforms the ERA-Interim over shrub and grassland regions. In most of these areas, there are significantly reduced in the station density of model forcing data, which may explain the observed overcome of satellite SM observations over the ERA-Interim. In addition, the ERA-Interim shows a higher SNR than the SMOS for the majority of Africa.

Therefore, SNR differences between the ERA-Interim and the satellite SM data sets (see Figure 9) can offer an indication about the potential improvements obtained by assimilating these observations (Draper et al., 2012). The largest improvements were in the areas where the SNR of the observations exceeded the ERA-Interim. For ASCAT, these areas were over savannas and grassland regions, while for SMAP the areas of improvement were over shrub and grasslands. The ERA-Interim identified more areas of higher SNR than the satellite observations but might still benefit from assimilating the observations. When SNR <0 dB, there is, however, a physical boundary at which the noise variance starts to exceed the signal variance. Thus, the assimilation of observations will probably not add much information to the model. Further research studies are required for a quantitative assessment of the possibilities of SNR in data assimilation.

5. Conclusions

This study investigated the performance of SMAP and SMOS and ASCAT SM products on the regional scale over Africa using comparative metrics (i.e., $R$, bias, and ubRMSE) to validate these products against both all available stations from ISMN and ERA-Interim reanalysis SM data as well as TC to estimate the error variance and SNR. MODIS land cover, NDVI, and GPCC precipitation were used to analyze results. Based on our results, the following conclusions can be drawn:

1. The validation of satellite soil moisture products against in situ and ERA-Interim over shrub and grassland land surface covers agrees. As, the performance of SMAP is better than the SMOS and ASCAT products in terms of overall average correlation value, less overall average bias value, and with the lowest average overall ubRMSE value. The overall Africa SMAP showed higher performance than SMOS and ASCAT with the lowest overall average ubRMSE value that do not exceed the SMAP mission requirement of 0.04 m³ m⁻³.

2. All satellite soil moisture products showed wet bias and less correlation with the ERA-Interim over the desert, given that hovmöller diagrams for these satellites displayed low variability and low frequency. However, SMAP and SMOS showed slightly better performance than ASCAT product over the desert.

3. Except in desert, hovmöller diagrams indicate that all satellite SM data sets have the same spatiotemporal SM dynamic on the regional scale. SMAP and SMOS showed higher frequency, while ASCAT is closer to ERA-Interim. This explains how active satellite sensors can penetrate densely vegetation regions like the deeper-layer model structure more than passive products, as shown by the comparatively high performance of ASCAT with the ERA-Interim.

4. The evaluation of soil moisture products based on TC method with respect to the different land surface covers shows that SMAP and SMOS showed slightly better performance in the desert than ASCAT, which
displayed the high relative error variance and negative SNR[db]. Over low vegetated regions (shrub) with low precipitation amount and low average NDVI value (0.21), SMAP and SMOS displayed better performance with a low average error variance and high average SNR[db] than an active product. Over moderate vegetated regions (grassland), SMAP displayed better performance with low average error and high average SNR[db] among SM products. While over densely vegetated areas with the highest precipitation amounts and highest average NDVI values, ASCAT overcomes other SM products with low error variance and high SNR[db].

5. The differences in SNR estimates between satellite SM data sets and the ERA-Interim reanalysis SM data were used to determine the areas where large improvements are expected in the model during the assimilation of the satellite SM observations. Practically, for ASCAT, these regions are selected to be over savannas and grassland regions, while for SMAP it is determined to be over grassland and shrub regions.

6. The consistency between different validation techniques shows that ASCAT and SMAP SM data sets can be considered more stable than SMOS for data assimilation and capturing the spatial distribution of surface SM on the regional scale over Africa.

Acknowledgments
This work is supported jointly by the National Key Research Development Program of China (No. 2017YFB0503604 and No. 2016YFB0502204), National Natural Science Foundation of China (No.61971316) and State Key Laboratory of Satellite Navigation System and Equipment Technology. Data sets were used in this study are made freely available via several repositories hosted by individual data product producers. SMAP, MCD12Q1, and MOD13C2 data sets are obtained from the open web repositories of NASA (https://search.earthdata.nasa.gov and https://landweb.modaps.eosdis.nasa.gov/search/, respectively). The ASCAT data are available online (http://hsaf.metoeoam.it). The SMOS data are accessed through CATDS (https://www.catds.fr/Products/Avaliable-products-from-CPTDC). The ERA-Interim product is available through ECMWF (http://apps.ecmwf.int/datasets/data/interim-full-daily). ISMN and GPCC products are available online (https://ismn.geo.tuwien.ac.at and https://opendata.dwd.de/climate_environment/GPCC/html/, respectively). The authors would like to thank Luca Brocca for providing source code for reading ASCAT data. The authors would like to thank M. El-Nokrashy and Stephen C. McClure for his enthusiastic support and valuable suggestions during the review of the manuscript.

References
Al-Bitar, A., Leroux, D., Kerr, Y. H., Merlin, O., Richaume, P., Sahoo, A., & Wood, E. F. (2012). Evaluation of SMOS soil moisture products over continental U.S. using the SCAN/SNOTEL network. IEEE Transactions on Geoscience and Remote Sensing, 50(5), 1572–1586. https://doi.org/10.1109/TGRS.2012.2186581
Albergel, C., de Rosnay, P., Gruhier, C., Muñoz-Sabater, J., Hasenauer, S., Isaksen, L., et al. (2012). Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations. Remote Sensing of Environment, 118, 215–226. https://doi.org/10.1016/j.rse.2011.11.017
Albergel, C., Dorigo, W., Reichle, R. H., Balsamo, G., de Rosnay, P., Muñoz-Sabater, J., et al. (2013). Skill and global trend analysis of soil moisture from reanalyses and microwave remote sensing. Journal of Hydrometeorology, 14(4), 1259–1277. https://doi.org/10.1175/JHM-D-12-0161.1
Albergel, C., Rüdiger, C., Carrer, D., Calvet, J.-C., Fritz, N., Naeimi, V., et al. (2009). An evaluation of ASCAT surface soil moisture products with in-situ observations in Southwestern France. Hydrology and Earth System Sciences, 13(2), 115–124. https://doi.org/10.5194/hess-13-115-2009
Al-Yaari, A., Wigneron, J. P., Dorigo, W., Colländer, A., Pellmar, T., Hahn, S., et al. (2019). Assessment and inter-comparison of recently developed/reprocessed microwave satellite soil moisture products using ISMN ground-based measurements. Remote Sensing of Environment, 224(November 2018), 289–303. https://doi.org/10.1016/j.rse.2019.02.008
Al-Yaari, A., Wigneron, J. P., Ducharme, A., Kerr, Y. H., Wagner, W., & De Lamny, G., et al. (2014). Global-scale comparison of passive (SMOS) and active (ASCAT) satellite based microwave soil moisture retrievals with soil moisture simulations (MERRA-Land). Remote Sensing of Environment, 152, 614–626. https://doi.org/10.1016/j.rse.2014.07.013
Anam, R., Chishitel, F., Ghufair, S., Qazi, W., & Shahid, I. (2017). Inter-comparison of SMOS and AMSR-E soil moisture products during flood years (2010–2011) over Pakistan. European Journal of Remote Sensing, 50(1), 442–451. https://doi.org/10.1080/22797524.2017.1152461
Balsamo, G., Albergel, C., Beljaars, A., Boussetta, S., Brun, E., Cloke, H., et al. (2015). ERA-Interim/Land: A global land surface reanalysis data set. Hydrology and Earth System Sciences, 19(11), 389–407. https://doi.org/10.5194/hess-19-389-2015
Blunden, J., Arndt, D., & E. (2016). State of the climate in 2015. Bulletin of the American Meteorological Society, 97(8). https://doi.org/10.1175/BAMS-D-16-0014.1
Brocca, L., Ciabatta, L., Massari, C., Camici, S., & Tarpanelli, A. (2017). Soil moisture for hydrological applications: Open questions and new opportunities. Water, 9(2). https://doi.org/10.3390/w9020140
Brocca, L., Melone, F., Moramarco, T., Wagner, W., & Hasenauer, S. (2010). ASCAT soil wetness index validation through in situ and modeled soil moisture data in central Italy. Remote Sensing of Environment, 114(11), 2745–2755. https://doi.org/10.1016/j.rse.2010.06.009
Brocca, L., Pellmar, T., Crow, W. T., Ciabatta, L., Massari, C., Ryu, D., et al. (2016). Rainfall estimation by inverting SMOS soil moisture estimates: A comparison of different methods over Australia. Journal of Geophysical Research: Atmospheres, 121, 12062–12079. https://doi.org/10.1002/2016JD025382
Chan, S. K., Bindlish, R., O’Neill, P. E., Njoku, E., Jackson, T., Colländer, A., et al. (2016). Assessment of the SMAP passive soil moisture product. IEEE Transactions on Geoscience and Remote Sensing, 54(8), 4994–5007. https://doi.org/10.1109/TGRS.2016.2561938
Chen, F., Crow, W. T., Bindlish, R., Colländer, A., Burging, M. S., Ananuma, J., & Aida, K. (2018). Global-scale evaluation of SMAP, SMOS and ASCAT soil moisture products using triple collocation. Remote Sensing of Environment, 214(May), 1–13. https://doi.org/10.1016/j.rse.2018.05.008
Collardier, A., Jackson, T. J., Bindlish, R., Chan, S., Das, N., Kim, S. B., et al. (2017). Validation of SMAP surface soil moisture products with core validation sites. Remote Sensing of Environment, 191, 215–211. https://doi.org/10.1016/j.rse.2017.01.021
Cui, C., Xu, J., Zeng, J., Chen, K. S., Bai, X., Lu, H., et al. (2018). Soil moisture mapping from satellites: An intercomparison of SMAP, SMOS, FY3B, AMSR2, and ESA CCI over two dense network regions at different spatial scales. Remote Sensing, 10(2), 33. https://doi.org/10.3390/rs10020033
Cui, Y., Long, D., Hong, Y., Zeng, C., Zhou, J., Han, Z., et al. (2016). Validation and reconstruction of FY-3B/MWRI soil moisture using an artificial neural network based on reconstructed MODIS optical products over the Tibetan Plateau. Journal of Hydrology, 543, 242–254. https://doi.org/10.1016/j.jhydrol.2016.10.005
Das, N. N., & Dunbar, R. S. (2015). Level 3 active/passive soil moisture product specification document. De Rosnay, P., Drusch, M., Vasiljevic, D., Balsamo, G., Albergel, C., & Isaksen, L. (2012). A simplified Extended Kalman Filter for the global operational soil moisture analysis at ECMWF. Quarterly Journal of the Royal Meteorological Society, 139(674), 1199–1213.
Mizilas, D. G., Crow, W. T., & Cosh, M. H. (2010). Estimating spatial sampling errors in coarse-scale soil moisture estimates derived from point-scale observations. Journal of Hydro meteorology, 11(6), 1423–1439. https://doi.org/10.1175/2010JHM1285.1

Palacios, S., Pettinato, S., & Santi, E. (2012). Combining L and X band SAR data for estimating biomass and soil moisture of agricultural fields. European Journal of Remote Sensing, 45(1), 99–109. https://doi.org/10.5721/EuJRS20124510

Parinussa, R. M., Holmes, T. R. H., Wanders, N., Dorigo, W. A., de Jeu, R. A. M., & Parinussa, R. M. (2015). A preliminary study toward consistent soil moisture from AMSR2. Journal of Hydro meteorology, 16(2), 932–947. https://doi.org/10.1175/JHM-D-13-0200.1

Parinussa, R. M., Meesters, A. G. C. A., Liu, Y. Y., Dorigo, W., Wagner, W., & de Jeu, R. A. M. (2011). Error estimates for near-real-time satellite soil moisture as derived from the land parameter retrieval model. IEEE Geoscience and Remote Sensing Letters, 9(4), 779–783. https://doi.org/10.1109/LGRS.2011.2114872

Paulik, C., Dorigo, W., Wagner, W., & Kidd, R. (2014). Validation of the ASCAT Soil Water Index using in situ data from the International Soil Moisture Network. International Journal of Applied Earth Observation and Geoinformation, 30, 1–8. https://doi.org/10.1016/J.IJAG.2014.01.007

Peng, J., Niesel, J., Loew, A., Zhang, S., & Wang, J. (2015). Evaluation of satellite and reanalysis soil moisture products over southwest China using ground-based measurements. Remote Sensing, 7(11), 15729–15747. https://doi.org/10.3390/rs71115729

Product User Manual (2018). Product User Manual (PUM) Metop ASCAT soil moisture CDR and of

Zeng, J. (2016). A preliminary evaluation of the SMAP radiometer soil moisture product over United States and Europe using ground-based observations. IEEE Transactions on Geoscience and Remote Sensing, 54(8), 4929–4940. Retrieved from https://www.academia.edu/26646826/A_Preliminary_Evaluation_of_the_SMAP_Radiometer_Soil_Moisture/Product_Over_United_States_and_Europe/Using_Ground‐Based_Measurements

Zeng, J., Li, Z., Chen, Q., Bi, H., Qiu, J., & Zou, P. (2015). Evaluation of remotely sensed and reanalysis soil moisture products over the Tibetan Plateau using in-situ observations. Remote Sensing of Environment, 163, 91–110. https://doi.org/10.1016/J.RSE.2015.03.008