Remote Sensing of Environment 193 (2017) 257–273

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Evaluating soil moisture retrievals from ESA's SMOS and NASA's SMAP brightness temperature datasets

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ARTICLE INFO

Article history:
Received 12 May 2016
Received in revised form 6 March 2017
Accepted 12 March 2017
Available online xxxx

Keywords:
SMOS
SMAP
Soil moisture
Statistical regression

ABSTRACT

Two satellites are currently monitoring surface soil moisture (SM) using L-band observations: SMOS (Soil Moisture and Ocean Salinity), a joint ESA (European Space Agency), CNES (Centre national d'études spatiales), and CDTI (the Spanish government agency with responsibility for space) satellite launched on November 2, 2009 and SMAP (Soil Moisture Active Passive), a National Aeronautics and Space Administration (NASA) satellite successfully launched in January 2015. In this study, we used a multilinear regression approach to retrieve SM from SMAP data to create a global dataset of SM, which is consistent with SM data retrieved from SMOS. This was achieved by calibrating coefficients of the regression model using the CATDS (Centre Aval de Traitement des Données) SMOS Level 3 SM and the horizontally and vertically polarized brightness temperatures (TB) at 40° incidence angle, over the 2013–2014 period. Next, this model was applied to SMAP L3 TB data from Apr 2015 to Jul 2016. The retrieved SM from SMAP (referred to here as SMAP_Reg) was compared to: (i) the operational SMAP L3 SM (SMAP_SCA), retrieved using the baseline Single Channel retrieval Algorithm (SCA); and (ii) the operational SMOSL3 SM, derived from the multiangular inversion of the L-MEB model (L-MEB algorithm) (SMOSL3). This inter-comparison was made against *in situ* soil moisture measurements from >400 sites spread over the globe, which are used here as a reference soil moisture dataset. The *in situ* observations were obtained from the International Soil Moisture Network (ISMN; https://ismn.geo.tuwien.ac.at/) in North of America (PBO_H2O, SCAN, SNOTEL, iRON, and USCRN), in Australia (Oznet), Africa (DAHRA), and in Europe (REMEDHUS, SMOSMANIA, FMI, and RSMN). The agreement was analyzed in terms of four classical statistical criteria: Root Mean Squared Error (RMSE), Bias, Unbiased RMSE (UnbRMSE), and correlation coefficient (R). Results of the comparison of these various products with *in situ* observations show that the performance of both SMAP products i.e. SMAP_SCA and SMAP_Reg is similar and marginally better to that of the SMOSL3 product particularly over the PBO_H2O, SCAN, and USCRN sites. However, SMOSL3 SM was closer to the *in situ* observations over the DAHRA and Oznet sites. We found that the correlation between all three datasets and *in situ* measurements is best ($R > 0.80$) over the Oznet sites and worst ($R = 0.58$) over the SNOTEL sites for SMAP_SCA and over the DAHRA and SMOSMANIA sites ($R = 0.51$ and $R = 0.45$ for SMAP_Reg and SMOSL3, respectively). The Bias values showed that all products are generally dry, except over RSMN, DAHRA, and Oznet (and FMI for SMAP_SCA). Finally, our analysis provided interesting insights that can be useful to improve the consistency between SMAP and SMOS datasets.

1. Introduction

Lately, the importance of soil moisture has become increasingly apparent, because soil moisture is a key variable in better understanding of the land-atmosphere interactions (Chen et al., 2016; Hirschi et al.,

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http://dx.doi.org/10.1016/j.rse.2017.03.010
0034-4257/

2014). The exchange of heat and water between the land surface and atmosphere is influenced by soil moisture (Berg et al., 2014; Hupet & Vanclooster, 2002; Seneviratne et al., 2010; Western et al., 2004), which was recognized as an Essential Climate Variable (ECV) in 2010 (GCOS, 2010).

Global soil moisture information has become available via different active and passive microwave remote sensing techniques with good temporal and spatial resolutions (Bartalis et al., 2007; Kerr et al., 2001; Njoku et al., 2002; Njoku et al., 2003; Owe et al., 2001; Ulaby et al., 1996; Wigneron et al., 1995). However, the required temporal and spatial resolutions strongly depend on the applications (e.g., agricultural applications vs. climate studies). Recently, new global soil moisture datasets, with a typical target accuracy of 0.04 m^3/m^3 (Jackson et al., 2016; Kerr et al., 2010; Kerr et al., 2012) over bare, low vegetation cover, and sparsely vegetated areas, have been produced based on microwave satellite observations at L-band (1.4 GHz, 21 cm). L-band is considered optimal for soil moisture monitoring (Kerr et al., 2001; Njoku et al., 2003; Wang & Choudhury, 1981) due to its higher sensitivity to soil moisture and penetration into vegetation and soil (Kerr, 2007; Njoku et al., 2003; Owe & Van de Griend, 1998; Wang & Choudhury, 1981) than other higher frequencies (e.g., C-band, X-band, etc.). The new L-band based datasets include surface soil moisture from two spaceborne missions: ESA's (European Space Agency) Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2012) and NASA's (National Aeronautics and Space Administration) Soil Moisture Active Passive (SMAP) (Entekhabi et al., 2010). The SMOS and SMAP satellites were launched in 2009 and 2015, respectively, and have been providing microwave brightness temperature (TB) observations since then. Soil moisture information is retrieved from SMAP's and SMOS's TB observations based on the principle that soil TB is mainly determined by soil moisture via soil dielectric constant (Njoku et al., 2002; Schmugge et al., 1976; Ulaby et al., 1996). Nevertheless, the sensitivity of the SMOS and SMAP TB observations to soil moisture is reduced by perturbing factors such as vegetation (attenuation of the emission from the soil and additional upwelling emission toward the space-borne sensor), surface roughness (scattering effects increase the emitting surface area), topography, soil texture, soil bulk density, and soil temperature (Choudhury et al., 1979; Grant et al., 2008; Holmes et al., 2006; Jackson & Schmugge, 1991; Kerr et al., 2012; Njoku & Li, 1999; Njoku et al., 2003; Wang et al., 1983; Wigneron et al., 2007; Wigneron et al., 2011; Wigneron et al., 2017).

There are several remotely sensed soil moisture products available (in addition to SMOS and SMAP); however, these cover different periods and are not consistent in terms of spatial and temporal resolutions, period availability, grid, etc. Given the wide availability of soil moisture datasets retrieved from different microwave observations, studies focusing on the merging of these products are important to advance in the field of producing long-term and consistent datasets of several climatic variables. A great effort has been made by the scientific community in the last decade to build a coherent and consistent long term soil moisture datasets such as the ESA Climate Change Initiative (CCI) soil moisture data record (e.g., Enenkel et al., 2015; Liu et al., 2012; http://www.esa-soilmoisture-cci.org/; Wagner et al., 2012), deemed necessary for global soil moisture monitoring, drought monitoring, climate forecasts, etc. The CCI product is estimated based on a posteriori merging i.e. merging the retrieved soil moisture datasets based on the relative errors of soil moisture products and a CDF (cumulative distribution function)-matching used to rescale the different soil moisture products into a common climatology. An alternative approach is to use data fusion i.e. merging of microwave datasets prior to the retrieval (e.g., through the use of a common retrieval algorithm as proposed later in this paper). This method allows better exploitation of the complimentary of information provided by the different sensors not included in the posteriori combination approach (Aires et al., 2012; Kolassa et al., 2013). A recent project was established by ESA to investigate the integration of SMOS soil moisture estimates within the CCI soil moisture data record using three approaches that implement the data fusion strategy:

(i) multi-linear regression (Al-Yaari et al., 2016);
(ii) neural networks (Rodríguez-Fernández et al., 2016); and
(iii) the Land Parameter Retrieval Model (LPRM; Van der Schalie et al., 2016).

Al-Yaari et al. (2016), for instance, demonstrated the efficiency of physically-based multiple-linear regression equations (Wigneron et al., 2004), referred to here as Linear Regression Method (LRM) in the following, to retrieve soil moisture from the Advanced Microwave Scanning Radiometer Earth Observing System (AMSR-E) TB observations. The LRM has several advantages: quickness, simplicity, and no strong demand on auxiliary datasets (Al-Yaari et al., 2016) such as the normalized difference vegetation index (NDVI) product used by the SMAP Single Channel Algorithm (SMAP_SCA), to estimate vegetation effects. The purpose of that initial study was to extend the SMOS soil moisture product into the past i.e., 2003–2009, using AMSR-E TB observations. The current study follows the same strategy to retrieve soil moisture from SMAP TB observations (SMAP_Reg) with a purpose to improve the temporal sampling rate together with the SMOS soil moisture product at the global scale. The main interest in the SMAP-Reg soil moisture product is that it is fully consistent (coherent in temporal dynamics and absolute values) with the SMOS Level 3 soil moisture product, as the regression equations are calibrated based on SMOS Level 3 data (soil moisture and TB). Furthermore, the idea here is to re-build a coherent and consistent soil moisture dataset rather than to develop a new algorithm or to surpass the well-established radiative transfer models (e.g. the L-band Microwave Emission of the Biosphere (L-MEB) model, LRPM, etc.).

To this end, two specific objectives of this study are listed below:

(i) produce a soil moisture product (SMAP_Reg) from SMAP TB that is consistent with SMOS soil moisture retrievals using physically-based regression equations; and
(ii) compare SMAP_Reg with operational SMAP and SMOS soil moisture retrievals against ground-based soil moisture measurements.

Since SMAP soil moisture products are relatively recent, their evaluation and their inter-comparison with other soil moisture datasets are required (Chan et al., 2016; Zeng et al., 2016). To advance our goal, therefore, the second objective of this study is two-fold: to evaluate the SMAP_Reg product, and to carry out a first evaluation of the agreement between SMAP and SMOS Level 3 soil moisture products on a global scale and against ground-based measurements (sparse and dense networks). The aim is not to establish which product is more accurate with respect to *in situ* but to understand the spatio-temporal patterns of SMAP relative to SMOS and how SMAP differs from SMOS globally. The agreement and degree of dispersion between the SMAP and SMOS soil moisture products are analyzed here in terms of four classical statistical criteria: Root Mean Squared Error (RMSE), Bias, Unbiased RMSE (UnbRMSE), and correlation coefficient (R) during the overlapping period (from Apr 2015 to Jul 2016).

The datasets, the local regression method, and the evaluation metrics used in this study are described in Section 2. Results are presented in Section 3. Finally, discussion and conclusions are provided in Section 4 and Section 5, respectively.

2. Materials and methods

2.1. Datasets

2.1.1. SMOS level 3 TB and soil moisture products

SMOS is a joint ESA, CNES (Centre national d'études spatiales), and CDTI (the Spanish government agency with responsibility for space) mission that was launched on November 2, 2009 (Kerr et al., 2012).