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# A regional scale performance evaluation of SMOS and ESA-CCI soil moisture products over India with simulated soil moisture from MERRA-Land

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Three multi-decadal satellite soil moisture (SM) products, obtained by merging two active and six passive, all-active-merged (CCI-ACT), all-passive-merged (CCI-PAS) and all-active-passive-merged (CCI-COMBINED), and Level-3 SM retrieved from Soil Moisture Ocean Salinity (SMOS) mission were evaluated over India. The evaluation strategy employed is twofold: (a) time series and correlation analysis of SM datasets with respect to the Modern Era Retrospective-analysis for Research and Applications-Land (MERRA-L) SM simulation and the India Meteorological Department (IMD) gridded rainfall; (b) investigate the spatial distribution of random error of the satellite products using Triple Collocation (TC) approach. The Pearson's correlation analysis showed that the performance of CCI-ACT and CCI-COMBINED are comparable to each other and they agree well with the MERRA-L simulated SM time series. They also had a good rank correlation with rainfall. The random error from TC is represented in terms of fractional Root Mean Square Error ($fRMSE_{TC}$). It also represents the sensitivity of satellite retrievals to changes in true state. The analysis of $fRMSE_{TC}$ showed that descending swath of SMOS SM has a lower error than ascending for 71% of the pixels over India. CCI-ACT was found to have the most number of pixels with the lowest errors, having a mean $fRMSE_{TC}$ of 0.7188, compared to 0.7705 for CCI-COMBINED, 0.7828 for CCI-PAS and 0.8308 for SMOS-D. However, the error in CCI-ACT was highest in arid desert regions of western India. The error in CCI-COMBINED, CCI-PAS and SMOS-D grew with an increase in vegetation density. The $fRMSE_{TC}$ maps were analysed against the maps of the probability of occurrence of Radio Frequency Interference (RFI), Normalized Difference Vegetation Index (NDVI), soil texture (percentage of clay, sand, and silt) and modified Köppen-Geiger climate classification. The climate classification map was used to classify $fRMSE_{TC}$ against the different homogeneous climate classes. The analysis of the maps revealed that the inconsistency in SMOS is because of the RFI events over India. However, a multiple linear regression based attribution study showed that SMOS-D is the least affected by vegetation (4%) and the spatial distribution of CCI-ACT and CCI-COMBINED error showed more affinity towards soil texture than vegetation density.



## 1. Introduction

Soil moisture (SM) is an important land surface control variable influencing the coupling between land surface and atmosphere (Charney et al., 1977; Delworth and Manabe, 1988, 1989; Koster et al., 2000; Koster and Suarez, 2001; Hirschi et al., 2011). While investigating the coupling strength between SM and precipitation during the multi-model Global Land Atmosphere Coupling Experiment (GLACE), three coupling hot spots were observed viz., over central India, equatorial Africa and the great plains of north America (Koster et al., 2004). Keeping these facts in mind, many modeling studies had investigated the impact of SM on the global climate (Seneviratne et al., 2013; IPCC, 2013; Whan et al., 2015; Koster et al., 2010; Seneviratne et al., 2010; Seneviratne et al., 2006). But there is no way to validate those results without a reliable global dataset of SM. Reliable estimates of SM can be obtained either by employing accurate measurement systems or by the use of a land Data Assimilation (DA) system. The skill of a DA system depends on the error characteristics of both model and observation, a good DA system needs not only a state-of-the-art model but also an accurate global observation system.

Space-borne measurements can facilitate a globally distributed SM monitoring without the representation error associated with in-situ measurements (Tolman, 1998; Gruber et al., 2013). These space-borne sensors are able to provide a global coverage in 2–3 days. Many SM products were retrieved from various space-borne sensors, both active

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and passive, using different radiative transfer models. But none of them individually spans for a period long enough to study the climate dynamics associated with SM. In this regard, Liu et al. (2012) used a new trend-preserving approach to successfully merge SM estimates from active and passive sensors to generate a 30 years time series and the European Space Agency (ESA) launched the Climate Change Initiative (ESA-CCI) program (Wagner et al., 2012), where six passive sensors (SMMR, SSM/I, TMI, AMSR-E, WindSat, AMSR2) and two active sensors (ERS1/2 AMI and ASCAT) were merged to produce three SM products (ESA-CCI passive, ESA-CCI active and ESA-CCI combined). Recently, dedicated SM missions were launched viz., ESA's Soil Moisture and Ocean Salinity (SMOS) mission (Kerr et al., 2001; Kerr et al., 2010) and the Soil Moisture Active Passive (SMAP) mission of the National Aeronautics and Space Administration (NASA) (Entekhabi et al., 2010). Both the satellites were equipped with L-band (1.4 GHz) microwave sensors, which is considered to be the most suitable microwave band for measuring SM because of its ability to penetrate deeper (~5 cm) into the soil layer than any available microwave sensor (Kerr et al., 2001).

Several validation studies were also carried out for both SMOS and ESA-CCI combined product. ESA-CCI combined SM product was validated against in-situ measurements (International Soil Moisture Network, ISMN) spread across the globe (Dorigo et al., 2015). The study revealed that the performance of SM product had an upward trend with time and observed an average unbiased Root Mean Square Deviation (*ubRMSD*) of 0.03 to 0.09 $m^3\ m^{-3}$. It was also able to capture the long-term trends in SM (Dorigo et al., 2012). Validation studies using SMOS retrievals suggested that it meets the mission requirement of an RMSD of 0.04 $m^3\ m^{-3}$, over specific sites/regions (Al Bitar et al., 2012; Jackson et al., 2012; Kaihotsu et al., 2013). But since, those validation studies were site specific they cannot be extrapolated to the global scale straightaway. To be used as a proxy to in-situ measurements, satellite SM products must be reliable. Thus a reliable distributed error analysis of SM products is a key requirement.

In recent years, Triple Collocation (TC) has developed as a reliable and powerful tool for a distributed error analysis. It estimates the error variance (or Root Mean Square Error ($RMSE_{TC}$)) by applying an additive error model on three datasets (triplets) with mutually independent errors and scaling two of the datasets relative to the third (we call it the reference dataset) (Stoffelen, 1998; Caires and Sterl, 2003; Gruber et al., 2016). One of the limitations of this scaled $RMSE_{TC}$ is that it depends on the standard deviation of the reference dataset, which may lead to similar spatial variability in $RMSE_{TC}$ of each triplet member. Draper et al. (2013) used the *fractional-*$RMSE_{TC}$ ($fRMSE_{TC}$) as the performance metric of SM error analysis, which is obtained by reducing the signal of reference standard deviation from $RMSE_{TC}$. It allows for more flexibility in inter-comparing the error estimates from different data triplets. Many studies have successfully used TC for estimating the random error variance of satellite SM over different regions of the world (Scipal et al., 2008; Miralles et al., 2010; Crow et al., 2012; Leroux et al., 2013; Dorigo et al., 2015; Yilmaz and Crow, 2014). The main goal of the present study is to perform a regional evaluation of the error characteristics of the satellite SM products, viz., SMOS, ESA-CCI products with MERRA-L dataset, over India using TC based *fRMSE* approach. One of the supplementary aims of this study is to investigate the effect of time of satellite measurement (ascending and descending overpass) on its random error. Studies have suggested a need to evaluate the overpasses before performing an SM analysis with them, as the overpasses are dependent not only on RFI but also on diurnal changes in land surface parameters, irrespective of sensor frequency (Saleh et al., 2006; Jackson et al., 2010; Dente et al., 2012; Rowlandson et al., 2012; Griesfeller et al., 2016; Peng et al., 2015). This study also includes a qualitative investigation and a Multiple Linear Regression (MLR) based attribution study about the relationship between $fRMSE_{TC}$ and vegetation density and soil texture parameters (percentage of sand, clay, and silt) (Leroux et al., 2013). The investigation is confined to India, as there is a need for a reliable SM dataset over India to better understand the interaction between SM and other control variables of the hydrological cycle.

The remainder of this paper is structured as follows. The datasets used in this study are described in Section 2 and the TC method used for quantifying the random error in satellite SM estimates is introduced in Section 3. The results from time-series and correlation analysis and the TC analysis of the SM datasets are discussed in detail in Section 4. Finally, a discussion of the implications of the results, and the conclusions drawn from this study are presented in Section 5.

## 2. Data description

ESA-CCI's three SM datasets viz., ESA-CCI all-passive-merged, ESA-CCI all-active-merged, and ESA-CCI active-passive-merged and SMOS were used in this study. A land surface model simulated SM is also used to check the consistency of the satellite SM products, viz., MERRA-L. The ability of these satellite products to capture the seasonal and anomalous patterns of rainfall is also investigated using India Meteorological Department (IMD) gridded rainfall. A map of the probability of occurrence of Radio Frequency Interference (RFI) as measured by SMOS averaged for 2010–2012 (Al-yaari et al., 2014a) along with MODIS-Terra Normalized Difference Vegetation Index (NDVI) product, averaged for a period from 2010 to 2013, and FAO's map of percentage of sand, silt and clay estimated from Land Data Assimilation System (LDAS) data (Reynolds et al., 2000) are also used to investigate the behaviour of satellite SM products.

### 2.1. ESA-CCI satellite soil moisture products

Under the aegis of the European Space Agency's Climate Change Initiative (ESA-CCI, http://www.esa-soilmoisture-cci.org), three multi-decadal satellite SM products are released. The objective of this project is to use C-band microwave scatterometers (ERS-1/2 scatterometer: SCAT and METOP-A advanced scatterometer: ASCAT) and multi-channel microwave radiometers (SMMR, SSM/I, TMI, AMSR-E, WindSat, AMSR2), that together span over three decades, to produce a long-term reliable time series of SM. It was produced by merging two SM datasets, one obtained by merging all scatterometer products (all-active) and the other from all radiometer products (all-passive) depending on their relative sensitivity to vegetation density. Different sensors show different ranges of SM values. Hence, the all-active products are rescaled to a common scatterometer climatology, viz., ASCAT and all-passive products are rescaled to a radiometer climatology, viz., AMSR-E using a backward propagating Cumulative Distribution Function (CDF) matching approach before merging. Then, to facilitate the final merging of all-active and all-passive SM, they are again rescaled to the common climatology of Global Land Data Assimilation System version-1 (GLDAS-1) before merging (Liu et al., 2011, 2012; Wagner et al., 2012). The CCI project released three SM products:

a. A merged product created from all active datasets (CCI-ACT: 1991–2013, version: 2.0)
b. A merged product created from all passive datasets (CCI-PAS: 1978–2013, version: 2.0)
c. A product created from merged active and merged passive products (CCI-COMBINED: 1978–2013, version: 2.1)

The SM products are in volumetric units ($m^3\ m^{-3}$), CCI-ACT is in degree of saturation and quality flags are provided for snow coverage or frozen soil and vegetation cover. These SM products have a grid resolution of 0.25°.