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Error decomposition of nine passive and active microwave satellite soil moisture data sets over Australia

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ABSTRACT

Soil moisture is one of the essential climate variables for the Global Climate Observing System (GCOS) that has been prioritized by the ESA's Climate Change Initiative to construct its homogeneous long-term climate record. This requires a consistent characterization of the error structures in the individual data sets, which vary due to changes in instrument configuration and calibration, and retrieval algorithm design. In this paper, the random error and systematic differences in nine passive and active microwave satellite soil moisture products over Australia (time coverage: 1978–present) are estimated in a same manner for SM components at subseasonal and seasonal-to-interannual timescales separately. The multi-scale error structures are found to be non-trivial and vary between the products, giving cause for conducting multi-scale merging with awareness of these differences. Noticeable similarities between the error structures of the satellite products derived from same retrieval algorithm and same measuring frequency however suggest transferability of error parameters between them. Using partial rank correlation analysis, the error maps are linked to statistics on vegetation index, digital elevation, soil moisture and soil temperature, and land cover fractions and mixing in order to explain the observed variability and the similarities between the products.

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1. Introduction

Soil moisture (SM) is a key component in land-surface schemes and is of great significance to atmospheric models (Douville & Chauvin, 2000), (Koster et al., 2004), global climate models (Fennessey & Shukla, 1999), hydrological models (Brocca et al., 2012; Alvarez-Garreton et al., 2015), water resource models (Van Dijk & Renzullo, 2011), ecological models (Yuste et al., 2007; Friend & Kiang, 2005), and many others. In particular, climate modellers have long recognized that accurate descriptions of land surface–atmosphere interactions mediated by SM are needed for understanding the causes and consequences of climate fluctuations on various temporal and spatial scales. SM affects rainfall (Koster, Suarez, & Heiser, 2000), drought occurrence (Fischer, Seneviratne, Vidale, Lüthi, & Schär, 2007), heatwaves (Lorenz, Davin, & Seneviratne, 2012), and hydrologic trends (Jung et al., 2006). Therefore, an accurate, long-term observational SM data suitable for model initialization, analysis, and validation over a greater range of situations and spatio-temporal scales is invaluable for long-term studies related to climate change and water resources availability. The European Space Agency (ESA) Climate Change Initiative (CCI) SM program (http://www.esa-soilmoisture-cci.org) is taking critical steps to close this gap by merging past and present passive and active microwave satellite observations to create a 1978–present climate record of SM (Wagner et al., 2012a).

Microwave remote sensing is an established method for estimating topsoil SM under a diverse of meteorological and land-surface conditions. However, periodic changes of the spaceborne instruments, platforms, sensor calibration, overpass times, and algorithms can induce substantial time-varying systematic errors (i.e., biases) in a blended product if the biases and random error statistics in individual satellite SM products are not fully resolved before merging (Yilmaz, Crow, Anderson, & Hain, 2012). For assimilating the satellite SM into models for re-analysis, these observational errors must also be accounted for.

There are now several methods for estimating these errors in SM with variable degrees of sophistication, differing in their underlying signal and error models, a priori assumptions about error characteristics, data

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requirements, and estimation principles. They include error propagation during retrieval (Naeimi, Scipal, Bartalis, Hasenauer, & Wagner, 2009; Parinussa, Meesters, et al., 2011), direct comparisons against in situ measurements (e.g. Albergel et al., 2012; Jackson et al., 2010; Su, Ryu, Young, Western & Wagner, 2013; Wagner et al., 2014), comparisons against model-simulated SM (Reichle, Koster, Dong, & Berg, 2004; Al-Yaari et al., 2014), power spectrum analysis (Su, Ryu, Crow, & Western, 2014b), and an instrumental variable (IV) technique that encompasses triple collocation (TC) analysis (Scipal, Holmes, de Jeu, Naeimi, & Wagner, 2008; Dorigo et al., 2010; Draper et al., 2013; Leroux, Kerr, Richaume, & Fieuzal, 2013; McColl et al., 2014; Gruber, Su, Zwieback, et al., 2016) and lagged-based instrument variable (LV) analysis (Su, Ryu, Crow, & Western, 2014a). These methods do not necessarily yield directly comparable results, especially when different choices of error metrics and reference data for defining the biases are made.

As the ESA CCI SM project enters its second phase that includes evolving its phase-1 prototype ECV processor, this paper aims to provide deeper insights into the error structures in satellite SM products used in the construction of its climate record. In particular, it addresses the following questions: How should the error structure be parameterized? How and why does the error structure vary between the SM products derived from different sensors but with the same retrieval algorithm? Can the error parameters be transferred between some of the SM products? This is achieved through a comprehensive assessment of the biases and random error in nine passive and active SM Level 3 gridded products over Australia. The passive products are derived from Nimbus-7's Scanning Multi-channel Microwave Radiometer (SMMR), Defense Meteorological Satellite Program (DMSP) satellites' Special Sensor Microwave Imager (SSM/I), Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), Aqua satellite's Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E), Coriolis satellite's WindSat radiometer, Soil Moisture and Ocean Salinity (SMOS), and Global Change Observation Mission-Water (GCOM-W1) Advanced Microwave Scanning Radiometer-2 (AMSR2). And, the active products are produced by Active Microwave Instrument (AMI) on the two European Remote Sensing satellites, ERS-1 and 2 and the Advanced Scatterometer (ASCAT) of the MetOp-A satellite. With the exception of SMOS, these products were used in the construction of the latest product release (v2.2) of ESA CCI SM. SMOS and ASCAT of MetOp-B are expected to be added in the future versions.

The model-simulated SM from MERRA-L (Modern Era Retrospective-analysis for Research and Applications-Land) (Reichle et al., 2011) serves as a common reference to define the biases in all the products. LV and ordinary least-square (OLS) regression are applied consistently across the products to distinguish the levels of additive bias, multiplicative bias and random error or unexplained variance in their subseasonal and seasonal-to-interannual SM components separately. Such consistency in the methodologies facilitates distinction of similarities and differences between the products' error structures. Subsequently, partial correlation analysis is used to link the estimated error maps with land-surface properties in order to explain variability in the errors and similarities between different satellite products.

This paper is organized as follows. Section 2 describes the nine satellite SM data sets, the MERRA-L data used in the error analyses, and the ancillary datasets used for the correlation analysis. Section 3 reviews the error estimation methods, and identifies the possible variables for explaining the estimated error maps. Results are presented in Section 4, and their implications to SM retrieval, data merging, and land-data assimilation are discussed in Section 5, which also offers our concluding remarks.

2. Data sets

2.1. Soil moisture data

The satellite SM products are described briefly as follows. Their spatiotemporal coverage over Australia is shown in Fig. 1(a), and their characteristics are summarized in Table 1. Fig. 1(b) shows the timeseries of the spatial statistics of modelled SM from MERRA-L.

2.1.1. LPRM passive soil moisture products

The Land Parameter Retrieval Model (LPRM) has been applied to estimate volumetric SM from the passive microwave observations from multi-channel (multi-frequency and dual-polarization) radiometers (Owe, de Jeu, & Holmes, 2008). These sensors include SMMR, SSM/I, TMI, AMSR-E, WindSat, and AMSR2. They measured orthogonally-polarized microwave emission from land surface at C-band (4–8 GHz), X-band (8–12 GHz) and/or K-band (18–27 GHz), as well as 37 GHz (K_a-band). The C, X and K-band brightness temperature are related directly to soil dielectric constant of the top-soil layer through the radiative transfer model of a vegetated soil surface. The retrieved dielectric constant is subsequently converted to volumetric units via a soil–water–air dielectric mixing model. LPRM uses the K_a-band data to estimate top-soil temperature, which are inputs to the both models. Distinguishing from the other retrieval approaches, LPRM uses the normalized difference of the measured brightness temperature between the two orthogonal polarizations to estimate vegetation optical thickness (VOD).

LPRM has a relatively simple land-surface parametrization that includes the assumption of thermal equilibrium without distinguishing the canopy-top temperature from soil temperature. It is therefore best suited for night-time retrievals (Lei, Crow, Shen, Parinussa, & Holmes, 2015) and thus following ESA CCI SM, this work focuses on the night-time retrievals from SMMR, TMI, AMSR-E and AMSR2 and the early morning data (around 6 am) from WindSat and SSM/I. Over Australia, the retrievals from AMSR-E, WindSat and AMSR2 are mostly based on their C-band (6.9 GHz) observations. The versions of their Level 3 daily, gridded products are identical to those used for creating the ESA CCI SM product. These products expressed in volumetric SM units are spatially resampled to a $1/4 \times 1/4°$ grid and temporally matched to the closest daily 0 h UTC reference time step for merging in the ESA CCI algorithm (Liu et al., 2012). Here we retain variable local observation times in our error analysis to avoid introducing timing errors.

2.1.2. ERS and ASCAT active soil moisture

The AMI on the ERS-1 and 2 and ASCAT of the MetOp-A satellite have used vertically-polarized backscatter at C-band at three different viewing directions to differentiate temporal vegetation and SM effects on the signal (Naeimi et al., 2009). ERS-1 operated between July 1991 and March 1996, and its successor ERS-2 was launched on April 1995 (Crapolicchio, Lecomte, & Neyt, 2005). Their intermittent coverage (Fig. 1(a)) is attributed to conflicting operations with the synthetic aperture rader (SAR) mode of the instrument, end of operation of ERS-1 in 2000, failure of ERS-2 tape drive in 2003 and mission completion of ERS-2 in 2010. ASCAT has been operating from January 2007 to the present day. The retrieval from the both instruments is based on a timeseries-based change detection algorithm of Wagner, Lemoine, and Rott (1999) that estimates current moisture status relative to historical minima and maxima, as a percentage of saturation within these bounds. Thus this approach is less susceptible to the influence of surface roughness as its variability occurs over a time scale longer than SM, and the influence of vegetation is explicitly corrected with multi-incidence angle observations. The active SM datasets were produced using the Soil Water Retrieval Package (WARP) (Naeimi et al., 2009) (v5.5). They are defined over a sinusoidal grid with a grid resolution of ~12.5 − 25 km, but were resampled to match the regular $1/4 \times 1/4°$ grid using a Hamming window with a latitude-dependent search radius. Both day (around 10 am local time) and night (10 pm) retrieved data are considered here because the retrieval performance is independent of observation times (Lei et al., 2015). The porosity data resampled from NASA's Global Land Data Assimilation System (GLDAS) was then used to convert the relative saturation estimates to volumetric units.

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