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SMOS disaggregated soil moisture product at 1 km resolution: Processor overview and first validation results

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ABSTRACT

The SMOS (Soil Moisture and Ocean Salinity) mission provides surface soil moisture (SM) maps at a mean resolution of ~50 km. However, agricultural applications (irrigation, crop monitoring) and some hydrological applications (floods and modeling of small basins) require higher resolution SM information. In order to overcome this spatial mismatch, a disaggregation algorithm called Disaggregation based on Physical And Theoretical scale Change (DISPATCH) combines higher-resolution data from optical/thermal sensors with the SM retrieved from microwave sensors like SMOS, producing higher-resolution SM as the output. A DISPATCH-based processor has been implemented for the whole globe (emerged lands) in the Centre Aval de Traitement des Données SMOS (CATDS), the French data processing center for SMOS Level 3 products. This new CATDS Level-4 Disaggregation processor (C4DIS) generates SM maps at 1 km resolution. This paper provides an overview of the C4DIS architecture, algorithms and output products. Differences with the original DISPATCH prototype are explained and major processing parameters are presented. The C4DIS SM product is compared against L3 and *in situ* SM data during a one year period over the Murrumbidgee catchment and the Yanco area (Australia), and during a four and a half year period over the Little Washita and the Walnut Gulch watersheds (USA). The four validation areas represent highly contrasting climate regions with different landscape properties. According to this analysis, the C4DIS SM product improves the spatio-temporal correlation with *in situ* measurements in the semi-arid regions with substantial SM spatial variability mainly driven by precipitation and irrigation. In sub-humid regions like the Little Washita watershed, the performance of the algorithm is poor except for summer, as result of the weak moisture-evaporation coupling. Disaggregated products do not succeed to have and additional benefit in the Walnut Gulch watershed, which is also semi-arid but with well-drained soils that are likely to cancel the spatial contrast needed by DISPATCH. Although further validation studies are still needed to better assess the performance of DISPATCH in a range of surface and atmospheric conditions, the new C4DIS product is expected to provide satisfying results over regions having medium to high SM spatial variability.

1. Introduction

Soil moisture (SM) is an essential component of the water cycle that impacts infiltration, runoff and evaporation processes. In addition, it modulates the energy exchange as well as the carbon exchange at the land surface (Daly & Porporato, 2005). SM has influence over a range of spatial scales: the climatic (Douville, 2004; Laio, Porporato, Ridolfi, & Rodríguez-Fernández, 2002), the meteorological (Dirmeyer, 2000; Drusch, 2007), the hydrological (Chen, Crow, Starks, & Moriasi, 2011; Draper, Reichle, De Lannoy, & Liu, 2012), the parcel and the local scale (Guérif & Duke, 2000).

Current satellite missions provide surface SM observations at large scales on a global basis. Passive microwave L-band observations are widely used for surface SM retrievals, but in practice they constrain the resolution of the retrievals to 30–60 km (Kerr & Njoku, 1990; Njoku & Entekhabi, 1996; Schmugge, 1998) with current technology. The Soil Moisture Ocean Salinity (SMOS) mission, launched in November 2009, incorporates an interferometric radiometer at L-band (1.4 GHz) and provides SM with a resolution of 30–55 km and a sensing depth of 3–5 cm (Kerr et al., 2001, 2010). SMOS Level 2 (L2) and Level 3 (L3) SM products have been validated extensively on a regular basis since the beginning of the mission (Al Bitar et al., 2012; Delwart et al., 2008) and they have been assessed as suitable for hydro-climate applications (Lievens et al., 2015; Wanders, Bierkens, de Jong, de Roo, & Karssenberg, 2014). However, most hydro-agricultural applications need SM measurements of sub-kilometer spatial resolution with a still

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representative temporal coverage (Walker & Houser, 2004). We should strive to provide a high resolution (HR) SM product that would enhance the knowledge of the hydrological processes at local scale.

Different satellite-based approaches have been proposed to retrieve SM. One of the most popular is the use of active sensors like the synthetic aperture radars (SAR) (ERS, ALOS, Sentinel 1) or scatterometers (ASCAT). These instruments provide observations with a variety of spatial and time resolutions but they are influenced to a great extent by the scattering produced by vegetation structure and surface roughness, among other factors. Unlike active sensors, passive instruments are much less sensitive to scattering but provide surface SM estimations at coarse resolutions (>40 km). C- and X-band radiometers like AMSR-E and WindSat have shown good results (Mladenova et al., 2011), but because of the frequency used, their sensing depth is shallow (~1 cm) and vegetation becomes rapidly opaque. In contrast, L-band radiometer acquisitions from SMOS provide SM estimations for a much wider range of vegetation conditions, with a sensing depth of around 5 cm and a revisit time of ~3 days. However, the spatial resolution provided is also coarse (35–55 km) as mentioned previously. The main strategies to work around this issue while maintaining the benefits of L-band consist of merging the L-band acquisitions with HR ancillary data, namely radar and optical observations.

Over the past decade, various methods have been proposed to combine active and passive sensors to produce HR SM (Das, Entekhabi, & Njoku, 2011; Narayan, Lakshmi, & Jackson, 2006; Zhan, Houser, Walker, & Crow, 2006). The NASA Soil Moisture Active Passive (SMAP) mission, launched in 2015, intended to combine L-band brightness temperatures (TB) and HR L-band radar backscatter data (Entekhabi, Njoku, O'Neill, Kellogg, Crow, Edelstein, et al., 2010). Despite the radar failure in July 2015, related previous studies showed that SM could have been delivered at 9 km and even 3 km resolution (Das et al., 2014).

Optical sensors (visible/near-infrared/thermal-infrared) can achieve finer spatial resolutions. However, the quality of their observations is critically compromised by the presence of clouds. Examples of optical sensors include the Landsat instruments and the Advanced Spaceborne Thermal Emission and Reflection radiometer (ASTER), with data at ~100 m resolution, and the MODerate resolution Imaging Spectroradiometer (MODIS), with data at ~1 km resolution. Such data include soil temperature and vegetation cover information, which are variables linked to soil water content (Fang et al., 2013). The relationship between land surface temperature (LST) and normalized difference vegetation index (NDVI) was first formalized in the 90s with the triangle (Carlson, 2007; Carlson, Gillies, & Perry, 1994) and the trapezoid (Moran, Clarke, Inoue, & Vidal, 1994) approaches.

Most of the methods for deriving HR SM from the synergy between optical and microwave observations are based on the triangle/trapezoid approaches. Chauhan, Miller, and Ardanuy (2003) stated that the relationship between LST, NDVI and SM can be formulated as a regression formula specific to the region and climatic conditions. Later, Piles et al. (2011) included SMOS TBs in the equation, which reduced the bias but slightly degraded the spatio-temporal correlation between the obtained HR SM and the *in situ* measurements. These empirical methods need local calibration of the regression coefficients at low resolution (LR) before applying them to the HR ancillary data. On the contrary, semi-physical methods replace the polynomial function by physically-based models that use evaporation as a proxy variable for SM variability. Merlin, Walker, Chehbouni, and Kerr (2008) linked the SM to the soil evaporative efficiency (SEE), defined as the ratio of actual to potential soil evaporation. Kim and Hogue (2012) established a linear relationship between the soil evaporative fraction of Jiang and Islam (2003) and SM. Both approaches improved the satellite SM spatial variability and showed better correspondence with ground measurements in the area of study (SMEX04).

The semi-physical methods have three important advantages with respect to the purely empirical methods: (i) the mean SM is preserved across the merging process (which justifies calling it 'disaggregation' or 'downscaling'), (ii) a physical link is established for HR between SM and the evaporation/evapotranspiration rate and (iii) no local calibration or fit is needed. These are key factors in developing a robust and global operational algorithm for HR SM.

Recent studies by Merlin et al. (2012); Merlin et al. (2013) have improved the evaporation rate calculation and the evaporation-SM link of Merlin et al. (2008). The DISaggregation based on Physical And Theoretical scale Change (DISPATCH) algorithm estimates SEE at high-resolution from soil temperature and vegetation data for modeling the spatial variations inside the microwave SM observation. In Merlin et al. (2012), DISPATCH included corrections for the microwave sensor weighting function and grid oversampling and provided an estimate of the uncertainty in the output disaggregated data. Later, Merlin et al. (2013) demonstrated that the linear approximation of the SEE—SM link model is suitable for kilometer scales and included soil temperature corrections for elevation effects. Both studies were conducted under semi-arid conditions, in a 500 × 100 km study area within the Murrumbidgee river catchment, in southeastern Australia, and in a 60 × 60 km study area east of Lleida in Catalunya, Spain. They showed that DISPATCH improves the spatio-temporal correlation with *in situ* measurements, but that the accuracy of disaggregated products is highly dependant on the SM-evaporation coupling. The downscaled resolution of 1 km (Merlin, Al Bitar, Walker, & Kerr, 2009; Merlin et al., 2013) and the combination of satellite data from different time stamps in DISPATCH (Malbéteau, Merlin, Molero, Rüdiger, & Bacon, 2016; Merlin et al., 2012) have been considered as a good trade-off between spatial representativeness and overall accuracy, given the current status of the algorithm.

Recently, a new Level-4 (L4) processor (C4DIS) based on DISPATCH has been implemented in the Centre Aval de Traitement des Données SMOS (CATDS), the French ground segment for SMOS Level-3 and Level-4 data. The aim is to disaggregate the SMOS CATDS Level-3 (L3) 1-day SM maps to produce maps of SM at 1 km resolution for any part of the globe on an operational basis. The ancillary temperature and vegetation data are retrieved from the MODIS mission.

This paper seeks (i) to provide an overview of the C4DIS architecture, processing algorithms, output products, strengths and weaknesses and (ii) to derive the first conclusions on the performance of the C4DIS product depending on the climatic and landscape conditions. To do so, we evaluate the C4DIS product against *in situ* data from the Murrumbidgee catchment and two additional contrasting networks. Former versions of DISPATCH have so far been evaluated mostly in semi-arid conditions (Malbéteau et al., 2016; Merlin et al., 2012, 2013). The Murrumbidgee network belongs to these previous studies, and it is included here to serve as a reference for the current version of DISPATCH and the C4DIS processor and for the other validation areas. The two other *in situ* networks considered in this study are located in the Little Washita watershed in Oklahoma, USA, which exhibits sub-humid conditions, and the Walnut Gulch watershed in Arizona, USA, which exhibits semi-arid to arid conditions. Their relief, soil properties and land use differ from the Murrumbidgee's. The L4 disaggregated SM product is evaluated using *in situ* 0–5 cm and *in situ* 0–8 cm measurements taken at the same time as SMOS overpasses (around 6 am, 6 pm) during the period 01/06/2010 to 31/05/2011 for the Australian network and 01/06/2010 to 31/12/2014 for the USA networks. These networks have been providing ground SM data in a continuous basis and have contributed to the validation of different satellite missions, SMOS among them (Cosh, Jackson, Bindlish, & Prueger, 2004; Jackson et al., 2010, 2012; Leroux et al., 2013; Peischl et al., 2012).

It is important to note that the DISPATCH algorithm will continue to evolve. Validation activities on the Level-4 processor C4DIS will provide valuable information for the improvement of the algorithm and processing chain. This current study is conducted on the products of the first version of the C4DIS processor.

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