SENTINEL-1 & SENTINEL-2 FOR SOIL MOISTURE RETRIEVAL AT FIELD SCALE

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ABSTRACT

Soil moisture content is an essential climate variable that is operationally delivered at low resolution (e.g. $36-9\ km$) by earth observation missions, such as ESA/SMOS, NASA/SMAP and EUMETSAT/ASCAT. However numerous land applications would benefit from the availability of soil moisture maps at higher resolution. For this reason, there is a large research effort to develop soil moisture products at higher resolution using, for instance, data acquired by the new ESA's Sentinel missions. The objective of this study is twofold. First, it presents the validation status of a pre-operational soil moisture product derived from Sentinel-1 at $1\ km$ resolution. Second, it assesses the possibility of integrating Sentinel-2 data and additional ancillary information, such as parcel borders and high resolution soil texture maps, in order to obtain soil moisture maps at "field scale" resolution, i.e. $\sim 0.1\ km$. Case studies concerning agricultural sites located in Europe are presented.

Index Terms— Soil moisture content, high resolution, Sentinel-1, Sentinel-2, SMOS, SMAP, ASCAT

1. INTRODUCTION

Soil moisture (SM) observations might be beneficial for numerous applications in the field of applied hydrology, precision agriculture, disaster prevention as well as Numerical Weather Prediction (NWP) and climate monitoring and therefore serve a wide range of the Global Earth Observation System of Systems (GEOSS) societal benefit areas. Figure 1 provides an overview about the characteristic spatial and temporal resolutions for various land applications, ranging from applied hydrology to climate applications. It is seen that current low resolution operational SM products, like SMOS, SMAP and ASCAT, correspond mainly to NWP/climate applications. Operational use of satellite SM observations for applications demanding observations at the local to regional scales at high temporal resolutions have been limited so far due to a lack of observational capabilities on the one hand and a lack of sustained observations on the other hand. Until recently, the available SAR based SM products were very limited in spatial and temporal coverage and could not guarantee a sustained observation.

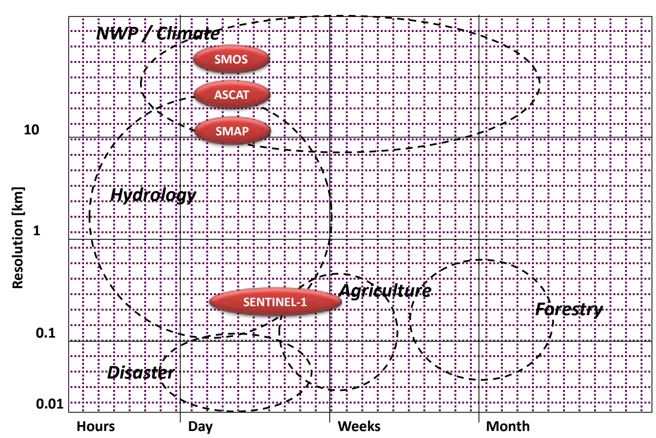

Figure 1. Selected potential application areas for soil moisture observations and their temporal and spatial resolution requirements in relation to existing soil moisture missions and S-1 (adapted from [1]).

Contrary, Sentinel-1 (S-1) now provides SAR observations at high spatial and moderate temporal resolutions and also has a sustained observation strategy for the next years which will facilitate the acceptance of these new observations for a variety of applications requiring resolutions in a range from $\sim 5\ km$ to $\sim 0.1\ km$.

This paper presents the validation status of a pre-operational SM product derived from *S-1* at $1\ km$ resolution. The product is developed within the context of an ESA SEOM study (seom.esa.int/page_project034.php). The analysis includes i) a comparison of S-1 SM estimates against in situ observations collected over various cal/val sites located in USA, Canada, Australia and Europe and ii) a cross comparison between S-1, SMAP, SMOS and ASCAT SM patterns observed over a large area of the Mediterranean basin. In addition, a strategy to derive SM fields at higher resolution, e.g., $\sim 0.1\ km$, is illustrated and initially assessed through case studies concerning agricultural sites located in Europe.

In the next section, a SM retrieval algorithm based on temporal change detection is briefly described, then the adopted validation strategy at local and regional scale is illustrated and, finally, the improvements deemed required in order to retrieve SM at "field" scale are discussed.

2. S-1 SM RETRIEVAL AT 1KM RESOLUTION

The investigated SM retrieval algorithm is a short term change detection (STCD) approach that transforms dense or quasi-dense time series (i.e., 6 or 12 days revisit) of N dual polarized (i.e. VV & VH) S-1 IW images into N-SM maps [2-4]. The code implementing the algorithm is referred to as SMOSAR ("Soil MOisture retrieval from multi-temporal SAR data"). The main concept underlying the STCD approach is that SM changes take place at relatively short temporal scales (e.g., few days), whereas the other surface parameters affecting the radar backscatter (e.g., soil roughness, canopy structure and vegetation biomass) are usually characterized by temporal scales significantly longer (e.g., some weeks). As a result, dense SAR time series (e.g., revisit with 1 week) are expected to track changes in SM only, since other parameters affecting radar backscatter can be considered as constant. The main physical approximations underlying the implementation of the algorithm are:

- First, SMOSAR applies to bare or vegetated soils dominated by surface attenuated scattering over which an adequate sensitivity to SM is observed. In other words, surfaces dominated by volume scattering showing little or no sensitivity to SM are masked using the approach developed in [5].

- Second, SMOSAR exploits the approximation that the backscatter ratio between two subsequent SAR dates depends only on the ratio between the surface reflection coefficients of the two dates, which can be mathematically expressed as

$$\frac{\left(\sigma_0\right)_{doy(i+1)}}{\left(\sigma_0\right)_{doy(i)}} \approx \frac{\left|\alpha_{VV}\left(\varepsilon,\theta\right)\right|^2_{doy(i+1)}}{\left|\alpha_{VV}\left(\varepsilon,\theta\right)\right|^2_{doy(i)}} \approx \frac{SM_{doy(i+1)}}{SM_{doy(i)}} \qquad (1),$$

where σ_0 is the VV S-1 backscatter coefficient, $\alpha_{VV}(\varepsilon,\theta)$ is the reflection coefficient, ε the surface relative dielectric constant and θ the incidence angle. The relationship $|\alpha_{VV}(\varepsilon,\theta)|^2 - SM$ can be roughly approximated as linear, though such an approximation is not adopted in SMOSAR. (1) explicitly implies that all the surface parameters affecting the radar backscatter but SM are constant between the SAR observations at doy (i) and doy $(\mathrm{i}+1)$. It is then clear that in order to meet this condition a fairly short SAR revisit is required and therefore this approach can be referred to as STCD. For each date, the quantitative retrieval of $\alpha_{VV}(\varepsilon,\theta)$ and, then SM, is based on (1). More precisely, $\alpha_{VV}(\varepsilon,\theta)$ is the solution of a stochastic underdetermined linear system, where its maximum likelihood solution ($\vec{\alpha}^*_{VV}$) can be expressed as [3]

$$\vec{\alpha}^*_{VV} = \alpha_{min} \cdot max\left(\frac{1}{\hat{S}_{iN}}\right) \cdot \left[\hat{S}_{1N}, \hat{S}_{2N}, \ldots . \hat{S}_{NN}\right] \ i = 1, \ldots N \ (2),$$

where N is the number of images in the S-1 time series, $\hat{S}_{iN} = \sqrt{(\sigma_0)_{doy(i)}/(\sigma_0)_{doy(N)}}$ and α_{min} is an estimate of the minimum reflection coefficient among the N S-1 images. Its estimate is obtained at low resolution (e.g., $\sim 40\ km$) using additional information such as EO SM operational products (e.g., SMOS, SMAP, ASCAT, etc.) (e.g., [4]) or a calibration curve expressing S-1 data versus SM values at low resolution, which is the option adopted in this study.

3. THE VALIDATION ACTIVITY AND ITS STATUS

The validation of the S-1 SM products at $\sim 1\ km$ resolution is carried out at the local and regional scale. Interferometric Wide Swath (IW) S-1 data are preprocessed in order to obtain time series of calibrated, co-registered, geocoded and temporally filtered stacks of VV and VH backscatter coefficients at 40 m pixel size (roughly corresponding to ~100m resolution) and with an equivalent number of looks (ENL) larger than 100.

At the **local scale**, the analysis focuses on the comparison of time series of retrieved versus observed SM values, collected over sites equipped with hydrologic networks, such as Yanco (Australia), TXSON and Little Washita (USA), Elm Creek (Canada), Remedhus (Spain), Hobe (Denmark) and Apulian Tavoliere (Italy). In addition, over each site the comparison at low resolution (i.e. site scale) between averaged S-1 SM estimates, operational SM products and in situ measurements is characterized. The performance of the retrieval is assessed by means of the standard statistical scores, e.g., root mean square error (RMSE), unbiased root mean square error (ubRMSE), bias, correlation. An open issue is the estimate of the measurement (sampling) error (MSE) due to the mismatch between the point scale in situ measurements and the retrieval at, e.g., $\sim 1\ km$ resolution. Such a measurement sampling error may produce significant biases in the values of the performance metrics and needs to be accounted for. This aspect has been widely investigated in the context of low resolution missions, e.g. [6], however its implications for SAR SM retrieval has received little attention and requires dedicated efforts. Of course, at site scale, where averages of observed and retrieved SM values are performed, MSE has a marginal impact. As an example, Figure 2 shows a comparison at site scale between S-1 SM and in situ measurements. The overall correlation and rmse are approximately 0.7 and 0.068 m^3/m^3, respectively. Overall the bias is negligible.

Table I reports the results of a comparison between S-1, SMAP, SMOS, ASCAT SM estimates and in situ observation for the same sites as in Figure 1. Observation dates of the various low resolution sensors have been selected with maximum a 1-day time-lag from S-1 acquisitions. The observation period range from 2015 to 2017. Only for ASCAT, it goes from 2015 to 2016. For SMOS and SMAP Level-3 SM products (daily composites of descending or ascending orbits and sampled to the global equal area EASE-2 grid with a 25 km or 36 km linear cell size, respectively) are used. The ASCAT L-2 products are available on a discrete global grid (DGG) with a spatial resolution of 25 km (grid spacing 12.5 km), so they have been resampled to the EASE-2 12.5 km by using a two-dimensional Hamming window function centered at every grid node. The SM maps were masked using the surface state flags and the Radio Frequency Interference probability (RFI > 10%) provided with the data. Furthermore, ASCAT SM differs from the other products in that it reports SM in the form of the percent saturation which has been converted in volumetric units (m^3/m^3) by scaling it with the maximum and minimum observed SM values.

At the **regional scale**, the objective is to compare S-1 SM patterns against other satellite SM data and auxiliary data like precipitation dynamics, and proxies, including model fields from operational (re)-analysis data in order to fully understand the information content of SM maps derived from S-1. Triple Collocation provides a technique to evaluate the SM product accuracy by comparing different datasets with uncorrelated error statistics [7]. Recent advances include the application of the triple collocation method for the identification of temporal variant SM errors and the determination of the signal to noise ratio in SM datasets [8-9]. The regional area selected in the study is a vast coastal zone in the Mediterranean basin, which is frequently covered with the S-1 data, features a wide range of environmental conditions, and has been a subject of numerous studies that can be used as a reference.

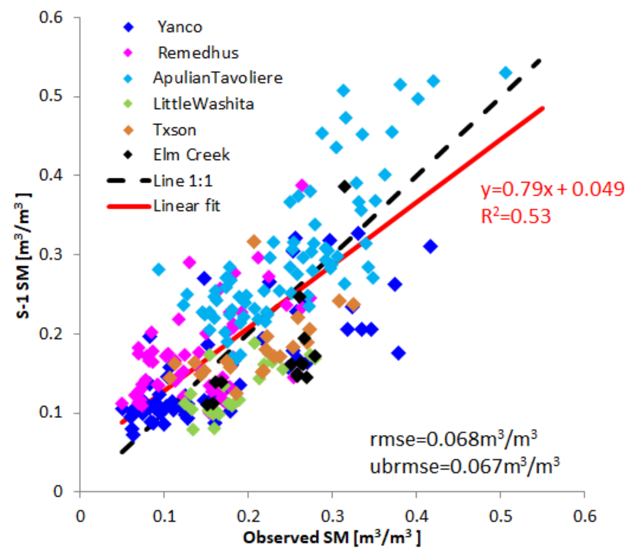

Figure 2. Site scale comparison between SM retrieved from S-1 and observed over the Yanco, Remedhus, Apulian Tavoliere, Little Washita, TxSON and Elm Creek sites. The comparison includes 248 dates covering the period from January 2015 to March 2017.

Table 1. Statistical scores of the comparison of S-1, SMAP, SMOS and ASCAT SM against in situ observations averaged at site scale over the same sites of Figure 1. Linear grid size: 0.5km (S-1), 36km (SMAP), 25km (SMOS), 12.5km (ASCAT).

	S-1	SMAP	SMOS	ASCAT
# dates	248	204	207	138
Correlation (R)	0.72	0.82	0.76	0.77
rmse [m^3/m^3]	0.068	0.059	0.072	0.061
ubrmse [m^3/m^3]	0.067	0.052	0.071	0.061
Mean-x (<x>) [m^3/m^3]	0.196	0.196	0.198	0.179
Mean-y (<y>) [m^3/m^3]	0.204	0.167	0.189	0.186

4. S-1 & S-2 SM RETRIEVAL AT FIELD SCALE

The strength of the STCD algorithm is its conceptual simplicity and its robustness due to the fact that the SM estimates depend on a single free parameter, i.e. α_{min}. In addition, its implementation essentially requires linear algebra calculations and therefore the SMOSAR code is fairly fast. Conversely, STCD is prone to the occurrence of abrupt changes of the vegetation and/or soil roughness status that can be wrongly interpreted as SM changes. Such changes may have a limited impact at a resolution equal or above $\sim 1\ km$, but they usually produce significant errors at "field scale" resolutions. Moreover, the fact that α_{min} is estimated at low resolution may affect the STCD capability to retrieve SM at very high resolution (e.g., $\sim 0.1\ km$). In this respect, it is worth mentioning that the drier are the surfaces the smaller is the expected spatial variability of SM [6] and, therefore, the minimum is the impact of adopting α_{min} at low resolution in (2). Conversely, the impact may be significant for fairly wet surfaces. It is then clear that additional information and algorithm improvements are required to derive accurate "field" scale SM estimates. In the framework of a H2020 project dedicated to the evolution of Copernicus services for agriculture (www.sensagri.eu), a strategy to improve the SMOSAR performance at high resolution has been identified and implemented. The main changes consist of i) an integrative use of S-1 and S-2 in order to support the masking of abrupt changes of surface parameters not due to SM changes and ii) an improved SM estimate that takes into account backscatter variabilities at pixel scale (i.e., $\sim 0.1\ km$). The identification and masking of abrupt changes of vegetation and roughness parameters at high resolution requires collocated time series of S-1 and S-2 NDVI and a multiscale change detection approach that can also lead to the detection of tillage changes. Further details are provided in [10]. Concerning ii), the implemented approach consists of using as prior knowledge those SM maps at $\sim 1\ km$ resolution derived under optimal conditions (i.e., minimum SM variability). This implies a nested retrieval approach in which, first, SM maps at $\sim 1\ km$ are retrieved. Then, those dates in which fairly dry SM maps have been observed at $\sim 1\ km$ resolution are identified. Finally, optimal SM estimates are propagated in time at pixel scale ($\sim 0.1\ km$). This is indeed possible because (1) can also be regarded as a recursive relationship, i.e.

$$\left|\alpha_{VV}(\varepsilon,\theta)\right|^2_{doy(i+1)} \approx \left|\alpha_{VV}(\varepsilon,\theta)\right|^2_{doy(i)} \bullet \frac{\left(\sigma_0\right)_{doy(i+1)}}{\left(\sigma_0\right)_{doy(i)}} \qquad (3).$$

It is worth mentioning that (3) does not depend on $\alpha_{\min}$, rather it provides an absolute estimate of $|\alpha_{VV}(\varepsilon,\theta)|^2_{doy(i+1)}$ based on the prior knowledge of $|\alpha_{VV}(\varepsilon,\theta)|^2_{doy(i)}$. Such an approach can highly benefit from ancillary information such as parcel borders that allow to perform averages at "field" scale preserving the mean, reducing the SAR signal standard deviation, and improving the geometrical resolution of the final maps. In addition, soil texture maps with resolutions in the order of few hundred meters proved to be crucial in improving the retrieval accuracy at "field" scale. An assessment of this approach is in progress over the Apulian Tavoliere and Remedhus sites with the objective of identifying irrigation events.

5. SUMMARY

High resolution S-1 SM products can be beneficial for a large number of land applications in many fields. Furthermore, the combined use of low and high resolution SM datasets is expected to enable the generation of high temporal and spatial resolution soil moisture products and facilitate a variety of applications. In this study, the validation status of a pre-operational S-1 SM product at $\sim 1\ km$ resolution is presented. As a part of the validation activity, the comparison between S-1 SM and operational low resolution SM products, such as SMOS, SMAP and ASCAT, is characterized. In addition, the study investigates a combined use of S-1 & S-2 in order to retrieve SM at "field" scale resolution, e.g., $\sim 0.1\ km$. The additional information required, such as parcel borders and high resolution soil texture maps, is discussed.

6. ACKNOWLEDGEMENTS

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