A MODIFIED DOWNSCALING APPROACH TO ESTIMATE SMOS SOIL MOISTURE AT HIGH RESOLUTION (300 M) USING COPERNICUS SENTINEL 3 NDVI

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ABSTRACT

A modification of the Barcelona Expert Center (BEC) algorithm to downscale the Soil Moisture and Ocean Salinity (SMOS) soil moisture (SM) to 300 m spatial resolution is presented. It maintains the same functional relationship as the currently implemented version but employs the following inputs: SMOS brightness temperature (TB) and SM (25 km), European Center for Medium Weather Forecast (ECMWF) skin temperature (9 km), and Sentinel 3 Normalized Difference Vegetation Index (NDVI, 300 m).

The performance of the downscaled SMOS SM at 300 m is analyzed by means of a temporal validation with *in-situ* observations from the Soil Moisture Measurements Stations Network of the University of Salamanca (REMEDHUS) and the Continuous Soil Moisture and Temperature Ground-based Observation Network (RSMN) during the year 2021. No significant differences in correlation, unbiased root mean square difference (ubRMSD) and bias are obtained over both networks compared to the 25 km and 1 km SM products, suggesting the BEC downscaling algorithm could work at hundreds of meters and result in a similar SM accuracy.

Index Terms— Soil moisture, disaggregation, downscaling, SMOS, Sentinel 3.

1. INTRODUCTION

Nowadays, soil moisture (SM) is an Essential Climate Variable (ECV) operationally retrieved by means of satellite microwave sensors, especially those on-board the Soil Moisture and Ocean Salinity (SMOS) and the Soil Moisture Active Passive (SMAP) missions, which provide global SM estimates from L-band observations at spatial scales of tens of km. This spatial resolution fulfills the requirements of several applications, such as hydrological land surface models and meteorological forecasting. Nevertheless, other applications, such as drought and flood monitoring, wildfire prevention, and crop irrigation, demand SM maps at higher spatial resolution. To bridge this gap, several SM pixel disaggregation (or downscaling) algorithms have been developed in the last decade.

Classical SM disaggregation approaches are generally based on the synergy of passive microwave data at coarse resolution with ancillary data at higher resolution (usually 1-10 km). Depending on the ancillary data used, these techniques can be roughly classified into: (i) radar-based downscaling algorithms, which combine passive and active microwave data, where SM is then estimated from previously disaggregated brightness temperature (TB) [1-3], and (ii) optical-based downscaling algorithms, which combine passive microwave and visible/thermal infrared (VIS/TIR) data to directly downscale SM [4-8]. Additionally, some approaches based on machine learning, which use large datasets and numerous input variables, have appeared in the last years [9-11]. In most cases, the pixel size of the resulting SM maps ranges between 1 and 10 km, regardless of the algorithm type, and only few recent studies have improved this resolution down to 100 m [12], [13] and even 20 m [14].

This study proposes a modification of the downscaling algorithm developed by the Barcelona Expert Center (BEC), aiming to estimate SMOS SM maps at 300 m over Europe and the Mediterranean countries. The last downscaling version implemented at BEC (v6.1) uses the following ancillary data to produce SMOS SM maps at 1 km [14]: (i) daily skin temperature (~9 km) provided by the European Center for Medium Weather Forecast (ECMWF) model and (ii) 16-day Normalized Difference Vegetation Index (NDVI, 1 km) provided by Terra Moderate Resolution Imaging Spectroradiometer (MODIS), specifically the MOD13A2 v6.1 product [15]. The modified approach maintains the same equation of downscaling but replaces the 16-day NDVI at 1 km from MODIS by the 10-day NDVI at 300 m from Copernicus Sentinel 3 Ocean and Land Color Instrument (OLCI) [16]. The resulting downscaled SM maps are in a grid of 300 m, which seems to be the effective spatial resolution.

2. DATA AND METHODS

2.1. Input datasets

The downscaling algorithm is fed by the following datasets:

(i) Daily SMOS L3 SM, produced and distributed by BEC [15]. These maps are built after discarding all ESA L2 SM retrievals with a Data Quality Index (DQX) $>0.07\ m^3m^{-3}$ and aggregating data to 25 km by means of a DQX-based weighted average.

(ii) Daily horizontal and vertical surface SMOS L3 TB at incidence angles of 32.5°, 42.5° and 52.5°, produced internally by BEC [15]. These maps are obtained after applying geometric, Faraday and atmospheric corrections to the ESA L1C TB, interpolating measurements to the desired angles, and aggregating data to 25 km by a simple average.

(iii) Daily analysis skin temperature at 12 UTC provided by the operational ECMWF model at ~9 km. It represents the temperature of the uppermost surface layer that satisfies the energy balance.

(iv) 10-Day NDVI from Sentinel 3 OLCI provided by the Copernicus Global Land Service (CGLS) at 1/336° (~300 m) [17].

2.2. BEC downscaling algorithm

This downscaling is a VIS/TIR-based algorithm, whose rationale is the relationship between the surface radiant temperature-vegetation index space and the SM variations, as modeled by the following linear regression:

$$SM = b_0 + b_1 LST_N + b_2 NDVI_N + \\ + \frac{b_3}{3}\sum_{i=1}^{3} TB_H(\theta_i)_N + \frac{b_4}{3}\sum_{i=1}^{3} TB_V(\theta_i)_N, \qquad (1)$$

where b_0, b_1, b_2, b_3 and b_4 are the regression coefficients, LST_N denotes the normalized land surface temperature (LST), $NDVI_N$ stands for the normalized difference vegetation index ($NDVI$), and $TB_H(\theta_i)_N$ and $TB_V(\theta_i)_N$ are the normalized surface TB at horizontal and vertical polarization, respectively, interpolated to the following incidence angles θ_i=32.5°, 42.5° and 52.5°. The normalization of the variables, denoted by the subscript N, is performed by considering the entire study region and the orbit type (ascending or descending).

The linear model is applied twice, first at coarse resolution (25 km) to compute the coefficients, and then at high resolution (300 m in this case) to estimate the downscaled SM. All orbits corresponding to the same day are jointly processed but separating ascending from descending passes. Previously, SM data gaps at coarse resolution are filled in areas where there are physically possible TB values within the orbit footprint for a specific day, but no retrieved SM. A shape adaptive moving window is used to calculate the coefficients in Eq. (1). It allows the method to be applied over any non-frozen soil region, independently of its size, and even if the region is highly heterogeneous [7, 15].

2.3. Performance validation

The downscaled SMOS SM at 300 m is validated against *in-situ* observations over two different networks: (i) the Soil Moisture Measurements Stations Network of the University of Salamanca (REMEDHUS, in Spain) and (ii) the Continuous Soil Moisture and Temperature Ground-based Observation Network (RSMN, in Romania). Only ascending maps (at 6 am local time) are analyzed. The temporal validation is carried out using one year of data (2021). Three metrics, i.e., the correlation, the unbiased root mean square difference (ubRMSD) and the bias, are computed using reference *in-situ* observations at the SMOS overpass times ±1 h. Considering the time zones of Spain and Romania, this corresponds to 5-7 UTC for REMEDHUS and 3-5 UTC for RSMN. Only stations with more than 100 days of data and significant statistics (p_{value}<0.01) are used. The same statistical scores are shown for the current BEC SMOS SM products (L3 at 25 km and L4 at 1 km) using the same number of samples for the sake of comparison.

3. RESULTS

Figure 1 shows three maps of SMOS SM at 25 km, 1 km, and 300 m in an area of 2°x2° over the states of North Rhine-Westphalia, Rhineland-Palatinate and Hesse, Germany, on July 15, 2021. This day was selected because of the heavy rainfall across Germany during the July 12-25 period, which caused important damages due to floods, including casualties, electricity cut-offs, and damage to many infrastructures (collapse of buildings, destruction of railway bridges, etc.). The poor resolution of the 25 km SM product is clearly observed. The 1-km SM product displays more details, while the 300-m SM product seems to better capture the spatial SM heterogeneity. The map of the corresponding NDVI is also included just to inform about the vegetation greenness in the scene. Unfortunately, there are no *in-situ* soil moisture observations available to validate the performance of the three SMOS SM products in this area.

Figure 2 shows the validation results with respect to the *in-situ* observations of both selected networks. Almost the same scores are obtained for the three SM datasets over REMEDHUS, showing negligible differences between them. Over RSMN, very similar statistics are also obtained for the three datasets, with a minimal decrease of correlation and bias, and a slight increase of ubRMSD for the SM at 300 m with respect to the 25 km and 1 km SM products.

Differences in the metrics obtained over REMEDHUS and RSMN could be due to several factors, such as the network type and size, environmental conditions, and utilized sensors, among others. REMEDHUS is a dense network of 1,300 km^2 in a semiarid continental Mediterranean climate at an altitude of 750-900 m and uses Stevens Hydra probes. By contrast, RSMN is a sparse network of 240,000 km^2 in a humid continental climate at an altitude of 300-500 m and employs Decagon 5TM devices.

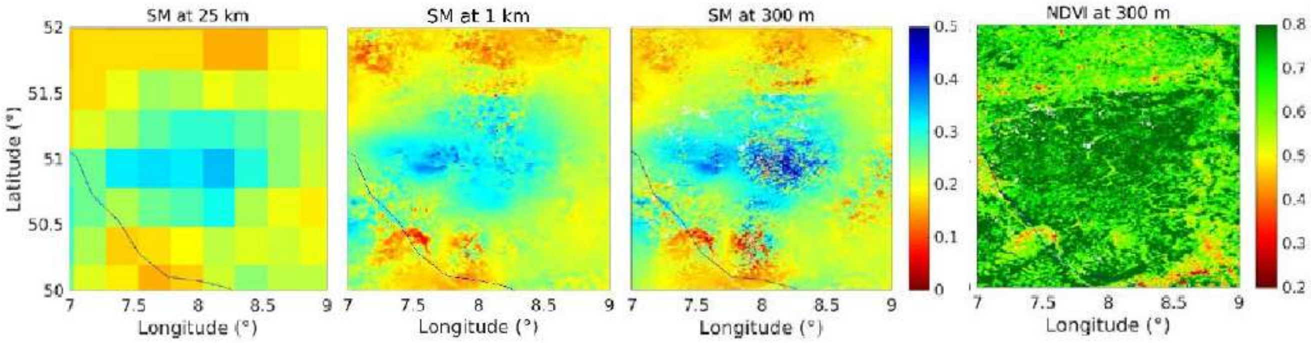

Fig. 1 Zoom of SMOS SM at 25 km, 1 km and 300 m over the states of North Rhine-Westphalia, Rhineland-Palatinate and Hesse, Germany, on July 15, 2021, and Sentinel 3 NDVI corresponding to July 11-20, 2021. The Rhine river is depicted with a blue line.

The presence of possible data gaps in the SM maps at 300 m due to cloud contamination in the Sentinel 3 NDVI product is almost equal to that observed in the SM at 1 km using the MODIS NDVI product. Note that, in both cases, a composite NDVI map of several days is employed (10 days for Sentinel 3 and 16 days for MODIS). Besides, the ECMWF LST used in the downscaling is free of clouds because it is obtained from a model. Hence, the SMOS revisit is the only constraint limiting the coverage of the downscaled SM map.

4. DISCUSSION

The BEC downscaling is a semi-empirical algorithm that links radiometric with VIS/TIR data. Since its v3.0, a modeled LST was used, instead of the MODIS LST, to ensure the resulting SM maps were not masked by clouds. This differs from previous works using the Disaggregation based on Physical And Theoretical scale Change (DisPATCh) algorithm to obtain SMOS/SMAP SM at 100 m, which are affected by cloud contamination due to the use of MODIS LST [12, 13]. Moreover, they used two steps in the disaggregation procedure employing additional information (Sentinel 1 backscatter [12] or Landsat 7/8 reflectances [13]), so that the coincidence of all input data under clear-sky conditions is sometimes challenging. In a recent work in which the DisPATCH is employed to obtain SMAP SM at 20 m, the Sentinel 3 LST was sharpened using Sentinel 2 optical images to produce an LST dataset with high spatio-temporal resolution [14]. Notwithstanding, the DisPATCh (or a modified DisPATCh) was only applied to specific small areas in the three aforementioned studies, not at the continental scale as the modified BEC downscaling.

According to the statistical office of the European Union (Eurostat), about two-thirds of the agricultural holdings in the European Union in 2020 have less than 5 ha (0.05 km^2) in size [18]. With the SM maps at 300 m, every pixel of the map covers an area of 9 ha (0.09 km^2), representing almost two agricultural fields. We know that this is still not enough to have a detailed soil moisture knowledge at the crop field level, but it is an important step forward to improve the management of the water resources used for irrigation at the basin level compared to the SM maps at 1 km. The 300 m SM could also help for more exhaustive monitoring of the increasingly frequent and intense drought or flood episodes caused by/resulting from climate change.

5. CONCLUSIONS

The 300 m SMOS SM maps covering Europe and the Mediterranean countries exhibit a similar accuracy to that of the lower resolution SM products (25 km and 1 km), when validating over the two selected networks (REMEDHUS and RSMN), with no significant changes in terms of correlation, ubRMSD and bias. Therefore, it seems that the BEC downscaling equation is also working at hundreds of meters, as already observed in previous research [19].

As far as we know, there is no other institution currently producing SMOS/SMAP SM maps at a spatial resolution <1 km in an operational setup. The promising results suggest that the proposed SMOS SM product at 300 m could be operationally distributed by BEC in a near future. However, further analysis should be done to assess its performance over other regions with different climates and environments. We might consider using an alternative modeled LST with a higher spatial resolution than that of ECMWF. Additionally, a spatial spectra analysis would serve to investigate the effective spatial resolution of the downscaled SM.

6. ACKNOWLEDGMENTS

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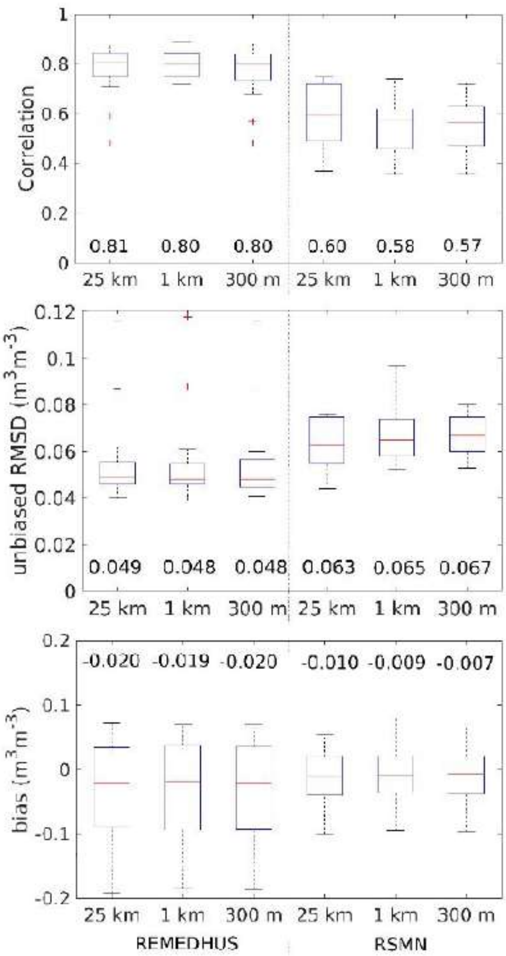

Fig. 2 Correlation, unbiased RMSD and bias obtained from the temporal validation of SMOS SM at 25 km, 1 km and 300 m against in-situ observations (19 stations of REMEDHUS and 10 stations of RSMN) during 2021. Median values, depicted with a red line in the boxplot, are included.

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