The merit of estimating high-resolution soil moisture using combined optical, thermal and microwave data

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Abstract—**Tremendous progress has been made to estimate soil moisture from satellite passive remote sensing data. Several global-scale coarse-resolution products have also been generated and released for a range of earth system applications. However, high-resolution soil moisture estimation is still in its infancy. Currently, two main types of methods are used for this purpose, namely downscaling approaches and direct retrieval from Sentinel 1 SAR data. Several studies have attempted to comprehensively evaluate the performance of these approaches and have found that all of them have strengths and weaknesses, with no one method outperforming the others. In this study, we aim to investigate the advantages of estimating soil moisture from the integration of optical, thermal and microwave data by leveraging an intensive soil moisture network and triple collocation method. Specifically, we firstly determined the best performed coarse-resolution microwave soil moisture produce via the triple collocation approach. Secondly, the 1-km soil moisture was generated from the best performed SMAP L3 descending product using a downscaling approach based on land surface temperature and vegetation index. Thirdly, the soil moisture measurements from the REMEDHUS stations network, ETOPO1 elevation, CHIRPS precipitation, and ESA CCI land cover map were used to evaluate the high-resolution downscaled soil moisture, Sentinel 1 soil moisture, and SMAP/Sentinel 1 combined soil moisture products. Finally, the merits of merging these products together were investigated and demonstrated via point-scale evaluation and large-scale spatial pattern comparison.**

Index Terms—**Soil moisture, triple collocation, land surface temperature, vegetation index, microwave remote sensing**

I. Introduction

Soil moisture (SM) is an important variable in the Earth system research and plays a key role in the exchange of water and energy between the land surface and the atmosphere [1]. Therefore, accurate estimation of soil moisture is essential for a wide range of Earth system related applications, such as weather forecasting, water resource management, and agriculture [2]. Various approaches have been developed to estimate soil moisture, including ground-based instruments, process-based numerical models, and satellite remote sensing. All of these approaches have their own strengths and limitations. For example, satellite remote sensing is a very promising way to provide large-scale soil moisture estimates. In particular, passive microwave remote sensing has become a mature technique for estimating soil moisture at regional and global scales, which is due to the availability of a large number of passive microwave satellites in space [3]. Several global-scale products have already been generated and released for public use, such as Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E/AMSR2), Soil Moisture and Ocean Salinity (SMOS), and Soil Moisture Active Passive (SMAP) [2]. Although various applications have benefited from the availability of these products, the coarse-resolution (normally coarser than 25 km) feature of these products limit their applications for many regional studies [4].

In order to address this challenge, two main types of methods have been proposed and applied to resolve the small-scale heterogeneity of the soil moisture at regional scale. The first type is downscaling approaches, which rely on simple or complex statistical methods to link the coarse-resolution passive soil moisture with various high-resolution soil moisture proxies, such as vegetation index, and land surface temperature [5]. Sabaghy et al., [6] comprehensively evaluated the state-of-the-art soil moisture downscaling approaches and found that the Vegetation Temperature Condition Index (VTCI)-based downscaling approach performed well against ground-based measurements and the flight campaign-derived soil moisture. However, its main limitation is the influence of clouds on the soil moisture estimates [7]. To overcome this limitation, the second type of high-resolution soil moisture estimation methods have been developed and benefited from the launch of the Sentinel-1 satellite, which can provide super-high resolution Synthetic Aperture Radar (SAR) measurements [8]. A few studies have attempted to derive 1-km resolution soil moisture using change detection approach, radiative transfer model, and machine learning method [8, 9]. The SMAP and Sentinel 1 data have also been fused together to derive a combined SMAP/Sentinel product at 1- and 3-km [9]. Despite these progress, limitations and uncertainties associated with these approaches remain in estimating high-resolution soil moisture at 1-km or even finer resolutions. One of the biggest challenges is the difficulty to properly consider the effects of surface roughness and vegetation water content on the backscatter signal of Sentinel-1 SAR [8]. It is therefore in urgent need to improve the retrieval approaches and explore the possibility to combine the use of multi-source satellite data including optical, thermal, and microwave to estimate high-resolution soil moisture. For coarse-resolution soil moisture estimation, two projects by European Space Agency (ESA) and National Oceanic and Atmospheric Administration (NOAA) have successfully merged existing multi-source passive and active microwave soil moisture products into one combined soil moisture product, namely ESA CCI soil moisture and SMOPS soil moisture [10, 11]. Both products have been proved to have better accuracy than the individual products used and widely used by a variety of applications [10]. Inspired by these projects, it is interesting to explore if the downscaled soil moisture and Sentinel-1 based soil moisture could be combined, and if the combined product can provide better quality and accuracy.

Therefore, the aim of this study is to investigate the performance of VTCI-downscaled soil moisture and Sentinel-1 based soil moisture, and demonstrate the merits of combing these products together to improve the accuracy of high-resolution soil moisture products. The triple collocation method was used to determine the best coarse-resolution microwave soil moisture, which was then downscaled to 1-km with VTCI approach using Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature and Normalized Difference Vegetation Index (NDVI) products. Furthermore, the downscaled soil moisture, Copernicus Global Land Service Sentinel-1 soil moisture, and fused SMAP/Sentinel-1 soil moisture were comprehensively evaluated using REMEDHUS ground measurements, ETOPO1 elevation, Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) precipitation, and ESA CCI land cover map. Finally, the combined soil moisture was generated and evaluated to show its performance compared to ground measurements and original soil moisture products.

II. Study area and data

A. Study area

The study area selected for this research is located in Spain (Fig.1), which covers a relatively flat terrain compared to other mountainous areas. The climate condition of the region is characterized by a semiarid Mediterranean climate, with hot/dry summers and mild/wet winters [12]. The REMEDHUS soil moisture observation network is also shown in Fig 1, which includes 19 soil moisture stations and covers a flat area with elevation that varies within the range of 700-900 m above sea level [13]. Overall, the flat terrain and the Mediterranean climate condition, as well as the availability of intensive soil moisture observation network makes it a suitable study area for investigating the performance of satellite-based soil moisture products.

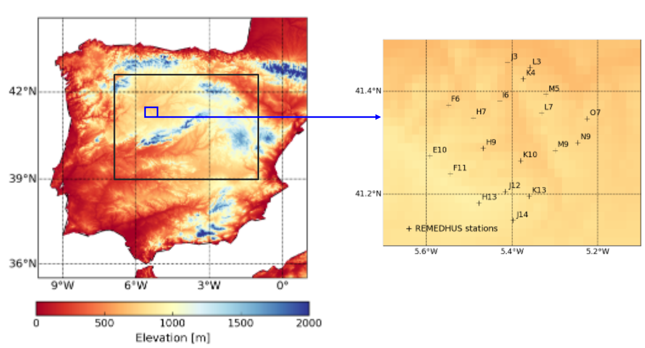


Fig 1: The overview of the study area and the REMEDHUS soil moisture observation network.

B. Data

Various satellite-based products are used this study, which include multiple soil moisture products, land surface temperature, NDVI, land cover map, precipitation, and elevation. In specific, SMAP L3 provides global daily soil moisture at 36-km from March 2015 to now, while SMOS-IC provides global soil moisture from January 2010 to now with a grid size of 25-km [14]. Another coarse resolution soil moisture product is ASCAT H115 which provides surface soil moisture climate data record at 12.5-km sampling from January 2007 to December 2018 [15]. In addition, high-resolution soil moisture products, including Sentinel-1 soil moisture delivered by Copernicus Global Land Service, and Sentinel-1/SMAP combined product from NASA National Snow and Ice Data Center are also used in this study [9]. The Sentinel-1 soil moisture provides 1-km relative soil moisture over Europe from January 2015 to now [8], while Sentinel-1/SMAP soil moisture is a global soil moisture product with 1- and 3-km resolution from April 2015 to present. MYD11A1 and MOD09GA products from MODIS Collection 6.1 provide global daily 1-km LST and daily 500 m surface reflectance. The daily NDVI is derived from the MOD09GA red and near-infrared band reflectance. The land cover map used in this study was obtained from the ESA CCI land cover product at 300 m resolution in 2015. The CHIRPS precipitation product used in this study is a satellite-based product providing precipitation at daily scale with 5-km spatial resolution from January 1981 to present on a global scale [16]. The elevation data is provided by ETOPO1, which covers the entire world at a spatial resolution of about 1.8 km and was first released in 2009. Details of these products are also listed in Table I. In addition to these satellite products, ground-based surface soil moisture measurements from 19 stations of the REMEDHUS observation network are also used in the study. It should be noted that all the data used in this study were collected over the period from May 6th, 2015 to September 27th, 2017, in order to ensure consistency and comparability across all of the data products.

TABLE I

The information of various Satellite products used in this study.

Satellite product	Variable	Grid size	Time span
Sentinel 1	Soil moisture	1 km	2015.01-now
SMAP L3	Soil moisture	36 km	2015.03-now
SMOS-IC	Soil moisture	25 km	2010.01-now
Sentinel 1/SMAP	Soil moisture	1 km	2015.04-now
ASCAT (H115)	Soil moisture	12.5 km	2007.01-2018.12
MOD09GA	Surface reflectance	500 m	2000.02-now
MYD11A1	LST	1 km	2002.07-now
CHIRPS	Precipitation	5 km	1981.01-now
ESA CCI LC	Land cover	300 m	1992-2015
ETOPO1	Elevation	1.8 km	2009

III. Methodology

A. Soil moisture downscaling with VTCI-based approach

The VTCI-based soil moisture downscaling approach was proposed by Peng et al., [7], and assumes that VTCI can represent the variation of soil moisture. It is calculated based on the triangular or trapezoidal feature space constructed by land surface temperature and vegetation index (Fig 2). The method has been included in a benchmarking comparison study of soil moisture downscaling methods by Sabaghy et al., [6]. It performs well in all methods and has the advantage of simplicity and high accuracy. It can be calculated as follows:

$$SM = VTCI * \frac{\overline{SM}}{\overline{VTCI}} \tag{1}$$

Where SM is the downscaled 1-km soil moisture, $\overline{SM}$ is the coarse-resolution soil moisture. $\overline{VTCI}$ refers to the resampled VTCI at the same resolution as $\overline{SM}$, and the VTCI is calculated from 1-km LST and NDVI as follows:

$$VTCI = \frac{T_{max} - T_s}{T_{max} - T_{min}} \quad (2)$$

Where T_s is the surface temperature for a given vegetation index value, and T_{max} and T_{min} are the maximum and minimum temperatures for the same vegetation index value. The equation is based on the fact that the variation of surface temperature is mainly due to the differences in soil moisture and evapotranspiration for a given vegetation index value. In this study, NDVI was used as the vegetation index and the difference between daytime and nighttime temperatures was used to represent surface temperatures in the triangular feature space.

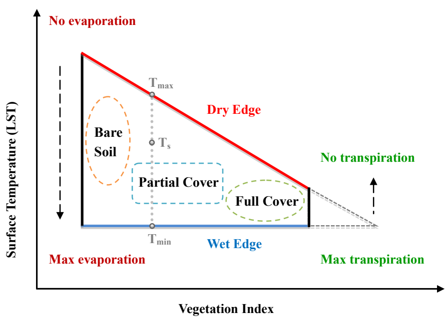


Fig 2: A conceptual triangular feature space constructed by land surface temperature and vegetation index (figure reprinted from Peng et al., [12]).

B. Evaluation metrics

The triple collocation (TC) method is used in this study to determine the best performed coarse-resolution soil moisture. TC is a statistical method used to estimate the error characteristics of three independent datasets that measure the same variable [17]. The signal-to-noise ratio (SNR) is normally calculated from the estimated error variances in TC to assess the quality of each dataset. The SNR is typically given in decibel units (dB), and the formula to calculate SNR is:

$$SNR_X = -10\log(\frac{\sigma_X^2 \sigma_{YZ}}{\sigma_{XY}\sigma_{XZ}} - 1) \quad (3)$$

$$SNR_Y = -10\log(\frac{\sigma_Y^2 \sigma_{XZ}}{\sigma_{YX}\sigma_{YZ}} - 1) \quad (4)$$

$$SNR_Z = -10\log(\frac{\sigma_Z^2 \sigma_{XY}}{\sigma_{ZX}\sigma_{ZY}} - 1) \quad (5)$$

Where σ_i^2 are the error variances of the three datasets X, Y and Z, and σ_{ij} is the covariance between the datasets. In this study, the three datasets refer to SMAP L3, SMOS-IC and ASCAT respectively. In addition to the triple collocation evaluation, the widely used statistical metrics as suggested by Gruber et al., [18] are used in this study to represent the error scores between ground-based measurements and satellite soil moisture products. They include Pearson correlation coefficient (*R*), Root Mean Squared Difference (*RMSD*), and unbiased *RMSD* (*ubRMSE*).

IV. Results and Discussion

A. Triple collocation analysis of SMAP L3, ASCAT and SMOS-IC

Although SMAP L3, ASCAT and SMOS-IC soil moisture products have been validated using International Soil Moisture Network (ISMN) and all presented reasonable performance, their accuracy vary from region to region [14, 19]. Triple collocation evaluation provides an effective alternative to quantify error characteristics without knowing the reference. Fig 3 shows the spatial patterns of TC-derived SNR for SMAP L3, ASCAT and SMOS-IC soil moisture. As all three satellites have descending and ascending orbits, which results in soil moisture products being delivered in both morning (6 am for SMOS and SMAP, 9:30 am for ASCAT) and afternoon (6 pm for SMOS and SMAP, 9:30 pm for ASCAT) overpass. The panels a and b in Fig 3 respectively present the results for morning and afternoon overpass times. It can be seen that SMAP L3 and SMOS-IC generally outperform ASCAT, showing high SNR values in most of the study area. Furthermore, SMAP L3 performs better than SMOS-IC with higher SNR. Regarding the morning and afternoon overpass, slightly better performance is found during morning overpass for all products. The results are consistent with the assumption that the temperature difference between vegetation canopy and soil surface is relatively small in the morning compared to the rest of the day [20]. Therefore, SMAP L3 soil moisture at the morning overpass was selected as the best performing coarse-resolution soil moisture in the study area. The 1-km SMAP L3 soil moisture was then estimated with the VTCI-based downscaling method using MODIS LST and NDVI as inputs.

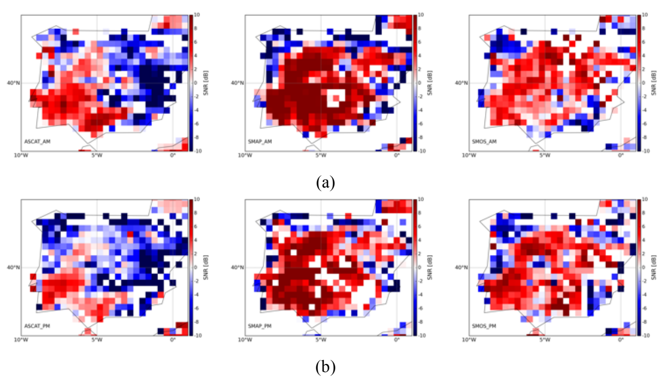
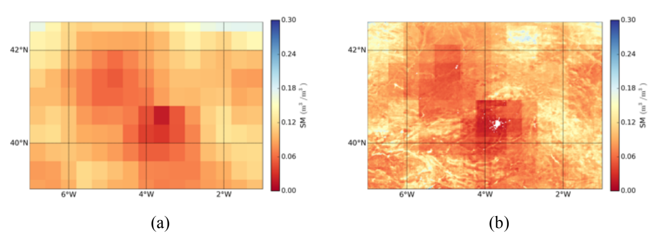


Fig 3: Signal-to-noise ratio (SNR) [dB] for ASCAT, SMAP L3 and SMOS-IC at both (a) morning and (b) afternoon overpass times.

B. Comparison of 1-km resolution soil moisture and the potential advantages of merging multi-source soil moisture

Fig 4 presents the comparison of spatial patterns of various soil moisture products and other variables including elevation, land cover and precipitation. It can be seen that the downscaled 1 km SMAP_AM soil moisture shows a similar pattern compared to the original SMAP_AM soil moisture, but with more spatial detail. Although all 1-km soil moisture products including Sentinel-1, SMAP/Sentinel-1 and downscaled SMAP_AM show some similarities, SMAP/Sentinel-1 presents relatively high soil moisture in the left and upper right of the study area compared to other 1 km soil moisture. These spatial distributions are also partially consistent with land cover, precipitation and elevation patterns. It can also be seen that large gaps in the middle of SMAP/Sentinel-1 soil moisture, which might be due to the missing of concurrent Sentinel-1 radar and SMAP radiometer observations. This is one limitation of the SMAP/Sentinel-1 combined product and has been reported by previous studies [21]. In addition to spatial pattern comparison, Fig 5 presents the temporal variability of the soil moisture products and ground-based soil moisture over the REMEDHUS network. All of the soil moisture products capture the general temporal dynamics of ground-based soil moisture, but there are differences between the satellite soil moisture products. In order to provide a quantitative evaluation of these products, Table II summarizes the statistical scores of the comparison between satellite soil moisture products and soil moisture measurements of REMEDHUS network. It can be seen that all the satellite soil moisture have good performance with correlation value higher than 0.7, RMSD less than 0.058 m^3/m^3, ubRMSD less than 0.049 m^3/m^3, which are consistent with reported evaluations on satellite soil moisture accuracy [19]. In specific, the downscaled SMAP_AM 1-km soil moisture has a higher correlation value than the original SMAP_AM, but the RMSD and ubRMSD values are almost identical. It indicates the effectiveness of downscaled soil moisture. Furthermore, it is also found that the SMAP/Sentinel-1 soil moisture has the highest correlation and lowest RMSD compared to SMAP_AM and downscaled SMAP_AM, but the highest ubRMSD. It is noted that Sentinel-1 soil moisture is not included in the evaluation, because it is relative soil moisture rather than volumetric soil moisture.

From the above spatial pattern comparison and evaluation analysis, it can be seen that the downscaled soil moisture and passive/active fused soil moisture both have advantages and disadvantages. The ESA CCI soil moisture and NOAA SMOPS initiatives have demonstrated that the merging of existing microwave soil moisture products lead to a better quality and long-term soil moisture estimate [10, 11]. However, to our knowledge, there are no studies investigating the potential advantages of fusing high-resolution 1-km soil moisture products yet. Both simple averaging method and complex triple collocation approaches have been applied to merging coarse-resolution soil moisture products. Similar performance of these two types of approaches have been reported by previous studies [17, 22]. On the other hand, triple collocation-based merging approaches require three independent soil moisture products, but the existing high-resolution soil moisture products do not meet this requirement. Therefore, the current study used the simple averaging method to merge downscaled SMAP_AM and SMAP/Sentinel-1 soil moisture products. In Fig 4 (h), it is found that the merged soil moisture combines the spatial patterns of both SMAP_AM and SMAP/Sentinel-1 soil moisture. From visual inspection, the merged soil moisture is in good agreement with the precipitation and land cover maps in terms of spatial distribution, which is also confirmed by the correlation analysis with R of 0.41 found between merged soil moisture and CHIRPS precipitation. In addition, it can also be seen from Table II that the merged soil moisture has the highest correlation value of 0.827 and lowest RMSD of 0.043 m^3/m^3 among all the satellite- soil moisture products. These error scores are also comparable to, if not better than, the published studies [4, 15, 19, 23]. These results suggest the better performance of the merged soil moisture and demonstrate the benefits of combing multi-source high-resolution soil moisture products. In particular, the synergy of thermal surface temperature, optical vegetation index, passive soil moisture, active SAR soil moisture can lead to a high-quality soil moisture estimate. It is therefore recommended that the satellite soil moisture community take into account the synergy of multiple sources of data (thermal/optical/microwave) when generating high-resolution soil moisture products.



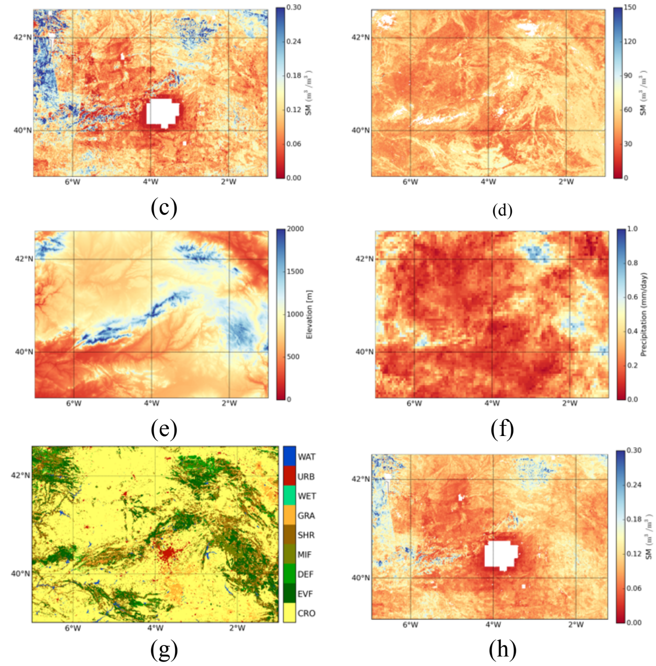


Fig 4: Spatial comparison of (a) SMAP_AM at 36-km, (b) downscaled SMAP_AM at 1-km, (c) SMAP/Sentinel-1 at 1-km, (d) Sentinel-1 at 1-km, (e) ETOPO1 elevation, (f) CHIRPS precipitation, (g) ESA CCI land cover map, and (h) merged soil moisture at 1-km over the study area. The land cover types include Croplands (CRO), Evergreen forest (EVF), Deciduous forest (DEF), Mixed forest (MIF), Shrublands (SHR), Grasslands (GRA), Wetlands (WET), Urban areas and built-up (URB), Water (WAT).

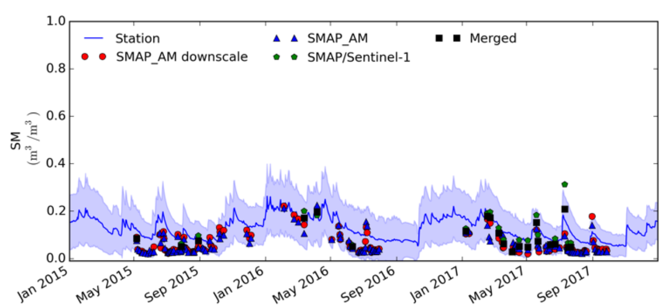


Fig 5: Time series of the averaged ground-based soil moisture, SMAP_AM soil moisture, downscaled SMAP_AM soil moisture, SMAP/Sentinel-1 combined soil moisture, and merged soil moisture over the REMEDHUS network.

TABLE II

STATISTICS ON ERROR METRICS BETWEEN SATELLITE SOIL MOISTURE AND GROUND MEASUREMENTS FROM REMEDHUS NETWORK.

	SMAP_AM	SMAP_AM downscale	SMAP/Sentinel-1	Merged
R	0.702	0.717	0.722	0.827
RMSD (m^3/m^3)	0.058	0.058	0.051	0.043
ubRMSD (m^3/m^3)	0.029	0.03	0.049	0034

V. Conclusion

This study investigates the potential advantages of estimating high-resolution 1-km soil moisture through merging multi-source soil moisture products derived from thermal, optical and microwave data. Firstly, the coarse-resolution soil moisture products were evaluated in this study, and then the best performing SMAP L3 morning overpass soil moisture was downscaled to 1-km resolution. The triple collocation approach is found to be very useful in providing error characteristics of soil moisture products without the need of reference data. The morning overpass soil moisture products generally performed better than afternoon overpass, which is due to the fact that the temperature difference between vegetation canopy and soil surface is minimal in the morning. Furthermore, the downscaled 1-km soil moisture, Sentinel-1 soil moisture, and SMAP/Sentinel-1 soil moisture were intercompared and evaluated with measurements from the REMEDHUS network. Different 1-km soil moisture products have both advantages and disadvantages and no one product performs better than the other. Finally, the simple averaging method was applied to merge the downscaled and SMAP/Sentinel-1 soil moisture. The merged soil moisture is found to have the best performance compared to other 1-km soil moisture products. The results presented here echo the ESA CCI and NOAA SMOPS initiatives that investigated the benefits of combining existing microwave soil moisture products. Furthermore, the results of this study demonstrate the importance of using thermal and optical data in combination with microwave data, rather than just combining multiple microwave data to estimate soil moisture.

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