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A New Method for Generating the SMOPS Blended Satellite Soil Moisture Data Product without Relying on a Model Climatology

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Abstract: Soil moisture operational product system (SMOPS) is developed by National Oceanic and Atmospheric Administration (NOAA) to provide the real-time blended soil moisture (SM) for numeric weather prediction and national water model applications. However, all individual satellite SM data ingested into the current operational SMOPS are scaled to global land data assimilation system (GLDAS) 0–10 cm SM climatology before the combination. As a result, the useful information from the original microwave SM retrievals could be lost, and the GLDAS model errors could be brought into the final SMOPS blended product. In this paper, we propose to scale the individual SM retrievals to the soil moisture active passive (SMAP) data through building regression models. The rescaled individual SM data and the SMAP observations then have similar climatology and dynamics, which allows producing the SMOPScdr (distinguishing with the current operational SMOPSopr) data using an equal-weight averaging approach. With respect to the in situ SM measurements, the developed SMOPScdr is more successful tracking the surface SM status than the individual satellite SM products with significantly decreased errors. The proposed method also preserves the climatology of the reference SMAP data for the period when SMAP is not available, allowing us to produce a long-term SMOPScdr data product.

Keywords: SMOPS; soil moisture; bias-correction

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1. Introduction

Surface soil moisture (SM) is a key parameter to control terrestrial water cycle, energy and carbon exchanges between land and the atmosphere through affecting the partitioning of incoming radiation into latent and sensible heat fluxes [1–3]. Benefiting from microwave remote-sensing techniques, there have been a number of satellite SM data products developed in the past decades, primarily including the advanced microwave scanning radiometer (AMSR)-earth observing system (AMSR-E), AMSR-2, WindSat, soil moisture and ocean salinity (SMOS), and soil moisture active passive (SMAP), as well as the advanced scatterometer (ASCAT) from the meteorological operational platform (MetOp)-A (ASCATA), MetOp-B (ASCATA) and MetOp-C (ASCATC) mission series [1,4–8]. However, these individual satellite SM observations not only lack complete coverages in time and space but also vary significantly in the archived formats, data accuracy and climatological characteristics.

To address those discrepancies, the soil moisture operational product system (SMOPS) is operationally produced by National Oceanic and Atmospheric Administration (NOAA) to offer the real-time blended satellite SM observations [9–14]. As NOAA requires high-quality satellite SM observations with short latency, the SMOPS combines all available individual SM observations within the numerical weather prediction (NWP) 6 h cut-off time and 24 h windows to generate the 6-hourly and daily blended products. Considering the operational users' feedback, the SMOPS was updated twice by removing old sensors, adding new satellite platforms and improving retrieval algorithms [13,14]. The current SMOPS version 3.0 combines the SM retrievals from ASCATA, ASCATB, AMSR-2, SMOS and SMAP [14]. Due to the different spatial resolution, polarization, frequency, revisit time and spatiotemporal coverage, the SM retrievals from different sensors must be processed toward a consistent mergeable dataset with the same climatology [15]. As a result, all individual satellite SM data products are remapped to SMOPS 0.25° latitude–longitude grids and then scaled to the 0–10 cm SM climatology of global land data assimilation system (GLDAS) V2.1-Noah model using the cumulative distribution function (CDF) matching method [9,10,13]. However, the useful information from the original microwave satellite observation could have been lost after scaling to model simulations [16,17]. Considering the requirements of model-free satellite SM observations are growing, we propose a new method in this paper for the SMOPS blended data product. Allowing the product features to purely depend on readily available microwave SM observations, the method is feasible for operational implementation without requiring ancillary datasets. For distinction with the current operational SMOPS product (SMOPSopr), the new blended product is expected to have climate data record quality and will be called SMOPScdr. Details of the new method and results are presented in this paper.

2. Data and Method

2.1. Satellite SM Data Products

The original daily ASCATA and SMOS level-2 SM data are retrieved from 1 January 2012 to 30 August 2021, while the initial availability periods for AMSR-2, ASCATB and SMAP products are 11 September 2012, 1 January 2013 and 1 April 2015, respectively (Table 1).

Table 1. CONUS domain-averaged RMSE, ubRMSE and correlation coefficients (r) for SMOPScdr and the original individual satellite soil moisture data products compared with SCAN measurements, as well as the corresponding statistical periods.

	ubRMSE (m^3/m^3)	RMSE (m^3/m^3)	r	Period
SMOS	0.099	0.132	0.379	01/01/2012–08/30/2021
ASMR-2	0.065	0.139	0.158	09/11/2012–08/30/2021
ASCATA	0.099	0.132	0.284	01/01/2012–08/30/2021
ASCATB	0.105	0.138	0.249	01/01/2013–08/30/2021
SMAP	0.061	0.105	0.559	04/01/2015–08/30/2021
SMOPScdr	0.057	0.101	0.440	01/01/2012–08/30/2021
SMOPScdr	0.057	0.102	0.315	01/01/2012–03/31/2015
SMOPScdr	0.058	0.099	0.506	04/01/2015–08/30/2021

ASCAT sensor operating in C-band (5.255 GHz) uses three-radar antenna beams to illuminate a continuous ground swath at three different azimuth angles [7]. The latest version ASCATA and ASCATB SM retrievals are obtained from the European Organization for the Exploitation of Meteorological Satellites. The AMSR-2 onboard GCOM-W1 satellite uses C-band (6.9 GHz) to estimate the surface SM status from about 700 km above the earth. The AMSR-2 version 1.0 SM data used in this paper are obtained from NOAA-National Environmental Satellite, Data, and Information Service (NESDIS). The SMOS and SMAP are specifically designed to sense SM based on L-band (1.42 GHz) observations [1,6]. The SMAP V5.0 is available from National Snow and Ice Data Center, while the real-time SMOS data V6.2 are distributed by the European Space Agency.

The current operational SMOPSopr data are also used in this paper to evaluate the developed SMOPScdr data. Given the same input individual satellite SM retrievals, the differences of in situ observations-based assessments are based only on the different development algorithm. The SMOPSopr V3.0 data from 1 April 2015 to 30 August 2021 are obtained from the NOAA-NESDIS.

2.2. In Situ Observations

Comprehensive assessments on the developed SMOPScdr in this paper were conducted with in situ SM measurements from Soil Climate Analysis Network (SCAN) and SMAP Validation (SMAPVAL) networks. The SCAN was specifically designed by the U.S. Department of Agriculture (USDA) to enable in situ observations focusing on the agricultural areas of the U.S. [18]. Hourly SCAN SM observations from 1 January 2012 to 30 August 2021 were reprocessed as daily time step to match the developed SMOPScdr. After quality control, in situ soil moisture measurements from 131 SCAN stations across the contiguous United States (CONUS) domain were selected for SMOPScdr quality evaluation.

SMAPVAL in situ SM data are from USDA-Agricultural Research Service (ARS) networks within the CONUS and the OzNet hydrological monitoring network in Australia. The USDA-ARS covers 5 watersheds, including the Walnut Gulch watershed in Arizona, the Little Washita and Fort Cobb watershed in Oklahoma, the Little River watershed in Georgia, the St. Joseph's experimental watershed and the South Fork experimental watershed in Iowa [19–21]. The Australian OzNet networks consist of the regional Murrumbidgee sites along with focused experimental areas in Yanco, Kyeamba, and Adelong Catchments [22]. Hourly USDA-ARS SM observations from 1 January 2012 to 31 December 2016 and hourly OzNet SM observations from 1 April 2015 to 31 December 2016 were reprocessed as daily time step to match the developed SMOPScdr. After quality control, SMAPVAL has approximately 200 stations selected to validate SMOPScdr.

2.3. Development of SMOPScdr

Previous studies have reported that the SMAP product has better performance than other available individual SM retrievals [23–25]. The NASA 0.25° SMAP data over the 2015–2021 time period are thus used as a reference in this paper. Considering the original ASCAT measurements offer the relative SM values from 0% to 100% to present moisture conditions [7], they are firstly converted to volumetric SM using a soil porosity map. All individual satellite SM data products are resampled to SMAP 0.25° latitude–longitude grids and then scaled to SMAP climatology and dynamics through developing multiple linear regression models for each grid cell over the global domain (Figure 1). The specific regression model parameters, including slop a and intercept b, are obtained to represent the relationships between the corresponding individual SM data product and the SMAP observations. One must bear in mind that the linear regression models are based on SMAP and other individual sensor SM products during the 1 April 2015–30 August 2021 time period when SMAP is available. The linear regression models are then applied to the entire available time period of each input individual satellite SM product. Given all individual satellite SM products are completely scaled to SMAP dynamics and climatology, the processed data and SMAP should have an equivalent performance, which allows combining them to generate the blended SMOPScdr soil moisture data using an equal-weight averaging approach. It can be found that the spatial patterns for the developed SMOPScdr are very reasonable over the global domain (Figure 1).

2.4. Validation Strategy

Based on the in situ SM observations from the SMAPVAL and SCAN networks, all individual satellite SM retrievals and the developed SMOPScdr data are evaluated by three widely used metrics, including correlation coefficient (r), root mean square error (RMSE) and unbiased RMSE (ubRMSE). The starting dates for the original SMAP, SMOS, AMSR-2, ASCATB and ASCATA are 1 April 2015, 1 January 2012, 11 September 2012, 1 January 2013 and 1 January 2012, while the ending dates are 31 December 2016 and 30 August 2021 for SMAPVAL and SCAN-based evaluations, respectively (Tables 1 and 2). Specifically, the developed SMOPScdr data are not only validated during the SMAP time period (after

1 April 2015) through intercomparing with SMAP but also focused on the period before SMAP is available to highlight the regression model validity. The SMOPScdr is matched up with the SMAPVAL observations scaled up from the SMAPVAL sites, and then the watershed-averaged comparison statistics are used to evaluate the SMOPScdr performance.

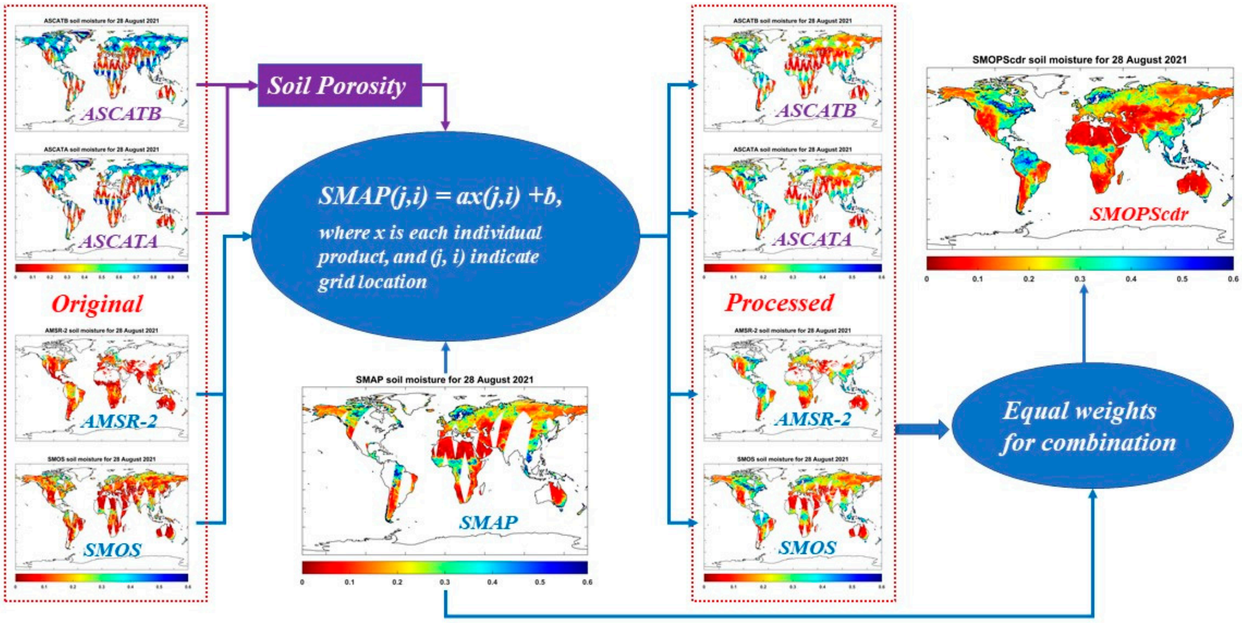

Figure 1. Process procedure of generating the 0.25° blended SMOPScdr soil moisture data product using ASCATA, ASCATB, SMOS, SMAP and AMSR-2 SM retrievals.

Table 2. With respect to the SMAPVAL soil moisture observations, statistics for studying domain-averaged RMSE, ubRMSE and correlation coefficients (*r*), as well as the corresponding statistical periods for the original individual satellite retrievals and the developed SMOPScdr data product.

	ubRMSE (m^3/m^3)	RMSE (m^3/m^3)	*r*	Period
SMOS	0.071	0.091	0.436	01/01/2012–12/31/2016
ASMR-2	0.045	0.081	0.260	09/11/2012–12/31/2016
ASCATA	0.084	0.112	0.378	01/01/2012–12/31/2016
ASCATB	0.082	0.098	0.344	01/01/2013–12/31/2016
SMAP	0.052	0.074	0.540	04/01/2015–12/31/2016
SMOPScdr	0.038	0.071	0.440	01/01/2012–12/31/2016
SMOPScdr	0.037	0.076	0.324	01/01/2012–03/31/2015
SMOPScdr	0.038	0.064	0.447	04/01/2015–12/31/2016

3. Results

Before ingested into SMOPScdr, all individual microwave satellite soil moisture data products are scaled to the SMAP climatology and dynamics. The daily SMOPScdr is thus first compared with the daily SMAP data. In Figure 2, the higher sample density area in warm color closer to the black 1:1 line indicates that the SMOPScdr and SMAP matches better. Resulting from the new method, seasonal regression curves overlapping with the ideal 1:1 line indicate SMOPScdr agrees well with the SMAP observations (Figure 2). The global domain-averaged correlation coefficients (*r*) between the daily SMAP and SMOPScdr reach to 0.975, 0.973, 0.967 and 0.973 for Winter (D-J-F), Spring (M-A-M), Summer (J-J-A) and Autumn (S-O-N), respectively. The strong agreements imply that all individual satellite SM observations ingested into SMOPScdr were successfully scaled to the SMAP climatology and dynamics, allowing for reasonably combining them into the blended SMOPScdr data using the equal-weight averaging approach.

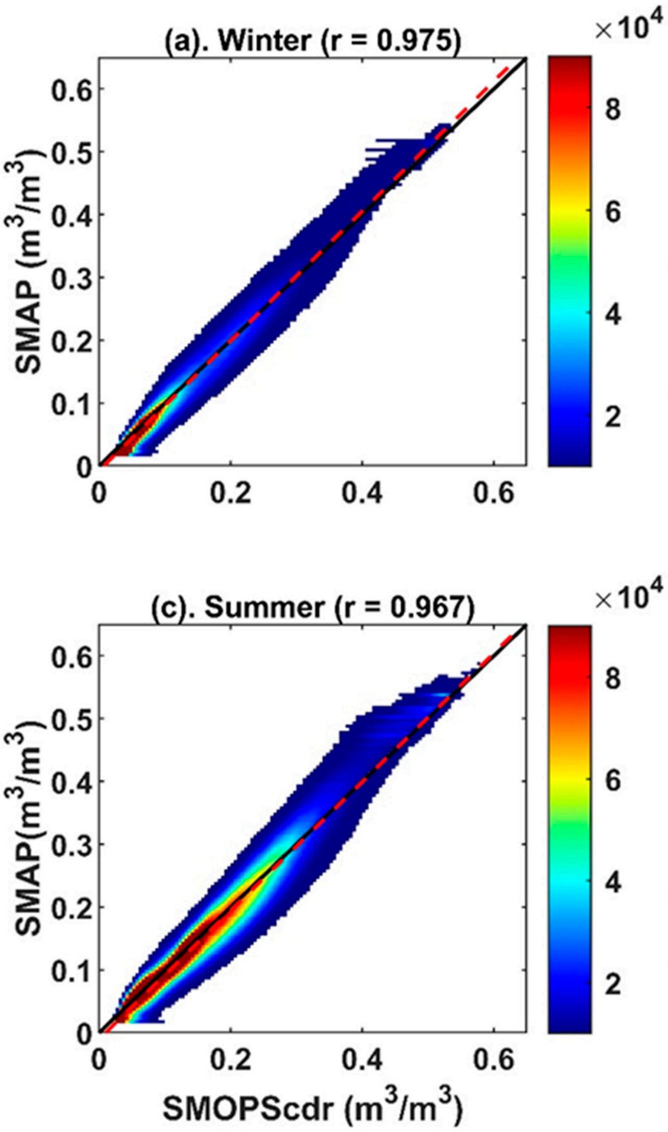

Figure 2. The daily SMAP versus the daily SMOPScdr soil moisture data over the global domain from 1 April 2015 to 30 August 2021: (**a**) Winter, December–January–February; (**b**) Spring, March–April–May; (**c**) Summer, June–July–August; and (**d**) Autumn, September–October–November. The black diagonal line represents they are perfectly matched. The red dashed line from the low-left to the upper-right is their linear regression curve. The color bar indicates sample density.

With respect to the quality-controlled SCAN measurements, SMOPScdr is assessed by comparing with the original individual satellite SM data products. Figure 3 shows differences in SCAN observations-based ubRMSE during the 1 April 2015–30 August 2021 time period with sites in blue color highlighting better performance. Relative to the SMAP, the SMOPScdr presents an equally good performance in the mid-west CONUS, while showing lower ubRMSE values in the east areas. SMOPScdr has overwhelming advantages in comparison with the original SMOS and ASCATA SM data products. Compared to AMSR-2, SMOPScdr exhibits slight improvements in the mid-west CONUS. The CONUS domain-averaged ubRMSEs for SMAP, SMOS, AMSR-2, ASCATA and ASCATB are 0.061 m^3/m^3, 0.099 m^3/m^3, 0.065 m^3/m^3, 0.099 m^3/m^3 and 0.105 m^3/m^3, which are significantly decreased by 5.17%, 70.69%, 12.07%, 70.69% and 81.03% by SMOPScdr (0.058 m^3/m^3), respectively (Table 1). The good performance is well mirrored during the 1 January 2012–31 March 2015 time period with SMOPScdr yielding a reasonable CONUS domain-averaged ubRMSE value (0.057 m^3/m^3).

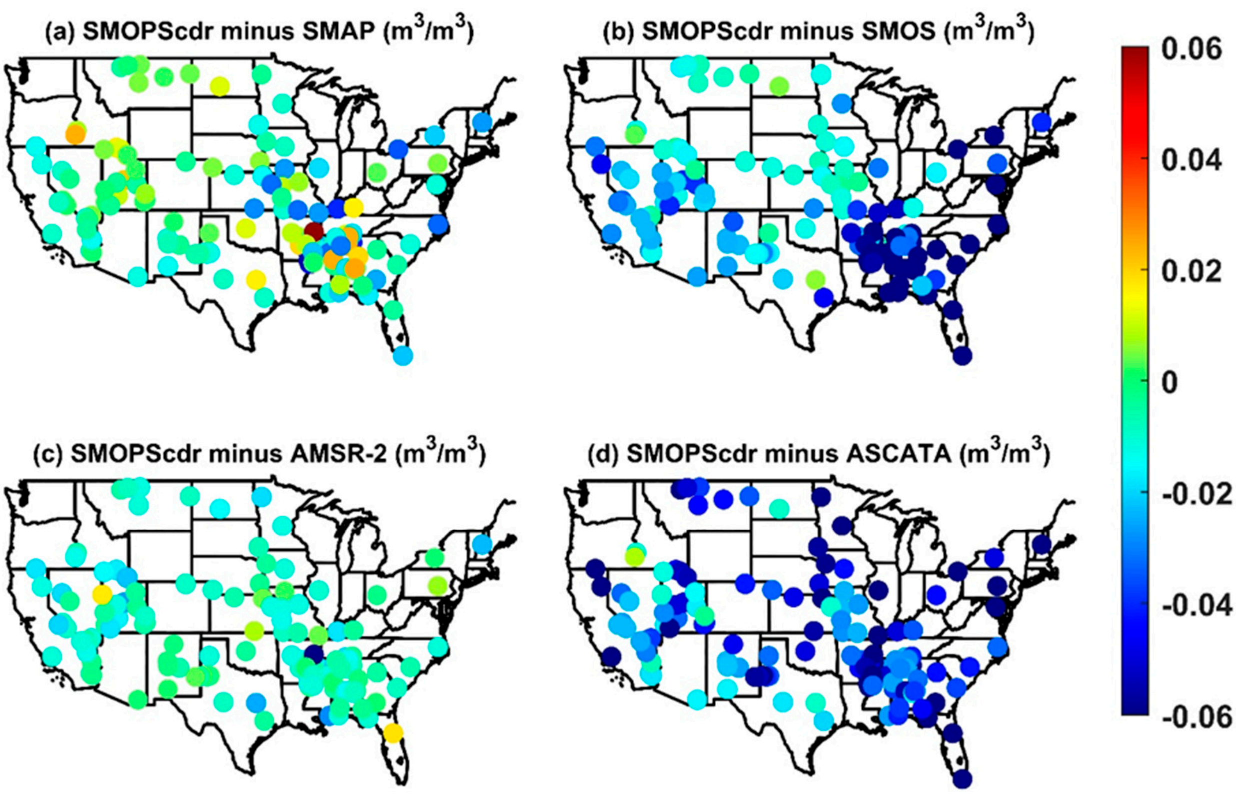

Figure 3. Differences in SCAN observations-based ubRMSE during 1 April 2015–30 August 2021 time period: (**a**) SMOPScdr minus SMAP, (**b**) SMOPScdr minus SMOS, (**c**) SMOPScdr minus AMSR-2, (**d**) SMOPScdr minus ASCATA. Patterns for ASCATA and ASCATB are very similar.

Further validations are conducted with RMSE and correlation coefficients. The CONUS domain-averaged RMSEs for the original SMAP, SMOS, AMSR-2, ASCATA and ASCATB are 0.105 m^3/m^3, 0.132 m^3/m^3, 0.139 m^3/m^3, 0.132 m^3/m^3 and 0.138 m^3/m^3, which are significantly decreased by 6.06%, 33.33%, 40.40%, 33.33% and 39.39% by SMOPScdr (0.099 m^3/m^3) over the 1 April 2015–30 August 2021 time period, respectively (Table 1). The SMOPScdr is more successfully in tracking surface SM dynamic trends in comparison with SMOS, AMSR-2, ASCATA and ASCATB but shows a weaker consistency with SCAN observation than the SMAP. It is worth to note that SMOPScdr performs reasonably well before and/or after the time period when SMAP is available, which means that the proposed method preserves the "memory" of the information from SMAP observations and thus allows us to produce a longer-term SMOPScdr with respect to the SMAP dynamics and climatology.

Complementary assessments on the new blended method are conducted with SMAPVAL SM observations. With respect to the SMAPVAL soil moisture measurements, the ubRMSEs for SMOPScdr span from 0.03 m^3/m^3 to 0.047 m^3/m^3 (Figure 4). Intercomparisons between SMOPScdr and SMAP are implemented by long-term SMAPVAL data from 1 January 2012 to 31 December 2016 over the five watershed regions to specifically highlight the disadvantages and advantages of the new blended method. Before the SMAP data are available, the SMOPScdr can successfully track soil moisture with respect to SMAPVAL and has a reasonable performance benefiting from SMAP data after 1 April 2015 (Figure 4). The global domain-averaged SMAPVAL-based ubRMSE values for SMOS, AMSR-2, ASCATA and ASCATB are 0.071 m^3/m^3, 0.045 m^3/m^3, 0.084 m^3/m^3 and 0.082 m^3/m^3, which can be significantly reduced by 86.84%, 18.42%, 121.05% and 115.79% by SMOPScdr (0.038 m^3/m^3), respectively. Compared to the SMAP (0.052 m^3/m^3), the SMOPScdr has a higher accuracy with the ubRMSE reduced by 36.84% (Table 2).

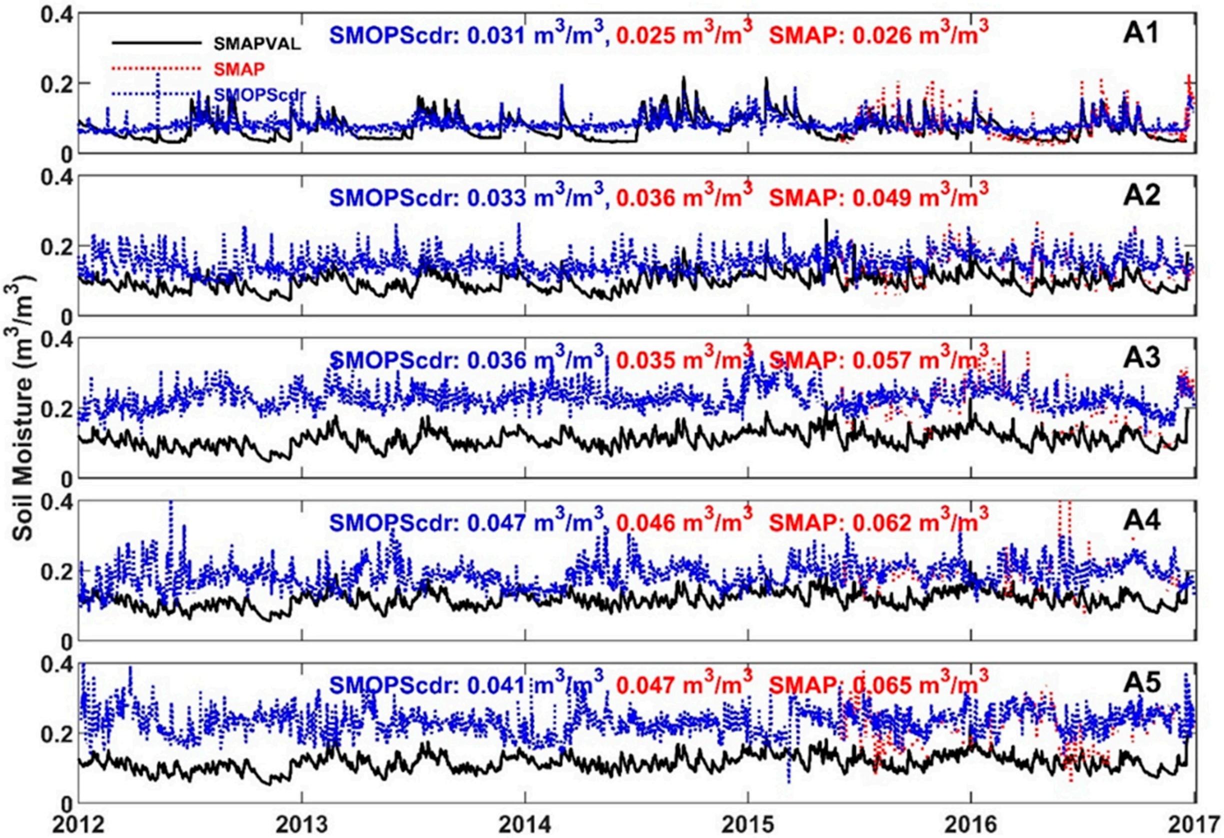

Figure 4. The watershed-averaged daily SMOPScdr and SMAP data versus daily SMAPVAL soil moisture measurements: A1—Walnut Gulch watershed, A2—Little Washita and Fort Cobb watershed, A3—Little River watershed, A4—St. Joseph's experimental watershed and A5—South Fork experimental watershed. The SMAP is from 1 April 2015 to 31 December 2016, while SMOPScdr starts from 1 January 2012. The ubRMSEs in blue and red colors for SMOPScdr indicate the time period before and after 1 April 2015 when SMAP becomes available. The ubRMSEs in red color for SMAP indicate the assessment over 1 April 2015 to 31 December 2016 period.

Benefiting from the new method, SMOPScdr yields RMSE values compatible with those for SMAP within and beyond the time period when SMAP data are available (Table 2). Based on correlation coefficient, the SMOPScdr (r = 0.440) is more consistent with SMAPVAL soil moisture observations than SMOS (0.436), AMSR-2 (0.260), ASCATA (0.378) and ASCATB (0.344), whereas it exhibits lower correlations than SMAP (0.540), resulting from, probably, the lower consistencies of the individual sensor retrievals with the SMAPVAL data. Correlation coefficient for SMOPScdr is 0.447 during the SMAP time period; yet, it drops sharply to 0.324 when SMAP is unavailable (Table 2).

4. Discussion and Conclusions

Blended satellite SM data have better consistency and more complete coverage in space and time. Before ingested into the blended product, the individual SM retrievals need to be scaled to a benchmark, as their characteristics vary significantly from each other. We, thus, propose to scale the available SM observations from the multiple single sensors to the currently most accurate satellite retrievals through building the corresponding regression models. The SMAP is used as a reference in this paper, but it is replaceable once another satellite SM product is proven to have higher accuracy in the future. The developed SMOPScdr combines the observations from ASCATA, ASCATB, AMSR-2, SMOS and SMAP in this paper, but the simple processing procedure and equal-weight averaging approach allow combining many more individual satellite SM products (e.g., ASCATC) into the SMOPScdr through building the corresponding regression models. Based on the validation results obtained in this paper, AMSR-2 yields the lowest agreement with in situ observations, resulting in SMOPScdr showing lower correlation coefficients than SMAP. It is, thus, expected to further improve the validation statistics for SMOPScdr through refining the AMSR-2 retrieval algorithm in the near future.

The motivation of this paper is to refine the current operational SMOPSopr product at NOAA-NESDIS. Figure 5 shows the differences in SCAN-based unRMSEs between the developed SMOPScdr and the current SMOPSopr with sites in blue (red) color indicating SMOPScdr presents a better (worse) performance. With respect to the SCAN SM measurements, SMOPScdr shows a better performance than SMOPSopr across the CONUS domain. Specifically, the CONUS domain-averaged ubRMSE value for SMOPSopr is 0.065 m^3/m^3 over the 1 April 2015–30 August 2021 time period, which can be significantly reduced by 12.24% by SMOPScdr (0.058 m^3/m^3). The only differences between SMOPSopr and SMOPScdr are their development technique, highlighting the advantages of the new methods proposed in this paper.

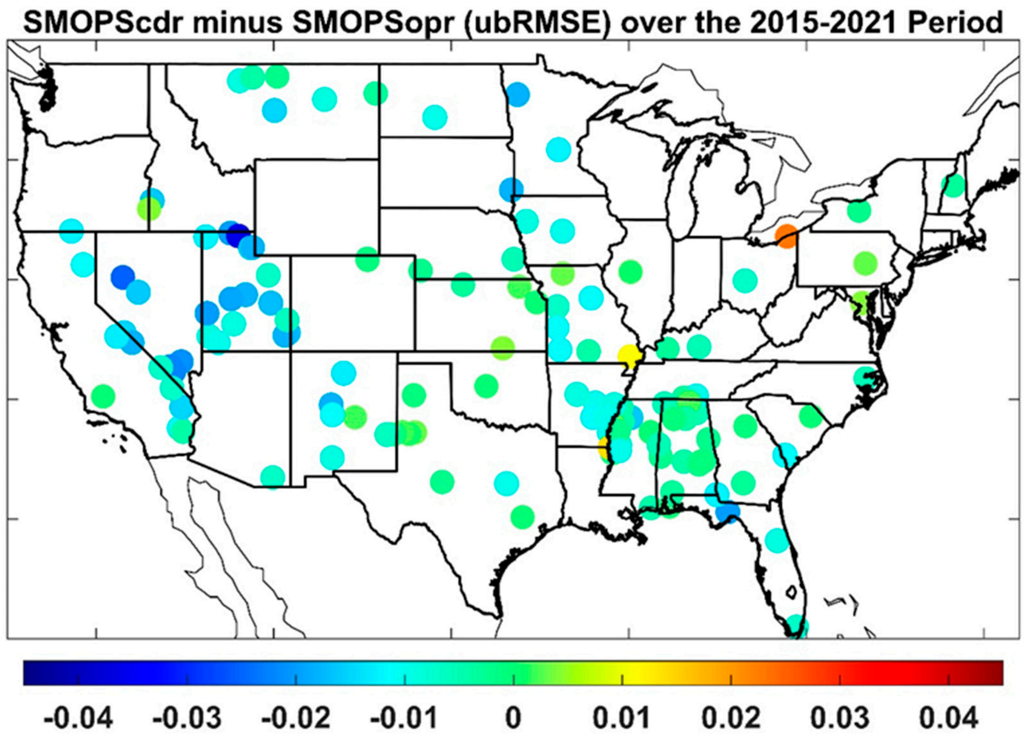

Figure 5. Differences in SCAN observations-based ubRMSE between the developed SMOPScdr and the current operational SMOPS (SMOPSopr) data products during the 1 April 2015–30 August 2021 time period.

The results of this study indicate that the developed SMOPScdr has a better performance than the ingested individual satellite SM data products. With respect to the SCAN SM measurements, SMOPScdr is more successful at tracking surface SM status with significantly smaller ubRMSE and RMSE values and larger correlation coefficient. The good performance of SMOPScdr is well mirrored in the further validation using the scaled-up in situ data from the USDA-ARS and the Australian OzNet SM networks. The developed SMOPScdr performs more reasonable not only during the SMAP time period but also during the period before the SMAP is available. It suggests that the proposed method preserves the information from SMAP observations and, thus, allows us to produce a longer-term SMOPScdr dataset based on the SMAP dynamics and climatology.

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Data Availability Statement: All individual soil moisture data products used in this paper can be obtained from the NOAA-NESDIS at http://www.ospo.noaa.gov/Products/land/smops/smops_loops.html (accessed on 23 March 2022).

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