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Ming Pan
Princeton University

Xitian Cai
Princeton University

Eric F. Wood
Princeton University

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Key Points:
- SMAP passive soil moisture retrievals are highly skillful
- SMAP active products are much less skillful due to short calibration length
- Retrieval skill is less sensitive to thicker vegetation than expected

Correspondence to:
M. Pan,
mpan@princeton.edu

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An initial assessment of SMAP soil moisture retrievals using high-resolution model simulations and in situ observations

Ming Pan[1], Xitian Cai[1], Nathaniel W. Chaney[2], Dara Entekhabi[3], and Eric F. Wood[1]

[1]Department of Civil and Environmental Engineering, Princeton University, Princeton, New Jersey, USA, [2]Program in Atmospheric and Oceanic Sciences, Princeton University, Princeton, New Jersey, USA, [3]Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, Massachusetts, USA

Abstract At the end of its first year of operation, we compare soil moisture retrievals from the Soil Moisture Active Passive (SMAP) mission to simulations from a land surface model with meteorological forcing downscaled from observations/reanalysis and in situ observations from sparse monitoring networks within continental United States (CONUS). The radar failure limits the duration of comparisons for the active and combined products (~3 months). Nevertheless, the passive product compares very well against in situ observations over CONUS. On average, SMAP compares to the in situ data even better than the land surface model and provides significant *added value* on top of the model and thus good potential for data assimilation. At large scale, SMAP is in good agreement with the model in most of CONUS with less-than-expected degradation over mountainous areas. Lower correlation between SMAP and the model is seen in the forested east CONUS and significantly lower over the Canadian boreal forests.

1. Introduction

The National Aeronautics and Space Administration's (NASA) Soil Moisture Active Passive (SMAP) satellite mission [*Entekhabi et al.*, 2010] was launched on 31 January 2015, and soil moisture retrievals started about 1 year ago on 31 March 2015 (passive sensor) and 13 April 2015 (active sensor). SMAP carries an L-band radiometer and radar and is the only satellite mission dedicated to surface soil moisture (and freeze/thaw status) observations other than the Soil Moisture and Ocean Salinity satellite [*Kerr et al.*, 2010]. The low frequency of the operating active and passive channels (centered at 1.26 GHz and 1.41 GHz, respectively) and large antenna (6 m diameter) are chosen to help SMAP reach a higher soil moisture measurement sensitivity compared to previous sensors. The combination of passive (radiometer) and active (radar) sensors, as well as better handling of radio frequency interference (RFI) [*Piepmeier et al.*, 2014], helps it achieve both good measurement accuracy and spatial resolution. Well-planned and lasting efforts in calibration/validation (Cal/Val) [*Jackson et al.*, 2012] across numerous in situ measurement sites in the continental United States (CONUS) and over other parts of the world will help improve the overall skill of the retrievals. Even though soil moisture retrievals from spaceborne microwave measurements have been well studied in the past [*Njoku*, 1977; *Schmugge*, 1984; *Jackson and Schmugge*, 1991; *Wagner et al.*, 1999b; *Owe et al.*, 2001; *Wigneron et al.*, 2007], the SMAP team continues to refine the soil moisture algorithm and optimal selection of channel and polarizations based on Cal/Val findings. Efforts have been made to validate SMAP products over limited periods by using in situ observations [*Chan et al.*, 2016] and sophisticated statistical techniques like triple collocation [*Chen et al.*, 2016].

With a full year of data now available, we perform a large-scale assessment of the current version of SMAP soil moisture product at point and regional scales, using in situ observations as well as high-resolution land surface model simulations forced with meteorological fields downscaled from observations and weather model reanalysis. Given the dense networks of meteorological stations and radars over CONUS, the meteorological forcing is considered to be high quality. The resulting soil moisture fields form a test data set that is spatially complete and complements sparse in situ soil moisture network comparisons. We also test that the *added value* that SMAP products can provide on top of the land surface model as an important target application of SMAP products to improve geophysical modeling through data assimilation [*Reichle et al.*, 2014; *Pan and Wood*, 2010].

2. Data and Methods

2.1. SMAP Product

SMAP generates different levels of products and soil moisture retrievals that are available as Levels 2 (half orbit based), 3 (daily composites), and 4 (model assimilated). We chose to compare SMAP Level 3 data to in situ and model values over the data-rich CONUS area. Since CONUS is in the midlatitudes, where the neighboring swaths do not overlap, there is essentially no difference between using Level 2 and Level 3. Three SMAP Level 3 soil moisture retrieval products were obtained from the National Snow and Ice Data Center: 36 km passive (radiometer) product (SMAP_P, CRID R13080) [*O'Neill et al.*, 2015], 9 km passive/active (radiometer/radar) combined product (SMAP_AP, CRID R12170) [*Entekhabi et al.*, 2015], and 3 km active (radar) product (SMAP_A, CRID R12170) [*Kim et al.*, 2015], all provided on Equal-Area Scalable Earth Grid, Version 2 (EASE-2).

2.2. Near-Real-Time High-Resolution Land Surface Modeling

As in situ observations are available only at specific points, we used a land surface model (VIC: Variable Infiltration Capacity [*Liang et al.*, 1994, 1996]) to assess the spatial variability of SMAP retrievals. VIC is designed to work at spatial scales ranging from 1 to 100 km. The partitioning of rainfall into direct runoff and infiltration is based on the concept of statistically distributed soil water holding capacity [*Wood et al.*, 1992]. The subgrid variability is handled through techniques like fractional storm area, subpixel vegetation tiles, elevation bands, and subpixel forcing adjustment for elevation. VIC has been implemented, calibrated, and validated for a large number of applications at regional, continental [*Mitchell et al.*, 2004], and global [*Sheffield and Wood*, 2007] scales.

In order to closely match the spatial resolution of the finest SMAP product resolution (3 km radar retrievals), the VIC simulation is performed on a 1/24° (~4 km) computing grid at an hourly time step over the CONUS, and the output is remapped to the 3 km EASE-2 grid. Here we use the 12 km (1/8°) National Data Assimilation System phase 2 (NLDAS-2) product [*Xia et al.*, 2012] as the backbone and blend in finer resolution products for different variables when available, including the 4 km Stage IV and Stage II radar/gauge products and the Level 2 shortwave radiation product from the GOES Surface and Insolation Products (GSIP). A gap-filling procedure is performed on Stage IV hourly data together with a daily rescaling to match the daily total from NLDAS-2 at 12 km. The GSIP Level 2 data, validated at 45 min past the hour, are first gridded to 4 km resolution and then adjusted for timing based on solar angles. Other 4 km forcing fields were downscaled from the 12 km NLDAS-2 data with adjustment for elevation effects and physical consistency [*Cosgrove et al.*, 2003]: air temperature (fixed lapse rate of −6 K/km), pressure (hydrostatic), specific humidity (adjustment according to both downscaled temperature and pressure), longwave radiation (radiative temperature adjusted according to the lapse rate), and wind speed (bilinear interpolation). The simulation is retrospectively performed from 2002 to provide sufficient model spin-up and data for historical analysis.

2.3. In Situ Observations

SMAP has driven an effort to organize and collect in situ soil moisture observations from sites and networks all over the world for the Cal/Val program [*Jackson et al.*, 2012]. Over CONUS, we took data from two national (sparse) networks, the Soil Climate Analysis Network (SCAN) and U.S. Climate Reference Network (CRN) [*Bell et al.*, 2013; *Schaefer et al.*, 2007]. SCAN has 154 stations within CONUS, and the records date back to 1990s for many stations. CRN consists of 114 stations, and their soil moisture records start relatively recently (most of them start no earlier than June 2009). SMAP also utilizes a number of local dense sensor networks over small watersheds, the Core Validation Sites (CVS), for the Cal/Val.

3. Comparisons

The study period started 13 April 2015 with all comparisons ending on 22 April 2016 (376 days) for passive retrievals (SMAP_P) and on 7 July 2015 (86 days) for passive/active combined (SMAP_AP) and active retrievals (SMAP_A). We first compare all the SMAP products and VIC 4 km simulations to the in situ point-scale observations. Among the hundreds of sites studied, four were selected from different vegetation/climate regimes and presented in Figure 1: two SCAN sites in Kentucky and New Mexico and two CRN sites Texas and Ohio. These sites include good, average, and not-so-good ones but very problematic ones are avoided. It is clear that the temporal dynamics of the passive SMAP_P time series follow the in situ observations very well over

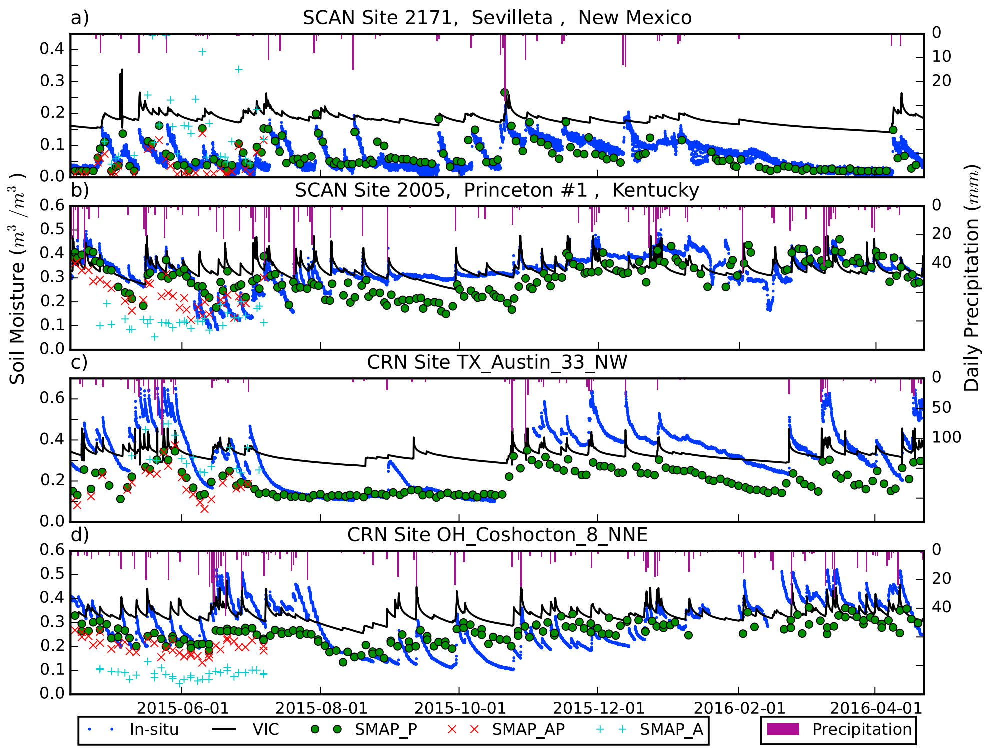

Figure 1. Time series of SMAP retrievals, VIC simulations, in situ observations, and daily site precipitation over: (a) SCAN site 2171 in Sevilleta, New Mexico; (b) SCAN site 2005 in Princeton #1, Kentucky; (c) CRN site Austin 33 NW, Texas; and (d) CRN site Coshocton 8 NNE, Ohio.

the first three sites (Figures 1a–1c), with almost all the precipitation events (purple bars) well captured except for those between revisit gaps (2–3 days). The SMAP_P also shows a reasonable dynamics over the Ohio site (Figure 1d), but the signal is rather damped in this forested Northern Appalachian area. The same can be said for the combined SMAP_AP product time series during the first 86 days. The active retrieval SMAP_A appears unable to reproduce the in situ observed temporal dynamics. This is true as well for the SMAP_P and SMAP_AP products—their dynamic ranges also differ significantly. The passive results here suggest that the SMAP 1.4 GHz L-band radiometer performs as expected and is able to capture the surface soil moisture dynamics accurately. The active sensor (radar) has a better spatial resolution, but the signal also has higher noise [*Wagner et al.*, 1999a]. A longer data record can help us to more adequately constrain the active retrievals (e.g., a few seasonal cycles) and filter out the noise; however, this will not be possible due to the sudden failure of SMAP's radar in July 2015. This left the SMAP_A product a very short data record (<3 months) to work with. VIC model simulations also reproduce the observed temporal dynamics well as seen in Figure 1.

In terms of the absolute value of the biases, SMAP_P and SMAP_AP are considerably biased over both the SCAN and CRN sites. The SMAP products are being calibrated over the CVS sites, but apparently not over SCAN or CRN at this time. This suggests that the bias, a static error, if known, can be constrained through calibrations, though such calibration may not be feasible globally without a different reference source (e.g., hydrologic models). Note that in situ data are point-scale measurements from single (SCAN) or triple (CRN) probes. Although the triple sensor configuration in CRN substantially improves the local sampling errors, there is still significant scale mismatch between the in situ data and satellite/model. We are assessing the potential differences between a SMAP footprint retrieval and measurements from sparsely monitored sites in a separate study.

The VIC model is also significantly biased over three out of the four sites with a wetter climatology and a relatively reduced dynamic range. Such a significant difference is due to both the physical representation of model layers (top soil layer in VIC is 0.1 m thick), model parameterizations (e.g., no direct soil evaporation if covered by vegetation), and errors in the meteorological inputs (particularly radar-based precipitation) and

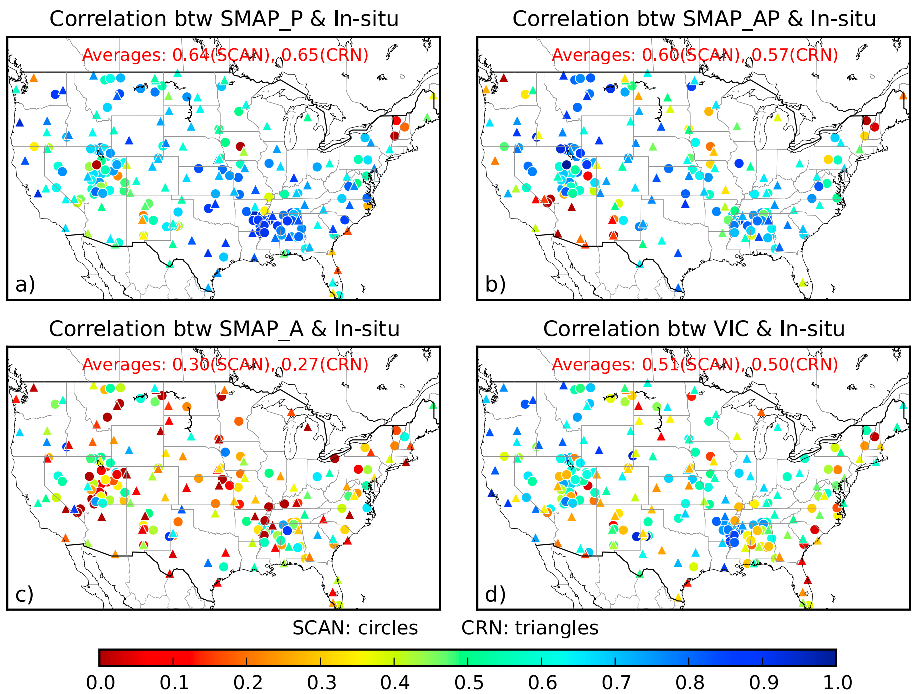

Figure 2. Correlation calculated against in situ observations (SCAN in circles and CRN in triangles): (a) SMAP_P, (b) SMAP_AP, (c) SMAP_A, and (d) VIC. Average correlation values across each network are reported at the top of the corresponding map.

model parameters (e.g., soil and vegetation properties.) Also, VIC was only calibrated against runoff measurement at a limited number (1130) of watersheds over CONUS at coarse resolution [*Troy et al.*, 2008] and never calibrated against soil moisture measurements. The VIC parameters at 4 km are simply interpolated from coarse ones (12 km).

Figure 2 shows the correlation against in situ observations for SMAP and VIC over the SCAN and CRN networks. Since both in situ networks and VIC provided at least hourly level time series, the time matching against SMAP was performed at the overpass hour. What is seen in Figure 1 can be generalized to the entire CONUS region. SMAP_P has a consistently high correlation with in situ measurements almost everywhere (Figure 2a) except for a few locations with low correlation on the east coast and some isolated points in the Rocky Mountains. In general, SMAP_AP (Figure 2b) follows the patterns seen in SMAP_P with a slightly lower performance. SMAP_A appears to have a hard time offering a good temporal correlation in most places. The VIC model simulations perform generally well but on average are slightly lower than SMAP_P and SMAP_AP. The SMAP_A correlation is significantly different than zero ($\alpha = 0.05$) only over a small number of sites due to both low correlation values and a short record length (26 days on average), while all other products have significant correlations over almost all sites.

The CONUS average correlation values are highlighted in red in Figure 2. The average correlations between SMAP_P and in situ data are 0.64 (SCAN) and 0.65 (CRN). These results are encouraging for the quality of the mission. First, they are significantly higher than the findings from a previous validation study on two Advanced Microwave Scanning Radiometer–EOS (AMSR-E) products performed in a similar way over CONUS [*Pan et al.*, 2014], which reported that the CONUS average correlation between AMSR-E retrievals and SCAN and CRN is around 0.48–0.56. Second, the correlations are considerably higher than model simulations (around 0.5; see Figure 2) forced with near-real-time meteorological inputs, even though the model was not calibrated against soil moisture measurements. Previously, model-derived soil moisture using high-quality inputs from regions like CONUS outperformed retrievals from sensors like AMSR-E.

Assuming that the VIC model reproduces reasonably well the temporal dynamics of the observed surface soil moisture—understanding that the average correlation against in situ data is lower than that of SMAP_P—we

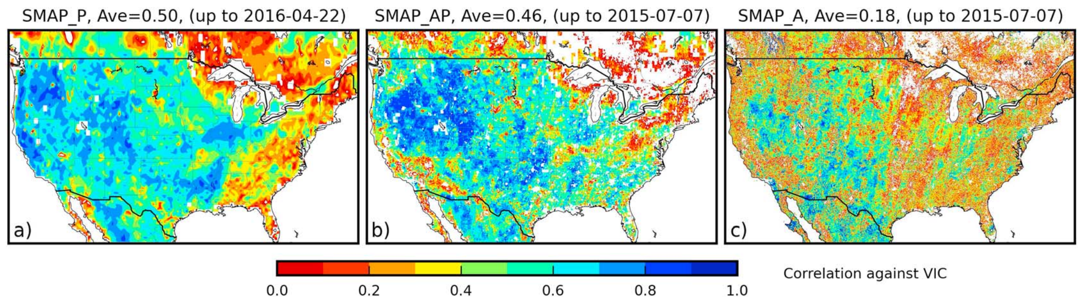

Figure 3. Maps of correlation between SMAP retrievals and VIC simulations: (a) SMAP_P, (b) SMAP_AP, and (c) SMAP_A with CONUS average values noted in map titles.

can examine how SMAP products compare to VIC over unobserved locations. Figure 3 shows the spatial maps of correlation between SMAP and VIC. The passive SMAP_P correlates well with VIC over most part of CONUS (Figure 3a). A poorer comparison is seen in SMAP_AP (Figure 3b), and it becomes much more degraded for the active SMAP_A (Figure 3c). We find it quite remarkable, and very encouraging, that SMAP_P and especially SMAP_AP correlate well with VIC over most of CONUS, including those forested and mountainous areas in the eastern and southeastern U.S., which are generally considered challenging for soil moisture retrievals due to the attenuation of the microwave signal by the vegetation. The CONUS average correlations against VIC are 0.50, 0.46, and 0.18 for SMAP_P, SMAP_AP, and SMAP_A. Note that in order to provide a most inclusive analysis and also to maintain a good sample size, data flags in SMAP products like heavy vegetation or RFI are not considered; i.e., every data point is used as long as SMAP offers a value.

Results of simple sensitivity analysis on the SMAP versus VIC correlation with respect to vegetation and soil characteristics are shown in Figure 4. Following the SMAP retrieval algorithm document [*O'Neill et al.*, 2015] as well as existing parameter sensitivity analysis [*Pan et al.*, 2014], correlation statistics are calculated against two important parameters: the vegetation water content (VWC, defined as the mass of vegetation water per unit area which largely determines the optical depth of canopy layer in microwave frequency) (Figures 4a–4c) and soil sand fraction (Figures 4d–4f). For SMAP_P and SMAP_AP, the correlation stays high for low VWC and decays gradually from VWC around 2–3 kg/m^2 and reaches the lowest at VWC around 5–7 kg/m^2. Note that the SMAP mission requirement targets the soil moisture content in the "top 5 cm for VWC ≤ 5 kg/m^2." Thicker vegetation also slightly lowers SMAP_A correlation (Figure 4c), and the low correlation becomes statistically insignificant due to a short record. The soil sand fraction (largely owing to the dielectric property of quartz) shows limited impact on passive retrievals (Figures 4d and 4e), and sand fraction higher than about 0.5 leads to a slightly lower correlation. Its effect on the active retrieval SMAP_A is unclear (flat line in Figure 4f).

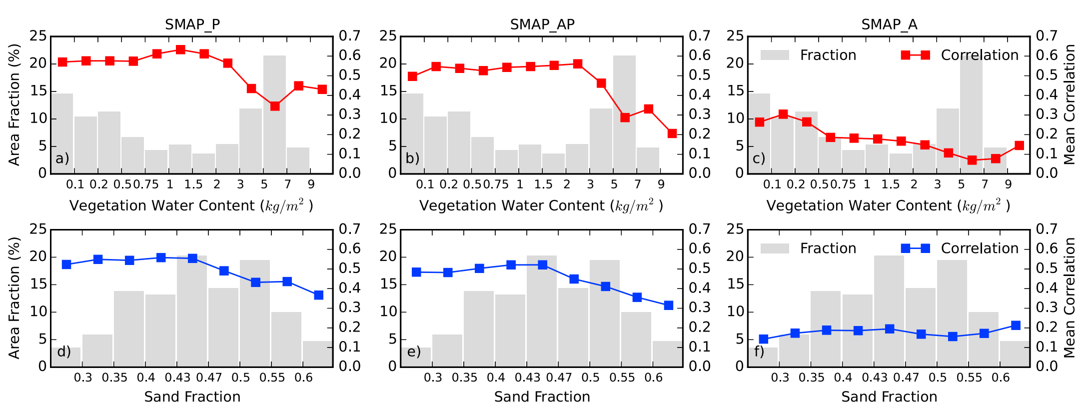

Figure 4. Statistics of SMAP versus VIC correlation across different (top row) vegetation water content and (bottom row) soil sand fractions. (left to right columns) SMAP_P, SMAP_AP, and SMAP_A products. Area fractions of vegetation water content or sand fraction ranges are shown as gray bars (left *y* axis) and correlation as lines with square symbols (right *y* axis).

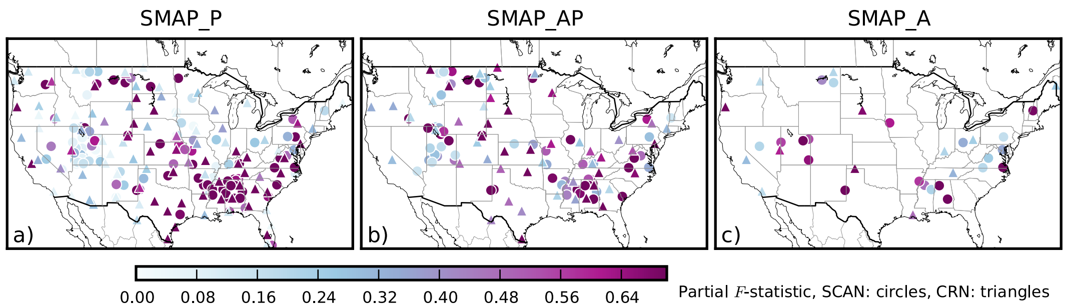

Figure 5. Partial F statistic over in situ sites to show the added value of SMAP retrievals on top of VIC simulations in predicting the observed soil moisture: (a) SMAP_P, (b) SMAP_AP, and (c) SMAP_A. Only sites with significant F statistic ($\alpha = 0.05$) are shown.

4. Added Value of SMAP on Top of the Land Surface Model

To measure the added value of SMAP retrievals on top of land surface model in a simple but more direct way than showing better correlation with observations, we consider a linear regression model that predicts in situ observations using both SMAP and VIC ("full" model) and another regression using VIC only ("reduced" model). If SMAP offers extra value beyond VIC, then the full model will have lower errors than the reduced model. We use the F test to measure the relative contribution of SMAP; it also reports the significance of this contribution. We define a partial F statistic as the difference between errors in reduced and full models divided by errors in the full model:

$$F = \frac{(\mathrm{SSE}_{\mathrm{reduced}} - \mathrm{SSE}_{\mathrm{full}})/1}{\mathrm{SSE}_{\mathrm{full}}/(n-3)}$$

$\mathrm{SSE}_{\mathrm{full}}$ and $\mathrm{SSE}_{\mathrm{reduced}}$ are the sum of squared errors in the full and reduced models. Numbers 1 and $n-3$ are the degrees of freedom in numerator and denominator, and n is the number of samples. This partial F statistic follows the F distribution with degrees of freedom 1 and $n-3$. Larger partial F statistic translates to higher added value of SMAP. Figure 5 shows the maps of partial F statistic calculated for three SMAP products over both SCAN and CRN sites. Only statistically significant F statistic values ($\alpha = 0.05$) are shown. Figure 5a suggests that the passive retrieval SMAP_P offers substantial added value beyond VIC (especially in the east) and it is significant almost everywhere. The added value of the combined product SMAP_AP (Figure 5b) falls below the 0.05 significance level over many places but stays strong over a majority of the tested sites. SMAP_A tends not to have a significant added value over most of CONUS though this could be related to the lack of samples.

5. Conclusions

Intercomparisons are made among SMAP passive/active/combined soil moisture retrievals, VIC 4 km hourly model simulations, and in situ measurements at point and regional scales during SMAP's first year of production. These simple comparisons suggest that the SMAP passive retrievals (SMAP_P) can reproduce the temporal dynamics of soil moisture well over most of CONUS, including mountainous areas in the western U.S. On average, SMAP_P has a better correlation with in situ measurements at the point scale than the VIC model; this correlation exceeds the level found in some previous studies on satellite soil moisture retrievals. The combined product at 9 km is slightly less skillful than the pure passive product but achieves higher correlation in the forested eastern and southeastern U.S. The biases between SMAP and in situ measurements are found to be due to various reasons that include scale mismatch and the sampling of landscape heterogeneity.

Simulations with the VIC model have similar and additional challenges related to input and model parameter uncertainty. Spatial comparisons against VIC simulations confirm that SMAP passive and combined retrievals retain a good skill over the forested mountains, but the skill decays toward the wetter part of the eastern CONUS and falls dramatically over the Canadian boreal forests in the north. As thicker vegetation affects the retrieval skills, its impact is gradual. Simple incremental regression analysis confirms that SMAP passive and combined retrievals offer significant added value beyond VIC land surface model in reproducing the in situ observed reference data, suggesting a good potential for data assimilation applications. Overall, our initial examination of the SMAP soil moisture products against available in situ and model data shows that the mission (apart from the failed radar) has been successful and that SMAP offers great promise for soil moisture retrievals over sparsely monitored regions.

Acknowledgments
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