Assessment of the SMAP Passive Soil Moisture Product

Steven K. Chan, *Senior Member, IEEE*, Rajat Bindlish, Peggy E. O'Neill, *Fellow, IEEE*, Eni Njoku, *Fellow, IEEE*, Tom Jackson, *Fellow, IEEE*, Andreas Colliander, *Senior Member, IEEE*, Fan Chen, Mariko Burgin, *Member, IEEE*, Scott Dunbar, Jeffrey Piepmeier, *Senior Member, IEEE*, Simon Yueh, *Fellow, IEEE*, Dara Entekhabi, *Fellow, IEEE*, Michael H. Cosh, Todd Caldwell, Jeffrey Walker, Xiaoling Wu, Aaron Berg, Tracy Rowlandson, Anna Pacheco, Heather McNairn, Marc Thibeault, José Martínez-Fernández, Ángel González-Zamora, Mark Seyfried, David Bosch, Patrick Starks, David Goodrich, John Prueger, Michael Palecki, Eric E. Small, Marek Zreda, Jean-Christophe Calvet, Wade T. Crow, and Yann Kerr, *Fellow, IEEE*

***Abstract*—The National Aeronautics and Space Administration (NASA) Soil Moisture Active Passive (SMAP) satellite mission was launched on January 31, 2015. The observatory was developed to provide global mapping of high-resolution soil moisture and freeze-thaw state every two to three days using an L-band (active) radar and an L-band (passive) radiometer. After an irrecoverable hardware failure of the radar on July 7, 2015, the radiometer-only soil moisture product became the only operational Level 2 soil moisture product for SMAP. The product provides soil moisture estimates posted on a 36 km Earth-fixed grid produced using brightness temperature observations from descending passes. Within months after the commissioning of the SMAP radiometer, the product was assessed to have attained preliminary (beta) science quality, and data were released to the public for evaluation in September 2015. The product is available from the NASA Distributed Active Archive Center at the National Snow and Ice Data Center. This paper provides a summary of the Level 2 Passive Soil Moisture Product (L2_SM_P) and its validation against *in situ* ground measurements collected from different data sources. Initial *in situ* comparisons conducted between March 31, 2015 and October 26, 2015, at a limited number of core validation sites (CVSs) and several hundred sparse network points, indicate that the V-pol Single Channel Algorithm (SCA-V) currently delivers the best performance among algorithms considered for L2_SM_P, based on several metrics. The accuracy of the soil moisture retrievals averaged over the CVSs was 0.038 m^3/m^3 unbiased root-mean-square difference (ubRMSD), which approaches the SMAP mission requirement of 0.040 m^3/m^3.**

***Index Terms*—Brightness temperature, land emission, L-band, Level 2 Passive Soil Moisture Product (L2_SM_P), Level 3 Daily Composite Version (L3_SM_P), passive microwave remote sensing, Soil Moisture Active Passive (SMAP), soil moisture, tau–omega ($\tau - \omega$) model, validation.**

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S. K. Chan, E. Njoku, A. Colliander, M. Burgin, S. Dunbar, and S. Yueh are with the NASA Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109 USA (e-mail: steven.k.chan@jpl.nasa.gov).

R. Bindlish and F. Chen are with Science Systems and Applications, Inc., Lanham, MD 20706 USA.

P. O'Neill and J. Piepmeier are with the NASA Goddard Space Flight Center, Greenbelt, MD 20771 USA.

T. Jackson, M. H. Cosh, and W. T. Crow are with the U.S. Department of Agriculture, Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD 20705 USA.

D. Entekhabi is with the Massachusetts Institute of Technology, Cambridge, MA 02139 USA.

T. Caldwell is with the University of Texas, Austin, TX 78713 USA.

J. Walker and X. Wu are with Monash University, Clayton, Vic. 3800, Australia.

A. Berg and T. Rowlandson are with the University of Guelph, Guelph, ON N1G 2W1, Canada.

A. Pacheco and H. McNairn are with Agriculture and Agri-Food Canada, Ottawa, ON K1A OC6, Canada.

M. Thibeault is with the Comisión Nacional de Actividades Espaciales (CONAE), Buenos Aires, Argentina.

J. Martínez-Fernández and Á. González-Zamora are with the Instituto Hispano Luso de Investigaciones Agrarias (CIALE), Universidad de Salamanca, 37185 Salamanca, Spain.

M. Seyfried is with the U.S. Department of Agriculture, Agricultural Research Service, Northwest Watershed Research Center, Boise, ID 83712 USA.

D. Bosch is with the U.S. Department of Agriculture, Agricultural Research Service, Southeast Watershed Research Laboratory, Tifton, GA 31793 USA.

P. Starks is with the U.S. Department of Agriculture, Agricultural Research Service, Grazinglands Research Laboratory, El Reno, OK 73036 USA.

D. Goodrich is with the U.S. Department of Agriculture, Agricultural Research Service, Southwest Watershed Research Center, Tucson, AZ 85719 USA.

J. Prueger is with the U.S. Department of Agriculture, Agricultural Research Service, National Laboratory for Agriculture and the Environment, Ames, IA 50011 USA.

M. Palecki is with the NOAA National Climatic Data Center, Asheville, NC 28801 USA.

E. E. Small is with the University of Colorado, Boulder, CO 80309 USA.

M. Zreda is with the University of Arizona, Tucson, AZ 85721 USA.

J.-C. Calvet is with the Centre National de la Recherches Météorologiques—GAME, UMR 3589 (Météo-France, Centre National de la Recherche Scientifique), 31057 Toulouse, France.

Y. Kerr is with the Centre d'Etudes Spatiales de la BIOsphère, Centre National d'Etudes Spatiales (CESBIO-CNES), 31401 Toulouse, France.

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I. Introduction

THE National Aeronautics and Space Administration (NASA) Soil Moisture Active Passive (SMAP) satellite mission was launched on January 31, 2015. The observatory was developed to provide global mapping of high-resolution soil moisture and freeze-thaw state every two to three days using an L-band radar (active) and an L-band radiometer (passive) onboard an observatory. The resulting measurements are expected to advance our understanding of the processes that link the terrestrial water, energy, and carbon cycles, improve our capability in flood prediction and drought monitoring, and enhance our skills in weather and climate forecasts [1].

Table I summarizes the key instrument specifications of the SMAP radiometer as well as the orbital parameters upon which the observations are acquired. One feature that distinguishes the SMAP radiometer from previous L-band radiometers is

TABLE I
KEY ORBITAL AND RADIOMETER SPECIFICATIONS OF SMAP

Parameters	Values
Frequency	1.41 GHz
Polarization	H, V, 3rd and 4th Stokes Parameters
Instrument native resolution	38 km × 49 km (3-dB IFOV)
Radiometric uncertainty	1.3 K
Antenna diameter	6 meters (fully deployed)
Antenna rotation rate	14.6 rpm
Beam efficiency	~90%
Incidence angle	~40 degrees (from nadir)
Orbit type	Near-polar, sun-synchronous
Orbit repeat period	8-day exact repeat every 117 orbits
Orbit altitude	685 km
Orbit period	98.5 minutes
Swath width	~1,000 km
Local time des/asc node	6:00 am / 6:00 pm
Complete global coverage	Every 2-3 days

its sophisticated hardware that allows high-rate acquisition of spectrogram data [2]. The resulting data are then applied to kurtosis-based algorithms to mitigate the radio frequency interference (RFI) due to anthropogenic emission sources on the ground [3]. Preliminary analyses of SMAP radiometer observations to date have demonstrated the effectiveness of this approach against RFI signals [4].

SMAP began simultaneous acquisition of radar and radiometer data in April 2015, with a goal of providing three soil moisture products: a radiometer-only product at a 40 km spatial resolution, a combined radar/radiometer product at a 10 km resolution, and a radar-only product at a 3 km resolution. However, the SMAP radar encountered an irrecoverable hardware failure on July 7, 2015 and was officially declared lost shortly thereafter. Despite this setback, the remaining SMAP radiometer has been nominally operating, collecting high-quality brightness temperature (T_B) data that enable the production of the standard Level 2 Passive Soil Moisture Product (L2_SM_P) and its Level 3 daily composite version (L3_SM_P). Since September 2015, both products have attained a preliminary (beta) science performance level and have been released to the public for evaluation from the NASA Distributed Active Archive Center (DAAC) at the National Snow and Ice Data Center (NSIDC). This release was expected to accelerate future product improvement in data accuracy and usability through feedback from the research and application communities.

This paper begins with an overview of the L2_SM_P product. The overview is followed by a description of the baseline and optional soil moisture retrieval algorithms that have been used in the operational product. The validation methodologies adopted by the project are then presented, followed by an early performance assessment of the product against *in situ* data from core validation sites (CVSs) and sparse networks through October 2015. Finally, an outlook for future improvements to the product is provided.

II. Product Overview

The L2_SM_P product is derived using SMAP L-band radiometer time-ordered observations (L1B_TB product) as the primary input [2]. The resulting soil moisture retrieval output fields, along with others carrying supplementary geolocation information, brightness temperatures, quality flags, and ancillary data, are posted on a 36 km Earth-fixed grid using the global cylindrical Equal-Area Scalable Earth Grid projection, Version 2 (EASEv2) [5], [6]. The 36 km grid resolution is close to the 3-dB native spatial resolution (see Table I) of the instrument observations, although the two measures of resolution do not have to be identical. The baseline L2_SM_P operational production uses observations acquired from the 6:00 A.M. descending passes only [7]. Soil moisture estimates using observations from the 6:00 P.M. ascending passes are also produced for validation analysis, but are not made available to the public at this time.

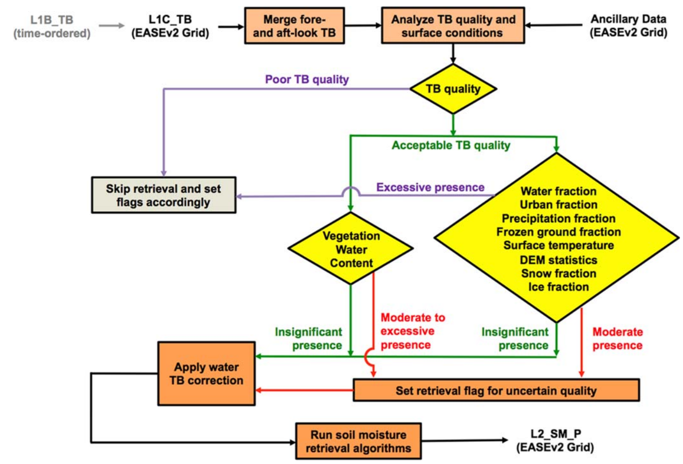


Fig. 1. Processing flow of the L2_SM_P SPS. The software uses the L1C_TB product as the primary input, along with other ancillary data on finer grid resolutions, to retrieve soil moisture (and other geophysical parameters as applicable) from a forward model.

Fig. 1 describes the processing flow of the L2_SM_P Science Production Software (SPS). The processing begins with the Level 1B time-ordered brightness temperature observations (L1B_TB) [8], being processed into the L1C_TB Gridded Radiometer Data Product on the global cylindrical 36 km EASEv2 Grid [9], [10]. The resulting fore- and aft-look gridded brightness temperature observations are then combined in the L2_SM_P SPS. External static and dynamic ancillary data preprocessed on finer grid resolutions are then brought into the processing to evaluate the feasibility and subsequent estimated quality of the retrieval. When surface conditions favorable to soil moisture retrieval are identified at a given grid cell, retrieval is performed. Corrections for water contamination, surface roughness, effective soil temperature, and vegetation water content are applied using five preselected candidate soil moisture retrieval algorithms (described in Section III-C) to produce the final output soil moisture retrieval fields on the same 36 km EASEv2 Grid as the input L1C_TB product. Data contents of the resulting L2_SM_P output files (granules) are described in the L2_SM_P Product Specification Document [11].

The ancillary data, as well as the corresponding grid/time resolutions at which they are used in the L2_SM_P SPS, are listed in Table II. As evident in the table, most ancillary data are preprocessed on grid resolutions finer than 36 km so as to provide more comprehensive information on the extent of heterogeneity at the 36 km spatial scale (for those ancillary data that have inherent spatial resolution finer than 36 km). In operational processing, ancillary data and model parameters at finer grid resolutions are aggregated to 36 km before they are used as inputs to the soil moisture retrieval algorithms. Most

TABLE II
EXTERNAL STATIC AND DYNAMIC ANCILLARY DATA USED IN L2_SM_P OPERATIONAL PROCESSING

Ancillary Data	Grid Resolution	Time Resolution	Primary Data Source
Permanent water fraction	3 km	Static	MODIS 250-m MOD44W [12]
Urban fraction	3 km	Static	Global Rural-Urban Mapping Project (GRUMP) [13]
DEM slope standard deviation	3 km	Static	USGS 250-m GMTED 2010 [14]
Soil texture	3 km	Static	FAO Harmonized World Soil Database (HWSD) [15]
Land cover classification	3 km	Static	MODIS 500-m MCD12Q1 (V051) [16]
NDVI	3 km	2000-2011 climatology	MODIS 1000-m MOD13A2 (V005) [17]
Snow fraction	9 km	Daily	Interactive Multisensor Snow and Ice Mapping System (IMS) [18]
Freeze/thaw fraction	9 km	1 hourly	GMAO Goddard Earth Observing System Model, Version 5 [19]
Soil temperatures	9 km	1 hourly	GMAO Goddard Earth Observing System Model, Version 5 [19]
Precipitation intensity	9 km	3 hourly	GMAO Goddard Earth Observing System Model, Version 5 [20]

ancillary data are aggregated by arithmetic averaging except for the vegetation water content, which follows the nonlinear aggregation scheme described in [21].

III. FORWARD MODELING

The zeroth-order radiative transfer model, which is more commonly known as the tau–omega ($\tau - \omega$) model, has been extensively used as an established forward model for passive remote sensing of soil moisture [22]–[24]. Over the past few decades, numerous soil moisture retrieval studies based on this model have been published. Despite the apparent simplicity of this model, there are significant differences in retrieval results among the studies. As pointed out in [25], a large part of the differences can be attributed to the particular choice of retrieval algorithms, ancillary data, and model parameterizations in the individual studies.

These issues were recognized by the SMAP passive soil moisture team early in the project development. In an effort to produce the best possible passive soil moisture product from SMAP radiometer observations and available ancillary data, a decision was made to implement multiple retrieval algorithms in the operational processing software [7], [11]. By this arrangement, it was intended that a more objective assessment of performance could be made among the algorithms when all were processed using the same input data, ancillary data, and *in situ* data during the postlaunch calibration and validation (cal/val) phase.

Soil moisture outputs from five different retrieval algorithms are included in the L2_SM_P beta-release product [11]. Common among these algorithms are the parameterizations of model coefficients (see Section III-A) and the way the effective soil temperature (T_{eff}) is accounted for (see Section III-B). Available resources limited the number of algorithms that could be considered for use by SMAP.

A. Model Parameterization

A number of model coefficients in the $\tau - \omega$ model must be initialized prior to application in operational production. These model coefficients describe how the surface roughness coefficient (h), vegetation single-scattering albedo (ω), and the "b" parameter in vegetation opacity should be parameterized. A simple lookup table (LUT) ascribing the model coefficients to land cover classes was adopted as the baseline approach to initialize the forward model [7]. Table III shows the LUT used in the L2_SM_P beta release.

TABLE III
LUT BETWEEN MODEL COEFFICIENTS AND LAND COVER CLASSES FOR L2_SM_P MODEL PARAMETER INITIALIZATION

Land Cover Class	h	b	ω
Evergreen needleleaf forest (ENF)	0.160	0.100	0.050
Evergreen broadleaf forest (EBF)	0.160	0.100	0.050
Deciduous needleleaf forest (DNF)	0.160	0.120	0.050
Deciduous broadleaf forest (DBF)	0.160	0.120	0.050
Mixed forest (MXF)	0.160	0.110	0.050
Closed shrublands (CSH)	0.110	0.110	0.050
Open shrublands (OSH)	0.110	0.110	0.050
Woody savannas (WSV)	0.125	0.110	0.050
Savannas (SAV)	0.156	0.110	0.080
Grasslands (GRS)	0.156	0.130	0.050
Croplands (CRP)	0.108	0.110	0.050
Urban and built-up (URB)	0.000	0.100	0.030
Cropland/vegetation Mosaic (MOS)	0.130	0.110	0.065
Barren or sparsely vegetated (BAR)	0.150	0.000	0.000

The coefficients listed in the table currently do not have polarization dependence, which means that for a given land cover class, the same coefficients (h, b, and ω) are used in forward-model computations of both horizontally and vertically polarized brightness temperature (T_{Bh} and T_{Bv}). These preliminary coefficients have yielded estimates of soil moisture that are in good agreement with *in situ* data (as will be shown in this paper). However, additional improvement is expected by further optimization of these coefficients during the cal/val phase of the product. The optimized coefficients will incorporate polarization dependence and variability within a given land cover class and may have seasonal dependence.

B. Effective Soil Temperature

Dynamic surface and soil temperature data from the Global Modeling and Assimilation Office (GMAO) Goddard Earth Observing System Model, Version 5 (GEOS-5) model are used to estimate T_{eff} in the forward radiative transfer model to provide the necessary surface temperature correction. The prelaunch approach was to compute T_{eff} as the average of the surface temperature (TSURF) and the layer-1 soil temperature (TSOIL1) GEOS-5 model fields. During the postlaunch cal/val phase, it was found that this approach did not adequately account for the temperature contributions to microwave emission from deeper soil layers. Therefore, the following modified form of the Choudhury model [26] was used instead. This model resulted in improved soil moisture retrievals particularly over arid areas, i.e.,

$$T_{\mathrm{eff}} = T_{\mathrm{soil\_deep}} + C(T_{\mathrm{soil\_top}} - T_{\mathrm{soil\_deep}}) \tag{1}$$

where $T_{\mathrm{soil\_top}}$ refers to GEOS-5's layer-1 soil temperature at 0–10 cm, and $T_{\mathrm{soil\_deep}}$ refers to the layer-2 soil temperature at 10–20 cm. This formulation of T_{eff} allows for more accurate modeling of emission emanating from deeper soil layers. C is a coefficient that depends on the observing frequency and was set to 0.246 for L-band frequencies, as reported in [26].

C. Retrieval Algorithms

There are five soil moisture retrieval algorithms implemented in the operational processing software. Soil moisture retrieval fields from all algorithms are available in the beta-release data products. For completeness, a brief description of these algorithms is given below; a more thorough discussion of them can be found in [7].

1) H-pol Single Channel Algorithm: In the H-pol Single Channel Algorithm (SCA-H) [24], the observed T_{Bh} data are used. After accounting for the presence of water within the inversion domain, corrections for T_{eff} [26] and vegetation water content [17] are applied to the emissivity, followed by correction for surface roughness. The last step in SCA-H invokes a soil dielectric model to relate the corrected horizontally polarized emissivity to soil moisture retrieval through the Fresnel equations. The soil dielectric model used is the Mironov model [27]. Other soil dielectric models are also under evaluation for possible future use [28], [29]. The SCA-H algorithm was considered the baseline algorithm at launch.

2) V-pol Single Channel Algorithm: The V-pol Single Channel Algorithm (SCA-V) is similar to the SCA-H except that T_{Bv} is used instead of T_{Bh}. As discussed in subsequent sections, it was found that SCA-V yielded the best overall soil moisture performance metrics among the five algorithms coded. For this reason, it was selected as the new (postlaunch) baseline retrieval algorithm for the beta release.

3) Dual Channel Algorithm: The Dual Channel Algorithm (DCA) makes use of complementary information in the T_{Bh} and T_{Bv} data to retrieve soil moisture and vegetation opacity [30], under the assumption that the vegetation opacity is the same for horizontal and vertical polarizations. In DCA, a cost function consisting of the sum of squares of the difference between the observed and estimated T_B is iteratively minimized until the corresponding retrieved quantities are determined. Polarization-dependent model coefficients (e.g., ω_h being different from ω_v) can also be specified in the DCA minimization process. Despite the apparent complexity of DCA, efficient and well-established algorithms exist that allow for DCA retrieval of soil moisture [31].

4) Microwave Polarization Ratio Algorithm: The Microwave Polarization Ratio Algorithm (MPRA) is based on the Land Parameter Retrieval Model [32] and was first applied to multifrequency satellites such as AMSR-E. Similar to DCA, MPRA attempts to solve for soil moisture and vegetation opacity using T_{Bh} and T_{Bv}. However, it does so under the assumptions that 1) the soil and canopy temperatures are considered equal and that 2) vegetation transmissivity (γ) and the vegetation single-scattering albedo (ω) are the same for both horizontal and vertical polarizations. When these assumptions are satisfied, it can be shown that the soil moisture and vegetation opacity can be analytically solved in closed form [33].

5) Extended Dual Channel Algorithm: In DCA, the T_{Bh} and T_{Bv} data are used together to construct a cost function that consists of the sum of squares of the differences between the observed and estimated T_B (V-pol and H-pol). Uncertainty in T_{eff} originating from its modeling or ancillary data source propagates to both V-pol and H-pol T_B terms in the cost function, potentially causing DCA nonconvergence. The Extended Dual Channel Algorithm (E-DCA) mitigates this problem by using the polarization ratio (PR), which is defined as $(T_{\mathrm{Bv}} - T_{\mathrm{Bh}})/(T_{\mathrm{Bv}} + T_{\mathrm{Bh}})$, as one of the cost function terms, since the PR is relatively insensitive to T_{eff}. Thus, in E-DCA, the first cost function term is the difference between the observed and estimated PR (in natural logarithm); the second term is the difference between the observed and estimated T_{Bh} (also in natural logarithm). Analytically, the cost function φ^2 can be written as

$$\varphi^2 = \left[\log\left(\frac{T_{\mathrm{Bv}}^{\mathrm{obs}} - T_{\mathrm{Bh}}^{\mathrm{obs}}}{T_{\mathrm{Bv}}^{\mathrm{obs}} + T_{\mathrm{Bh}}^{\mathrm{obs}}}\right) - \log\left(\frac{T_{\mathrm{Bv}}^{\mathrm{est}} - T_{\mathrm{Bh}}^{\mathrm{est}}}{T_{\mathrm{Bv}}^{\mathrm{est}} + T_{\mathrm{Bh}}^{\mathrm{obs}}}\right)\right]^2 + \left[\log\left(T_{\mathrm{Bh}}^{\mathrm{obs}}\right) - \log\left(T_{\mathrm{Bh}}^{\mathrm{est}}\right)\right]^2 \quad (2)$$

where the superscripts obs and est represent, respectively, the observed and estimated quantities. Under nominal conditions, E-DCA and DCA converge to the same solutions, since solutions that globally minimize the DCA cost function also globally minimize the E-DCA cost function.

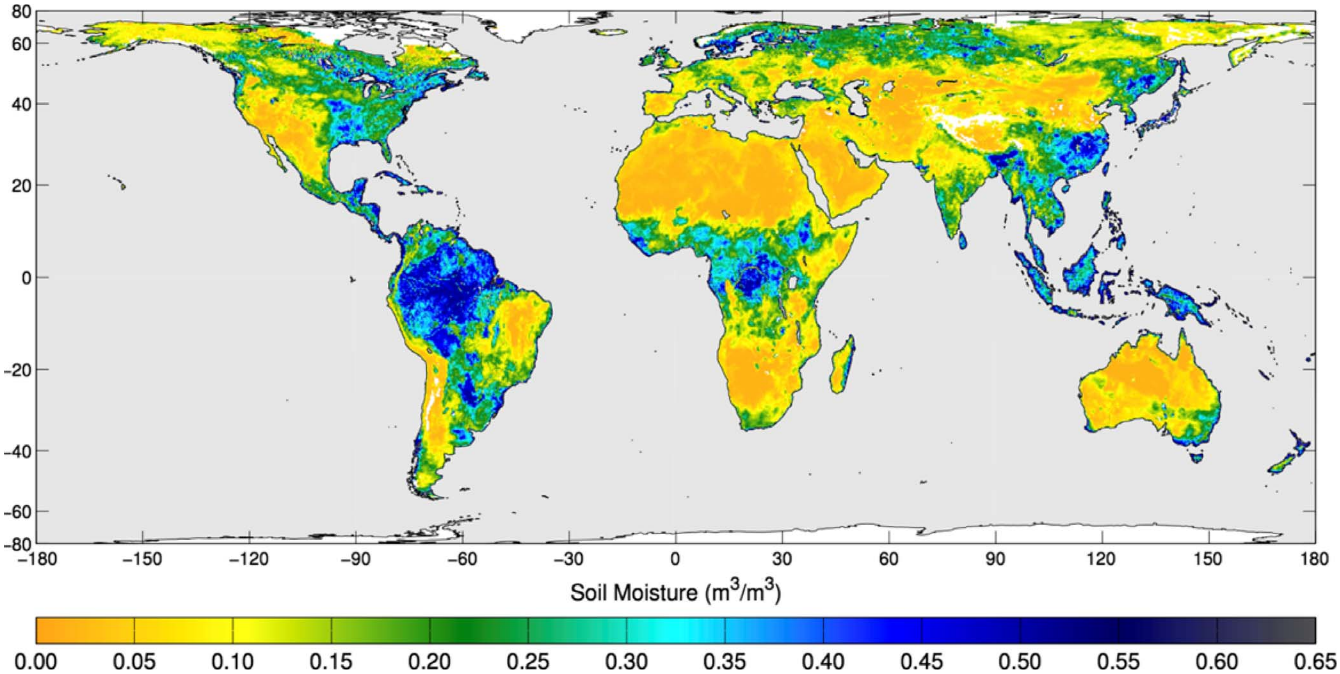
IV. Product Assessment

This section describes results of the soil moisture retrieval performance assessment leading up to the beta release. Of the five soil moisture retrieval algorithms implemented, only SCA-H, SCA-V, and DCA are discussed in this assessment. Analyses of the MPRA and E-DCA are similar to DCA in their current implementation. The performance of MPRA and E-DCA will be more fully investigated along with the SCA-H, SCA-V, and DCA as cal/val moves toward the validated release of the product in May 2016.

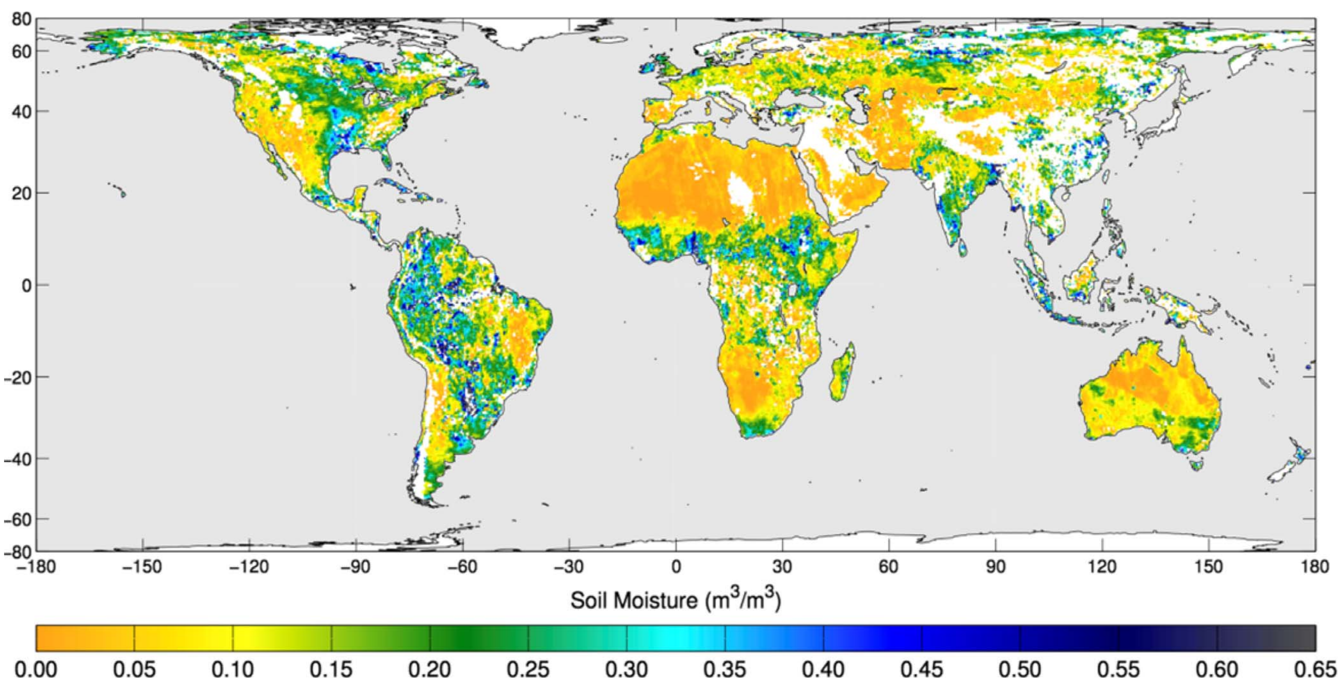
A. General Methodology

All soil moisture retrieval algorithms considered in this assessment are compared with the same *in situ* data sets with the same performance metrics applied. The *in situ* data sets consist of appropriately scaled aggregations of ground-based *in situ* soil moisture observations from 1) CVSs and 2) individual stations of sparse networks. Agreement between the L2_SM_P soil moisture and the *in situ* data sets over space and time are reported in 1) time-series correlation; 2) bias; 3) root-mean-square difference (RMSD); and 4) unbiased root-mean-square difference (ubRMSD). Together, these metrics provide a more comprehensive description of product performance than any one alone [34]. The ubRMSD (in units of $\mathrm{m}^3/\mathrm{m}^3$) is the metric adopted by SMAP for reporting product accuracy across all Level 2 through Level 4 soil moisture products. The SMAP Level 1 mission requirement for the active/passive soil moisture product accuracy is ubRMSD $= 0.040\ \mathrm{m}^3/\mathrm{m}^3$. The same accuracy target was adopted for the L2_SM_P soil moisture product.

The L2_SM_P product is processed on a relatively coarse grid (36 km EASEv2 Grid). To mitigate the comparison error caused by misalignment between the L2_SM_P grid cell domain and the distribution of *in situ* soil moisture sensors, validation grid (VG) processing uniquely tailored to each CVS and sparse network location is used for the L2_SM_P cal/val. The VG processing adopts a shift-and-retrieve approach allowing the L2_SM_P retrieval grid cell domain to more accurately align with the distribution of *in situ* soil moisture sensors at the CVSs and sparse networks. In VG processing, a 36 km grid cell ("inversion domain") is defined for each CVS and sparse network location. The exact position of the domain depends on the actual distribution of the sensors relative to the closest 36 km EASEv2 grid lines. If most of the sensors fall within a standard 36 km EASEv2 grid cell, the resulting 36 km inversion domain will coincide with that grid cell. If, however, the sensors cover more than one standard 36 km



(a) SMAP Level 2 soil moisture between June 1–7, 2015 (version T11880)



(b) SMOS Level 3 soil moisture between June 1–7, 2015 (version 300)

Fig. 2. Global patterns of soil moisture retrieved by (a) SMAP SCA-V and (b) SMOS over a one-week period from June 1, 2015 to June 7, 2015. Retrievals from both missions exhibit the expected spatial patterns of soil moisture but show some differences over densely vegetated areas and areas contaminated by radio frequency interference (RFI). SMAP retrievals demonstrate a higher upper bound on soil moisture estimates.

EASEv2 grid cell, the resulting 36 km inversion domain will be defined such that its final position will 1) capture most of the sensors and 2) align with the standard 3 km EASEv2 grid lines. Such a 3 km grid permits finer alignment between the VG inversion domain and the distribution of the sensors, although other grid resolutions are also possible and are being evaluated. Once the exact position of the VG inversion domain is defined for a given CVS, the same L2_SM_P processing depicted in Fig. 1 is applied to the L1B_TB observations to produce passive soil moisture estimates at the 36 km shifted VG locations.

B. Global Patterns

Global maps of soil moisture serve as the first step in the assessment. Fig. 2 shows global composites of 6:00 A.M. descending soil moisture of SMAP and the Soil Moisture and Ocean Salinity (SMOS) mission [35] over a one-week period from June 1, 2015 to June 7, 2015.

TABLE IV
CVSs USED IN L2_SM_P BETA-RELEASE ASSESSMENT

Site Name	Site PI(s)	State, Country	Climate Regime	Land Cover	Number of Sensors
Walnut Gulch	Cosh, Goodrich	AZ, USA	Arid	Shrub open	29
Reynolds Creek	Cosh, Seyfried	ID, USA	Arid	Grasslands	20
Fort Cobb	Cosh, Starks	OK, USA	Temperate	Grasslands	15
Little Washita	Cosh, Starks	OK, USA	Temperate	Grasslands	20
South Fork	Cosh	IA, USA	Cold	Croplands	20
Little River	Cosh, Bosch	GA, USA	Temperate	Cropland/mosaic	28
TxSON	Caldwell	TX, USA	Temperate	Grasslands	36
Kenaston	Berg, Rowlandson	Canada	Cold	Croplands	28
Carman	McNairn, Pacheco	Canada	Cold	Croplands	9
Monte Buey	Thibeault	Argentina	Arid	Croplands	14
REMEDHUS	Martinez	Spain	Semi-arid	Croplands	19
Yanco	Walker	Australia	Arid	Croplands/grasslands	28
Kyeamba	Walker	Australia	Temperate	Grasslands	9

In Fig. 2(a), both the nominal and flagged soil moisture retrievals from SMAP are shown. The flagged retrievals include results that should be used/interpreted with caution due to surface/instrument conditions that may lead to inaccurate passive soil moisture retrieval (e.g., frozen ground, mountainous terrain, excessive vegetation, high noise equivalent delta temperature (NEDT) due to residual uncorrectable RFI, etc.). A complete description of the flags and their thresholds used in L2_SM_P operational production can be found in [11].

Soil moisture retrievals from SMAP and SMOS in Fig. 2 showed the expected spatial patterns of soil moisture, from the drier arid regions to the wetter forest regions. There are differences however, particularly over densely vegetated areas and areas depicted in white (e.g., some parts of the Middle-East and Asia) where SMOS is more susceptible to low-to-moderate RFI contamination than SMAP.

C. Core Validation Sites

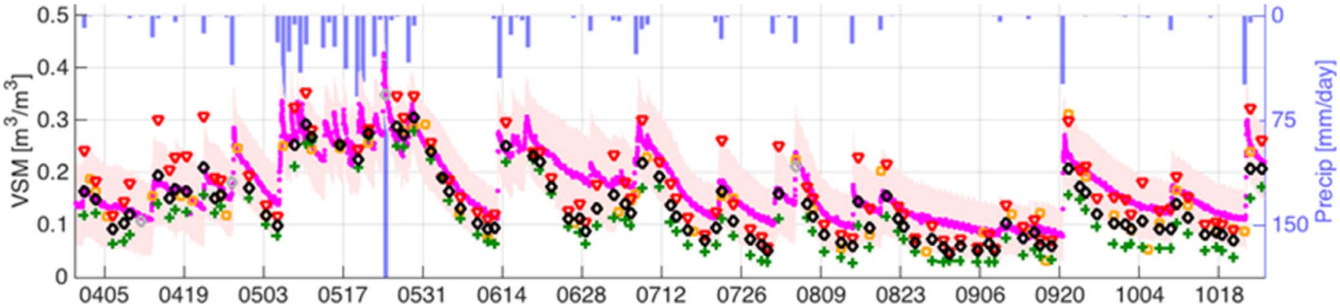
The first stage of cal/val involves comparisons of SMAP soil moisture with ground-based *in situ* observations that have been aggregated to provide a reliable spatial average of soil moisture at the 36 km grid scale [34]. The availability of high-quality *in situ* observations is important as these data provide a basis for algorithm refinement and performance evaluation of the L2_SM_P product. Early in the mission, SMAP established a Cal/Val Partners Program to foster collaboration with domestic and international partners who operate field sites populated with dense clusters of well-calibrated soil moisture sensors. Under this program, the partners agreed to make their data available to support SMAP cal/val in exchange for early access to SMAP data products for their research. Sites that are used in the quantitative assessment of SMAP soil moisture product performance are referred to as CVSs. A total of 13 CVSs are identified in [36] and are listed in Table IV. Analyses of error estimates using ground-based *in situ* observations at a depth of 5 cm from these CVSs are the primary means for the first stage of cal/val for L2_SM_P.

Fig. 3 shows time-series comparisons between L2_SM_P soil moisture and *in situ* data from a few selected CVSs between March 31, 2015 and October 26, 2015.

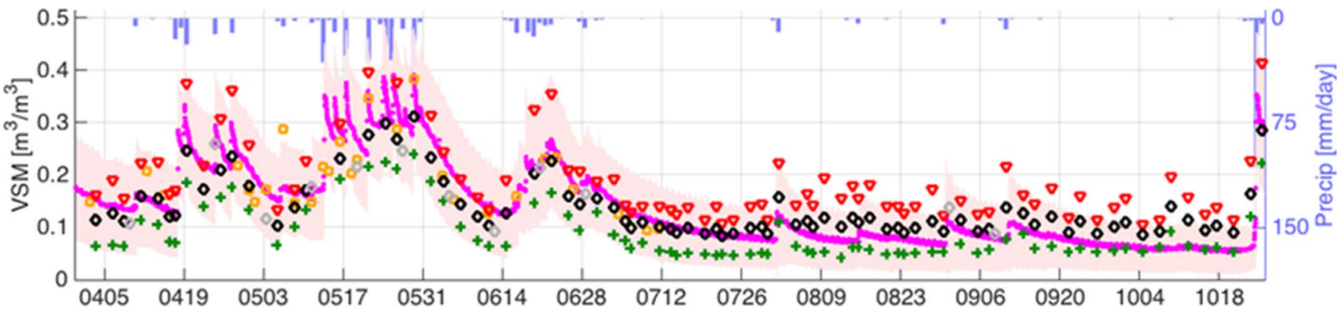
The Little Washita watershed in Oklahoma has been utilized for many microwave soil moisture validation and scaling studies; hence, there is high confidence in the *in situ* estimates for this site. Fig. 3(a) shows the wide range of soil moisture observed at the Little Washita site during the three-month assessment period. Dry conditions in April were followed by historic amounts of precipitation in May. This was followed by an extended dry-down (end of May) that clearly illustrates the correlation of the *in situ* and satellite observations. A subsequent dry-down in June shows a difference in the rate of decrease in soil moisture, with the satellite soil moisture drying out faster than the *in situ* measured soil moisture. This difference may be associated with the satellite versus *in situ* contributing depths or with vegetation changes not adequately accounted for. Multiple wetting and drying periods followed in July and later, exhibiting similar patterns. Overall, the site exhibits very high correlation between the satellite and *in situ* soil moisture. SMAP and SMOS have approximately the same level of performance.

The recently instrumented TxSON site in Texas was specifically designed for validation of all three SMAP surface soil moisture products (L2_SM_A, L2_SM_AP, and L2_SM_P, at 3, 9, and 36 km spatial scales, respectively). As shown in Fig. 3(b), the precipitation pattern over the six months was similar to Oklahoma, with dry conditions followed by a very wet May followed by an extended dry-down period. This site also shows high correlation between satellite-derived and *in situ* soil moisture, with similar performance between SMOS and SMAP SCA-V. The larger errors and positive bias of the DCA appear to be associated with rain events. This type of error could involve smaller rain events that wet the near surface but not the depth of the *in situ* sensor, thus causing SMAP DCA to overestimate the soil moisture present.

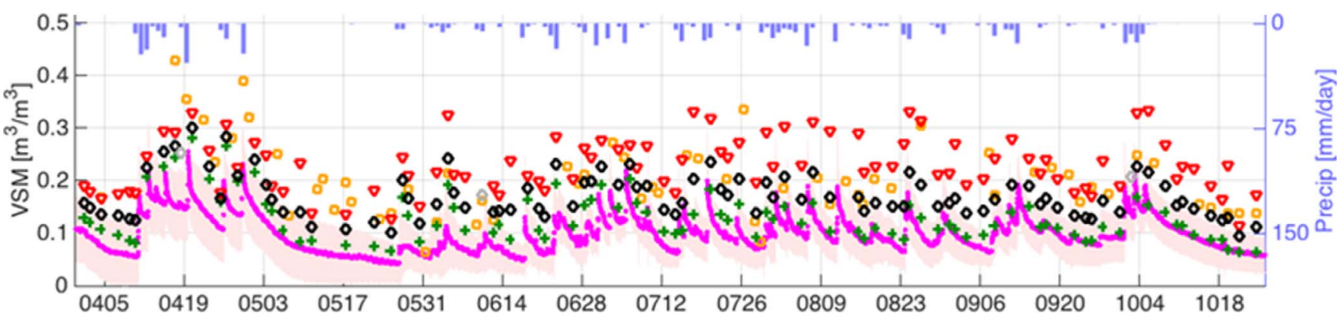
The Little River watershed in Georgia has served as a satellite *in situ* soil moisture validation site since the beginning of the AMSR-E mission [37] and was the only site representing humid agricultural environments. It includes a substantial amount of tree cover, has very sandy soils, and utilizes irrigation. Fig. 3(c) indicates overestimation by SMOS while SCA-H performs best followed by SCA-V. Regardless of the ubRMSD and bias, all algorithms have high correlations. The results for Little River illustrate that there may be inherent performance limitations in some algorithms under specific conditions. These differences between *in situ* observations and different algorithm outputs can challenge the assumptions and premises that have



(a) L2_SM_P performance at Little Washita, OK: ubRMSD = 0.025 m^3/m^3, bias = –0.029 m^3/m^3, R = 0.929



(b) L2_SM_P performance at TxSON, TX: ubRMSD = 0.035 m^3/m^3, bias = 0.003 m^3/m^3, R = 0.934



(c) L2_SM_P performance at Little River, GA: ubRMSD = 0.021 m^3/m^3, bias = 0.072 m^3/m^3, R = 0.872

Fig. 3. Soil moisture time series at (a) Little Washita, OK; (b) TxSON, TX; and (c) Little River, GA between March 31, 2015 and October 26, 2015. *In situ* soil moisture data are in magenta, and precipitation data are in blue. In all cases, L2_SM_P soil moisture showed good correlation $(R > 0.750)$ with the *in situ* data. Retrieval results by SCA-V, SCA-H, DCA, and SMOS are indicated by black diamonds, green crosses, red triangles, and orange squares, respectively. Whenever inversion succeeded but the corresponding retrieval was deemed to have insufficient quality due to instrument/surface conditions (e.g., high NEDT, frozen ground, mountainous terrain, dense vegetation with vegetation water content in excess of 5 kg/m^2, etc.), the data point was masked in gray.

been used in algorithm development. In the case of this site, a possible source of the overestimation may be the parameterization of the forest land cover effects.

Table V summarizes the assessment of L2_SM_P retrieval accuracy based on *in situ* comparisons at all the CVSs [36]. The ubRMSD varies considerably among sites. For example, ubRMSD is far below 0.040 m^3/m^3 at Walnut Gulch, Fort Cobb, Little Washita, Little River, and Kenaston for the baseline algorithm (SCA-V). It is noticeably above 0.040 m^3/m^3 at South Fork and Carman. Sources of these differences will be investigated in future studies.

All SMAP algorithms have about the same ubRMSD, differing only by 0.006 m^3/m^3, which are close to the SMAP Level-1 mission accuracy target of 0.040 m^3/m^3. The correlations are also very similar among algorithms. For both of these metrics, the SCA-V yields slightly better values. More obvious differences among the algorithms are found in the bias with DCA being unbiased, whereas SCA-H and SCA-V underestimate the CVS soil moisture. However, the SCA-V bias is also relatively low. The SMAP and SMOS averages are based on the respective average values reported for each CVS. It is clear from the table that the results of both missions are quite comparable for all metrics. However, this assessment is based on a limited time frame, and the relative performances of algorithms and products could vary as the record lengths and seasons captured expand.

Based on the metrics and considerations discussed, the SCA-V was selected as the baseline algorithm for the L2_SM_P beta release. Going forward, additional investigations will be completed on model coefficient optimization for all algorithms, additional CVS will be incorporated, and a longer period of observations will be considered, all of which will influence the decision on which algorithm to designate as the SMAP baseline algorithm at the validated release scheduled for May 2016.

D. Sparse Networks

The CVS validation activity previously described is complemented for SMAP by the use of *in situ* data from sparse networks as well as by new/emerging types of soil moisture

TABLE V
PERFORMANCE ASSESSMENT OF L2_SM_P AT CVSs BETWEEN MARCH 31, 2015 AND OCTOBER 26, 2015. BEST PERFORMANCE AMONG SMAP ALGORITHMS IN EACH SITE/METRIC IS TYPESET IN BOLDFACE

Site Name	ubRMSD (m^3/m^3)			Bias (m^3/m^3)			RMSD (m^3/m^3)			*R*		
	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA
Reynolds Creek	0.045	**0.043**	0.058	-0.071	-0.036	**-0.016**	0.084	**0.056**	0.060	0.483	**0.602**	0.576
Walnut Gulch	**0.027**	0.031	0.045	-0.023	**-0.007**	0.018	0.036	**0.032**	0.048	0.581	**0.715**	0.639
TxSON	0.037	**0.035**	0.036	-0.044	**0.003**	0.057	0.058	**0.036**	0.067	**0.940**	0.934	0.881
Fort Cobb	0.037	**0.032**	0.041	-0.077	-0.054	**-0.030**	0.086	0.062	**0.051**	0.858	**0.881**	0.840
Little Washita	**0.025**	**0.025**	0.041	-0.058	-0.029	**0.007**	0.063	**0.038**	0.042	**0.931**	0.929	0.865
South Fork	0.059	0.056	**0.054**	-0.075	-0.072	**-0.068**	0.095	0.091	**0.087**	**0.558**	0.516	0.457
Little River	0.025	**0.021**	0.036	**0.031**	0.072	0.132	**0.040**	0.075	0.137	0.840	**0.872**	0.739
Kenaston	0.037	**0.027**	0.041	-0.075	-0.048	**-0.004**	0.084	0.055	**0.041**	0.669	**0.792**	0.699
Carman	0.082	**0.061**	0.063	-0.088	-0.088	**-0.079**	0.120	0.107	**0.102**	0.614	**0.677**	0.567
Monte Buey	0.041	0.028	**0.027**	-0.041	-0.019	**0.016**	0.058	0.034	**0.032**	0.809	**0.886**	0.874
REMEDHUS	**0.036**	0.045	0.057	-0.063	-0.053	**-0.042**	0.073	**0.069**	0.071	**0.575**	0.456	0.332
Yanco	0.055	0.045	**0.041**	**0.024**	0.035	0.046	0.060	**0.057**	0.061	0.943	**0.946**	0.934
Kyeamba	0.052	0.051	**0.033**	**0.042**	0.065	0.062	**0.067**	0.082	0.070	0.926	**0.952**	0.940
SMAP Average	0.043	**0.038**	0.044	-0.040	-0.018	**0.008**	0.071	**0.061**	0.067	0.748	**0.781**	0.719
SMOS Average	0.047			-0.019			0.068			0.751		

networks. The defining feature of these networks is that the measurement density is low, usually resulting in (at most) one point within an SMAP footprint. These observations cannot be used for validation without addressing two issues: verifying that they provide a reliable estimate of the 0–5 cm surface soil moisture layer and that the one measurement point is representative of the footprint.

SMAP has been evaluating methodologies for upscaling data from these networks to SMAP footprint resolutions. A key element of the upscaling approach is the triple collocation technique [39], [40] that combines the *in situ* data and SMAP soil moisture data with another independent source of soil moisture such as a model-based product. The implementation of this technique will be part of the later L2_SM_P product assessment.

Although limited, sparse networks do offer a large number of sites in varied environments and are typically operational with very predictable latency. Table VI lists the set of networks used by SMAP in the current assessment.

Because of the larger number of sites, it is possible to examine the intercomparison metrics between satellite-derived and sparse network *in situ* soil moisture, aggregated by land cover types according to the International Geosphere-Biosphere Programme (IGBP) land cover classification used in the MODIS products. The results are summarized in Table VII [36]. The reliability of the analyses based upon these classes depends on the number of sites available. The SMAP average was based on the average values reported for each land cover class.

Overall, the ubRMSD and bias values are similar to those obtained from the CVS. This result provides additional confidence in the previous conclusions based on the CVS. In addition, the SCA-V has, marginally, the best overall bias, ubRMSD, and correlation. These are similar to the results observed for the CVS.

Interpreting the results based on land cover is more complex. There are no clear patterns associated with broader vegetation types. The ubRMSD values for SCA-V range from 0.025 m^3/m^3 for barren lands to 0.077 m^3/m^3 for evergreen broadleaf forests. In general, large ubRMSD values were observed in forest classes. This is not surprising since forests have high vegetation water content. However, the large ubRMSD and bias for grasslands warrant further investigation.

SMOS metrics are also included in Table VII as supporting information. Overall, the SMOS products show a higher bias and ubRMSD than the SCA-V when partitioned by land cover class. Although the errors for the forest categories are large, the values of N are small.

V. OUTLOOK

The SMAP Level 2 Passive Soil Moisture Product (L2_SM_P) has been in routine production since March 2015. Cal/val analyses and assessments indicate that the product quality is suitable for beta release based on comparisons with *in situ* data from CVSs and sparse networks. These comparisons demonstrate a retrieval accuracy level approaching 0.040 m^3/m^3, as described in Section IV. The spatial and temporal patterns of the soil moisture have also been shown to correspond well with recent flood and rainstorm events [41], [42].

Despite these initial findings, some important issues remain to be addressed prior to the validated product release (currently scheduled for May 2016). Among these issues are the following.

- Limited SMAP observations and *in situ* data: The current assessment was based on only six months of SMAP observations and *in situ* data at a limited number of CVSs and sparse networks. It is anticipated that by the time of the validated release, there will be a year of data covering the full annual cycle. This will help improve the statistical representativeness of the current performance assessment.
- Optimization of model parameters: The current L2_SM_P beta release uses a version of model parameters largely adopted before launch. Time-series approaches are being developed to determine optimal parameters over time for the same grid on which the retrieval of soil moisture is performed. A particular objective is to better represent the polarization dependence of vegetation parameters in the $\tau - \omega$ model.

TABLE VI
SPARSE NETWORKS USED IN L2_SM_P BETA-RELEASE ASSESSMENT

Sparse Network Name	Contact/PI	Country	Number of Sites
NOAA Climate Reference Network	Palecki	USA	110
USDA NRCS Soil Climate Analysis Network	Cosh	USA	155
GPS	Small	Western USA	123
COSMOS	Zreda	Mostly USA	53
SMOSMANIA	Calvet	Southern France	21
Pampas	Thibeault	Argentina	20

TABLE VII
PERFORMANCE ASSESSMENT OF L2_SM_P AT SPARSE NETWORKS BETWEEN MARCH 31, 2015 AND OCTOBER 26, 2015. BEST PERFORMANCE AMONG SMAP ALGORITHMS IN EACH NETWORK/METRIC IS TYPESET IN BOLDFACE

IGBP Land Cover Class	ubRMSD (m^3/m^3)				Bias (m^3/m^3)				RMSD (m^3/m^3)				*R*				*N*
	SCA-H	SCA-V	DCA	SMOS	SCA-H	SCA-V	DCA	SMOS	SCA-H	SCA-V	DCA	SMOS	SCA-H	SCA-V	DCA	SMOS	
ENF	0.081	**0.077**	0.086	0.060	-0.037	**-0.001**	0.056	-0.079	0.107	**0.093**	0.114	0.109	0.476	**0.515**	0.490	0.540	13
EBF	0.066	0.063	**0.061**	0.073	0.166	0.154	**0.108**	-0.092	0.181	0.172	**0.153**	0.190	**0.726**	0.687	0.466	0.546	2
DBF	0.048	**0.047**	0.064	0.067	**0.004**	0.036	0.083	-0.127	0.121	**0.109**	0.125	0.157	0.622	**0.641**	0.515	0.488	11
MXF	**0.046**	**0.046**	0.063	0.077	**0.016**	0.050	0.106	-0.082	**0.086**	0.090	0.137	0.153	**0.708**	0.703	0.559	0.447	20
OSH	**0.033**	0.037	0.053	0.053	-0.048	-0.020	**0.014**	-0.008	0.066	**0.060**	0.076	0.075	**0.585**	0.577	0.561	0.400	47
WSV	**0.047**	**0.047**	0.065	0.065	**-0.021**	0.028	0.108	-0.059	0.099	**0.098**	0.147	0.114	**0.707**	0.683	0.486	0.515	24
SAV	**0.027**	0.030	0.038	0.047	-0.024	**0.002**	0.023	-0.005	0.062	**0.057**	0.070	0.060	**0.684**	0.620	0.577	0.519	7
GRS	0.047	**0.048**	0.059	0.057	-0.069	-0.038	**-0.002**	-0.031	0.091	**0.077**	0.082	0.082	**0.708**	0.705	0.675	0.642	162
CRP	0.065	**0.058**	0.064	0.070	-0.037	-0.028	**-0.012**	-0.041	0.107	**0.098**	0.101	0.111	0.621	**0.624**	0.532	0.586	80
URB	**0.052**	0.056	0.068	0.065	**-0.019**	0.021	0.085	-0.075	**0.091**	0.098	0.137	0.105	**0.394**	0.300	0.244	0.411	5
MOS	0.050	**0.045**	0.056	0.073	-0.029	**0.000**	0.043	-0.078	0.078	**0.070**	0.086	0.135	0.675	**0.720**	0.631	0.560	35
BAR	**0.023**	0.025	0.038	0.050	-0.024	**0.004**	0.052	-0.004	**0.039**	0.043	0.077	0.057	**0.452**	0.429	0.383	0.361	10
Average	0.049	**0.048**	0.060	0.062	-0.044	**-0.016**	0.020	-0.042	0.091	**0.081**	0.095	0.099	**0.655**	0.654	0.590	0.561	416

- Tuning of flag thresholds: A set of two-tier flag thresholds is used in the operational processing to provide information on retrieval quality and land surface conditions encountered in the inversion process. Many of these thresholds were designated before launch. The values of these thresholds will be revisited in light of SMAP observations to provide improved flagging of the output data fields.

VI. CONCLUSION

Following SMOS and Aquarius, SMAP became the third mission in less than a decade utilizing an L-band radiometer to estimate soil moisture in the top 5 cm of soil. The sophisticated RFI mitigation hardware and software used in the SMAP radiometer design has allowed SMAP to acquire brightness temperature observations that are relatively well filtered against RFI. Despite the premature failure of the SMAP radar, the radiometer has been operating nominally, collecting data that enable the production of high-quality soil moisture products at level 2 (L2_SM_P, half-orbit) and level 3 (L3_SM_P, daily global composite). Since September 2015, both products have been made available to the public for evaluation, as beta release, from the NASA DAAC at the NSIDC.

This paper has provided a description of the design, operational processing, algorithm implementation, and preliminary validation of the L2_SM_P soil moisture product. Based on comparisons with *in situ* data from CVSs and sparse networks over a period of six months (March 31, 2015 and October 26, 2015), it was found that SCA-V delivered better ubRMSD, bias, and correlation than SCA-H, and SCA-H had better ubRMSD and correlation than DCA. DCA had the lowest bias of all the algorithms (essentially zero bias); however, the bias of SCA-V was only 0.018 m^3/m^3 over that of CVSs. These differences were relatively small. Based on these results, the SCA-V was adopted as the baseline algorithm for the beta release. The overall ubRMSD of the SCA-V is 0.038 m^3/m^3 over CVS, which approaches the SMAP mission requirement of 0.040 m^3/m^3.

The sparse networks of *in situ* data available to SMAP provide many more data locations than the CVSs, although of lesser ability to represent soil moisture at the SMAP footprint scale. Despite this limitation, the analyses of sparse network data presented in this paper support the conclusions reached using data from the CVSs.

This assessment was based on an evaluation period of only six months of SMAP observations, and *in situ* data at a limited number of CVSs and sparse networks. As such, it is anticipated that by the time of the validated release, there will be a year of data covering the full annual cycle. This will help improve the statistical representativeness of the current performance assessment. Additional tasks remain prior to the planned L2_SM_P validated product release in May 2016. Among these tasks are more robust comparisons with *in situ* data from additional sites and networks, optimization of model parameters, and adjustments of flag thresholds. Improvements in the L2_SM_P retrieval performance are expected upon conclusion of these tasks.

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Steven K. Chan (M'01–SM'03) received the Ph.D. degree in electrical engineering, specializing in electromagnetic wave propagation in random media, from the University of Washington, Seattle, WA, USA, in 1998.

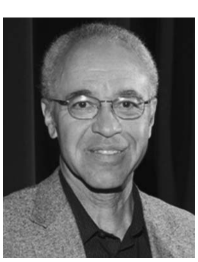
He is currently a Scientist in hydrology with the NASA Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA. His research interests include microwave remote sensing of soil moisture and its applications. His work in soil moisture retrieval algorithm development encompasses the NASA Aqua/AMSR-E (2002–2011), the JAXA GCOM-W/AMSR2 (2012–present), and, more recently, the NASA Soil Moisture Active Passive Mission (2015–present).

Rajat Bindlish received the B.S. degree from the Indian Institute of Technology, Bombay, India, in 1993 and the M.S. and Ph.D. degrees from The Pennsylvania State University, State College, PA, USA, in 1996 and 2000, respectively, all in civil engineering.

He is currently with Science Systems and Applications, Inc., Lanham, MD, USA, working in the U.S. Department of Agriculture, Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD. His research interests include the application of microwave remote sensing in hydrology. He is currently working on soil moisture estimation from microwave sensors and their subsequent application in land surface hydrology.

Peggy E. O'Neill (F'16) received the B.S. degree (*summa cum laude* with University Honors) in geography from Northern Illinois University, DeKalb, IL, USA, in 1976 and the M.A. degree in geography from the University of California, Santa Barbara, CA, USA, in 1979.

She has done postgraduate work in civil and environmental engineering through Cornell University. She is currently the SMAP Deputy Project Scientist. Since 1980, she has been a Physical Scientist with the Hydrological Sciences Laboratory, NASA/Goddard Space Flight Center, Greenbelt, MD, USA, where she conducts research in soil moisture retrieval and land surface hydrology, primarily through microwave remote sensing techniques.



Eni Njoku (M'75–SM'83–F'95) received the B.A. degree in natural and electrical sciences from the University of Cambridge, Cambridge, U.K., in 1972 and the M.S. and Ph.D. degrees in electrical engineering from the Massachusetts Institute of Technology, Cambridge, MA, USA, in 1974 and 1976, respectively.

He is currently a Senior Research Scientist with the Surface Hydrology Group, Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA. Until recently, he was the Project Scientist of the Soil Moisture Active Passive Mission. His research interests include passive and active microwave sensing of soil moisture for hydrology and climate applications.

Dr. Njoku is a member of the U.S. Advanced Microwave Scanning Radiometer Science Team. He is an Editor-in-Chief of the *Encyclopedia of Remote Sensing*. He was a recipient of the NASA Exceptional Service Medal.

Tom Jackson (SM'96–F'02) received the Ph.D. degree from the University of Maryland in 1976.

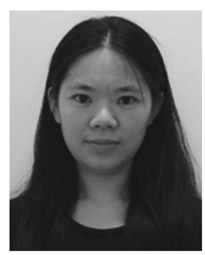
He is a Research Hydrologist with the U.S. Department of Agriculture, Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD, USA. His research involves the application and development of remote sensing technology in hydrology and agriculture, primarily microwave measurement of soil moisture.

Dr. Jackson is or has been a member of the Science and Validation Team of the Aqua, ADEOS-II, Radarsat, Oceansat-1, Envisat, ALOS, SMOS, Aquarius, GCOM-W, and SMAP remote sensing satellites. He is a Fellow of the Society of Photo-Optical Instrumentation Engineers, the American Meteorological Society, and the American Geophysical Union. In 2003, he received the William T. Pecora Award (NASA and Department of Interior) for his outstanding contributions toward understanding the Earth by means of remote sensing and the AGU Hydrologic Sciences Award for his outstanding contributions to the science of hydrology. He also received the IEEE Geoscience and Remote Sensing Society Distinguished Achievement Award in 2011.

Andreas Colliander (S'04–A'06–M'07–SM'08) received the M.Sc. (Tech.), Lic.Sc. (Tech.), and D.Sc. (Tech.) degrees from the Helsinki University of Technology (TKK; now Aalto University), Espoo, Finland, in 2002, 2005, and 2007, respectively.

He is currently a Research Scientist with the Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA.

Dr. Colliander is a member of the Science Algorithm Development Team for the Soil Moisture Active and Passive Mission, focusing on calibration and validation of the geophysical products.



Fan Chen received the Ph.D. degree in climatology from the University of North Carolina, Chapel Hill, NC, USA, in 2006.

She is currently a Visiting Scientist with the U.S. Department of Agriculture, Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD, USA. Her research interests include methods of validating remotely sensed soil moisture retrievals and assimilation of satellite soil moisture in hydrologic models.

Mariko Burgin (S'09–M'14) received the M.S. degree in electrical engineering and information technology from the Swiss Federal Institute of Technology (ETH), Zurich, Switzerland, in 2008 and the M.S. and Ph.D. degrees in electrical engineering from the Radiation Laboratory, University of Michigan, Ann Arbor, MI, USA, in 2011 and 2014, respectively.

From 2014 to 2015, she was a California Institute of Technology (Caltech) Postdoctoral Scholar with the Water and Carbon Cycles (now Surface Hydrology) Group, Jet Propulsion Laboratory (JPL), Caltech, Pasadena, CA, USA. In 2016, she joined the Radar Science Group at JPL. Her research interests include theoretical and numerical studies of random media, development of forward and inverse scattering algorithms for geophysical parameter retrieval, and the study of electromagnetic wave propagation and scattering properties of vegetated surfaces.

Scott Dunbar received the B.S. degree in physics and astronomy from the University of Albany, Albany, NY, USA, in 1976 and the Ph.D. degree in physics from Princeton University, Princeton, NJ, USA, in 1980.

Since 1981, he has been with the Jet Propulsion Laboratory. Over the last 30 years, he has contributed to the development of science algorithms for the NSCAT and SeaWinds ocean vector wind scatterometer projects. Since 2009, he has worked on SMAP soil moisture and freeze-thaw algorithm development.

Jeffrey Piepmeier (S'93–M'99–SM'10) received the B.S. degree in engineering (electrical concentration) from LeTourneau University, Longview, TX, USA, in 1993 and the M.S. and Ph.D. degrees in electrical engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 1994 and 1999, respectively.

He is currently a Chief Engineer for passive microwave instruments with the Instrument Systems and Technology Division, NASA Goddard Space Flight Center, Greenbelt, MD, USA. He is an Instrument Scientist for the SMAP Microwave Radiometer and the GPM Microwave Imager and is on the Aquarius Science Team. Previously at GSFC, he was an Associate Head in the Microwave Instruments and Technology Branch. Prior to NASA, he was with Vertex Communications Corp. and was a Schakleford Fellow with the Georgia Tech Research Institute. His research interests include microwave radiometry and technology development to enable the next generation of microwave sensors.

Dr. Piepmeier is a member of Union Radio—Scientifique Internationale (Commission F) and the American Geophysical Union. He was the Chairperson of the National Academies' Committee on Radio Frequencies. He has received NASA's Exceptional Engineering Achievement Medal for advances in radio-frequency interference mitigation technology and Exceptional Achievement Medal for his significant contributions to the Aquarius/SAC-D mission and four NASA Group Achievement Awards.

Simon Yueh (M'92–SM'01–F'09) received the Ph.D. degree in electrical engineering from the Massachusetts Institute of Technology, Cambridge, MA, USA, in 1991.

From February to August 1991, he was a Postdoctoral Research Associate with the Massachusetts Institute of Technology. In September 1991, he joined the Radar Science and Engineering Section, Jet Propulsion Laboratory (JPL). From 2002 to 2007, he was the Supervisor of the radar system engineering and algorithm development group. He was the Deputy Manager of the Climate, Oceans and Solid Earth section from 2007 to 2009 and the Section Manager from 2009 to 2013. He served as the Project Scientist of the National Aeronautics and Space Administration (NASA) Aquarius mission from January 2012 to September 2013 and the Deputy Project Scientist of the NASA Soil Moisture Active Passive (SMAP) mission from January 2013 to September 2013 and has been the SMAP Project Scientist since October 2013. He has been the Principal/Coinvestigator of numerous NASA and DOD research projects on remote sensing of soil moisture, terrestrial snow, ocean salinity, and ocean wind. He has authored four book chapters and published more than 150 publications and presentations.

Dr. Yueh is an Associate Editor of the IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING. He received the IEEE GRSS Transaction Prize Paper Award in 1995, 2002, 2010, and 2014. He also received the 2000 Best Paper Award in the IEEE International Geoscience and Remote Symposium. He received the JPL Lew Allen Award in 1998 and Ed Stone Award in 2003. He also received the NASA Exceptional Technology Achievement Medal in 2014.

Dara Entekhabi (M'04–SM'09–F'15) received the B.S. and M.S. degrees from Clark University, Worcester, MA, USA, and the Ph.D. degree from the Massachusetts Institute of Technology (MIT), Cambridge, MA, in 1990.

He is currently a Professor with the MIT Department of Civil and Environmental Engineering. He is the Science Team Lead for the National Aeronautics and Space Administration's Soil Moisture Active and Passive mission that was launched on January 31, 2015. His research interests include terrestrial remote sensing, data assimilation, and coupled land–atmosphere systems modeling.

Dr. Entekhabi is a Fellow of the American Meteorological Society and the American Geophysical Union.

Michael H. Cosh received the Ph.D. degree from Cornell University, Ithaca, NY, USA, in 2002.

He is a Research Hydrologist with the U.S. Department of Agriculture, Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD, USA. His research involves the monitoring of soil moisture from both in situ resources and satellite products. Currently, he is serving as the Acting Research Leader for the Hydrology and Remote Sensing Laboratory, which includes 12 scientists working in areas of soil moisture remote sensing, evapotranspiration, and water quality.

Dr. Cosh served as the Chairperson of both the Remote Sensing Technical Committee and the Large Scale Field Experiments Technical Committee for the American Geophysical Union.

Todd Caldwell received the B.S. degree in earth and planetary sciences from the University of New Mexico, Albuquerque, NM, USA, in 1997 and the M.Sc. and Ph.D. degrees in hydrogeology from the University of Nevada, Reno, NV, USA, in 1999 and 2007, respectively.

Since 2012, he has been a Research Hydrologist and Geoscientist with the Bureau of Economic Geology, Jackson School of Geosciences, University of Texas at Austin, Austin, TX, USA. From 2002 to 2012, he was a Research Soil Scientist with the Desert Research Institute, Reno. He is a Principal Investigator for the Texas Soil Observation Network, an SMAP core calibration and validation site. His current research focuses on field investigations and modeling of soil and vadose zone processes across multiple scales and environments.

Jeffrey Walker received the B.E. (Civil) and B.Surv. degrees (with Hons 1 and University Medal) and the Ph.D. degree in water resources engineering from the University of Newcastle, Callaghan, Australia, in 1995 and 1999, respectively. His Ph.D. thesis was among the early pioneering research on the estimation of root-zone soil moisture from assimilation of remotely sensed surface soil moisture observations.

He then joined the NASA Goddard Space Flight Center to implement his soil moisture work globally. In 2001, he moved to the Department of Civil and Environmental Engineering, University of Melbourne, Melbourne, Australia, as a Lecturer, where he continued his soil moisture work, including the development of the only Australian airborne capability for simulating new satellite missions for soil moisture. In 2010, he was appointed as a Professor in the Department of Civil Engineering at Monash University, Clayton, Australia, where he is continuing this research. He is contributing to soil moisture satellite missions at NASA, ESA, and JAXA, as a Science Team Member for the Soil Moisture Active Passive mission and as a Cal/Val Team Member for the Soil Moisture and Ocean Salinity and Global Change Observation Mission—Water, respectively.

Xiaoling Wu, biography not available at the time of publication.

Aaron Berg received the B.Sc. and M.Sc. degrees in geography from the University of Lethbridge, Lethbridge, AB, Canada, in 1995 and 1997, respectively; the M.S. degree in geological sciences from the University of Texas at Austin, Austin, TX, USA, in 2001; and the Ph.D. degree in earth system science from the University of California at Irvine, Irvine, CA, USA, in 2003.

Since 2003, he has been with the Department of Geography, University of Guelph, Guelph, ON, Canada. He teaches physical geography, hydrology, and remote sensing, with research interests focused on the modeling and observation of soil moisture.

Tracy Rowlandson received the B.Sc. degree in environmental science and the M.Sc. degree from the University of Guelph, Guelph, ON, Canada, in 2003 and 2006, respectively, and the Ph.D. degree in agricultural meteorology from Iowa State University, Ames, IA, USA, in 2011.

She is currently a Research Associate with the Department of Geography, University of Guelph. Her research interests include investigating the impact of vegetation and soil management practices on soil moisture retrieval using passive and active microwave remote sensing.

Anna Pacheco is a Remote Sensing Specialist with the Science and Technology Branch of Agriculture and Agri-Food Canada (AAFC), Ottawa, ON, Canada. She has 14 years of research experience in developing methods to map and monitor soils and crops using a myriad of remote sensing technologies [multispectral, hyperspectral, and synthetic aperture radar (SAR)]. In 2003, she joined AAFC where she coled research projects assessing the contribution of radar sensors, including the various frequencies and polarizations for the characterization of land management practices. These studies examined the contribution of various satellite platforms (RADARSAT-1/2, Envisat ASAR, TerraSAR-X, and ALOS PALSAR) to derive information on tillage. Her current research is centered on the development of methods to monitor soil moisture from SAR sensors over agricultural landscapes.

Heather McNairn received the Bachelor's degree in environmental studies from the University of Waterloo, Waterloo, ON, Canada, in 1987; the Master's degree in soil science from the University of Guelph, Guelph, ON, in 1991; and the Ph.D. degree in geography from Université Laval, Quebec City, QC, Canada, in 1999.

She is a Senior Scientist with Agriculture and Agri-Food Canada, Ottawa, ON. She has 25 years of experience researching methods to monitor crops and soil using multispectral, hyperspectral, and synthetic aperture radar sensors. He is an Adjunct Professor with the University of Manitoba, Winnipeg, MB, Canada, and Carleton University, Ottawa.

Marc Thibeault received the B.Sc. degree in physics from Laval University, Québec City, QC, Canada, in 1982; the B.Sc. degree in mathematics from the University of Montréal, Montréal, QC, in 1988; and the D.Sc. degree in science from the University of Buenos Aires, Buenos Aires, Argentina, in 2004.

He is currently the Strategic Applications Coordinator for the Satellites for Observation and Communications (SAOCOM) Project, which is a new L-band mission of the Argentinian Space Agency. His research interests include soil moisture, polarimetry, and other synthetic aperture radar applications.

José Martínez-Fernández was born in Moratalla, Spain, in 1961. He received the B.S. (Degree Award) degree in physical geography, the M.S. degree in water science and technology, and the Ph.D. degree in physical geography from the Universidad de Murcia (UM), Murcia, Spain, in 1985, 1991, and 1992, respectively.

He was a Research Fellow (1988–1992) and a Junior Researcher (1992–1994) with the Department of Geography, UM. In 1995, he was an Assistant Professor with the Department of Geography, Universidad de Salamanca (USAL), Salamanca, Spain, where he has been an Associate Professor since 1997. He is currently the Principal Investigator (PI) of the Water Resources Research Group at the Instituto Hispano Luso de Investigaciones Agrarias (CIALE), USAL. He has been a PI in 20 national and international (Regional and Spanish Research Programs, European Union, and European Space Agency) research projects and a collaborator in 12. He is the author or coauthor of 156 publications.

Dr. Martínez-Fernández has been a member of the Spanish National Biodiversity, Earth Sciences and Global Change Program R&D Projects Selection Committee.

Ángel González-Zamora was born in Salamanca, Spain, in 1984. He received the B.S. degree in physics from the Universidad de Salamanca, Salamanca, in 2011 and the M.S. degree in geophysics and meteorology from the Universidad Complutense de Madrid, Madrid, Spain, in 2012. He is currently working toward the Ph.D. degree with the Water Resources Research Group (HIDRUS), Instituto Hispano Luso de Investigaciones Agrarias (CIALE), Universidad de Salamanca, working on hydrologic and agricultural applications of remote sensing.

Mark Seyfried, biography not available at the time of publication.

David Bosch received the Ph.D. degree in hydrology from the University of Arizona, Tucson, AZ, USA, in 1990.

He is currently a Research Hydrologist with the Southeast Watershed Research Laboratory, Agricultural Research Service, Tifton, GA, USA. In 1986, he joined the Agricultural Research Service. He leads a watershed research program investigating the impacts of land use on water balance and quality. Since 2000, he has been active in the validation of remotely sensed soil moisture products. His primary research interests include watershed and landscape scale hydrology, agricultural impacts on water quality, hydrologic and solute transport modeling of watershed processes, riparian buffer hydrology and solute transport, and developing new methods for assessing the impact of agricultural chemicals on ground and surface water supplies.

Dr. Bosch is a long-time member of the American Geophysical Union, the American Society of Agricultural and Biological Engineers, the American Society of Agronomy, and the Soil and Water Conservation Society.

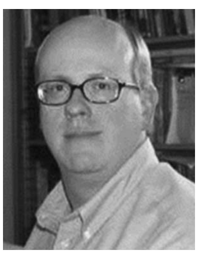
Patrick Starks received the B.S. degree in physical geography from the University of Central Arkansas, Conway, AR, USA, in 1979; the M.A. degree in physical geography from the University of Nebraska Omaha, NE, USA, in 1984; and the Ph.D. degree from the University of Nebraska—Lincoln, Lincoln, NE, in 1990.

From 1990 to 1992, he was a Postdoctoral Fellow with the Department of Atmospheric Science, University of Missouri, Columbia, MO, USA. Since 1992, he has been a Research Soil Scientist with the United States Department of Agriculture's Agricultural Research Service (USDA-ARS). He is currently stationed at the USDA-ARS Grazinglands Research Laboratory in El Reno, Oklahoma.

David Goodrich received the Ph.D. degree from the University of Arizona, Tucson, AZ, USA, in 1990.

His early work experience includes positions with the U.S. Geological Survey in Wisconsin and Alaska and consulting with Autometric in Washington, D.C. Since 1988, he has been a Research Hydraulic Engineer with the Southwest Watershed Research Center, U.S. Department of Agriculture Agricultural Research Service, Tucson. He coled the interdisciplinary multiagency SALSA (Semi-Arid Land-Surface—Atmosphere) Research Program. He was an Executive Member of the National Science Foundation Sustainability of semi-Arid Hydrology and Riparian Areas (SAHRA) Science and Technology Center and, since 2000, has worked closely with elected officials and decision-makers in the San Pedro Basin. Areas of research during his career have been directed to scaling issues in watershed rainfall—runoff response, identification of dominant hydrologic processes over a range of basin scales, climatic change impacts on semiarid hydrologic response, incorporation of remotely sensed data into hydrologic models, the functioning of semiarid riparian systems, nonmarket valuation of ecosystem services, flash-flood forecasting, and rapid postfire watershed assessments.

John Prueger, biography not available at the time of publication.



Michael Palecki received the B.S. degree (*summa cum laude*) in physics from the University of Massachusetts, Boston, MA, USA, in 1984; the M.A. degree in geography from the University of Colorado, Boulder, CO, USA, in 1986; and the Ph.D. degree in geography from The Pennsylvania State University, State College, PA, USA, in 1991.

He is the Science Project Manager for the U.S. Climate Reference Network (USCRN) in NOAA's National Centers for Environmental Information. He has worked on projects ranging from the validation and use of climate measurements taken in the mid-19th Century to studying climate using the USCRN, a national research quality modern system to collect climate observations. Soil moisture and temperature are primary observations of the USCRN and are used in coarse network validation of Soil Moisture Active Passive Mission products. His research interests focus on the use of surface climate observations to better understand climate change and variation, including extreme events.

Eric E. Small received the B.A. degree in geological sciences from Williams College, Williamstown, MA, USA, in 1993 and the Ph.D. degree in earth sciences from the University of California, Santa Cruz, CA, USA, in 1998.

He is a Professor with the Department of Geological Sciences, University of Colorado, Boulder, CO, USA. His research is focused on land surface hydrology.

Marek Zreda, biography not available at the time of publication.

Jean-Christophe Calvet received the M.Eng. degree in agronomy from AgroParisTech, Paris, France, in 1990; the M.Sc./Eng. degree in meteorology from the Ecole Nationale de la Météorologie, Toulouse, France, in 1990; the Ph.D. degree from the Université Paul Sabatier, Toulouse, in 1996; and the Habilitation degree in 2002.

He joined Météo-France, Toulouse, the French meteorological service, in 1990 and the Centre National de la Recherches Météorologiques in 1994, where he has been the Head of a land modeling and remote sensing section since 2003. His research interests include land–atmosphere exchange modeling and the use of remote sensing over land surfaces for meteorology. His most recent works concern the joint analysis of soil moisture and vegetation biomass and the representation of carbon cycle in climate models.

Wade T. Crow received the Ph.D. degree from Princeton University, Princeton, NJ, USA, in 2001.

He is currently a Research Physical Scientist and Project Lead Scientist with the U.S. Department of Agriculture (USDA) Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD, USA. His research focuses on the development of hydrologic and agricultural applications for remote sensing data and the development of appropriate data assimilation approaches to facilitate this goal, with a special emphasis on techniques that fuse information from various disparate remote sensing sources. This work has lead to extensive collaboration with operational USDA agencies involved in drought monitoring missions.

Dr. Crow has served (or currently serves) on the Science Team of the NASA GPM, Hydros, SMAP, and AirMOSS missions and was an Editor of the American Meteorological Society's *Journal of Hydrometeorology*.

Yann Kerr (M'88–SM'01–F'13) received the B.Eng. degree from the Ecole Nationale Supérieure de l'Aéronautique et de l'Espace, Toulouse, France; the M.Sc. degree in electronics and electrical engineering from Glasgow University, Glasgow, U.K.; and the Ph.D. degree in astrophysique géophysique et techniques spatiales from the Université Paul Sabatier, Toulouse.

From 1980 to 1985, he was with the Centre d'Etudes Spatiales de la BIOsphère, Centre National d'Etudes Spatiales (CNES-CESBIO). In 1985, he joined LERTS, of which he was the Director during 1993–1994. He spent 19 months at the Jet Propulsion Laboratory, Pasadena, CA, USA, during 1987–1988. Since 1995, he has been with CESBIO, where he was the Deputy Director and Director during 2007–2016. He has been involved with many space missions. He was an EOS Principal Investigator (PI; interdisciplinary investigations) and PI and precursor of the use of the SCAT over land. In 1989, he started working on the interferometric concept applied to passive microwave earth observation and subsequently became the science lead on the MIRAS project for the European Space Agency (ESA) with the MMS and OMP. He was also a Coinvestigator on IRIS, OSIRIS, and HYDROS for NASA. He was a Science Advisor for MIMR and Co I on AMSR. He is a member of the SMAP Science Team. In 1997, he first proposed the natural outcome of the previous MIRAS work with what was to become the SMOS Mission to CNES, a proposal that was selected by ESA in 1999 with him as the SMOS mission Lead Investigator and Chair of the Science Advisory Group. He is also in charge of the SMOS science activity coordination in France. He is currently involved in the exploitation of SMOS data, in the Cal Val activities, and related level-2 soil moisture and level-3 and level-4 development and SMOS Aquarius SMAP synergistic uses and on the soil moisture essential climate variable. He is also working on the SMOS-Next concept and is involved in both the Aquarius and SMAP missions. His fields of interest are in the theory and techniques for microwave and thermal infrared remote sensing of the Earth, with emphasis on hydrology, water resources management, and vegetation monitoring.

Dr. Kerr has organized all the SMOS workshops and was a Guest Editor on three IEEE Special Issues and one RSE. He received the World Meteorological Organization First Prize (Norbert Gerbier), the U.S. Department of Agriculture Secretary's Team Award for excellence (SALSA Program), the GRSS Certificate of Recognition for leadership in the development of the first synthetic aperture microwave radiometer in space and success of the SMOS mission, and the ESA Team Award. He was nominated as Highly Cited Scientist by Thomson Reuters in 2015.