Soil Moisture Active Passive (SMAP) Project: Calibration and Validation for the L2/3_SM_P Version 5 and L2/3_SM_P_E Version 2 Data Products

Citation:

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1 EXECUTIVE SUMMARY

During the post-launch Cal/Val Phase of SMAP there are two objectives for each science product team: 1) calibrate, verify, and improve the performance of the science algorithms, and 2) validate accuracies of the science data products as specified in the L1 science requirements according to the Cal/Val timeline. This report provides analysis and assessment of the SMAP Level 2 Soil Moisture Passive (L2SMP) Version 5 and the L2SMP Enhanced (L2SMP_E) Version 2 data products. The L2SMP product is provided on a 36-km grid and the L2SMP_E on a 9-km grid. The SMAP Level 3 Soil Moisture Passive (L3SMP, L3SMP_E) products are simply a daily composite of the L2 half-orbit files. Hence, analysis and assessment of the L2SMP and L2SMP_E products can also be considered to cover the L3SMP and L3SMP_E products.

The new versions of the products incorporate three changes that may have an impact on performance: 1) a recalibration of the L1 brightness temperature (TB) products, 2) inclusion of an L1 water body correction of TB over land, and 3) a revised method for computing the effective temperature used to normalize TB to emissivity as part of the soil moisture retrieval process.

Assessment methodologies utilized include comparisons of SMAP soil moisture retrievals with *in situ* soil moisture observations from core validation sites (CVS) and sparse networks, and intercomparison with products from ESA's Soil Moisture Ocean Salinity (SMOS) mission. The primary assessment methodology is the CVS comparisons using established metrics and time series plots. These metrics include unbiased root mean square error (ubRMSE), bias, and correlation. The ubRMSE captures time-random errors, bias captures the mean differences or offsets, and correlation captures phase compatibility between data series. In addition, beginning with this assessment the overall mean absolute bias (MAB) is included in the metrics tables for each algorithm. It should be noted that some changes have been made in the calibration and upscaling of select CVS based upon follow-up investigations by Cal/Val Partners. In addition, the assessment period is now 36 months (as opposed to 19 months in the L2SMP Version 4 and L2SMP_E Version 1 assessments [1]).

SMAP L2SMP supports a total of five alternative retrieval algorithms. Of these, the Single Channel Algorithm–H polarization (SCA-H), Single Channel Algorithm–V polarization (SCA-V), and Dual Channel Algorithm (DCA) are the most mature and are the focus of this assessment. These same retrieval algorithms were also used in L2SMP_E.

The first step in assessment was the comparison of the L2SMP AM (Descending) and PM (Ascending) Version 5 products to the CVS and sparse network observations. CVS (AM) results indicated that the SCA-V provided the best overall performance with an ubRMSE of 0.037 m^3/m^3, bias of -0.001 m^3/m^3 and correlation of 0.821. These metrics exceed the SMAP mission requirements and those of the SMOS products. A portion of the change in the metrics may be associated with the longer period of record (19 vs 36 months) since longer records may include a wider range of anomalous conditions or a more typical set of conditions. Sparse network results confirmed the trends seen in the CVS comparisons. The overall conclusion is that the L2SMP AM and PM products have improved performance with a reduction in bias and ubRMSE that exceeds the mission accuracy requirements for L2 passive retrieved soil moisture (the L2SMP soil moisture shall meet or exceed an accuracy of 0.040 m^3/m^3 ubRMSE over land in the absence of frozen ground, permanent snow/ice, or dense vegetation; this requirement is actually written for retrieved soil moisture at 10 km spatial resolution, but has been applied by the SMAP team to all L2 passive soil moisture products). The combination of analyses using the CVS and sparse networks, intercomparison with products from the SMOS mission, and recent triple colocation analyses have contributed to a better understanding of the performance uncertainties. The assessment now includes 36 months of intercomparisons, and several papers have been published in peer-reviewed journals [2-5] as well as numerous investigations listed in the Bibliography section of the report. These analyses satisfy the criteria established by the Committee on Earth Observing Satellites (CEOS) for Stage 4 validation.

The L2SMP_E are posted at 9 km but the contributing domain (i.e. primary spatial area contributing to the radiometer brightness temperature response) is larger than this, approximately 33 km. A different set of CVS domains than those used for the L2SMP were identified in order to assess the performance of the L2SMP_E product; all ground measurements of soil moisture within the 33-km domain were used and compared to the SMAP retrieved soil moisture at each CVS. Additional information on the L2SMP_E product can be found in [1].

Version 2 of the L2SMP_E, for both AM and PM orbits, were assessed using the CVS and sparse networks. Both the AM and PM products meet the mission requirements and reflect the patterns for L2SMP. SCA-V had the best overall metrics of all the retrieval algorithms with an ubRMSE of 0.038 m^3/m^3, bias of -0.001 m^3/m^3 and correlation of 0.814 for AM orbits, and an ubRMSE of 0.036 m^3/m^3, bias of -0.002 m^3/m^3 and correlation of 0.818 for the PM orbits. For the same reasons noted for the L2SMP, the maturity of the L2SMP_E product is now at CEOS Stage 4.

Overall conclusions in this assessment:

- *L2SMP and L2SMP_E performances continue to meet the SMAP Project requirements.*
- *The changes made to the L1 products and L2 algorithms have had little impact on the overall ubRMSE but improved the bias (which also led to a drop in overall RMSE below 0.05 m^3/m^3).*
- *SCA-V continues to outperform the alternative algorithms.*
- *Both the L2SMP and L2SMP_E products have achieved CEOS Validation Stage 4.*

2 OBJECTIVES OF CAL/VAL

During the post-launch Cal/Val (Calibration/Validation) Phase of SMAP there are two objectives for each science product team:

- Calibrate, verify, and improve the performance of the science algorithms, and
- Validate accuracies of the science data products as specified in Level 1 science requirements according to the Cal/Val timeline.

The process is illustrated in Figure 2.1. In this Assessment Report the progress of the Level 2 Soil Moisture Passive Team in addressing these objectives is described. The approaches and procedures utilized follow those described in the SMAP Cal/Val Plan [6] and Algorithm Theoretical Basis Document for the Level 2 & 3 Soil Moisture (Passive) Data Products [7].

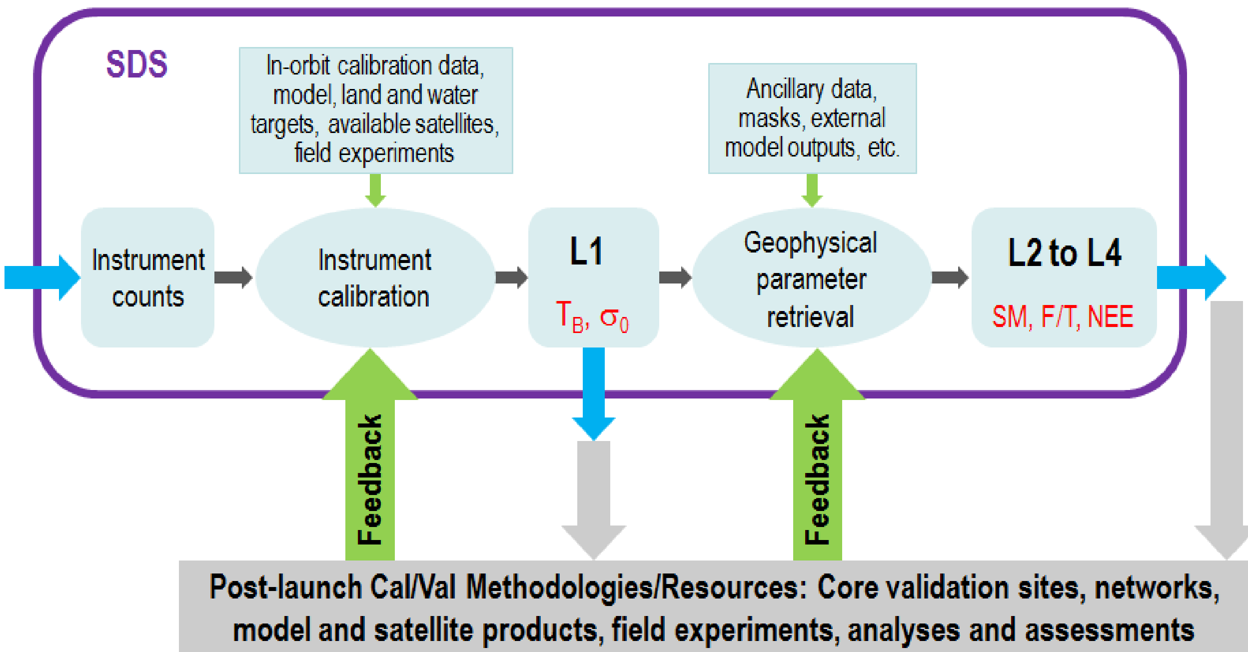


Figure 2.1. Overview of the SMAP Cal/Val Process.

SMAP established a unified definition base in order to effectively address the mission requirements. These are documented in the SMAP Handbook/ Science Terms and Definitions [8], where Calibration and Validation are defined as follows:

- *Calibration*: The set of operations that establish, under specified conditions, the relationship between sets of values or quantities indicated by a measuring instrument or measuring system and the corresponding values realized by standards.
- *Validation:* The process of assessing by independent means the quality of the data products derived from the system outputs.

The L2SMP Team adopted the same soil moisture retrieval accuracy requirement for the fully validated L2SMP data (0.040 m^3/m^3) that is listed in the L1 Mission Requirements Document [9] for the active/ passive soil moisture product.

In assessing the maturity of the L2SMP (and L2SMP_E) products, the team considered the guidance provided by the Committee on Earth Observation Satellites (CEOS) Working Group on Calibration and Validation (WGCV) [10]:

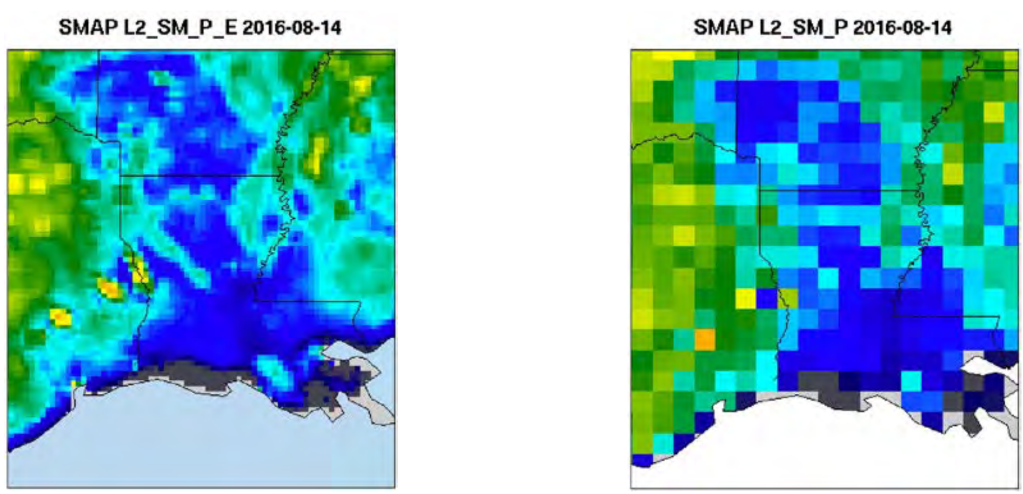
- Stage 1: Product accuracy is assessed from a small (typically < 30) set of locations and time periods by comparison with *in situ* or other suitable reference data.
- Stage 2: Product accuracy is estimated over a significant set of locations and time periods by comparison with reference *in situ* or other suitable reference data. Spatial and temporal consistency of the product and with similar products has been evaluated over globally representative locations and time periods. Results are published in the peer-reviewed literature.
- Stage 3: Uncertainties in the product and its associated structure are well quantified from comparison with reference *in situ* or other suitable reference data. Uncertainties are characterized in a statistically robust way over multiple locations and time periods representing global conditions. Spatial and temporal consistency of the product and with similar products has been evaluated over globally representative locations and periods. Results are published in the peer-reviewed literature.
- Stage 4: Validation results for stage 3 are systematically updated when new product versions are released and as the time series expands.

Based on the extensive validation analyses to date, the number of peer reviewed publications as well as numerous investigations listed in the Bibliography section of the report, the length of the SMAP period of record, and the utilization of feedback of validation in a systematic update, with this Version of L2SMP and L2SMP_E the team has completed Stage 4. The Cal/Val program will continue with the goals of increasing the robustness of the soil moisture products and addressing specific site issues.

3 BRIEF DESCRIPTION OF THE L2SMP AND L2SMP_E

The L2SMP product is derived using SMAP L-band radiometer time-ordered observations (L1CTB product) as the primary input [7] along with other ancillary data on finer grid resolutions, to retrieve soil moisture (and other geophysical parameters as applicable) from a forward model. 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). The 36-km grid resolution is close to the 3-dB native spatial resolution of the instrument observations. The use of the fixed grid facilitates temporal analyses and ingestion of the products into some user applications. However, it presents challenges to validation given that many core validation sites (CVS) are not centered or contained in a single 36-km EASE grid cell. As a result, a shifted variation of the L2SMP grid is used for validation and assessment purposes (Validation Grid-VG).

Following the SMAP launch, methodologies for improving the spatial information of the SMAP radiometer products were explored that resulted in the L1CTB_E (Enhanced) product. Backus-Gilbert (BG) optimal interpolation methodology is used that takes advantage of the radiometer oversampling on orbit. The processing results in data at a higher spatial density by virtue of TB interpolation at a 9-km grid resolution in L1BTB_E. It is important to note that the L1CTB_E processing does not improve the native resolution (~36 km) of the original TB measurements acquired by the SMAP radiometer. It is a posting of data interpolated to a 9-km grid, which can enhance spatial information (see Figure 3.1). The fine grid resolution (9 km) of L1CTB_E provides a convenient basis to produce passive soil moisture retrieval at the same fine grid resolution. Operationally, this is achieved by applying the same soil moisture inversion algorithms used for the standard 36-km L2SMP product to the enhanced 9-km L2SMP_E product. The 9-km posting provides more flexibility in co-locating the grids and CVS data and therefore does not require the use of the VG in validation and assessment of the L2SMP_E product.



(a) Enhanced Passive Soil Moisture Product (b) Standard Passive Soil Moisture Product

Figure 3.1. Compared with the current standard L2SMP soil moisture product in (b), the enhanced L2SMP_E soil moisture product in (a) demonstrates a more detailed distribution of surface soil moisture and shows spatial features more clearly than does the standard product.

4 L1 RADIOMETER PRODUCT UPDATES

The L2SMP soil moisture retrievals are based on Version 4 of the radiometer Level 1B and 1C brightness temperature data [http://nsidc.org/data/smap/smap-data.html]. An assessment of data quality and calibration is available at NSIDC [http://nsidc.org/data/docs/daac/smap/sp_l1b_tb/index.html], from which the material in this section is drawn. A more detailed discussion of the radiometer calibration and products can be found in [11,12,13]. The Version 4 TB data meet the noise equivalent delta temperature (NEDT) and geolocation requirements with margin as they did in Version 3 (see Table 4.1) [14].

The SMAP L1 radiometer calibration algorithm for the Version 4 release has been significantly improved compared to the Version 3 dataset. The calibration changes can be summarized as follows: (1) improved SMAP reflector emissivity values, (2) concurrent antenna pattern correction (APC), noise-diode, and reference load calibration, and (3) improved galaxy correction model over the ocean.

The new SMAP calibration adjusted V and H-pol microwave emissivity values for the reflector based on antenna temperature deviations observed during annual SMAP eclipse seasons. An emissivity correction slightly impacts the gain and bias of the radiometer front-end antenna temperatures. In addition to an emissivity correction, SMAP implemented an optimized concurrent calibration scheme that utilizes cold-sky looks with ocean back-lobes, cold-sky looks with ocean/land transition back-lobes, vicarious global mean ocean observations, and nadir ocean and land observations. The retrieved noise-diode temperature, reference load temperature and APC value calibration coefficients along with ocean bias correction provide a completely bias free full-range SMAP calibration. The final calibration correction for ocean regions is a reflected galaxy correction upgrade, where wind speed-dependent sky maps are used to correct for any galaxy contribution into the antenna temperature. Any previously observed fore-aft differences in L1C_TB radio frequency interference (RFI) still remain. The RFI behavior is similar as before: conditions in the Americas and Europe are good with poorer conditions in Asia.

These changes in SMAP calibration resulted in a change in metrics when comparing SMAP TB to SMOS TB. Global average brightness temperature comparisons over land areas are now 1.15 K (for H pol) and 0.66 K (for V pol) greater than SMOS (mean difference at top of the atmosphere after Faraday rotation correction was applied). In summary, the radiometer calibration is very stable over time, and changes in agreement with SMOS are consistent with intentional calibration changes in SMAP data. The noise and geolocation performance meet requirements with margin. Excellent performance should be expected over homogeneous land surfaces.

Table 4.1. Version 3* Characteristics of SMAP L1 Radiometer Data
(*now superceded by Version 4)

Parameter		**Mission Requirement**
NEDT[1]	1.1 K	< 1.6 K[1]
Geolocation accuracy	2.7 km	< 4 km
Land SMAP/SMOS bias (H pol)	-2.65 K	n/a
Land SMAP/SMOS bias (V pol)	-2.71 K	n/a

[1]An NEDT of 1.6 K for a single-look L1B_TB footprint is equivalent to an NEDT of 0.51 K on a 30 x 30 km grid (Table 2.1 in SMAP Radiometer Error Budget, JPL D-61632 [14]). When combined with other error terms in the L1 radiometer error budget, the current single-look footprint NEDT of 1.1 K should result in an NEDT of less

It is a challenge to validate brightness temperatures over land targets due to the heterogeneity of the land surface. SMOS L1 brightness temperature provides an opportunity to check the consistency in brightness temperature between the two L-band missions. SMOS has in general benefitted from more extensive Cal/Val activities than SMAP due to its relative longevity in operational data acquisition (SMOS launched in November 2009). SMOS observations at the top of the atmosphere were reprocessed to 40° incidence angle (after applying Faraday rotation correction). SMAP L1B observations were co-located with reprocessed SMOS observations (only SMAP and SMOS observations acquired less than 30 minutes apart were used). The current L1B radiometer data (T15560) were compared with the most recent SMOS L1B data (version 620) for this analysis.

Figure 4.1 shows the density plot of the brightness temperature (top of the atmosphere) comparison between SMOS and SMAP over land targets for V-pol and H-polarization. SMOS and SMAP observations show a very strong correlation over land targets (Table 4.2). SMAP observations show a warmer TB bias (about 0.66 K for V pol and 1.15 K for H pol) as compared to SMOS for both polarizations. Most of the RMSD can be attributed to the bias between the two satellites. Global average brightness temperature comparisons over ocean areas with SMOS are quite favorable indicating less than 0.25 K mean bias at top of the atmosphere. Efforts will be made to address these differences in TB calibration and to develop a consistent L-band brightness temperature dataset between SMOS and SMAP missions. The impact of these TB differences on soil moisture comparisons between the two satellites is more complex because the two missions use different soil moisture algorithms and ancillary datasets.

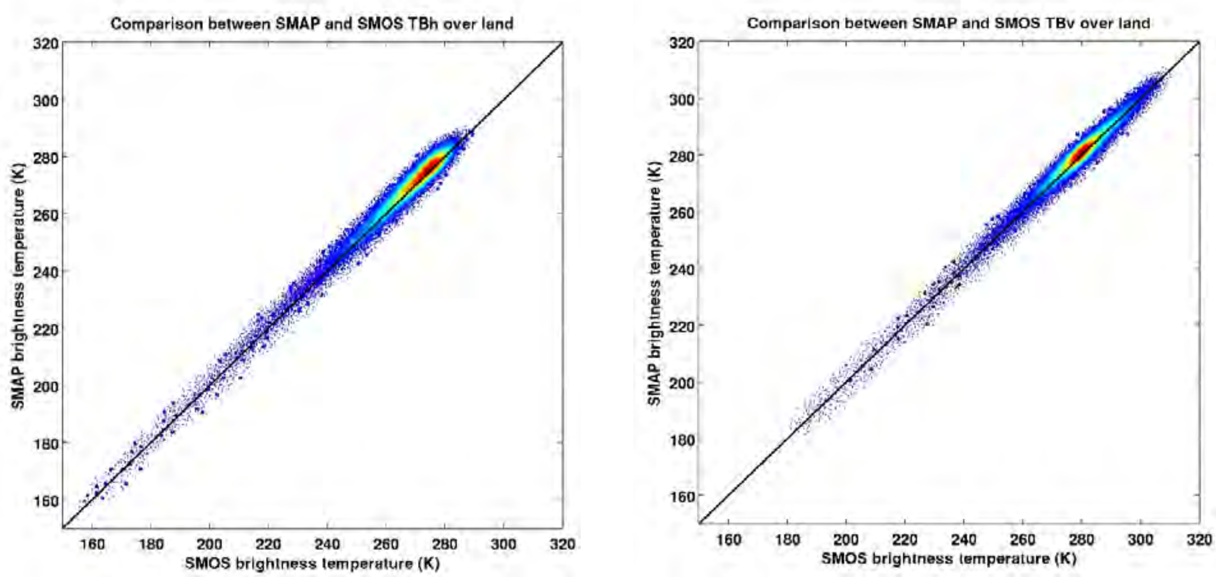


Figure 4.1. Density plot of the L1 brightness temperature comparison (top of the atmosphere) between SMAP (T15560) and SMOS (version 620) observations over land targets for V-pol (right) and H-pol (left).

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than 0.51 K on a 30 x 30 km grid. If all other error sources are within the requirements, this level of NEDT (< 0.51 K) should result in a total radiometric uncertainty of less than 1.3 K as required in the L2SMP error budget.

Table 4.2. Summary statistics of the brightness temperature comparison between SMOS (version 620) and SMAP (T15560) for May 5, 2015-March 31, 2018.

		RMSD (K)	R	Bias [SMAP-SMOS] (K)	ubRMSD (K)
H pol	Land	3.40	0.9921	**1.15**	3.20
	Ocean	2.44	0.7061	0.08	2.44
	Overall	2.71	0.9994	0.38	2.69
V pol	Land	3.05	0.9968	**0.66**	2.98
	Ocean	2.52	0.7679	-0.23	2.51
	Overall	2.66	0.9994	-0.02	2.66

4.1 Water Body Correction

Prior to implementing the actual soil moisture retrieval, a preliminary step in the processing is to perform a water body correction to the brightness temperature data for cases where a significant percentage of the grid cell contains open water. For the Version 5 L2SMP and Version 2 L2SMP_E, water correction is performed at the footprint level using the SMAP radiometer antenna gain pattern. This correction procedure is performed in the Version 4 SMAP L1B Radiometer Half-Orbit Time-Ordered Brightness Temperatures (L1BTB) product. Both the horizontally and vertically polarized L1B brightness temperatures over land are corrected for the presence of water within the antenna field of view (FOV). The resulting L1B brightness temperatures are then interpolated on the 36-km EASE Grid 2.0 projections using the inverse-distance squared interpolation method and on the 9-km EASE Grid 2.0 projections using the Backus-Gilbert optimal interpolation method. Overall it is expected that over land, the resulting brightness temperatures will become warmer upon the removal of the contribution of water to the original uncorrected observations. As stated in the product page of the Version 4 SMAP L1BTB product, water correction is performed as long as the antenna-gain-weighted water fraction within the antenna FOV is less than or equal to 0.9 and when the antenna boresight falls on a land location as indicated by a static high-resolution land/water mask. Further details of this procedure can be found in the User Guide, ATBD [13], or Assessment Report of the Version 4 SMAP L1B Radiometer Half-Orbit Time-Ordered Brightness Temperatures (L1BTB) product.

5 ALTERNATIVE L2SMP/L2SMP_E ALGORITHMS

The current L2SMP/L2SMP_E products contain soil moisture retrieval fields produced by the baseline and several optional algorithms. Inside an L2SMP/L2SMP_E granule the *soil_moisture* field is the one that links to the retrieval result produced by the currently-designated baseline algorithm. At present, the operational L2SMP/L2SMP_E Science Production Software (SPS) produces and stores soil moisture retrieval results from the following five algorithms:

1. Single Channel Algorithm V-pol (SCA-V)
2. Single Channel Algorithm H-pol (SCA-H)
3. Dual Channel Algorithm (DCA)
4. Microwave Polarization Ratio Algorithm (MPRA)
5. Extended Dual Channel Algorithm (E-DCA)

All algorithms operate on the same zeroth-order microwave emission model commonly known as the *tau-omega* model. In essence, this model relates brightness temperatures (SMAP L1 observations) to soil moisture (SMAP L2 retrievals) through ancillary information (e.g. soil texture, soil temperature, and vegetation water content) and a soil dielectric model. The algorithms differ in their approaches to solve for soil moisture from the model under different constraints and assumptions. Of these, the Single Channel Algorithm–V polarization (SCA-V), Single Channel Algorithm–H polarization (SCA-H), and Dual Channel Algorithm (DCA) are the most mature and are the focus of this assessment. Below is a concise description of these three algorithms. Further details are provided in [7].

Given the results to date from the L2SMP/L2SMP_E Cal/Val analyses, the SCA-V algorithm continues to deliver slightly better performance overall than the alternative algorithms. For this reason, the SCA-V will continue to be the operational baseline algorithm for this release of L2SMP/L2SMP_E data. Throughout the rest of the SMAP mission, the choice of the operational algorithm of the product will be evaluated on a regular basis as analyses of new observations and Cal/Val data become available or if significant improvements can be achieved by algorithm modifications.

5.1 Single Channel Algorithm V-pol (SCA-V)

In the SCA-V, the vertically polarized TB observations are converted to emissivity using a surrogate for the physical temperature of the emitting layer. The derived emissivity is corrected for vegetation and surface roughness to obtain the soil emissivity. The Fresnel equation is then used to determine the dielectric constant from the soil emissivity. Finally, a dielectric mixing model is used to solve for the soil moisture given knowledge of the soil texture. [Note: The software code includes the option of using different dielectric models. Currently, the software switch is set to the Mironov model [15]]. Analytically, SCA-V attempts to solve for one unknown variable (soil moisture) from one equation that relates the vertically polarized TB to soil moisture. Vegetation information is provided by a 11-year climatological data base of global NDVI and a table of *tau-omega* parameters based on land cover.

5.2 Single Channel Algorithm H-pol (SCA-H)

The SCA-H is similar to SCA-V in that the horizontally polarized TB observations are converted to emissivity using a surrogate for the physical temperature of the emitting layer. The derived emissivity is corrected for vegetation and surface roughness to obtain the soil emissivity. The Fresnel equation is then used to determine the dielectric constant. Finally, a dielectric mixing model is used to obtain the soil moisture given knowledge of the soil texture. Analytically, SCA-H attempts to solve for one unknown variable (soil moisture) from one equation that relates the horizontally polarized TB to soil moisture.

Vegetation information is provided by a 11-year climatological data base of global NDVI and a table of *tau-omega* parameters based on land cover.

5.3 Dual Channel Algorithm (DCA)

In the DCA, both the vertically and horizontally polarized TB observations are used to solve for soil moisture and vegetation optical depth. The algorithm iteratively minimizes a cost function (Φ^2) that consists of the sum of squares of the differences between the observed and estimated TBs:

$$\min \Phi_{\mathrm{DCA}}^2 = (\mathrm{T}_{\mathrm{B,v}}^{\mathrm{obs}} - \mathrm{T}_{\mathrm{B,v}}^{\mathrm{est}})^2 + (\mathrm{T}_{\mathrm{B,h}}^{\mathrm{obs}} - \mathrm{T}_{\mathrm{B,h}}^{\mathrm{est}})^2 \tag{1}$$

In each iteration step, the soil moisture and vegetation opacity are adjusted simultaneously until the cost function attains a minimum in a least squares sense. Similar to SCA-V and SCA-H, ancillary information such as effective soil temperature, surface roughness, and vegetation single scattering albedo must be known *a priori* before the inversion process. DCA permits polarization dependence of coefficients in the forward modeling of TB observations. As currently implemented for this release, the H and V parameters are set the same. During ongoing Cal/Val activities leading up to future releases of the L2SMP data, implementing polarization dependence for the *tau-omega* model parameters will be investigated.

5.4 An Improved Effective Temperature Methodology

New to the June, 2018 data release is an improved depth correction scheme for the effective soil temperature, which is a critical parameter in passive soil moisture retrieval. At L-band frequency, the contributing soil depth of microwave emission may be different from the pre-defined discrete soil depths at which the soil temperatures are available from a land surface model. The resulting discrepancy can contribute to a dry bias of retrieved soil moisture (i.e., retrieval lower than *in situ* soil moisture) if the model-based effective soil temperature is colder than the soil temperature "seen" by the radiometer. Conversely, wet bias of retrieved soil moisture will occur if the model-based effective soil temperature is warmer than the soil temperature "seen" by the radiometer. Since the contributing soil depth of microwave emission varies with soil moisture, the corresponding depth correction scheme for the effective soil temperature must account for soil moisture variability for brightness temperature observations acquired between AM (descending overpasses) and PM (ascending passes). To achieve this objective, the following modified formulation of the Choudhury model [16] has been found to result in good agreement between the *in situ* soil moisture data and the retrieved soil moisture:

$$\mathrm{Teff} = \mathrm{K} \times [\ \mathrm{T_{soil2}} + \mathrm{C}\ (\mathrm{T_{soil1}} - \mathrm{T_{soil2}})\ ]$$

where C = 0.246 for AM soil moisture retrieval and 1.000 for PM soil moisture retrieval, and K = 1.000 for IGBP land cover classes 1 through 5 (dense vegetation classes) and 1.020 elsewhere. $\mathrm{T_{soil1}}$ refers to the average soil temperature for the first soil layer (0-10 cm) and $\mathrm{T_{soil2}}$ refers to the average soil temperature for the second soil layer (10-20 cm) of the GMAO GEOS-5 land surface model.

6 METHODOLOGIES USED FOR L2SMP/L2SMP_E CAL/VAL

Validation is critical for accurate and credible product usage, and must be based on quantitative estimates of uncertainty. For satellite-based retrievals, validation should include direct comparison with independent correlative measurements. The assessment of uncertainty must also be conducted and presented to the community in normally used metrics in order to facilitate acceptance and implementation.

During mission definition and development, the SMAP Science Team and Cal/Val Working Group identified the metrics and methodologies that would be used for L2-L4 product assessment. These metrics and methodologies were vetted in community Cal/Val workshops and tested in SMAP pre-launch Cal/Val rehearsal campaigns. The methodologies identified and their general roles are:

- Core Validation Sites (CVS): Accurate estimates of products at matching scales for a limited set of conditions
- Sparse Networks: One point in the grid cell for a wide range of conditions
- Satellite Products: Estimates over a very wide range of conditions at matching scales
- Model Products: Estimates over a very wide range of conditions at matching scales
- Field Campaigns: Detailed estimates for a very limited set of conditions

In the case of the L2SMP/L2SMP_E data products, all of these methodologies can contribute to product assessment and improvement.

6.1 Validation Grid (VG)

The scanning radiometer on SMAP provides elliptical footprint observations across the scan. The orientation of this ellipse varies across the swath, and on successive passes a point on the ground might be observed with very different azimuth angles. A standard assumption in using radiometer observations is that the signal is dominated by the energy originating within the 3 dB (half-power) footprint (ellipse). The validity of this contributing area assumption will depend upon the heterogeneity of the landscape.

A major decision was made for SMAP to resample the radiometer data to an Earth-fixed grid at a resolution of 36 km. This was to facilitate temporal analyses and the disaggregation algorithm planned for the AP (active/passive) product. It ignores azimuth orientation and some contribution beyond the 3 dB footprints mentioned above, although the SMAP L1B_TB data do include a sidelobe correction. An important point is that TBs on the Earth-fixed 36-km grid are used in the retrieval of soil moisture, and it is the soil moisture for these 36-km grid cells that must be validated and improved.

The standard SMAP processor provides L2 surface (0-5 cm) soil moisture using only the radiometer (passive) data posted on a 36-km EASE2 Grid. The standard SMAP grid was established without any consideration of where the CVS might be located. In addition, the CVS were established in most cases to satisfy other (non-SMAP) objectives of the Cal/Val Partners. One of the criteria for categorizing a site as a CVS is that the number of individual *in situ* stations (N) within the site is large (target is $N \geq 9$ for 36 km). It was observed when examining the distribution of points at a site that in many cases only a few points fell in any specific standard 36-km grid cell. Therefore, it was decided that special SMAP validation grids (VGs) would be established for validation assessment that would be tied to the existing SMAP 3-km standard grid but would allow the shifting of the 36-km grids at a site to fully exploit N being as large as possible (i.e. the validation grid would be centered over the collection of *in situ* points at a given CVS to the extent possible). The approach used for validation grid processing is illustrated in Figure 6.1.

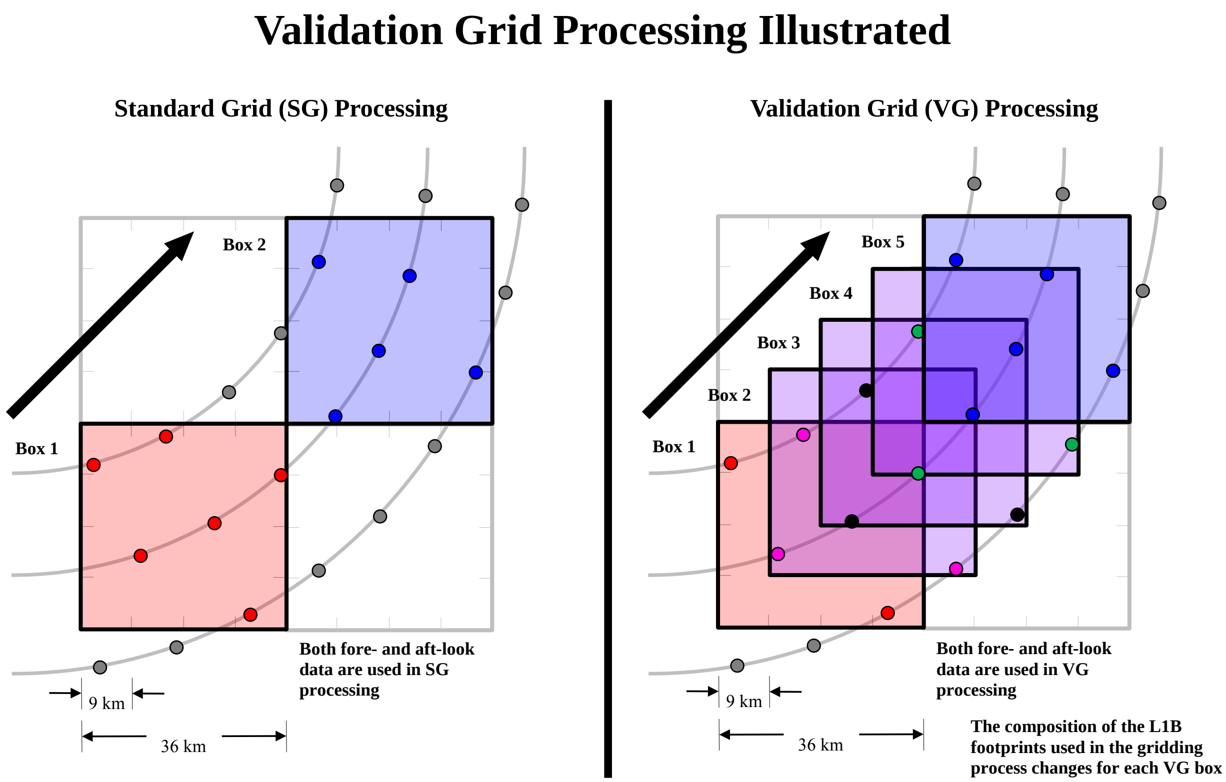

Figure 6.1. Illustration of validation grid processing. The EASE2 grid boxes are shifted by 3-km increments (although 9-km shifts are shown for clarity) to allow a better geographical match with the *in situ* validation sites.

Computationally the L2 and L3 VG products are the same as the standard product. The selection of the VGs for each site was done by members of the SMAP Algorithm Development Team and Science Team. As noted, the 3-km grid does not change. The selection of the VGs also considered avoiding or minimizing the effects of land features that were not representative of the sampled domain or were known problems in retrieval (e.g., non-representative terrain, large water bodies, etc.).

7 SUMMARY OF REFINEMENTS IN L2SMP VERSION 5 AND L2SMP_E VERSION 2 AND VALIDATION

- *Expanded Assessment Period*: For the previous validated (Version 4) data release report, the analysis time period was April 1, 2015 - October 31, 2016 (19 months). The start date in 2015 was based on when the radiometer data were judged to be stable following instrument start-up operations. The end date was based upon the closing date of the Version 4 release report. The current assessment report expands the time period from April 1, 2015 through March 31, 2018, which provides a more robust 3-year assessment.

- *Changes to Teff*: Improved the depth correction scheme for the effective soil temperature, which is a critical parameter in passive soil moisture retrieval.

- *Changes in the Calibration and Upscaling of Some CVS*:
  - Little River: A temporarily installed ground *in situ* measurement network was used to relate the average soil moisture measured with the permanent network with the soil moisture observed in areas not covered by the permanent network. This comparison resulted in a relatively significant average offset adjustment in the upscaled soil moisture compared to the upscaled soil moisture used in previous assessments.
  - Carman: Based on analysis of vertically and horizontally installed *in situ* soil moisture sensors in the permanent network and a temporary network, it was concluded that the vertically installed sensors capture surface soil moisture behavior that corresponds better with what the SMAP radiometer observes. Earlier analyses used the horizontal sensors for the computation of performance metrics between the SMAP soil moisture retrievals and the upscaled *in situ* soil moisture.
  - TxSON: Soil samples harvested from the station locations were used to test different soil moisture probe calibration equations. The analyses resulted in a change of the previously used calibration equation. This change has a non-negligible impact on the upscaled soil moisture and estimated performance metrics.

- *Improved Quality Control of CVS Data*: The *in situ* data downloaded from the Cal/Val Partners is now run through an improved automatic quality control before determining the upscaled soil moisture values for each grid cell. This process can result in the removal of stations that then requires modification of the upscaling function.

8 ASSESSMENTS

In this section several assessments and intercomparisons are presented. The standard L2SMP AM and PM (Version 5) and L2SMP_E AM and PM (Version 2) are examined for the expanded time period. Changes from the previous assessment (L2SMP Version 4 and L2SMP_E Version 1 [1]) will be noted if they occur. These assessments utilize CVS, sparse network, and SMOS comparisons.

8.1 L2SMP

8.1.1 Core Validation Sites

The primary validation for the L2SMP soil moisture is a comparison of retrievals at 36 km with ground-based observations that have been verified as providing a spatial average of soil moisture at the same scale, referred to as core validation sites (CVS) in the SMAP Calibration/Validation Plan [6].

In situ data are critical in the assessment of the SMAP products. These comparisons provide error estimates and a basis for modifying algorithms and/or parameters. A robust analysis will require many sites representing diverse conditions. However, there are relatively few sites that can provide the type and quality of data required. SMAP established a Cal/Val Partners Program in order to foster cooperation with these sites and to encourage the enhancement of these resources to better support SMAP Cal/Val. The current set of sites that provide data for L2SMP are listed in Table 8.1.

Not all of the sites in Table 8.1 have reached a level of maturity that would support their use as CVS. Prior to initiating the beta-release assessments, the L2SMP and Cal/Val Teams reviewed the status of all sites to determine which sites were ready to be designated as CVS. This process is repeated prior to each new assessment (Version 5), with the addition of new screening procedures for *in situ* data as well as changes in upscaling at some CVS. The basic process is as follows:

- Develop and implement the validation grid
- Assess the site for conditions that would introduce uncertainty
- Determine if the number of points is large enough to provide reliable estimates
- Assess the geographic distribution of the *in situ* points
- Determine if the *in situ* instrumentation has been either (1) widely used and known to be well-calibrated or (2) calibrated for the specific site in question
- Perform quality assessment of each point in the network
- Establish a scaling function (default function is a linear average of all stations)
- Conduct pre-launch assessment using surrogate data appropriate for the SMAP L2SMP product (i.e. SMOS soil moisture)
- Review any supplemental studies that have been performed to verify that the network represents the SMAP product over the grid domain

The current CVS for the L2SMP product are marked with an asterisk in Table 8.1. A total of 15 CVS were used in this assessment. Each of these should have at least 9 points (ground *in situ* measurement stations); however, exceptions are made to allow fewer *in situ* stations if the site has a well-established scaling and calibration function. The status of candidate sites will continue to be reviewed periodically to determine if they should be classified as CVS and used in future assessments. Note that the table includes comments on sites that are used for some of the L2SMP_E analyses discussed later.

The *in situ* data downloaded from the Cal/Val Partners is run through an automatic quality control (QC) before determining the upscaled soil moisture values for each pixel (grid cell). The QC is implemented largely following the approach presented in [17]. The procedure includes checks for missing data, out of control values, spikes, sudden drops, and physical temperature limits. Additionally, the physical temperature is checked to be above 4°C because many sensors experience change in behavior at colder temperatures. In several cases the sites include stations that do not perform as expected, or at all, during the comparison period. These stations are removed from consideration altogether, and a new configuration is set for the site accounting for only the stations that produce a reasonable amount of data over the comparison period. Consequently, the upscaling functions for these sites are also based on the remaining set of stations.

The key tool used in L2SMP CVS analyses is illustrated by Figure 8.1. These charts are updated as changes are made to L1 data, L2 algorithms, or in preparation for periodic reviews with Cal/Val Partners. It includes a time series plot of *in situ* and retrieved soil moisture as well as flags that were triggered on a given day, an XY scatter plot of SMAP retrieved soil moisture compared to the average *in situ* soil moisture, and the quantitative statistical metrics. It also shows the CVS site distribution. When the *in situ* values are marked with a magenta color instead of red, it means that the *in situ* quality flag is raised. Several alternative algorithms and the SMOS soil moisture product are also displayed (SMOS L2 v650 was used). These plots are carefully reviewed and discussed by the L2SMP Team and Cal/Val Partners on a periodic basis. Systematic differences and anomalies are identified for further investigation. This particular site (HOBE) was selected for illustration because it was relatively new in the last assessment process.

All sites are then compiled to summarize the metrics and compute the overall performance. Tables 8.2 and 8.3 present the overall results for the current L2SMP Version 5 validated data sets. The combined scatter plots associated with these results are shown in Figure 8.2. These metrics and plots include the removal of questionable-quality and retrieval-flagged data.

The key results for this assessment are summarized in the SMAP Average results row in Table 8.2. First, all algorithms have about the same ubRMSE, differing by 0.009 m^3/m^3, and exceed or are very close to the SMAP mission goal of 0.04 m^3/m^3. Second, the correlations are also very similar. For both of these metrics, the SCA-V shows superior performance. More obvious differences among the algorithms were found in the bias, with the SCA-V now having an overall bias close to zero while the bias for the other algorithms is larger.

Based upon the metrics and considerations discussed, the SCA-V has been selected to continue as the operational baseline algorithm for this release (Version 5). As a longer period of observations builds and additional CVS are added, the evaluations will be repeated on a periodic basis.

For guidance in expected performance, the SMOS soil moisture products for each site over the same time period were analyzed. Summary statistics are included in Table 8.2. For the CVS analyzed here, SMAP SCA-V outperforms SMOS for all metrics.

Also shown in Tables 8.2 and 8.3 are the metric averages from the L2SMP Version 4 assessment. As noted previously, in addition to the product changes, there is also a longer period of record associated with Version 5. Comparing the two versions, the ubRMSE decreased only for the SCA-V, while the others were constant. There was a decrease in the bias for the SCA-V. Overall, the algorithms appear to be stable over time.

Table 8.1. SMAP Cal/Val Partner Sites Providing L2SMP Validation Data

Site Name	Site PI	Area	Climate regime	IGBP Land Cover
Walnut Gulch*	M. Cosh	USA (Arizona)	Arid	Shrub open
Reynolds Creek*	M. Cosh	USA (Idaho)	Arid	Grasslands
Fort Cobb*	M. Cosh	USA (Oklahoma)	Temperate	Grasslands
Little Washita*	M. Cosh	USA (Oklahoma)	Temperate	Grasslands
South Fork*	M. Cosh	USA (Iowa)	Cold	Croplands
Little River*	M. Cosh	USA (Georgia)	Temperate	Cropland/natural mosaic
TxSON*	T. Caldwell	USA (Texas)	Temperate	Grasslands
Millbrook	M. Temimi	USA (New York)	Cold	Deciduous broadleaf
Kenaston*	A. Berg	Canada	Cold	Croplands
Carman*	H. McNairn	Canada	Cold	Croplands
Monte Buey*	M. Thibeault	Argentina	Arid	Croplands
Bell Ville	M. Thibeault	Argentina	Arid	Croplands
REMEDHUS*	J. Martinez	Spain	Temperate	Croplands
Valencia	E. Lopez-Baeza	Spain	Arid	Woody Savannas
Twente*	Z. Su	Netherlands	Cold	Cropland/natural mosaic
HOBE*	F. Udall	Denmark	Temperate	Croplands
Kuwait	H. Jassar	Kuwait	Temperate	Barren/sparse
Niger	T. Pellarin	Niger	Arid	Grasslands
Benin	T. Pellarin	Benin	Arid	Savannas
Naqu	Z. Su	Tibet	Polar	Grasslands
Maqu	Z. Su	Tibet	Cold	Grasslands
Ngari	Z. Su	Tibet	Arid	Barren/sparse
MAHASRI*	J. Asanuma	Mongolia	Cold	Grasslands
Yanco*	J. Walker	Australia	Arid	Croplands
Kyeamba	J. Walker	Australia	Temperate	Croplands
*=CVS used in both L2SMP and L2SMP_E assessments.				

It should be noted that a small underestimation bias should be expected when comparing satellite retrievals to *in situ* soil moisture sensors during drying conditions. Satellite L-band microwave signals respond to a surface layer of a depth that varies with soil moisture (this depth is taken to be ~0-5 cm for average soils under average conditions). The *in situ* measurement is centered at 5 cm and measures a layer from ~ 3 to 7 cm. For some surface conditions and climates, it is expected that the surface will be slightly drier than the layer measured by the *in situ* sensors. For example, Adams et al. [18] reported that a mean difference of 0.018 m^3/m^3 existed between the measurements obtained by inserting a probe vertically from the surface versus horizontally at 5 cm for agricultural fields in Manitoba, Canada. Drier conditions were obtained using the surface measurement and this difference was more pronounced for mid- to dry conditions and minimized during wet conditions.

A review of the individual CVS indicates that several sites (South Fork, Little River, Carman, Fort Cobb and Twente) have larger bias values. Of these, South Fork, Carman and Twente also have large ubRMSE, which may suggest error sources that cannot be accounted for with the current algorithm/parameter approach. Efforts are under way at South Fork and Carman to better understand the causes of the errors and to determine if there is anything that can done to mitigate these errors.

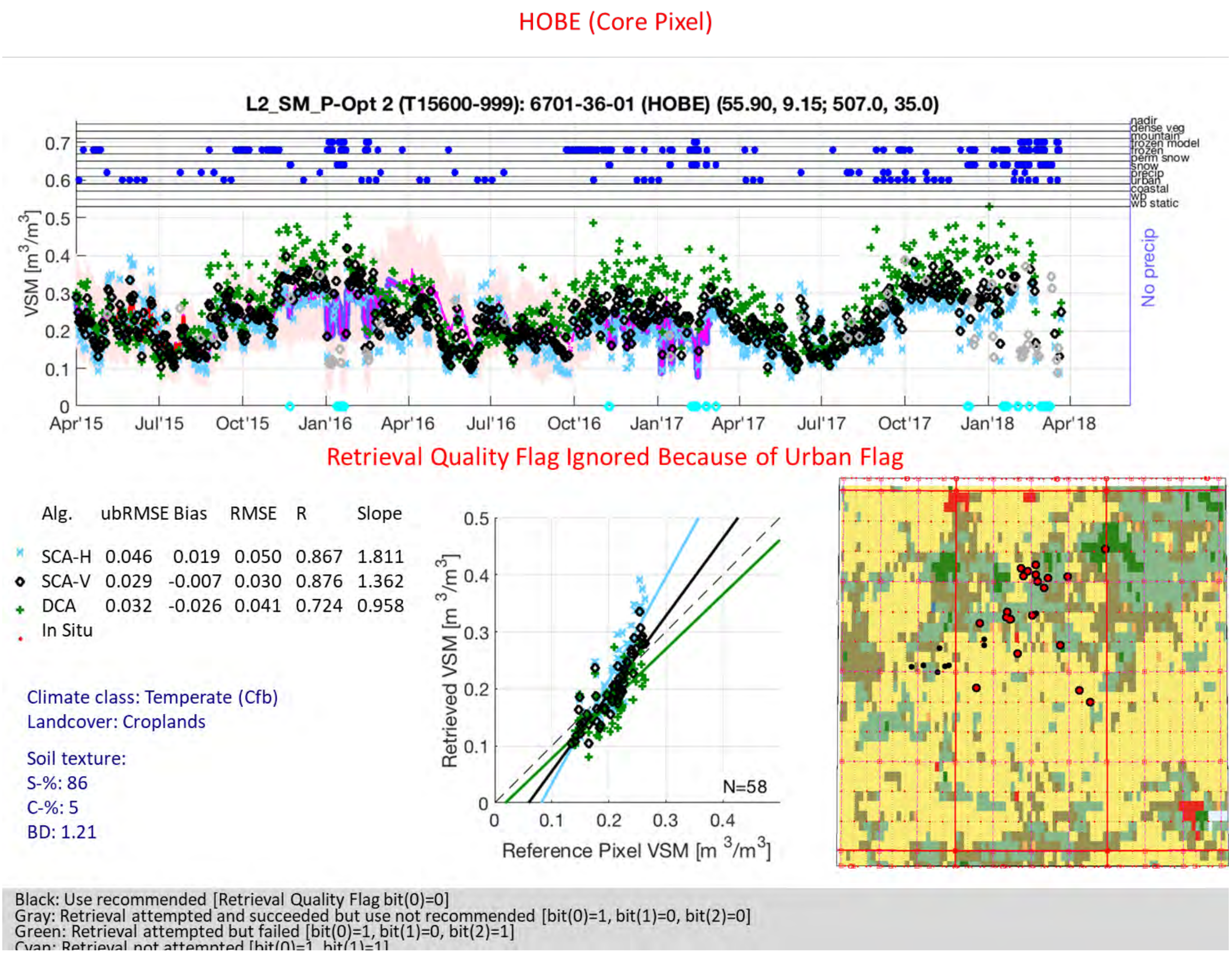

Figure 8.1. L2SMP Assessment Tool Report for the HOBE Network, Denmark Descending (AM) Passes.

Table 8.2. SMAP L2SMP Version 5 CVS Assessment for Descending (AM) Overpasses

CVS	ubRMSE (m^3/m^3)			Bias (m^3/m^3)			RMSE (m^3/m^3)			R			N		
	SCA-H	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**
Reynolds Creek	0.044	0.041	0.054	-0.053	-0.007	0.037	0.069	0.042	0.065	0.62	0.674	0.646	230	266	266
Walnut Gulch	0.023	0.023	0.040	-0.019	0.008	0.036	0.03	0.025	0.054	0.768	0.817	0.814	272	354	352
TxSON	0.021	0.021	0.041	-0.066	-0.007	0.096	0.069	0.022	0.104	0.921	0.925	0.830	446	446	435
Fort Cobb	0.033	0.028	0.044	-0.067	-0.029	0.026	0.074	0.041	0.051	0.861	0.885	0.816	463	463	462
Little Washita	0.024	0.021	0.041	-0.057	-0.013	0.061	0.061	0.025	0.073	0.893	0.918	0.824	490	490	483
South Fork	0.062	0.053	0.056	-0.033	-0.010	0.023	0.071	0.054	0.061	0.600	0.647	0.624	321	327	327
Little River	0.042	0.033	0.047	0.009	0.058	0.144	0.043	0.067	0.152	0.859	0.875	0.641	481	481	473
Kenaston	0.038	0.028	0.041	-0.053	-0.022	0.030	0.065	0.035	0.051	0.769	0.828	0.65	215	215	215
Carman	0.099	0.070	0.074	-0.076	-0.063	-0.035	0.124	0.094	0.082	0.469	0.515	0.444	239	239	239
Monte Buey	0.072	0.049	0.044	-0.030	-0.013	0.001	0.078	0.05	0.044	0.711	0.864	0.754	146	156	159
REMEDHUS	0.037	0.037	0.050	-0.022	0.005	0.028	0.043	0.037	0.058	0.858	0.848	0.817	371	380	379
Twente	0.072	0.054	0.059	0.023	0.045	0.078	0.076	0.071	0.098	0.879	0.889	0.751	330	347	347
HOBE	0.046	0.029	0.032	0.019	-0.007	-0.026	0.05	0.03	0.041	0.867	0.876	0.724	58	58	58
MAHASRI	0.031	0.032	0.035	0.000	0.003	0.008	0.031	0.032	0.035	0.792	0.799	0.802	223	222	220
Yanco	0.044	0.038	0.045	0.001	0.033	0.068	0.044	0.051	0.082	0.949	0.953	0.917	283	288	289
Mean Absolute Bias				**0.035**	**0.022**	**0.046**									
SMAP L2SMP Average V5	**0.046**	**0.037**	**0.047**	**-0.028**	**-0.001**	**0.038**	**0.062**	**0.044**	**0.070**	**0.788**	**0.821**	**0.737**			
SMOS L2SM Average V5	**0.053**			**-0.024 (MAB=0.035)**			**0.065**			**0.671**					
SMAP L2SMP Average V4	***0.046***	***0.039***	***0.047***	***-0.037***	***-0.028***	***-0.015***	***0.071***	***0.061***	***0.066***	***0.772***	***0.795***	***0.700***			
SMOS L2SMP Average V4	***0.053***			***-0.028***			***0.072***			***0.710***					

Table 8.3. SMAP L2SMP Version 5 CVS Assessment for Ascending (PM) Overpasses

CVS	ubRMSE (m^3/m^3)			Bias (m^3/m^3)			RMSE (m^3/m^3)			R			N		
	SCA-H	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**
Reynolds Creek	0.046	0.042	0.050	-0.061	-0.013	0.037	0.076	0.044	0.062	0.618	0.696	0.696	266	307	307
Walnut Gulch	0.026	0.026	0.041	-0.030	-0.001	0.028	0.040	0.026	0.049	0.710	0.739	0.714	391	515	513
TxSON	0.019	0.020	0.037	-0.056	-0.002	0.089	0.059	0.029	0.096	0.926	0.921	0.802	485	485	479
Fort Cobb	0.038	0.030	0.038	-0.063	-0.033	0.008	0.074	0.044	0.039	0.857	0.876	0.802	492	492	491
Little Washita	0.025	0.022	0.038	-0.045	-0.008	0.051	0.052	0.024	0.063	0.899	0.911	0.782	504	504	501
South Fork	0.061	0.045	0.056	-0.031	-0.017	0.008	0.068	0.048	0.057	0.630	0.739	0.659	346	349	349
Little River	0.042	0.034	0.055	0.016	0.061	0.138	0.045	0.070	0.149	0.849	0.829	0.436	418	418	411
Kenaston	0.035	0.024	0.046	-0.047	-0.020	0.027	0.059	0.031	0.054	0.810	0.878	0.648	278	278	278
Carman	0.088	0.056	0.061	-0.072	-0.066	-0.047	0.114	0.087	0.077	0.510	0.622	0.521	212	215	215
Monte Buey	0.065	0.043	0.045	0.001	-0.001	-0.012	0.065	0.043	0.047	0.816	0.890	0.697	132	143	146
REMEDHUS	0.035	0.036	0.048	-0.032	-0.007	0.017	0.048	0.036	0.050	0.853	0.844	0.815	383	407	406
Twente	0.073	0.052	0.050	0.043	0.050	0.062	0.085	0.072	0.080	0.894	0.910	0.814	416	435	439
HOBE	0.041	0.026	0.032	0.031	0.004	-0.018	0.051	0.026	0.036	0.842	0.821	0.576	58	58	58
MAHASRI	0.032	0.033	0.035	-0.012	-0.005	0.000	0.034	0.033	0.035	0.701	0.679	0.681	303	325	310
Yanco	0.054	0.041	0.040	0.011	0.034	0.056	0.055	0.053	0.069	0.957	0.960	0.936	315	319	322
Mean Absolute Bias				**0.037**	**0.021**	**0.040**									
SMAP L2SMP Average V5	**0.045**	**0.035**	**0.045**	**-0.023**	**-0.002**	**0.030**	**0.062**	**0.044**	**0.064**	**0.791**	**0.821**	**0.724**			
SMOS L2SMP Average V5	**0.051**			**-0.031 (MAB=0.036)**			**0.066**			**0.686**					
SMAP L2SMP Average V4	***0.046***	***0.039***	***0.047***	***-0.037***	***-0.028***	***-0.015***	***0.071***	***0.061***	***0.066***	***0.772***	***0.795***	***0.700***			
SMOS L2SMP Average V4	***0.053***			***-0.028***			***0.072***			***0.710***					

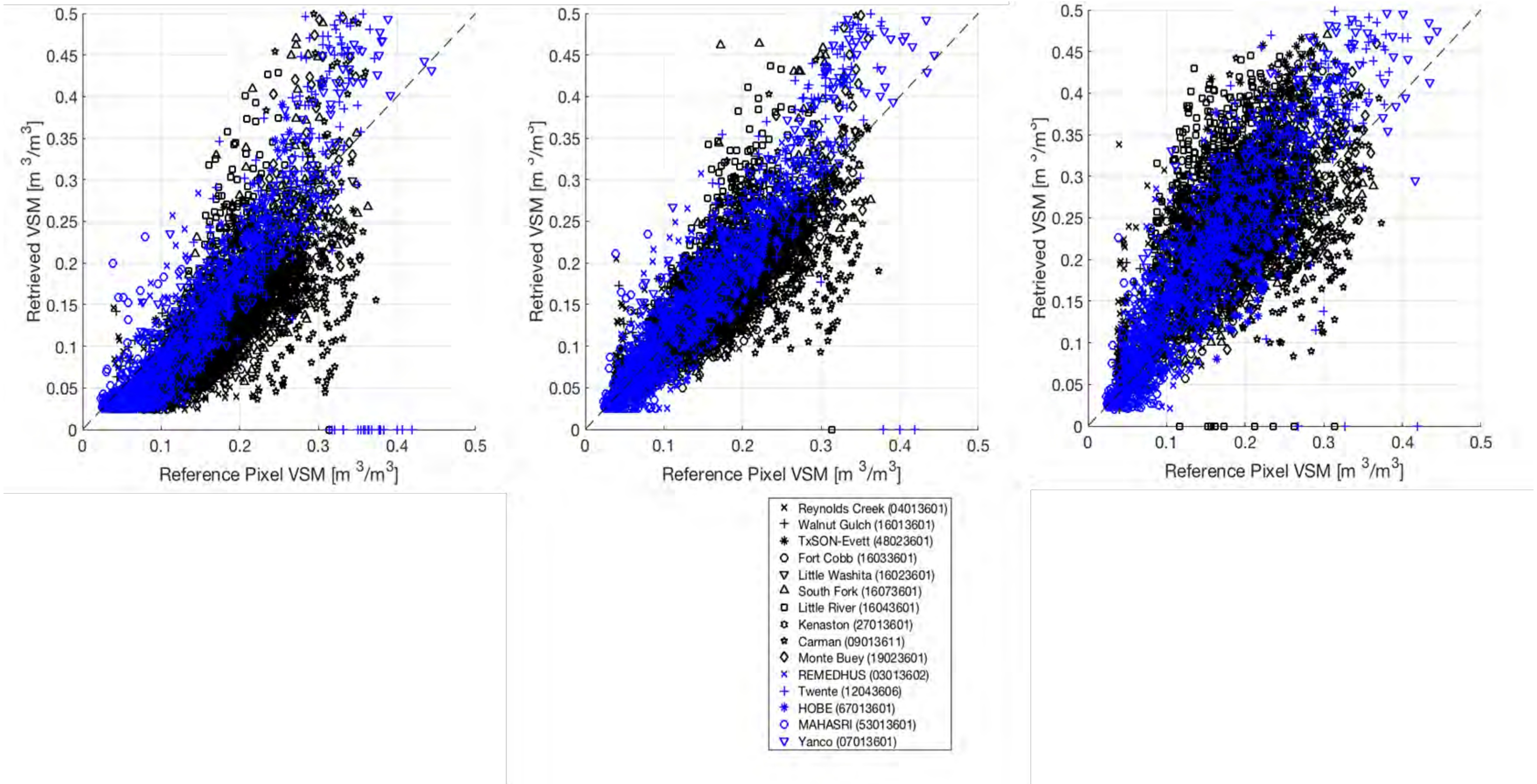

Figure 8.2. Scatterplot of SMAP L2SMP Version 5 CVS Assessment for Descending (AM) Overpasses (SCA-H left panel, SCA-V middle panel, and DCA right panel).

8.1.2 *Sparse Networks*

The intensive network CVS validation described above can be complemented by sparse networks as well as by new/emerging types of soil moisture networks. The current set of networks being utilized by SMAP are listed in Table 8.4.

The defining feature of these networks is that the measurement density is low, usually resulting in one ground measurement point per 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 conditions across the entire SMAP footprint.

SMAP has been evaluating methodologies for upscaling data from these networks to SMAP footprint resolutions. A key element of the upscaling approach is Triple Colocation that combines the *in situ* data and SMAP soil moisture product with another independent source of soil moisture, likely to be a model-based product [5].

Although limited by upscaling, sparse networks do offer many sites in different environments and are typically operational with very low latency. They are very useful as a supplement to the limited number of CVS.

Table 8.4. Sparse Networks Providing L2SMP and L2SMP_E Validation Data

Network Name	PI/Contact	Area	No. of Sites (L2SMP)	No. of Sites (L2SMP_E)
NOAA Climate Reference Network (CRN)	M. Palecki	USA	60	56
USDA NRCS Soil Climate Analysis Network (SCAN)	M. Cosh	USA	101	100
GPS	E. Small	Western USA	80	77
COSMOS	M. Zreda	Mostly USA	30	32
SMOSMania	J. Calvet	Southern France	10	11
Pampas	M. Thibeault	Argentina	16	14
Oklahoma Mesonet	-	Oklahoma, USA	94	96
Mongolian Grasslands (MAHASRI)	J. Asanuma	Mongolia	13	13

The sparse network metrics are summarized in Table 8.5 and 8.6. Because of the larger number of sites, it is possible to also examine the results based upon the IGBP land cover classification used by SMAP. For these comparisons the SMOS metrics are included for each category. The reliability of the analyses based upon these classes will depend upon the number of sites available (N).

Overall, the relative performance of the algorithms based on ubRMSE is similar to that obtained from the CVS -- SCA-V has the best metrics, with an ubRMSE of 0.049 m^3/m^3, bias of 0.004 m^3/m^3 and correlation of 0.664 for AM orbits, and an ubRMSE of 0.049 m^3/m^3, bias of 0.008 m^3/m^3 and correlation of 0.637 for the PM orbits. Compared to the CVS results, the sparse network values are higher for ubRMSE and bias and lower for R, which is expected due to the significant change in scale between a point and the grid product. When comparing Version 5 AM to Version 4 AM, both the ubRMSE and correlation show a slight improvement with a significant improvement in bias. Considering the many caveats that must be considered in making sparse network comparisons, the algorithm performance is quite good. This result provides additional confidence in the previous conclusions based on the CVS.

Interpreting the results based on land cover is more complex. There are no clear patterns associated with broader vegetation types. The ubRMSE values for SCA-V are all between 0.022 and 0.065 m^3/m^3. Grasslands had larger bias values, which needs to be investigated. Forest results are based on very limited sites and should not be generalized.

Figure 8.3 contains scatterplots of the SCA-V retrieved versus observed *in situ* soil moisture for SMAP standard and enhanced L2 passive soil moisture products. Focusing on Figure 8.3a and 8.3b for the L2SMP AM & PM Version 5, the distribution reflects the summary metrics discussed above.

SMOS (Level 2 UDP) metrics are also included in Tables 8.5 and 8.6 (in blue) as supporting information. It should be noted that while SMOS retrievals are based on a different land cover classification scheme (ECOCLIMAP), this does not have any impact on the comparisons shown, which compares the soil moisture retrievals to the *in situ* observations for the points that fall into these categories. Overall, the SMOS products are showing a higher bias and ubRMSE and lower correlation than the SMAP SCA-V retrievals. There was a small increase in ubRMSE and decrease in bias in the SMOS results from the Version 4 analysis.

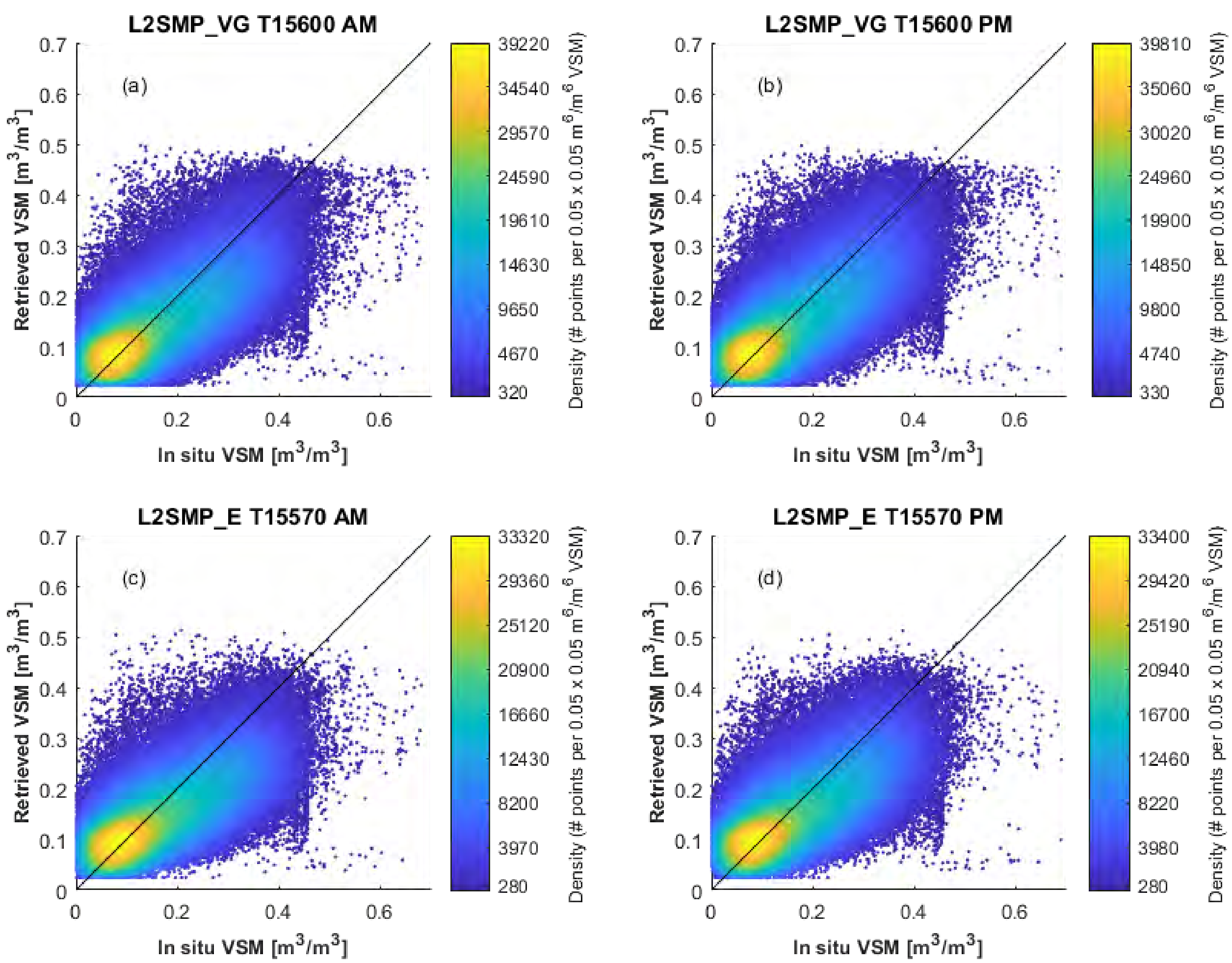

Figure 8.3. Scatterplots of the sparse network *in situ* observations and SMAP baseline SCA-V retrievals: (a) L2SMP AM Version 5, (b) L2SMP PM Version 5, (c) L2SMP_E AM Version 2, and (d) L2SMP_E PM Version 2.

Table 8.5. SMAP L2SMP Version 5 Sparse Network Assessment for Descending (AM) Overpasses

IGBP Class	ubRMSD (m3/m3)				Bias (m3/m3)				RMSD (m3/m3)				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	
Evergreen needleleaf forest	0.059	0.037	0.052	0.068	-0.051	-0.008	0.073	-0.064	0.081	0.038	0.091	0.096	0.548	0.843	0.772	0.521	3
Evergreen broadleaf forest																	
Deciduous needleleaf forest																	
Deciduous broadleaf forest																	
Mixed forest	0.045	0.044	0.061	0.081	-0.041	0.012	0.095	-0.094	0.062	0.053	0.115	0.125	0.689	0.693	0.604	0.682	2
Closed shrublands																	
Open shrublands	0.040	0.041	0.051	0.052	-0.039	-0.002	0.042	-0.010	0.062	0.056	0.077	0.065	0.559	0.571	0.561	0.504	47
Woody savannas	0.063	0.057	0.073	0.098	-0.034	0.016	0.096	-0.062	0.093	0.086	0.134	0.140	0.678	0.709	0.511	0.499	22
Savannas	0.046	0.045	0.050	0.057	-0.039	0.002	0.043	-0.021	0.071	0.061	0.081	0.070	0.878	0.870	0.836	0.824	6
Grasslands	0.050	0.049	0.059	0.061	-0.067	-0.026	0.034	-0.046	0.089	0.069	0.084	0.088	0.690	0.701	0.651	0.608	240
Permanent wetlands	0.083	0.072	0.071	0.097	-0.014	0.008	0.047	-0.058	0.084	0.072	0.085	0.113	0.366	0.349	0.203	0.406	1
Croplands	0.079	0.067	0.072	0.080	-0.036	-0.010	0.033	-0.049	0.115	0.099	0.106	0.122	0.562	0.605	0.531	0.560	61
Urban and built-up																	
Crop/Natural vegetation mosaic	0.060	0.053	0.068	0.084	-0.013	0.031	0.102	-0.084	0.084	0.082	0.133	0.153	0.684	0.736	0.577	0.504	16
Snow and ice																	
Barren/Sparse	0.025	0.026	0.034	0.043	-0.015	0.014	0.063	-0.004	0.039	0.045	0.082	0.051	0.580	0.570	0.484	0.483	6
Mean Absolute Bias					**0.065**	**0.055**	**0.085**	**0.085**									
SMAP L2SMP_E Average V2 (SMOS)	**0.055**	**0.049**	**0.059**	**0.072**	**-0.035**	**0.004**	**0.063**	**-0.049**	**0.078**	**0.066**	**0.099**	**0.102**	**0.623**	**0.664**	**0.573**	**0.559**	
SMAP L2SMP_E Average V1 (SMOS)	***0.053***	***0.05***	***0.057***	***0.066***	***-0.061***	***-0.031***	***0.01***	***-0.049***	***0.093***	***0.077***	***0.081***	***0.099***	***0.643***	***0.663***	***0.633***	***0.576***	
Average is based upon all sets of observations, not the average of the land cover category results.																	

Table 8.6. SMAP L2SMP Version 5 Sparse Network Assessment for Ascending (PM) Overpasses

IGBP Class	ubRMSD (m3/m3)				Bias (m3/m3)				RMSD (m3/m3)				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**	
Evergreen needleleaf forest	0.059	0.038	0.054	0.060	-0.046	-0.003	0.083	-0.046	0.077	0.039	0.100	0.076	0.555	0.799	0.705	0.633	3
Evergreen broadleaf forest																	
Deciduous needleleaf forest																	
Deciduous broadleaf forest																	
Mixed forest	0.048	0.046	0.063	0.083	-0.040	0.011	0.089	-0.048	0.063	0.051	0.110	0.096	0.641	0.649	0.533	0.669	2
Closed shrublands																	
Open shrublands	0.040	0.041	0.051	0.053	-0.043	-0.005	0.043	-0.008	0.063	0.055	0.078	0.069	0.526	0.521	0.483	0.472	48
Woody savannas	0.063	0.058	0.073	0.097	-0.013	0.027	0.093	-0.050	0.092	0.089	0.130	0.131	0.679	0.690	0.474	0.526	22
Savannas	0.047	0.047	0.055	0.056	-0.034	0.007	0.049	-0.031	0.071	0.063	0.089	0.077	0.864	0.847	0.787	0.828	6
Grasslands	0.049	0.048	0.057	0.060	-0.062	-0.024	0.030	-0.042	0.086	0.069	0.084	0.086	0.696	0.703	0.638	0.621	240
Permanent wetlands	0.086	0.069	0.067	0.087	-0.003	0.006	0.025	-0.071	0.086	0.069	0.071	0.113	0.359	0.372	0.246	0.450	1
Croplands	0.078	0.065	0.070	0.078	-0.019	-0.004	0.026	-0.047	0.113	0.098	0.103	0.116	0.573	0.612	0.516	0.558	61
Urban and built-up																	
Crop/Natural vegetation mosaic	0.062	0.055	0.073	0.081	0.014	0.047	0.102	-0.072	0.083	0.089	0.136	0.137	0.665	0.707	0.488	0.490	15
Snow and ice																	
Barren/Sparse	0.027	0.027	0.037	0.047	-0.018	0.014	0.071	0.006	0.040	0.046	0.089	0.055	0.507	0.467	0.353	0.359	6
Mean Absolute Bias					**0.064**	**0.056**	**0.085**	**0.078**									
SMAP L2SMP_E Average V2 (SMOS)	**0.056**	**0.049**	**0.060**	**0.070**	**-0.026**	**0.008**	**0.061**	**-0.041**	**0.077**	**0.067**	**0.099**	**0.096**	**0.606**	**0.637**	**0.522**	**0.561**	
SMAP L2SMP_E Average V1 (SMOS)	***0.053***	***0.051***	***0.059***	***0.065***	***-0.063***	***-0.043***	***-0.016***	***-0.043***	***0.097***	***0.083***	***0.084***	***0.095***	***0.618***	***0.629***	***0.595***	***0.578***	
Average is based upon all sets of observations, not the average of the land cover category results.																	

8.2 L2SMP_E

8.2.1 Core Validation Sites

The new L2SMP_E Version 2 is assessed using the same approach as that employed for L2SMP. The major difference between L2SMP_E and L2SMP is that this product is assessed using a different set of CVS. Because it is possible to now provide a retrieval for every SMAP 9-km grid cell where feasible, the need for using the validation grid (as used for L2SMP) is not expected to be as important an issue in performing validation. It should be noted that the validation grid allowed centering the retrieval on any 3-km grid, whereas the L2SMP_E retrieval process can only be centered on a 9-km grid. Thus, the ability to match the *in situ* network to the grid may be more restrictive for L2SMP_E. Each available CVS was reviewed to identify the 9-km grid cell that satisfied the CVS criteria for the new 33-km contributing domain. Therefore, the mix/weighting of *in situ* stations and grid center will be different between the CVS sets used for the two products.

The CVS results are summarized in Tables 8.7 and 8.8 for the AM and PM overpasses, respectively. The best algorithm choice remains the SCA-V and the ubRMSE meets/exceeds the SMAP mission requirements. When compared to the L2SMP retrievals, the differences in the metrics are negligible. These results indicate that the L2SMP_E products can be used in place of L2SMP without loss of accuracy.

8.2.2 Sparse Networks

The sparse network results are summarized in Tables 8.9 and 8.10 for the AM and PM overpasses, respectively. Comparing the overall metrics for the L2SMP products to the L2SMP_E products, the results are nearly identical and therefore support the trends observed in the CVS analysis.

Table 8.7. SMAP L2SMP_E Version 2 CVS Assessment for Descending (AM) Overpasses

CVS	ubRMSE (m^3/m^3)			Bias (m^3/m^3)			RMSE (m^3/m^3)			R			N		
	SCA-H	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**	**SCA-H**	**SCA-V**	**DCA**
Reynolds Creek	0.040	0.040	0.055	-0.058	-0.013	0.036	0.070	0.042	0.065	0.627	0.644	0.592	138	141	141
Walnut Gulch	0.022	0.024	0.042	-0.013	0.018	0.052	0.025	0.030	0.067	0.816	0.834	0.815	158	188	188
TxSON	0.022	0.022	0.041	-0.067	-0.009	0.087	0.070	0.024	0.096	0.930	0.931	0.821	404	404	396
Fort Cobb	0.033	0.028	0.044	-0.083	-0.045	0.009	0.089	0.053	0.045	0.861	0.882	0.813	445	445	445
Little Washita	0.024	0.022	0.042	-0.062	-0.018	0.055	0.066	0.028	0.069	0.891	0.912	0.815	429	429	425
South Fork	0.062	0.055	0.055	-0.059	-0.038	-0.012	0.085	0.067	0.057	0.655	0.671	0.628	259	265	265
Little River	0.047	0.037	0.050	0.015	0.062	0.144	0.049	0.072	0.152	0.746	0.781	0.550	419	419	415
Kenaston	0.039	0.027	0.041	-0.026	0.006	0.057	0.046	0.028	0.070	0.753	0.800	0.585	187	187	187
Carman	0.086	0.064	0.066	-0.062	-0.047	-0.022	0.106	0.080	0.070	0.513	0.571	0.488	235	237	237
Monte Buey	0.074	0.049	0.043	-0.032	-0.016	-0.001	0.081	0.052	0.043	0.712	0.838	0.777	181	191	195
REMEDHUS	0.040	0.039	0.053	-0.016	0.012	0.038	0.043	0.041	0.065	0.850	0.846	0.818	343	348	348
Twente	0.072	0.054	0.059	0.023	0.045	0.078	0.076	0.071	0.098	0.879	0.889	0.751	330	347	347
HOBE	0.049	0.036	0.065	0.004	-0.003	0	0.049	0.036	0.065	0.723	0.860	0.755	117	117	117
MAHASRI	0.031	0.032	0.035	0	0.003	0.008	0.031	0.032	0.035	0.792	0.799	0.802	223	222	220
Yanco	0.045	0.039	0.046	-0.004	0.029	0.064	0.045	0.049	0.079	0.947	0.951	0.915	284	289	290
Mean Absolute Bias				**0.035**	**0.024**	**0.044**									
SMAP L2SMP_E Average V2	**0.046**	**0.038**	**0.049**	**-0.029**	**-0.001**	**0.039**	**0.062**	**0.047**	**0.072**	**0.780**	**0.814**	**0.728**			
SMOS L2SMP_E Average V2	**0.053**			**-0.022**			**0.067**			**0.665**					
SMAP L2SMP_E Average V1	***0.046***	***0.038***	***0.047***	***-0.034***	***-0.015***	***0.010***	***0.067***	***0.054***	***0.064***	***0.781***	***0.819***	***0.739***			
SMOS L2SMP_E Average V1	***0.052***			***-0.011***			***0.067***			***0.748***					

Table 8.8. SMAP L2SMP_E Version 2 CVS Assessment for Ascending (PM) Overpasses

CVS	ubRMSE (m^3/m^3)			Bias (m^3/m^3)			RMSE (m^3/m^3)			R			N		
	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA
Reynolds Creek	0.045	0.042	0.053	-0.064	-0.016	0.044	0.078	0.045	0.069	0.555	0.624	0.621	180	191	191
Walnut Gulch	0.024	0.024	0.038	-0.026	0.005	0.034	0.035	0.024	0.051	0.722	0.760	0.730	286	386	383
TxSON	0.020	0.020	0.035	-0.058	-0.005	0.081	0.061	0.021	0.089	0.927	0.929	0.822	442	442	440
Fort Cobb	0.038	0.029	0.038	-0.079	-0.048	-0.007	0.087	0.057	0.038	0.850	0.869	0.795	479	479	478
Little Washita	0.025	0.022	0.037	-0.050	-0.013	0.045	0.056	0.026	0.058	0.900	0.911	0.788	463	463	461
South Fork	0.062	0.047	0.058	-0.054	-0.045	-0.027	0.083	0.065	0.064	0.668	0.737	0.608	268	271	271
Little River	0.045	0.037	0.059	0.022	0.064	0.134	0.050	0.074	0.146	0.763	0.746	0.314	367	368	365
Kenaston	0.035	0.023	0.047	-0.021	0.008	0.056	0.041	0.024	0.073	0.823	0.890	0.665	255	255	255
Carman	0.080	0.051	0.055	-0.056	-0.050	-0.031	0.097	0.071	0.064	0.553	0.656	0.550	205	207	207
Monte Buey	0.063	0.042	0.040	-0.002	-0.004	-0.015	0.063	0.043	0.043	0.832	0.901	0.773	152	164	168
REMEDHUS	0.037	0.037	0.050	-0.026	0.002	0.027	0.045	0.037	0.057	0.863	0.851	0.817	388	395	393
Twente	0.073	0.052	0.050	0.043	0.050	0.062	0.085	0.072	0.080	0.894	0.910	0.814	416	435	439
HOBE	0.047	0.034	0.063	0.015	0.006	0.006	0.050	0.035	0.064	0.687	0.849	0.767	117	117	117
MAHASRI	0.032	0.033	0.035	-0.012	-0.005	0.000	0.034	0.033	0.035	0.701	0.679	0.681	303	325	310
Yanco	0.054	0.041	0.040	0.008	0.031	0.053	0.054	0.051	0.066	0.958	0.960	0.936	316	320	323
Mean Absolute Bias				**0.036**	**0.023**	**0.041**									
SMAP L2SMP_E Average V2	**0.045**	**0.036**	**0.047**	**-0.024**	**-0.002**	**0.031**	**0.061**	**0.045**	**0.066**	**0.780**	**0.818**	**0.712**			
SMOS L2SMP_E Average V2	**0.055**			**-0.026**			**0.068**			**0.677**					
SMAP L2SMP_E Average V1	***0.047***	***0.039***	***0.049***	***-0.036***	***-0.027***	***-0.011***	***0.070***	***0.060***	***0.066***	***0.772***	***0.814***	***0.729***			
SMOS L2SMP_E Average V1	***0.052***			***-0.016***			***0.068***			***0.750***					

Table 8.9. SMAP L2SMP_E Version 2 Sparse Network Assessment for Descending (AM) Overpasses

IGBP Class	ubRMSD (m3/m3)				Bias (m3/m3)				RMSD (m3/m3)				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	
Evergreen needleleaf forest	0.029	0.029	0.049	0.095	-0.028	0.023	0.090	-0.043	0.051	0.045	0.103	0.124	0.654	0.641	0.571	-0.031	2
Evergreen broadleaf forest																	
Deciduous needleleaf forest																	
Deciduous broadleaf forest																	
Mixed forest	0.056	0.057	0.066	0.057	-0.045	-0.008	0.047	-0.069	0.072	0.058	0.081	0.090	0.655	0.640	0.579	0.711	1
Closed shrublands																	
Open shrublands	0.039	0.040	0.049	0.053	-0.040	0.000	0.049	-0.009	0.063	0.054	0.079	0.064	0.529	0.547	0.540	0.473	45
Woody savannas	0.059	0.055	0.072	0.095	-0.011	0.033	0.108	-0.054	0.087	0.087	0.140	0.140	0.728	0.736	0.497	0.434	19
Savannas	0.032	0.030	0.039	0.045	-0.037	-0.008	0.012	-0.025	0.063	0.052	0.063	0.060	0.869	0.869	0.859	0.851	3
Grasslands	0.050	0.049	0.058	0.062	-0.069	-0.028	0.035	-0.045	0.092	0.071	0.084	0.088	0.687	0.697	0.644	0.612	239
Permanent wetlands																	
Croplands	0.076	0.065	0.072	0.079	-0.039	-0.013	0.032	-0.048	0.112	0.098	0.105	0.116	0.563	0.600	0.519	0.559	61
Urban and built-up																	
Crop/Natural vegetation mosaic	0.067	0.059	0.070	0.093	-0.024	0.014	0.081	-0.093	0.096	0.087	0.122	0.166	0.636	0.674	0.548	0.463	23
Snow and ice																	
Barren/Sparse	0.022	0.022	0.029	0.031	-0.014	0.014	0.058	-0.003	0.035	0.035	0.067	0.039	0.618	0.603	0.539	0.526	6
Mean Absolute Bias					**0.063**	**0.055**	**0.080**	**0.083**									
SMAP L2SMP_E Average V2 (SMOS)	**0.048**	**0.045**	**0.056**	**0.068**	**-0.034**	**0.003**	**0.057**	**-0.043**	**0.075**	**0.065**	**0.094**	**0.099**	**0.660**	**0.668**	**0.588**	**0.511**	
SMAP L2SMP_E Average V1 (SMOS)	***0.054***	***0.051***	***0.060***	***0.065***	***-0.062***	***-0.032***	***0.010***	***-0.049***	***0.095***	***0.079***	***0.084***	***0.098***	***0.642***	***0.654***	***0.608***	***0.572***	
Average is based upon all sets of observations, not the average of the land cover category results.																	

Table 8.10. SMAP L2SMP_E Version 2 Sparse Network Assessment for Ascending (PM) Overpasses

IGBP Class	ubRMSD (m3/m3)				Bias (m3/m3)				RMSD (m3/m3)				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	
Evergreen needleleaf forest	0.036	0.036	0.053	0.077	-0.034	0.023	0.107	-0.039	0.058	0.054	0.120	0.124	0.498	0.485	0.403	0.007	2
Evergreen broadleaf forest																	
Deciduous needleleaf forest																	
Deciduous broadleaf forest																	
Mixed forest	0.057	0.055	0.057	0.056	-0.038	-0.002	0.052	-0.055	0.068	0.055	0.077	0.078	0.676	0.704	0.694	0.724	1
Closed shrublands																	
Open shrublands	0.039	0.040	0.050	0.055	-0.045	-0.003	0.052	-0.006	0.064	0.053	0.083	0.069	0.526	0.524	0.466	0.425	45
Woody savannas	0.058	0.055	0.073	0.094	0.004	0.042	0.107	-0.045	0.087	0.090	0.140	0.126	0.724	0.717	0.452	0.485	19
Savannas	0.033	0.033	0.041	0.049	-0.031	-0.002	0.016	-0.024	0.060	0.054	0.067	0.073	0.864	0.842	0.814	0.774	3
Grasslands	0.050	0.049	0.057	0.062	-0.064	-0.025	0.032	-0.041	0.089	0.071	0.084	0.087	0.695	0.702	0.634	0.619	239
Permanent wetlands																	
Croplands	0.075	0.063	0.069	0.077	-0.025	-0.008	0.025	-0.048	0.111	0.097	0.102	0.114	0.570	0.607	0.513	0.551	61
Urban and built-up																	
Crop/Natural vegetation mosaic	0.066	0.058	0.069	0.090	0.001	0.028	0.075	-0.088	0.092	0.088	0.117	0.153	0.633	0.674	0.531	0.494	23
Snow and ice																	
Barren/Sparse	0.023	0.024	0.033	0.039	-0.017	0.015	0.067	-0.002	0.038	0.036	0.075	0.048	0.509	0.461	0.356	0.389	6
Mean Absolute Bias					**0.063**	**0.057**	**0.083**	**0.081**									
SMAP L2SMP_E Average V2 (SMOS)	**0.049**	**0.046**	**0.056**	**0.067**	**-0.028**	**0.008**	**0.059**	**-0.039**	**0.074**	**0.067**	**0.096**	**0.097**	**0.633**	**0.635**	**0.540**	**0.497**	
SMAP L2SMP_E Average V1 (SMOS)	***0.053***	***0.051***	***0.059***	***0.065***	***-0.063***	***-0.041***	***-0.012***	***-0.043***	***0.097***	***0.083***	***0.084***	***0.094***	***0.639***	***0.645***	***0.601***	***0.575***	
Average is based upon all sets of observations, not the average of the land cover category results.																	

8.3 Summary

Three alternative L2SMP retrieval algorithms were evaluated using three methodologies in preparation for this release. The algorithms included the Single Channel Algorithm–H Polarization (SCA-H), Single Channel Algorithm–V Polarization (SCA-V), and Dual Channel Algorithm (DCA). Assessment methodologies were Core Validation Sites (CVS), sparse networks, and intercomparisons with SMOS.

For the current validated release (Version 5) of L2SMP, the goal was to update the previous assessment based primarily on CVS comparisons using metrics and time series plots. This assessment was supported by global assessments using sparse networks and SMOS intercomparisons. These analyses indicated that the SCA-V had better unbiased root mean square error and correlation and lower bias than the SCA-H or DCA. Based on the results, it is recommended that the SCA-V be continued as the operational baseline algorithm for this release. The overall ubRMSE of the SCA-V retrieved soil moisture from the descending (AM) orbits is 0.037 m^3/m^3, which is better than the mission requirement. Overall bias has also been reduced significantly compared to earlier versions of the L2SMP product.

Sparse network comparisons are more difficult to interpret due to upscaling but provide many more locations than the CVS. The analyses conducted here supported the conclusion reached in the CVS assessment, and contributed to improving validation through Triple Colocation analyses of uncertainties. The sparse network data also allowed the evaluation of performance based on land cover.

SMAP CVS and sparse network retrievals were compared to SMOS. These analyses supported the conclusions of prior assessments that the L2SMP currently has better performance metrics than SMOS.

The analyses described above were repeated for the L2SMP PM products. These show comparable performance to the AM results for all metrics. The comparable performance for AM and PM retrievals is attributed to the improved land surface temperature correction approach implemented in the new version.

The L2SMP_E Version 2 product was assessed using CVS chosen specifically to exploit the posting (9 km) and contributing domain (33 km) of the product. Results were essentially the same as those obtained in the L2SMP Version 5 analyses, which suggests that the product is as reliable as L2SMP.

Based on the extensive validation analyses to date, the number of peer reviewed publications (including the numerous independent investigations noted in the bibliography section), the length of the SMAP period of record, and the utilization of feedback of validation in a systematic update, with this version of L2SMP and L2SMP_E the team has completed CEOS Stage 4 validation [10]. The Cal/Val program will continue throughout the mission with the goals of increasing the robustness of the soil moisture products and addressing specific site issues.

9 OUTLOOK AND FUTURE PLANS

Satellite passive microwave retrieval of soil moisture has been the subject of intensive study and assessment for the past several decades. Over this time there have been improvements in the microwave instruments used, primarily in the availability of L-band sensors on orbit. However, sensor resolution has remained roughly the same over this period, which is actually an achievement considering the increase in sensor wavelength from X band to C band to L band over the years. With spatial resolution in the 25-50 km range, there will always be heterogeneity within the satellite footprint that will influence the accuracy of the retrieved soil moisture as well as its validation. Precipitation types and patterns are one of the biggest contributors to this heterogeneity. As a result, one should not expect that the validation metric ubRMSE will ever approach zero except in very homogeneous domains. In contrast, bias tends to be indicative of a systematic error, possibly related to algorithm parameterization and model structure. High quality data are needed to discover and address these systematic errors. Some issues that should be considered during the extended SMAP mission include:

- *Increasing the number of CVS.* There are several candidate calibration/validation sites that may yet qualify as CVS. Several will require additional time for further development (such as Millbrook, Kuwait, India).

- *Evaluate the impacts of algorithm structure and components on retrieval.* There are some aspects of soil moisture retrieval algorithms that are used because they facilitate operational soil moisture retrieval. One of these simplifying aspects is the use of the Fresnel equations that specify that conditions in the microwave contributing depth are uniform. While there is ample evidence that this is true in most cases, it should be recognized that this assumption is a potential source of error – some effort should be made to evaluate when and where it limits soil moisture retrieval accuracy. Another assumption is that a single dielectric mixing model applies under all conditions globally. All of the commonly-used dielectric models are highly dependent on the robustness of the data set used in their development. The impact of this assumption on retrieval error needs further evaluation. Another consideration in the current DCA is the assumption of equality of the vegetation parameters for the H and V polarizations. This assumption does simplify retrieval but it is not valid for all categories of vegetation.

- *Optimization of algorithm parameters.* The current release retains the same set of algorithm parameters used previously in SMAP Data Versions 2 to 4. Because the current algorithm parameters do not vary in time, they are likely to be inadequate for producing accurate retrieval results in agricultural areas where there is often high temporal variability of vegetation amount, land cover heterogeneity, and terrain roughness due to tillage. Initial attempts with spatio-temporal optimization of algorithm parameters have resulted in modest gains in retrieval performance at CVS. Full implementation of the optimization results would require more rigorous validation involving sparse network comparison in addition to CVS comparison, as well as a significant redesign of the current SMAP operational processing codes. It is anticipated that the benefits of using optimal coefficients will be demonstrated in future releases of the L2SMP product, along with other improvements.

- *Possible subdivision of crop land cover class into distinct crop subclasses.* Another source of error is SMAP's use of a single IGBP land cover class to cover the great variety of global crops. One area of future work will examine the possibility of subdividing the single crop class into a number of distinct subclasses (e.g., corn, soybeans, wheat, rice) with appropriate parameterization which would better represent the main global crop structural categories. Due to the latency problem in acquiring up-to-date crop maps, this issue is not likely to be addressed until the final bulk reprocessing of SMAP data.

- *Incorporating field campaign results into algorithm assessments and improvements.* Several SMAP field campaigns were conducted in 2016. Analyses of the data are ongoing and results from these field campaigns will be used in future assessments and algorithm improvements. It is expected that the results of the Iowa and Manitoba campaigns in 2016 will be of great value in resolving the significant error in soil moisture retrievals at these CVS (South Fork and Carmen).

- *Precipitation flag improvement.* Satellite observations made shortly after (or during) a rain event can be difficult to interpret and use in validation. A wet surface will dominate what the radiometer observes, which may be much wetter than at the 5 cm depth of an *in situ* sensor (due to the lag time for the wetting front to infiltrate down to the *in situ* sensor depth). Smaller precipitation events may be more problematic than larger events that wet a thicker surface layer. The divergence in these satellite observations will also be dependent on antecedent conditions (i.e., rain on a very dry soil). At the present time the GMAO model precipitation forecast for the three hours preceding a SMAP overpass at a given site is used. There is evidence that this approach is not adequate and that a longer time window might be necessary. However, achieving a longer time window for the SMAP precipitation flag will require additional/alternative processing of the GMAO data. Additionally, a comparison between using GMAO forecast model data and the GPM blended satellite data for the SMAP precipitation flag has begun.

- *Improvement of retrievals over forests.* Dense forests (where VWC > 5 kg/m^2) typically exceed the currently accepted threshold for accurate soil moisture retrieval. SMAP provides a flagged retrieval over forests, and the spatial extent of these flagged areas is quite large. At this point there is no supporting validation of the L2SMP soil moisture retrieved for forest areas, and the SMAP forest retrievals are quite different from SMOS. While extending accurate soil moisture retrievals to forests would likely be very beneficial to a variety of end users of the data, the SMAP team has little confidence in the accuracy and the appropriateness of the current baseline retrieval approach for soil moisture retrieval in forests. Future efforts to improve these retrievals should include both a careful evaluation of alternative algorithms and improving validation resources through a combination of CVS, temporary networks, and field campaigns. Planning is underway for a 2019 field campaign.

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