Soil Moisture Active Passive (SMAP) Project
Calibration and Validation for the L2/3_SM_P Version 3 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) product specifically for the validated release (Version 3). The SMAP Level 3 Soil Moisture Passive (L3SMP) product is simply a daily composite of the L2SMP half-orbit files. Hence, analysis and assessment of the L2SMP product can also be considered to cover the L3SMP product.

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 inter-comparison with products from ESA's Soil Moisture Ocean Salinity (SMOS) mission. These analyses satisfy the basic criteria established by the Committee on Earth Observing Satellites (CEOS) for Stage 2 validation, which supports validated release of the data based on the following definition: "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 have been evaluated over globally representative locations and time periods. Results are published in the peer-reviewed literature." The analyses now include nearly a full year of global intercomparisons and a paper that has been accepted for publication in a peer-reviewed journal [1].

The previous beta release assessment demonstrated that the baseline algorithm (Single Chanel Algorithm-Vertical, SCA-V) was meeting the project established performance criteria (unbiased root mean square error, ubRMSE < 0.04 m^3/m^3) for the core validation sites (CVS). However, this initial assessment was limited to six months of observations and a subset of potential CVS, due mainly to *in situ* data quality control or delivery issues. The current release expands the assessment time period to 11 months (which now includes all four seasons) and increases the number and diversity of CVS.

The primary assessment methodology was based on 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. 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. Analyses indicated that the SCA-V had better unbiased root mean square error (ubRMSE), bias, and correlation R than either the SCA-H or DCA. The differences in performance metrics between the three algorithms were relatively small (generally to the third decimal place). Based upon these results, it is recommended that the SCA-V be adopted as the operational baseline algorithm for the current validated release. The overall ubRMSE of the SCA-V is 0.039 m^3/m^3, which is better than the mission requirement of 0.040 m^3/m^3. In addition, since the beta release, a more rigorous quality control and upscaling of the CVS *in situ* data has been implemented.

Comparisons with sparse network *in situ* data are subject to upscaling issues and were not used as a primary methodology for performance assessment. However, the results from over 400 sparse network sites mirrored the CVS results. Intercomparisons with SMOS soil moisture retrievals serve as a means of assessing global performance, considering that SMOS provides a mature product. SMOS products were first assessed against data from the CVS, which showed similar levels of performance to SMAP. Global intercomparisons of SMOS to SMAP retrievals showed good agreement over most land cover types but indicated significant differences over forest covers.

Based upon the results of the previous beta release assessment, several investigations were initiated. These included a preliminary evaluation of parameter optimization, the impact of using Normalized Difference Vegetation Index (NDVI) climatology versus actual NDVI, and field campaigns to resolve anomalous behavior for selected agricultural CVS (South Fork and Carman). This report notes several other limitations in the current products that should also be investigated in the future. These issues include upscaling effects, changes to the algorithm approach that may improve performance in agricultural domains, and performance over very dense vegetation (specifically forests). In addition, the methodologies will expand in the future to include more CVS as issues are resolved at specific sites, model-based inter-comparisons, and the results of the intensive field experiments mentioned above. Despite these recognized issues, the L2SMP product is now considered by the L2SMP Team to have reached a sufficient level of maturity and quality that it meets the requirements of validation.

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 L1 science requirements according to the Cal/Val timeline.

The process is illustrated in Figure 2.1. In this Assessment Report the progress of the L2 Soil Moisture Passive Team in addressing these objectives prior to validated release is described. The approaches and procedures utilized follow those described in the SMAP Cal/Val Plan [2] and Algorithm Theoretical Basis Document for the Level 2 & 3 Soil Moisture (Passive) Data Products [3].

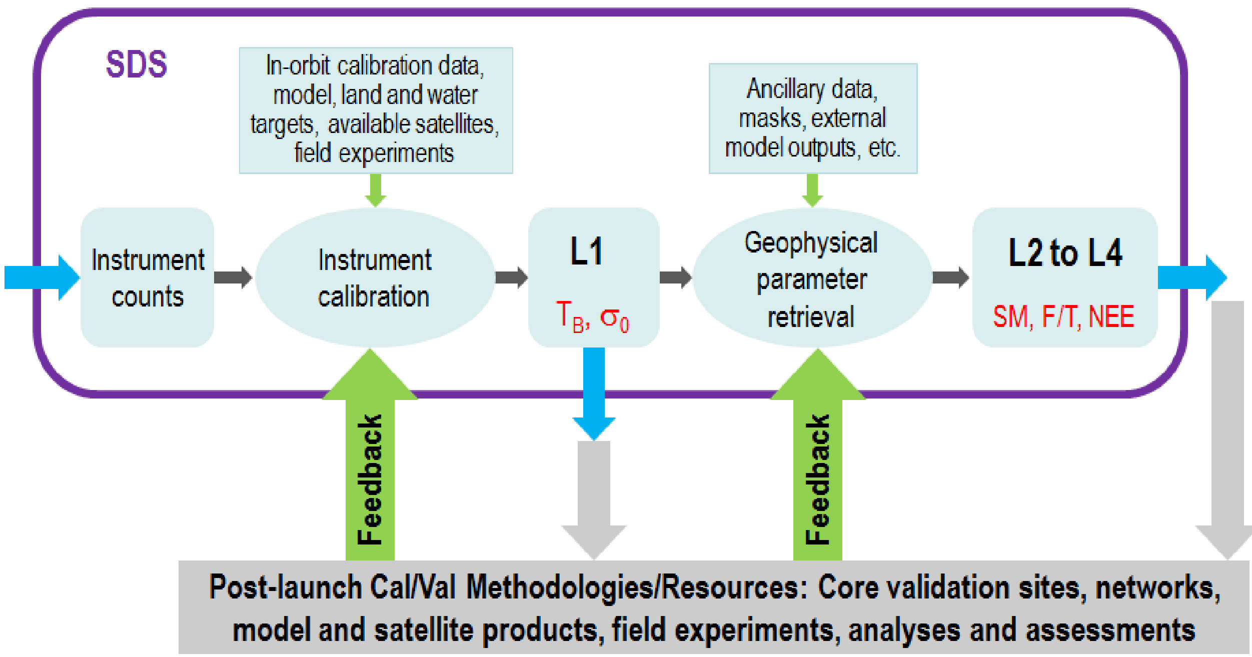

Figure 2.1. Overview of the SMAP Cal/Val Process.

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 [4], 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 Mission L1 Requirements Document [5] for the active/ passive soil moisture product.

In assessing the maturity of the L2SMP product, the L2SMP team considered the guidance provided by the Committee on Earth Observation Satellites (CEOS) Working Group on Calibration and Validation (WGCV) [6]:

- 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.

For the current release the L2SMP team has completed Stage 2, which is the criteria for a validated release. This was accomplished using CVS combined with sparse networks and SMOS intercomparisons over almost a full year and by submitting assessment results to a peer-reviewed journal. Details of the assessments are provided in Section 7. The Cal/Val program will continue through these CEOS stages over the SMAP mission life span with the goal of achieving Stages 3 and 4.

3 EXPECTED PERFORMANCE OF L1 RADIOMETER DATA AND IMPACT ON L2SMP

The L2SMP soil moisture retrievals are based on Version 3 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. The data meet the noise equivalent delta temperature (NEDT) and geolocation requirements with margin (see Table 3.1). The Version 3 calibration includes a revised thermal model for the instrument reflector. The inclusion of the new thermal model required a recalibration of the instrument, which resulted in a change in comparison to SMOS. Global average brightness temperature comparisons over land areas are 2 K lower than SMOS (mean difference at top of the atmosphere after Faraday rotation correction was applied). A future but small change in reflector or radome emissivity (predicted for the next major data release, likely in 2017) will subtlety modify this bias. Calibration drift is less ±0.1 K relative to the global ocean, much improved over Version 1 and 2 data. Previously observed fore-aft differences in L1C_TB due to antenna sidelobe contamination and radio frequency interference (RFI) still remain. Asymmetric antenna sidelobes create fore-aft differences of several K along coastlines. A similar effect is possible in highly heterogeneous land areas, especially those with mixed land and water. Finally, RFI behavior is similar as before: conditions in the Americas and Europe are good with poorer conditions in Asia. 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 3.1. Version 3 Characteristics of SMAP L1 Radiometer Data

Parameter		**Mission Requirement**
NEDT	1.1 K	< 1.6 K[1]
Geolocation accuracy	2.7 km	< 4 km
Land SMAP/SMOS bias (H pol)	–2.2 K	n/a
Land SMAP/SMOS bias (V pol)	–2.3 K	n/a

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^o incidence angle (after applying the Faraday rotation correction). SMAP L1B observations were co-located with reprocessed SMOS observations (less than 30 min difference). The current L1B radiometer data (T12400) were compared with the most recent SMOS L1B data (version 620) for this analysis.

[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 [7]). 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 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.

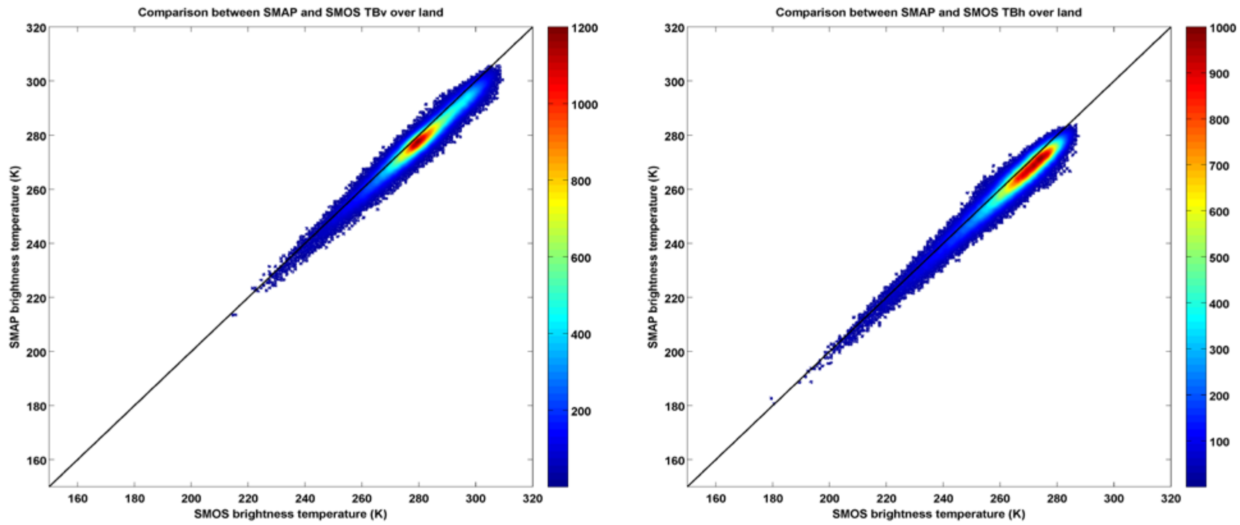

Figure 3.1 Density plot of the L1 brightness temperature comparison (top of the atmosphere) between SMAP and SMOS observations over land targets for V-pol (left) and H-pol (right).

Table 3.2. Summary statistics of the brightness temperature comparison between SMOS and SMAP observations.

		RMSD (K)	R	Bias [SMAP-SMOS] (K)
H pol	Land	4.32	0.9753	-2.20
	Ocean	2.48	0.7035	0.01
	Overall	3.05	0.9994	-0.54
V pol	Land	4.17	0.9737	-2.27
	Ocean	2.55	0.7767	-0.34
	Overall	3.04	0.9994	-0.82

Figure 3.1 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 3.2). SMAP observations show a colder T_B bias (about 2 K) 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 0.4 K mean difference at top of the atmosphere. Efforts will be made to address these differences in T_B calibration and to develop a consistent L-band brightness temperature dataset between SMOS and SMAP missions. The impact of these T_B differences on soil moisture comparisons between the two satellites is more complex because the two missions use different soil moisture algorithms and ancillary datasets.

4 ALTERNATIVE L2SMP ALGORITHMS

The current L2SMP contains soil moisture retrieval fields produced by the baseline and several optional algorithms. Inside an L2SMP 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 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)

Given the results to date from the L2SMP 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 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.

All five 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. Below is a concise description of the algorithms. Further details are provided in [3].

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

In the SCA-V, the vertically polarized T_B 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 L2SMP software code includes the option of using different dielectric models. Currently, the software switch is set to the Mironov model [8]]. Analytically, SCA-V attempts to solve for one unknown variable (soil moisture) from one equation that relates the vertically polarized T_B to soil moisture. Vegetation information is provided by a 13-year climatological data base of global NDVI and a table of parameters based on land cover and polarization.

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

The SCA-H is similar to SCA-V, in that the horizontally polarized T_B 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 $T_{\mathbf{B}}$ to soil moisture. Vegetation information is provided by a 13-year climatological data base of global NDVI and a table of parameters based on land cover and polarization.

4.3 Dual Channel Algorithm (DCA)

In the DCA, both the vertically and horizontally polarized T_B 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 T_Bs:

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

In each iteration step, the soil moisture and vegetation opacity are adjusted simultaneously until the cost function attains a minimum in a least square 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. Unlike MPRA (Section 4.4), DCA permits polarization dependence of coefficients in the forward modeling of T_B observations. As currently implemented for the validated release, the H and V parameters are set the same. During ongoing intensive Cal/Val activities leading up to the next release of the L2SMP data, implementing polarization dependence for the tau-omega model parameters will be investigated.

4.4 Microwave Polarization Ratio Algorithm (MPRA)

The MPRA is based on the Land Parameter Retrieval Model [9] and was first applied to multi-frequency satellites such as AMSR-E. Like DCA, MPRA attempts to solve for soil moisture and vegetation optical depth using the vertically and horizontally polarized T_B observations. However, it does so under the assumptions that (1) the soil and canopy temperatures are considered equal, and (2) vegetation transmissivity (γ) and the single-scattering albedo (ω) are the same for both H and V polarizations. When these assumptions are satisfied, it can be shown that the soil moisture and vegetation optical depth can be solved analytically in closed form, resulting in the same solutions as would be obtained iteratively using DCA. Similarly to DCA, ancillary information such as effective soil temperature, surface roughness, and vegetation single scattering albedo must be known *a priori* before the inversion process.

4.5 Extended Dual Channel Algorithm (E-DCA)

The E-DCA is a variant of DCA. Like DCA, E-DCA uses both the vertically and horizontally polarized T_B observations to solve for soil moisture and vegetation optical depth. In E-DCA, however, the cost function (Φ^2) is formulated in a way different from that of DCA. Instead of minimizing the sum of squares of the differences between the observed and estimated T_Bs as in DCA (Equation 1 above), the E-DCA attempts to minimize the sum of squares of the difference between the observed and estimated normalized polarization differences (expressed in natural logarithm) and the difference between the observed and estimated T_Bs (also expressed in natural logarithm) as follows:

$$\min \Phi_{\mathrm{E-DCA}}^2 = \left[\log\left(\frac{T_{B,v}^{obs} - T_{B,h}^{obs}}{T_{B,v}^{obs} + T_{B,h}^{obs}}\right) - \log\left(\frac{T_{B,v}^{est} - T_{B,h}^{est}}{T_{B,v}^{est} + T_{B,h}^{est}}\right)\right]^2 + \left[\log\left(T_{B,h}^{obs}\right) - \log\left(T_{B,h}^{est}\right)\right]^2 \tag{2}$$

In each iteration step, soil moisture and vegetation opacity are adjusted simultaneously until the cost function attains a minimum in a least square sense. It is clear that when both Φ_{DCA}^2 and $\Phi_{\mathrm{E-DCA}}^2$ attain their theoretical minimum value (i.e. zero) in the absence of uncertainties of modeling, observations, and ancillary data, $T_{B,v}^{obs} = T_{B,v}^{est}$ and $T_{B,h}^{obs} = T_{B,h}^{est}$, implying that DCA and E-DCA converge to the same solutions. The advantage of E-DCA over DCA, however, is apparent when in reality there is finite uncertainty (e.g., a dry bias associated with the ancillary soil temperature data) -- this uncertainty will be cancelled from the numerator and denominator in the calculation of the normalized polarization difference in Φ_{E-DCA}^2, leaving such uncertainty affecting only one component of the cost function instead of two components as in Φ_{DCA}^2. This reduction in the impact of soil temperature uncertainty on soil moisture retrieval should make E-DCA more tolerant of soil temperature uncertainty, resulting in fewer instances of retrieval failure than DCA. At present, there are a few caveats associated with E-DCA: (1) its exact performance is being evaluated in the ongoing Cal/Val activities and is not included in this assessment report, and (2) the choice of the horizontally polarized T_B in the Φ_{E-DCA}^2 formulation is subject to further assessment as analyses of new observations and Cal/Val data become available.

5 METHODOLOGIES USED FOR L2 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 the 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: 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 data product, all of these methodologies can contribute to product assessment and improvement.

5.1 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 facilitates temporal analyses and the disaggregation algorithm used for the AP 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 T_Bs 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.

SMAP provides L2 surface (0-5 cm) soil moisture using the radiometer (passive) data only posted on a 36 km EASE2 Grid. The standard SMAP grid was established without any acknowledgement of where the CVS might be located. In addition, the CVS were established in most cases to satisfy other 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 $N \geq 9$). 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 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 process of the validation grid processing is illustrated in Figure 5.1.

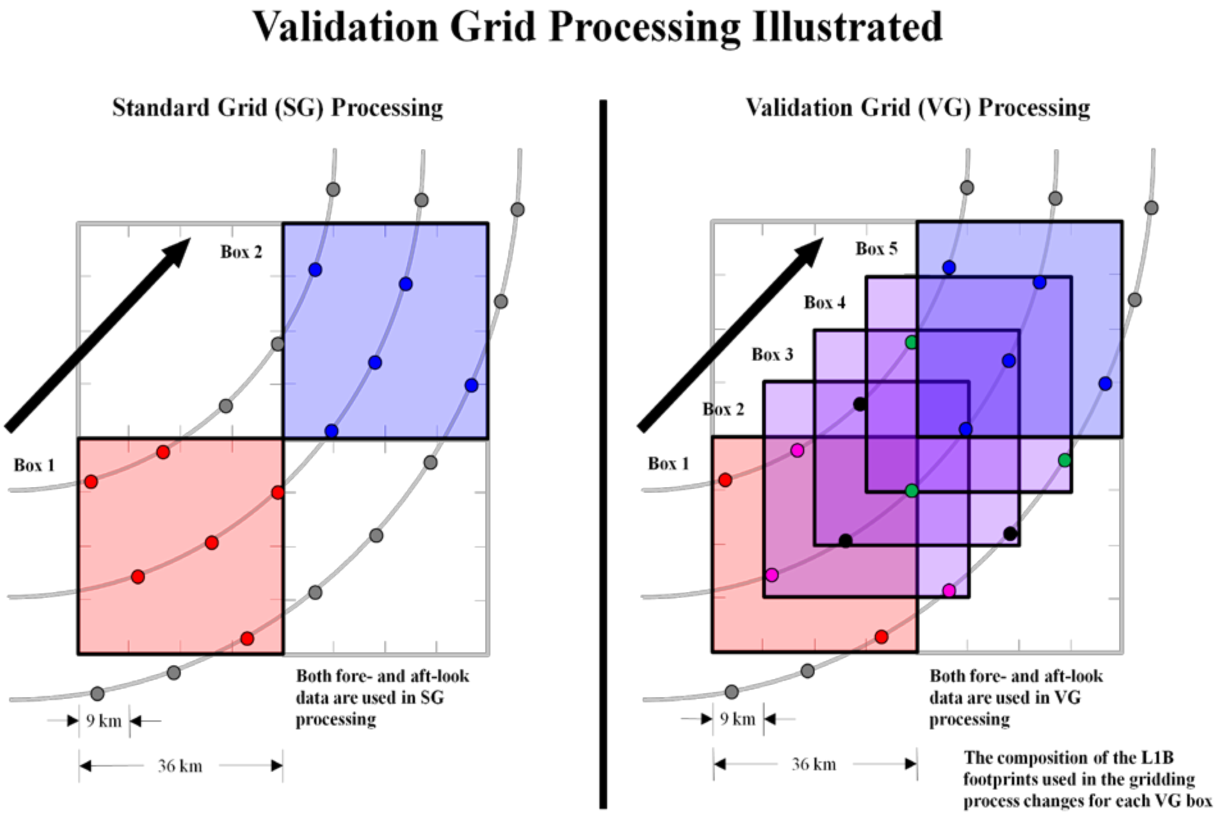

Figure 5.1. Illustration of validation grid processing. The EASE GRID2 boxes are shifted by 3 km increments (although 9 km shifts are shown for clarity) to allow a better geographical match with the *in situ* validation sites.

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.). All of the quantitative analyses and metrics in this Assessment Report are based on results using the 36 km validation grid.

6 L2SMP REFINEMENTS IN VERSION 3

- *Expanded Assessment Period*: For the previous beta release report, the analysis time period was April 1- October 26, 2015. The start date 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 beta release report. The current assessment report expands the time period from April 1, 2015 through February 29, 2016, which provides a more robust assessment of four seasons over approximately a full year (11 months).

- *Increased Number of CVS*: Two sites were added to the list of those used in the beta report assessment, Twente (Netherlands) and MAHASRI (Mongolia). Both sites have latency issues that prevented their use in previous assessments. Both sites are well-calibrated sites and contribute to the diversity of the CVS.

- *Increased Number of Sparse Networks*: Two networks were added, the Oklahoma Mesonet and MAHASRI (Mongolia). The Oklahoma Mesonet greatly increases the number of available stations (+140) and is one of the most utilized data sources for soil moisture investigations.

- *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 validation grid. This process can result in the removal of stations that then requires modification of the upscaling function.

- *Improved Screening of L1 T_B data*: A more rigorous screening process has also been implemented for the L1 brightness temperature data. This screening involves checking the master bit of the T_B quality flag and then taking appropriate action (e.g., whether the master bit indicates that the T_B data should be excluded from soil moisture retrievals due to the presence of significant RFI, etc.).

- *Incorporated the Recent Calibrations of the L1 T_B Data*: As mentioned in Chapter 3, the L2SMP soil moisture retrievals are now based on Version 3 of the radiometer Level 1B and 1C brightness temperature data. This new T_B calibration generally resulted in slightly lower T_B over land as compared to the SMAP beta release data (Version 2).

7 ASSESSMENTS

7.1 Global Patterns and Features

In this section, prior to the quantitative assessments that follow, the general features of global images are reviewed for various combinations of algorithms and products. All images are global composites of SMAP L2SMP over a one-week period in June (June 1-7, 2015); averaging is performed for locations where orbits overlap. These images are composites of all 6 am Equator crossing (descending) L2SMP half-orbits within the stated period. This is equivalent to the SMAP L3SMP product composited over the same time period. Note that complete global coverage can be achieved by compositing three days of SMAP L2SMP descending orbits. The global images shown below include:

- Three SMAP algorithms (SCA-V, SCA-H, DCA) without flags applied.
- SCA-V without and with flags applied.
- SCA-V and SMOS without flags applied.
- SCA-V and SMOS with flags applied.

Figure 7.1 shows global images developed from the three SMAP L2SMP algorithms being evaluated in this report. The regions that are expected to be very dry (i.e., the Sahara desert) and wet (i.e., the Amazon Basin) reflect the expected levels of retrieved soil moisture. In general, the world appears to be a little wetter from SCA-H to SCA-V to the DCA results. Otherwise, the global patterns are similar.

There are a number of quality flags that are applied to SMAP products. Some of these flags indicate that the data should be used with caution while others imply that the data should not be used at all. A complete description of the flags and flag thresholds used in L2SMP processing can be found in the ATBD [3]. In Figure 7.2 the impact of applying the quality flags is illustrated for the SMAP L2SMP SCA-V retrieved soil moisture. A significant portion of global land surface area is removed (white areas show where flags indicate a possible issue with retrieval quality). A large amount of the white area is related to the vegetation water content (VWC). The reliability of soil moisture retrieval algorithms is known to decrease when the VWC exceeds 5 kg/m^2 – this VWC value is used by SMAP as a flag threshold to indicate areas of dense vegetation where soil moisture retrievals are possibly less accurate. It is anticipated that some of the flag thresholds may be relaxed in time as the algorithms are improved for the presence of certain currently problematic surface conditions.

An important comparison is made in Figure 7.3 where the SMAP L2SMP SCA-V global composite is shown compared with the SMOS L3 (version v280: April 1-April 30, 2015; version v300: May 1, 2015-Feb 29, 2016) soil moisture product composited over the same period using 6 am Equator crossing orbits. Some features are similar (i.e., the Sahara), but there are some very obvious differences between the soil moisture from the two missions. Areas where SMAP or SMOS do not provide soil moisture retrievals (for whatever reason) are shown as white in the images. For SMOS this results in large blanked out areas (i.e. some parts of the Middle-East and Asia) compared to SMAP, which has more sophisticated RFI detection and mitigation. Other flags (mountainous topography) are likely also being applied to the SMOS data. The other significant difference is that the SCA-V algorithm predicts higher soil moisture in forested domains. This difference will be addressed as improved SMAP and SMOS forest algorithms are developed.

As a follow-on to the discussion above, the flagged SMAP L2SMP SCA-V and SMOS L3 products are compared in Figure 7.4. When both sets of mission flags are applied, a significant fraction of the data are eliminated from comparison. In general, SMAP appears to be more aggressive in its use of the VWC flag than SMOS. The entire Amazon, Central Africa, and Eastern U.S. are flagged by SMAP but less so by SMOS. Another difference is the additional RFI flagging by SMOS that seems to eliminate all retrievals in Asia. SMOS also flags retrievals over several obvious arid domains (i.e. the southwestern USA and the Sahara). The source of these differences needs to be investigated with the SMOS team.

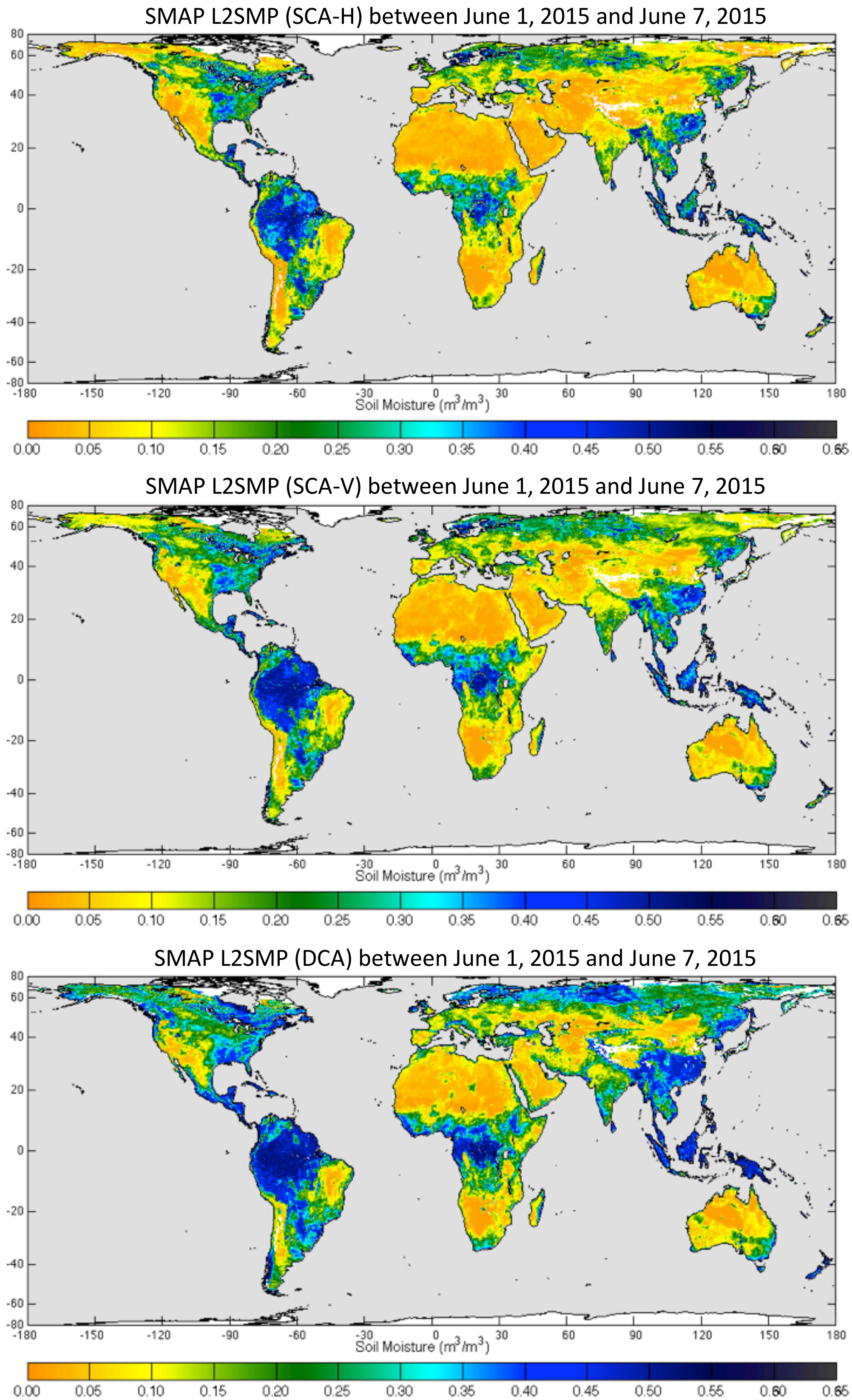

Figure 7.1. SMAP L2SMP global images of soil moisture for three alternative algorithms.

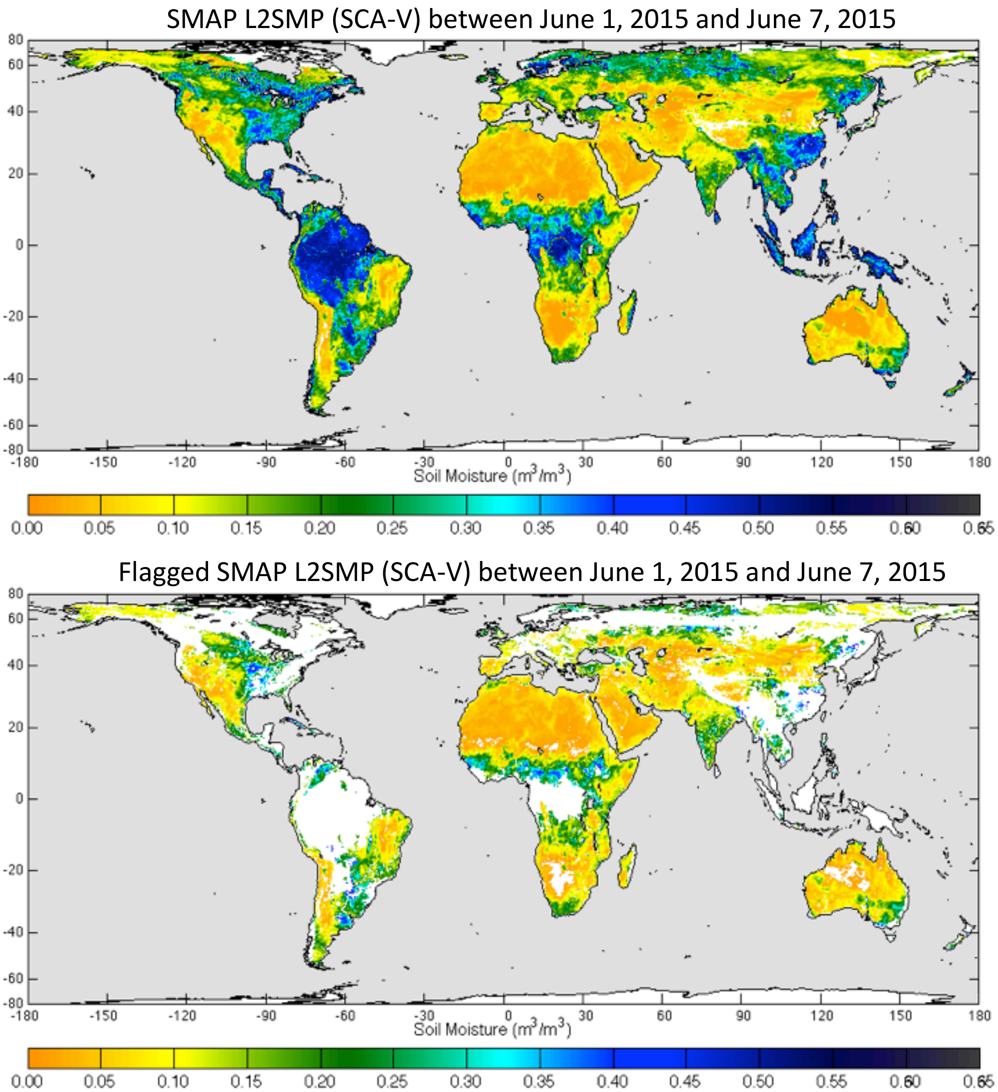

Figure 7.2. SMAP L2SMP global images of soil moisture including (top) or excluding (bottom) flagged data.

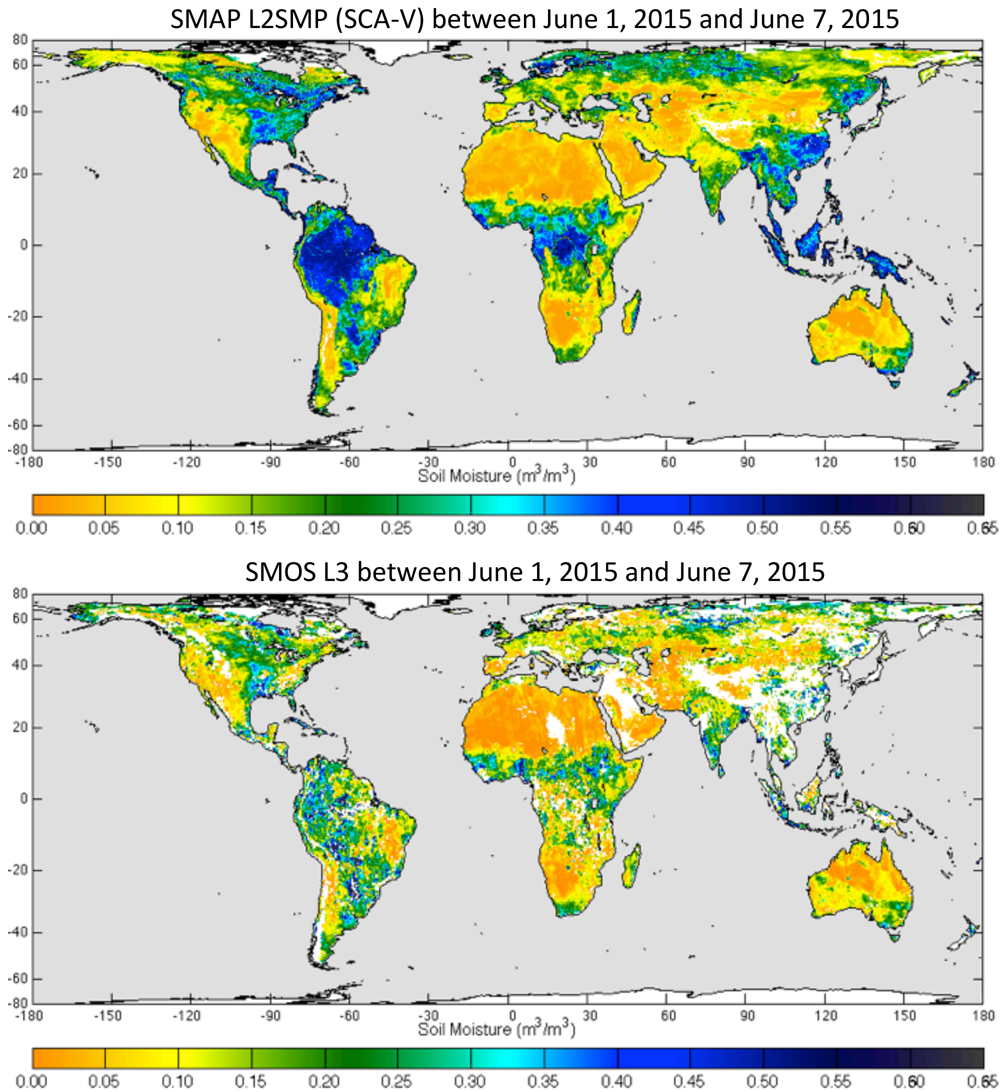

Figure 7.3. SMAP L2SMP and SMOS L3 global images including flagged soil moisture data.

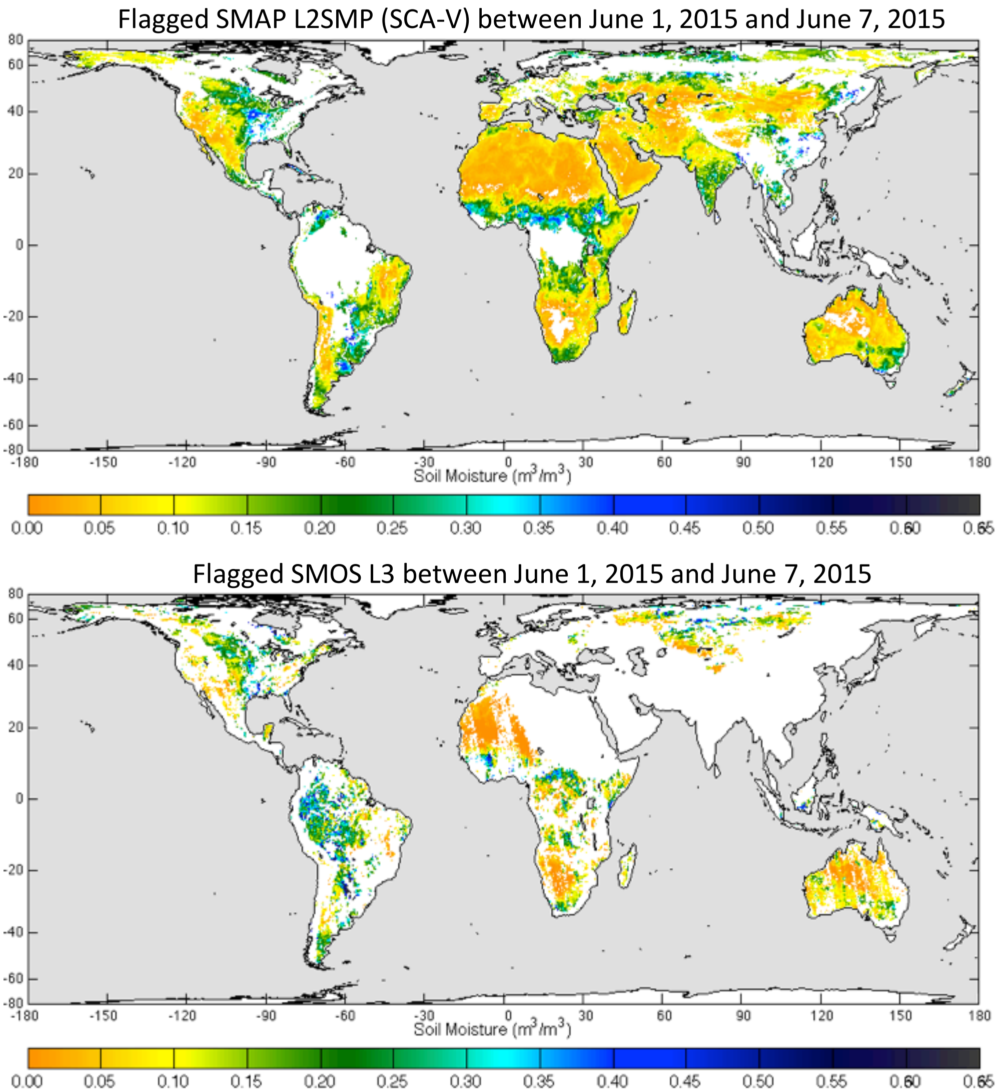

Figure 7.4. SMAP L2SMP and SMOS L3 global images of soil moisture excluding flagged data.

7.2 Core Validation Sites (CVS)

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 [2].

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 7.1.

Not all of the sites in Table 7.1 have reached a level of maturity that would support their use as CVS. In some cases this is simply a latency problem that will be resolved in time. 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 was repeated prior to the current assessment, with the addition of the new screening procedure for *in situ* data. 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 are marked with an asterisk in Table 7.1. A total of 15 CVS were used in this assessment. 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.

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 [10]. 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 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 are the charts illustrated by Figures 7.5-7.8. 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 L3 v280 was used for April 1-May 4, 2015 and SMOS L3 v300 was used for May 5, 2015-February 29, 2016). 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.

All sites are then compiled to summarize the metrics and compute the overall performance. Table 7.2 gives the overall results for the current validated data set. The combined scatter plots associated with these results are shown in Figure 7.9. 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 7.2. First, all algorithms have about the same ubRMSE, differing by 0.006 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 has slightly better values (it exceeds the ubRMSE mission requirement). More obvious differences among the algorithms were found in the bias, with the SCA-V having a slight dry bias and DCA having a slight wet bias.. SCA-V had the best performance for all metrics.

For guidance in expected performance, the SMOS soil moisture products for each site over the same time period were analyzed and these summary statistics are included in Table 7.2. For the CVS analyzed here, SMAP SCA-V outperforms SMOS for all meterics, although they are generally of the same order of magnitude.

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

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. [11] 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.

The results for individual CVS reveal many features that support the quality of the algorithms and/or possible directions for improvement. Four examples are presented here.

Table 7.1. 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
Twente*	Z. Su	Netherlands	Cold	Cropland/natural mosaic
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 assessment.				

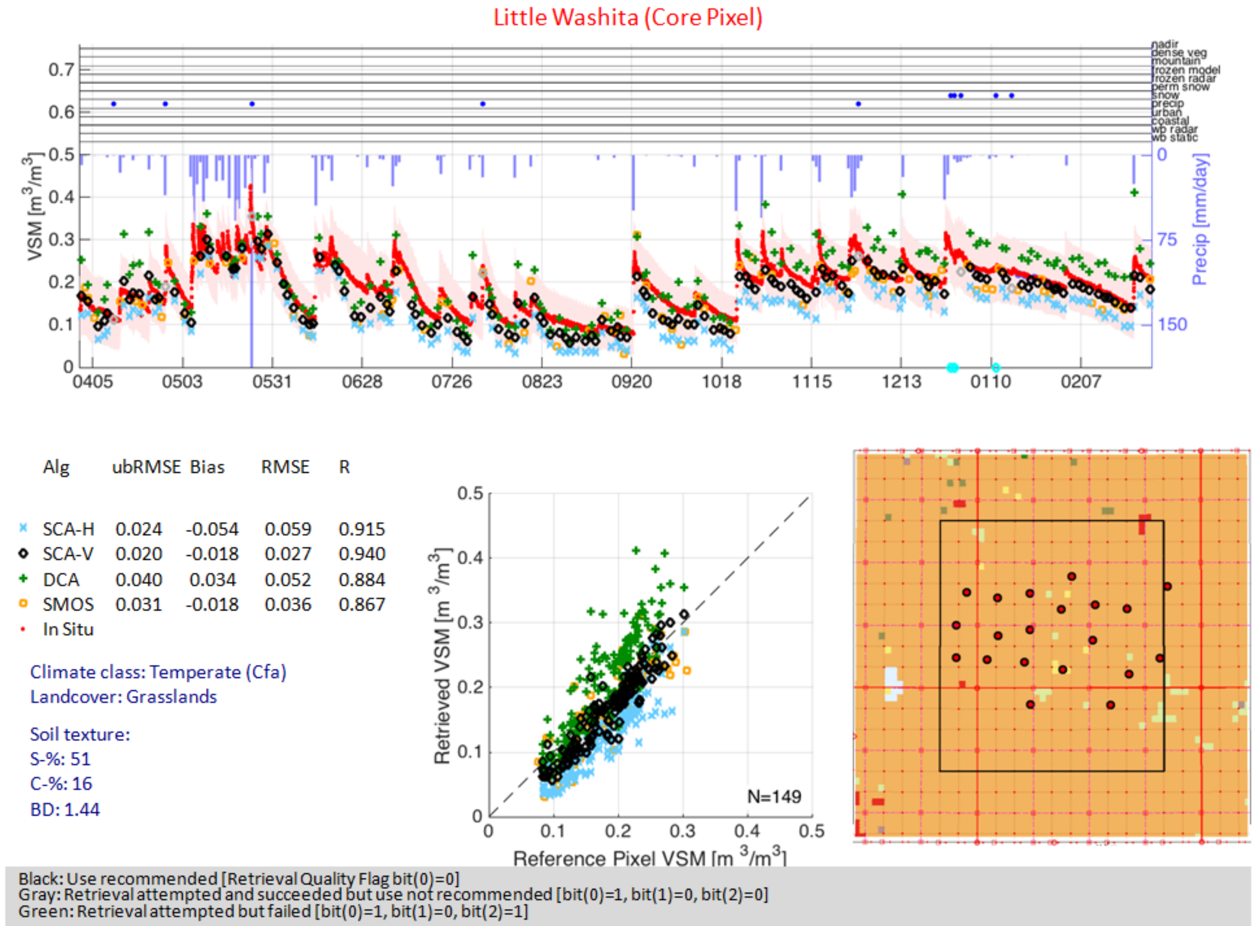

Figure 7.5. L2SMP Assessment Tool Report for Little Washita, OK.

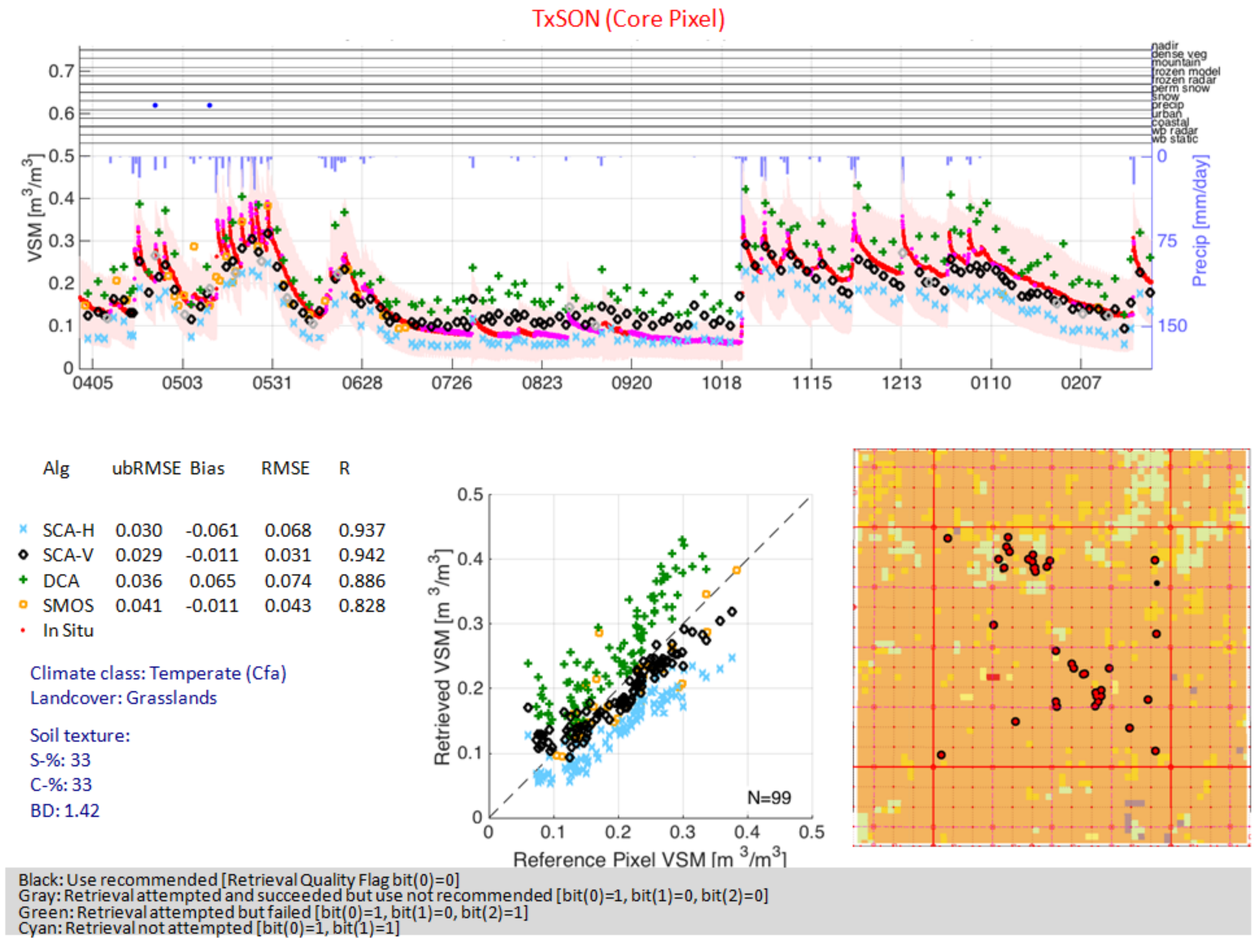

Figure 7.6. L2SMP Assessment Tool Report for TxSON, TX.

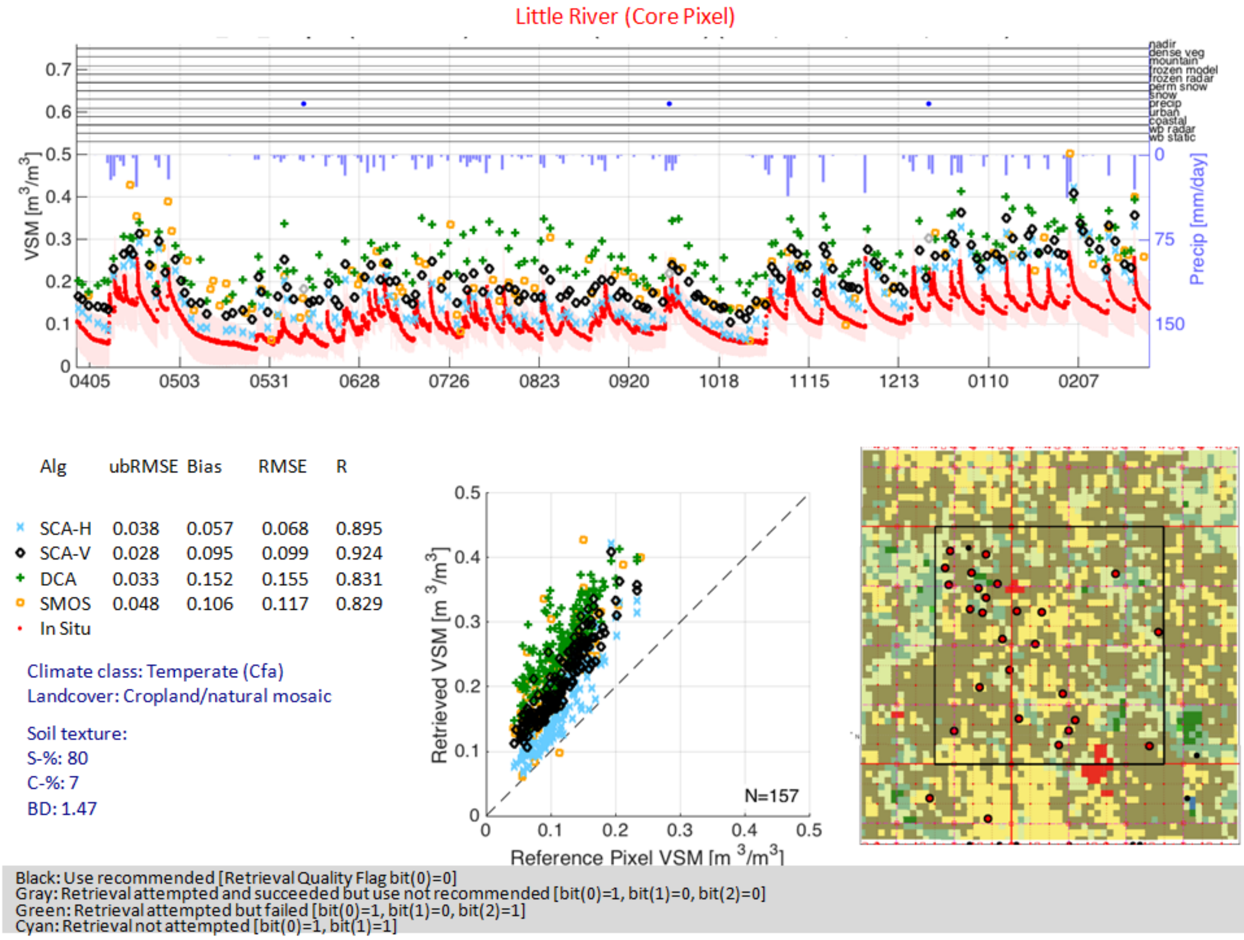

Figure 7.7. L2SMP Assessment Tool Report for Little River, GA.

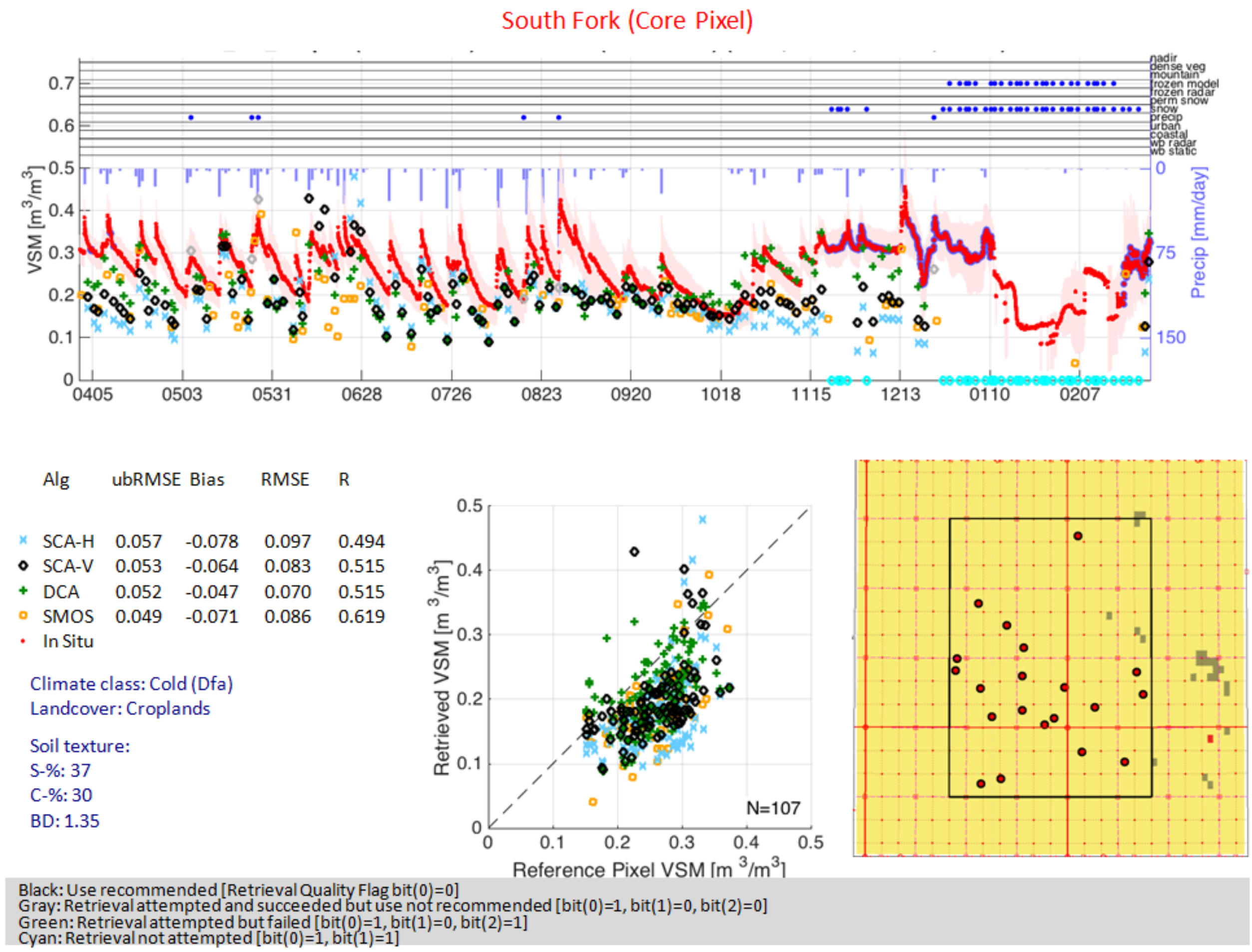

Figure 7.8. L2SMP Assessment Tool Report for South Fork, IA.

Table 7.2. SMAP L2SMP Version 3 CVS Assessment

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	0.041	0.041	0.055	-0.065	-0.030	-0.003	0.077	0.051	0.055	0.638	0.670	0.650	86	93	93
Walnut Gulch	0.026	0.028	0.041	-0.028	-0.006	0.015	0.038	0.028	0.043	0.587	0.688	0.674	86	101	97
TxSON	0.030	0.029	0.036	-0.061	-0.011	0.065	0.068	0.031	0.074	0.937	0.942	0.886	99	99	97
Fort Cobb	0.033	0.029	0.042	-0.069	-0.040	-0.003	0.076	0.049	0.042	0.870	0.883	0.815	137	137	137
Little Washita	0.024	0.020	0.040	-0.054	-0.018	0.034	0.059	0.027	0.052	0.915	0.940	0.884	149	149	148
South Fork	0.057	0.053	0.052	-0.078	-0.064	-0.047	0.097	0.083	0.070	0.494	0.515	0.515	104	107	107
Little River	0.038	0.028	0.033	0.057	0.095	0.152	0.068	0.099	0.155	0.895	0.924	0.831	157	157	157
Kenaston	0.037	0.026	0.039	-0.061	-0.035	0.008	0.071	0.043	0.040	0.661	0.774	0.584	76	76	76
Carman	0.084	0.058	0.055	-0.088	-0.085	-0.075	0.121	0.103	0.093	0.570	0.620	0.471	101	102	102
Monte Buey	0.072	0.056	0.045	0.004	0.013	-0.010	0.072	0.058	0.047	0.776	0.885	0.682	74	87	88
REMEDHUS	0.034	0.039	0.050	-0.031	-0.013	0.004	0.046	0.041	0.050	0.908	0.897	0.882	142	138	132
Twente	0.070	0.054	0.047	0.021	0.035	0.049	0.073	0.064	0.068	0.909	0.919	0.847	153	157	157
MAHASRI	0.030	0.037	0.034	-0.007	-0.008	-0.005	0.031	0.037	0.034	0.788	0.765	0.782	63	47	51
Yanco	0.040	0.037	0.038	-0.012	0.013	0.034	0.042	0.039	0.051	0.923	0.936	0.930	104	105	105
Kyeamba	0.056	0.054	0.043	-0.019	0.004	0.017	0.059	0.054	0.046	0.918	0.948	0.942	99	116	122
SMAP Average	0.045	0.039	0.043	-0.033	-0.010	0.016	0.067	0.054	0.061	0.786	0.820	0.758			
SMOS Average	0.048			-0.023			0.066			0.750					

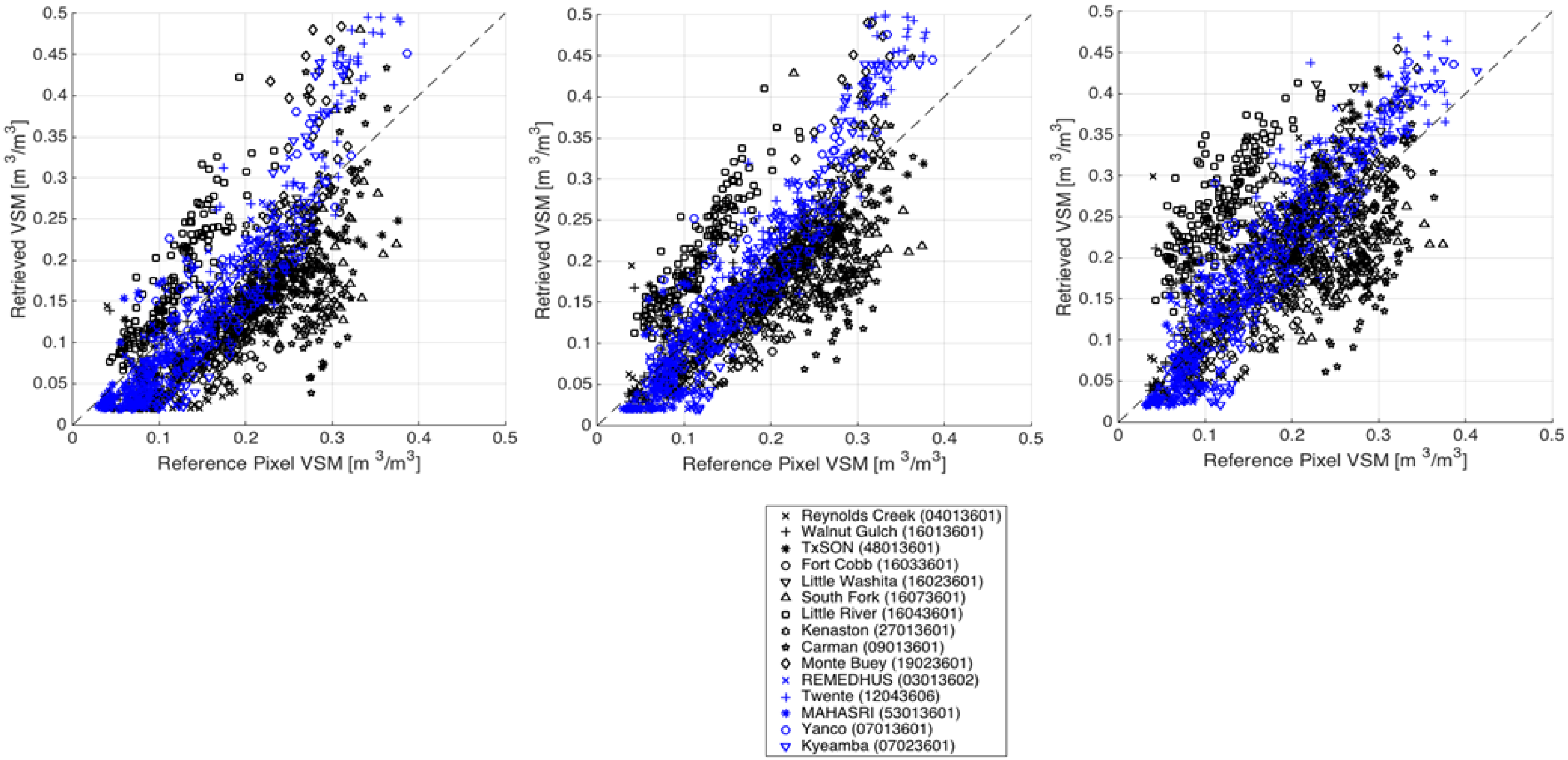

Figure 7.9. Scatterplot of SMAP L2SMP Version 3 CVS Assessment (SCA-H left panel, SCA-V middle panel, and DCA right panel).

7.2.1 Little Washita, OK: Benchmark Site

The Little Washita watershed in Oklahoma has been utilized for many microwave soil moisture validation studies in the past that have incorporated both sensor calibration and upscaling. Therefore, confidence is higher in the *in situ* estimate for this site, and performance at this site is considered to be an important factor in algorithm performance.

The first feature to note in Figure 7.5 is the wide range of soil moisture observed during the 11-month assessment period. Dry conditions in April were followed by historic amounts of precipitation in May. This was followed by an extended drydown (end of May) that clearly illustrates the correlation of the *in situ* and satellite observations (it also corresponded to the same type of data set observed here in 1992 [12]). The next drydown later 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. Numerous wetting and drying periods followed and exhibited similar patterns. Overall, the site exhibits exceptionally high correlation, 0.940 for SCA-V, and one of the lowest RMSE and ubRMSE values. SMAP and SMOS have approximately the same level of performance.

7.2.2 TxSON, TX: New Site

While Little Washita is one of the oldest sites, TxSON is one of the newest and was designed specifically to satisfy validation of all three of the original SMAP L2/L3 soil moisture products (at 3, 9, and 36 km spatial scales). As shown in Figure 7.6, the precipitation pattern over the eleven months was similar to Oklahoma: dry followed by a very wet May and then an extended drydown.

This site also has an exceptionally high correlation between the observed and estimated soil moisture. It too shows similar performance for SMOS and SCA-V. It seems that the larger errors and positive bias of the DCA are associated with rain events. This type of error could involve smaller rain events that wet the near surface but do not wet to the depth of the *in situ* sensor, thus causing SMAP DCA to overestimate the soil moisture present. Neither of the SCA algorithms reflect this issue. An important point to note concerning this site is that it demonstrates that a new site can make a major contribution to validation of satellite products if the proper protocols are followed during development and implementation.

7.2.3 Little River, GA: Known Issues

Little River has been providing *in situ* soil moisture since the beginning of the AMSR-E mission [13] and was the only site representing humid agricultural environments in that study. Beyond these features, it includes a substantial amount of tree cover, has very sandy soils, and utilizes irrigation. The SCA-H has been applied here previously with success but SMOS has had issues in its retrievals [14], which are reflected in the results shown in Figure 7.7. All algorithms suffer from large overestimation bias, including SMOS. However, correlations are high and scatter is low (reflected in the low ubRMSE). 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 been used in algorithm development. In the case of this site, one potential source of the overestimation may be the parameterization of the forest land cover effects.

7.2.4 South Fork, IA: New and Complex

South Fork is an agricultural region dominated by summer crops of corn and soybeans. Conditions in April were mostly bare soil/stubble. These early season conditions were followed by intensive tillage that created large surface roughness not accounted for by the land cover-based surface roughness parameter used in the tau-omega model. This roughness decreased with subsequent soil treatments and rainfall, and became less of an issue as the growing season proceeded. By mid-July corn would have a high VWC (~5 kg/m^2) while soybeans would be much smaller (~1 kg/m^2) [15]. In the fall there would be a harvest and some tillage again, resulting in a significant variation in roughness throughout the year.

As shown in Figure 7.8, all algorithms, including the DCA, have a moderate underestimation bias. In fact, all metrics for all the algorithms, including SMOS, are similar. There are periods over the 11-month window when SMOS and SMAP are correlated (i.e., July) and others where the behavior is difficult to explain (i.e., June). Later in the summer when the canopy reaches its maximum vegetation water content (late August), the effect of canopy attenuation may be present. Several rain events that are reflected in the *in situ* data are not evident in the satellite retrievals.

The first aspect of the overall underestimation bias that was examined was the reliability of the *in situ* estimates. This was addressed by an extended study involving sensor calibration and additional point sampling that clearly showed that the network represents the average soil moisture of the 0-5 cm soil layer of the SMAP grid cell [16].

The anomalous behavior here led to the inclusion of South Fork in the SMAP Validation Experiments (field campaigns) in 2016. The campaign is expected to provide high quality temporal and spatial observations of T_B, soil moisture and vegetation that can be used to resolve the source of these errors.

7.2.5 Evaluation of South Fork Parameterization

One analysis that was completed involved attempting to optimize the b and h parameters of the SCA-V in order to reduce bias and ubRMSE. First b was optimized for the entire period of record, then a seasonal optimization was performed. These results are shown in Table 7.3 and Figures 7.10 and 7.11.

It has been recognized that large retrieval error can occur at agricultural sites during periods of the year when VWC is near zero (pre-planting, post-harvesting), which might be explained by tillage and varying roughness. The current L2SMP algorithms operate with a single set of h and b values (based on land cover at the site). Previous studies have shown that surface roughness in agricultural fields will vary with treatment, accumulated rainfall, and season [17]. In order to explore the impact of constant year-long coefficients on soil moisture retrieval performance, two separate analysis were conducted in which the South Fork h and b parameters were optimized for (a) the complete data record of 11 months, and (b) where the observations were divided into the crop growth season and Fall-Spring, less winter frozen soils/snow. For the complete data record, site specific values of h=0.2 and b=0.15 were obtained. For the growth season, the value of h was fixed at 0.19 and the value of b was optimized (a value of b=0.14 was obtained). Following this analysis, the value of h was optimized for the bare soil period (resulting in h=0.3) (Fall-Spring). These parameters were then applied in the soil moisture retrieval. The key result is that in using this approach, it is possible to remove the large bias formerly present at this core site. However, this seasonally varying optimization had little impact on the ubRMSE between the *in situ* soil moisture and the SMAP-retrieved soil moisture. The results were slightly better when seasonal parameters were used in the retrieval [RMSE (yearly)=0.055 m^3/m^3; RMSE (seasonal)=0.052 m^3/m^3]. This may be due to site heterogeneity, the use of climatology for NDVI, or algorithm limitations. The results show that it is possible to improve the soil moisture estimates in agricultural domains by using seasonally varying parameters. Further evaluation is required before such an approach is implemented.

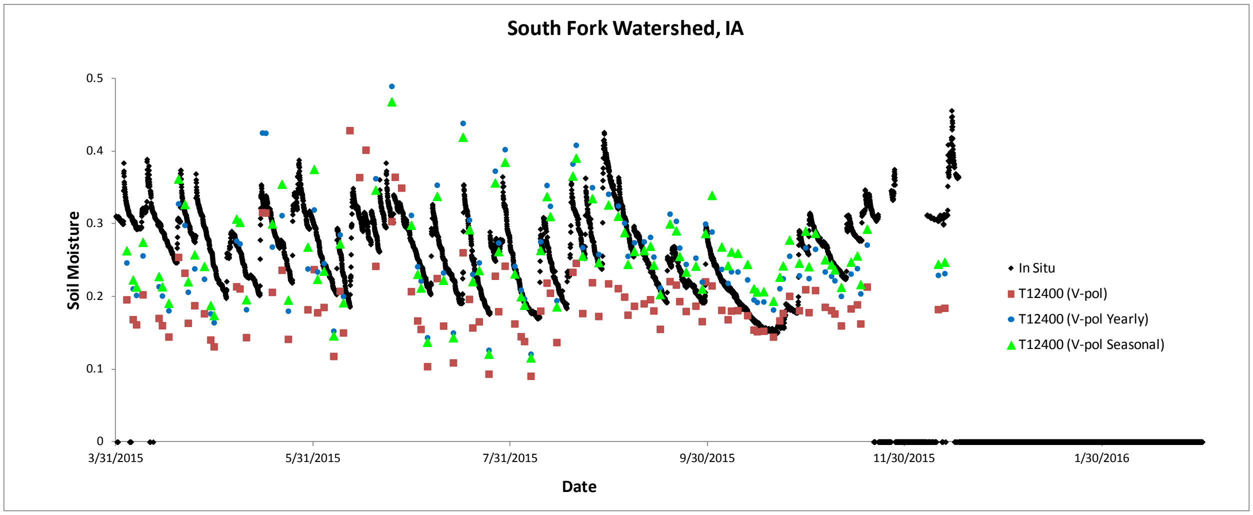

Figure 7.10 Time series of (a) *in situ* observations [black], (b) SCA-V soil moisture (same as that used in the assessment report) [maroon], (c) SCA-V soil moisture with site specific h and b parameters optimized over the entire 11-month observation period [blue], (d) SCA-V soil moisture with site specific seasonal optimized h and b parameters [green] using T12400 observations over South Fork watershed.

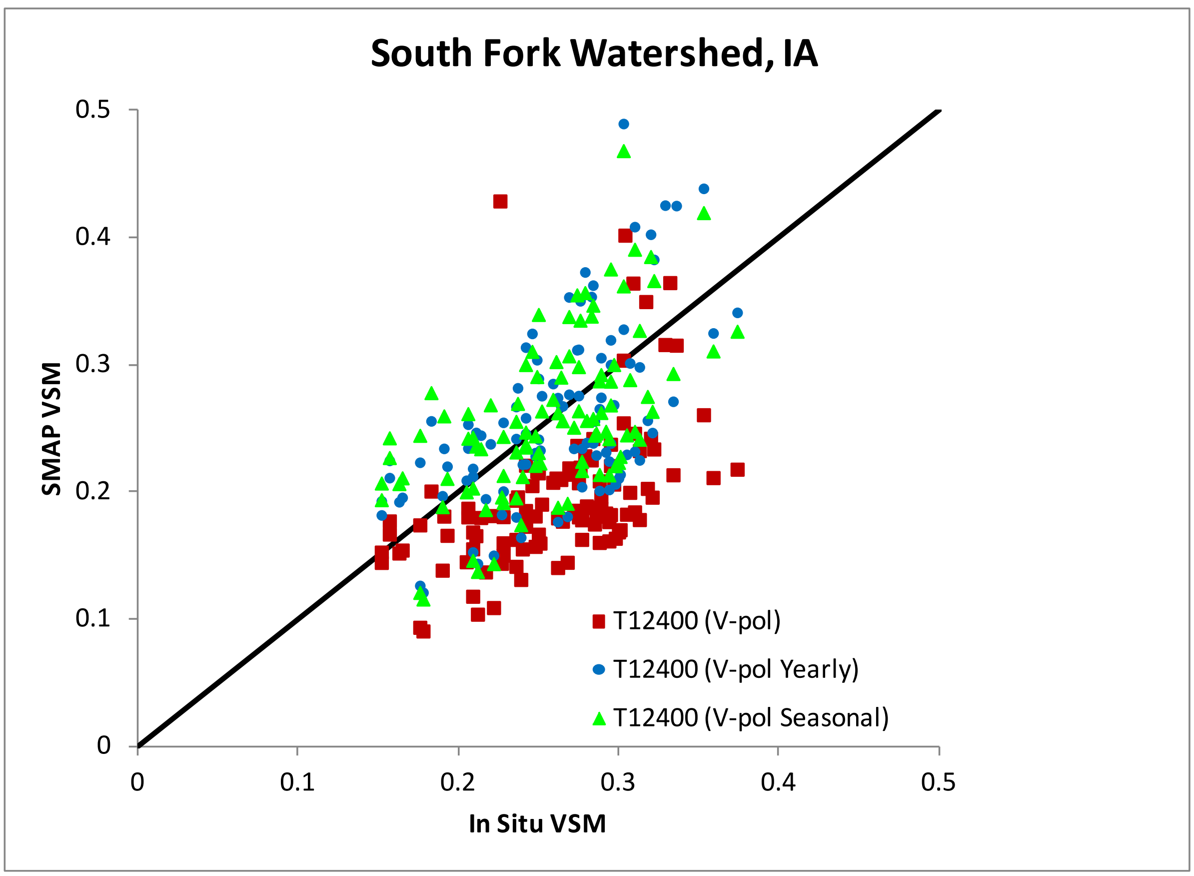

Figure 7.11. Scatter plot of *in situ* observations with (a) SCA-V soil moisture (same as that used in the assessment report) [maroon], (b) SCA-V soil moisture with site specific h and b parameters optimized for the 11-month period [blue], (c) SCA-V soil moisture with site specific seasonal optimized h and b parameters [green] using T12400 observations over South Fork watershed.

Table 7.3. Summary statistics of the soil moisture results for the different parameter optimizations at the South Fork, IA core site.

	ubRMSE	Bias	RMSE	R
T12400 SCA-V (Baseline Optimization)	0.053	-0.064	0.083	0.515
T12400 SCA-V (Yearly Optimization)	0.055	0.000	0.055	0.597
T12400 SCA-V (Seasonal Optimization)	0.052	0.001	0.052	0.633

7.3 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 7.4.

The defining feature of these networks is that the measurement density is low, usually resulting in one 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 will be a method called Triple Co-location 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. The exploration and implementation of this technique will be part of future L2SMP product assessments.

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

Table 7.4 Sparse Networks Providing L2SMP Validation Data

Network Name	PI/Contact	Area	No. of Sites
NOAA Climate Reference Network (CRN)	M. Palecki	USA	110
USDA NRCS Soil Climate Analysis Network (SCAN)	M. Cosh	USA	155
GPS	E. Small	Western USA	123
COSMOS	M. Zreda	Mostly USA	53
SMOSMania	J. Calvet	Southern France	21
Pampas	M. Thibeault	Argentina	20
Oklahoma Mesonet	-	Oklahoma, USA	140
MAHASRI	J. Asanuma	Mongolia	13

The sparse network metrics are summarized in Table 7.5 (SMAP in green columns) and Figure 7.12. 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. 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. The values are higher, which is expected due to the significant change in scale between a point and the grid product. The bias values increased for the two SCA algorithms while the DCA bias was about the same as with the CVS. Considering the many caveats that must be considered in making sparse network comparisons, the algorithm performance is still good. This result provides additional confidence in the previous conclusions based on the CVS. The SCA-V has the best overall ubRMSE and correlation while the DCA has the lowest bias.

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 0.025 and 0.064 m^3/m^3. Categories with larger bias values are the deciduous broadleaf forest, grasslands, and croplands. It is not surprising that there would be issues with forests at this stage of validation because they typically have large VWC. However, this forest result is based on only 1 site. The larger ubRMSE and bias for grasslands and croplands needs to be addressed.

SMOS metrics are also included in Table 7.5 (SMOS in blue columns) 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 than the SCA-V.

Table 7.5. SMAP L2SMP Version 3 Sparse Network Assessment

	ubRMSE (m^3/m^3)				Bias (m^3/m^3)				RMSE (m^3/m^3)				R				*N*
IGBP Class	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	0.043	0.041	0.051	0.053	-0.047	0.001	0.073	-0.065	0.063	0.045	0.094	0.087	0.667	0.682	0.630	0.628	3
Evergreen broadleaf forest																	
Deciduous needleleaf forest																	
Deciduous broadleaf forest	0.047	0.031	0.029	-	-0.091	-0.066	-0.028	-	0.102	0.073	0.040	-	-0.663	-0.266	0.710	-	1
Mixed forest	0.052	0.031	0.048	0.080	-0.080	-0.054	-0.008	-0.153	0.095	0.062	0.049	0.173	0.513	0.635	0.240	0.666	1
Closed shrublands																	
Open shrublands	0.036	0.037	0.049	0.048	-0.041	-0.009	0.030	0.001	0.062	0.054	0.070	0.061	0.571	0.581	0.575	0.494	42
Woody savannas	0.052	0.047	0.056	0.084	-0.044	-0.007	0.052	-0.085	0.084	0.068	0.088	0.133	0.718	0.751	0.687	0.594	20
Savannas	0.049	0.047	0.046	0.054	-0.039	-0.011	0.020	-0.025	0.072	0.060	0.070	0.065	0.892	0.886	0.869	0.776	6
Grasslands	0.048	0.047	0.055	0.059	-0.075	-0.041	0.003	-0.038	0.096	0.076	0.078	0.084	0.691	0.703	0.674	0.654	243
Permanent wetlands																	
Croplands	0.074	0.064	0.068	0.076	-0.041	-0.027	-0.004	-0.040	0.118	0.103	0.101	0.117	0.575	0.604	0.534	0.576	60
Urban and built-up																	
Crop/Natural vegetation mosaic	0.059	0.049	0.058	0.070	-0.018	0.008	0.051	-0.087	0.080	0.072	0.094	0.147	0.633	0.697	0.644	0.631	19
Snow and ice																	
Barren/Sparse	0.024	0.025	0.032	0.042	-0.015	0.012	0.054	-0.001	0.039	0.042	0.067	0.050	0.475	0.463	0.415	0.393	7
Average	**0.051**	**0.048**	**0.056**	**0.062**	**-0.060**	**-0.030**	**0.011**	**-0.039**	**0.093**	**0.076**	**0.082**	**0.091**	**0.655**	**0.674**	**0.640**	**0.619**	**402**
Average is based upon all sets of observations, not the average of the land cover category results.																	

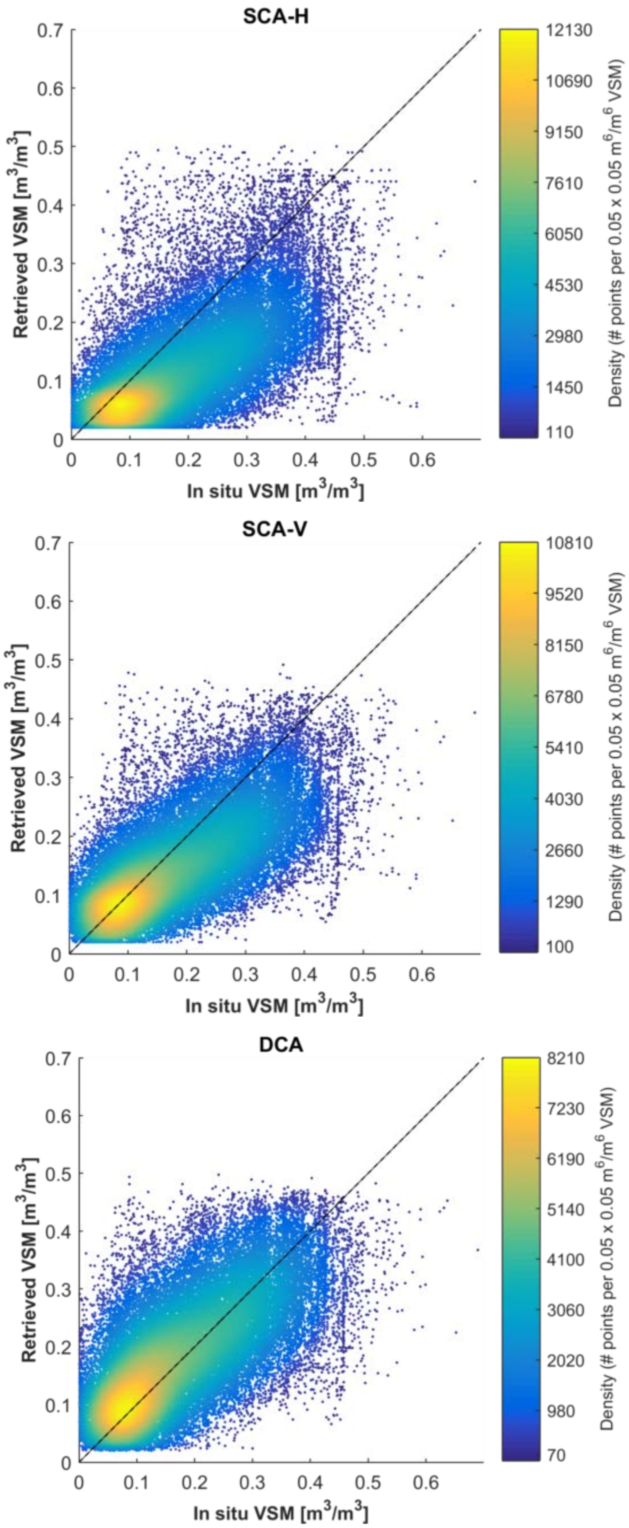

Figure 7.12. Scatterplots of the Sparse Network *In Situ* Observations and SMAP Retrievals.

7.4 SMOS Satellite Intercomparison

Intercomparison of SMAP soil moisture with products from other satellite missions is useful in Cal/Val if these other missions are mature and comparable to SMAP (in terms of spatial resolution, time of day, and soil penetration depth). Candidate satellite products include those from SMOS, Aquarius, JAXA's GCOM-W, and ASCAT. Some features of these products are:

- SMOS observes the Earth with an L-band radiometer at the same time of day (6 am/pm) and with a similar spatial resolution as SMAP, although ascending (SMOS 6 am) and descending (SMAP 6 am) orbits are reversed.
- Aquarius had an L-band radiometer observing at the same time of day (6 am/pm) but with a much coarser spatial resolution and repeat-pass interval than SMAP. It ceased operation on June 7, 2015 and as a result there is very limited temporal overlap with SMAP.
- GCOM-W AMSR2 operates at higher frequencies (C- and X-band) that respond to shallower soil depths. It does have a similar nominal spatial resolution as the SMAP radiometer products but AMSR2 observes at different times of the day (1:30 am/pm). As a result, any intercomparison must be interpreted very carefully.
- ASCAT is a higher frequency (C-band) radar-based product. The time of day is different (9:30 am/pm) as is the contributing depth. In addition, it does not provide a direct estimate of volumetric soil moisture without additional value-added analyses.

All of these products may eventually be considered in SMAP validation; however, at this point SMOS products are considered to be the most relevant for SMAP L2SMP validation.

For this intercomparison, SMOS L3 data on a 25 km EASE grid are used. The soil moisture product from the ascending pass (6 am) is used to match SMAP's 6 am descending pass product. Bilinear interpolation was used to re-grid the 25 km SMOS data to the SMAP 36 km EASE grid. This involves a double-gridding of the SMOS data and is likely to introduce some noise into the analyses. Flags provided in the respective product files are applied to both SMAP and SMOS to allow comparison of high quality soil moisture retrievals. For SMAP, pixels recommended for retrieval based on the SMAP quality flag are considered. For SMOS, pixels flagged for nominal retrieval and an RFI probability of less than 10 percent are considered. The SMOS data used are based on v280 (April 1, 2015-April 30, 2015) and v300 (May 1, 2015-February 29, 2016). Details on these SMOS versions are found in [18].

The intercomparisons with SMOS are based on SMAP-SMOS data pairs and are summarized in Table 7.6. As noted above, data and retrieval quality flags have been applied, which greatly reduced or eliminated forest categories. In this intercomparison, the unbiased root mean square difference (ubRMSD) is used because it cannot be assumed that either product is correct. An obvious feature of the ubRMSD values in Table 7.6 is that they are larger than the ubRMSE found when comparing either SMAP or SMOS to *in situ* CVS or sparse network observations. Some sources of this variability include resampling, product resolution, residual RFI after flagging, and the inclusion of a wider range of land covers and climates. For this intercomparison analysis, SMAP and SMOS products were composites for 7-day periods. This temporal compositing could result in some uncertainty due to the possible temporal offset between the two satellite retrievals for a particular location. The difference in SMOS and SMAP brightness temperatures (~ 2 K as shown in Section 3) will also result in another source of uncertainty in soil moisture retrievals. Quantifying these factors will be the subject of future research.

The bias values for a specific algorithm and land cover pair are indicative of fundamental differences between SMOS and SMAP retrievals. They should not be interpreted as one algorithm or product being right and another wrong. Large values may indicate that a different implementation or parameterization is being used. Overall, the bias between SMAP (SCA-V) and SMOS is near zero (Table 7.6). However, this varies in specific categories. The match-up between SMAP and SMOS based on ubRMSE is best for SCA-V.

One problem category is permanent wetland. There are very large differences between SMOS and SMAP for this land cover class, and the causes of these differences are still being investigated. However, in the future SMAP will no longer retrieve soil moisture in this land cover class, but will flag all such retrievals since soil moisture retrieval in a permanent wetland makes little sense.

As noted above, the use of the flags resulted in the elimination of most forest data from the analyses. In order to assess how SMAP and SMOS are behaving relative to each other in these categories, an additional analysis was conducted that ignored these flags. The resulting metrics for the forest categories are shown in Table 7.7. The obvious feature of the SCA-V results is the large bias between SMOS and SMAP. Unlike in the previous result, here SMAP predicts wetter conditions than SMOS. Although retrieval of soil moisture under dense forest conditions is not required of the SMAP mission, implementing a reliable and accurate algorithm for this category is a goal of future research.

The overall conclusion from the assessment using SMOS is that the two missions are producing similar results for most short vegetation types and that there are significant differences in the retrievals over forests. This intercomparison supports the SMAP Stage 2 validation required for a validated product by providing a global intercomparison over almost a full year of observations.

Table 7.6. SMAP L2SMP Version 3 SMAP-SMOS Assessment

	ubRMSD (m^3/m^3)			**Bias (m^3/m^3)**			**RMSD (m^3/m^3)**			**R**			**N**		
IGBP Class	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
Evergreen Needleleaf forest															
Evergreen Broadleaf forest															
Deciduous Needleleaf forest	0.080	0.077	0.084	-0.010	0.046	0.153	0.081	0.090	0.174	0.545	0.593	0.554	350	350	347
Deciduous Broadleaf forest	0.071	0.071	0.073	-0.013	0.023	0.068	0.072	0.075	0.100	0.813	0.812	0.760	97	97	97
Mixed forest															
Closed shrublands	0.093	0.086	0.083	-0.090	-0.044	0.017	0.129	0.096	0.084	0.654	0.707	0.702	387	398	382
Open shrublands	0.066	0.051	0.063	-0.066	-0.030	0.023	0.093	0.059	0.067	0.653	0.833	0.819	173185	191704	178181
Woody savannas	0.106	0.097	0.122	0.004	0.041	0.098	0.106	0.106	0.157	0.662	0.747	0.585	61763	62843	58770
Savannas	0.073	0.071	0.077	-0.023	-0.007	0.002	0.077	0.072	0.077	0.775	0.792	0.765	45044	46812	43192
Grasslands	0.056	0.049	0.053	-0.033	-0.009	0.019	0.065	0.049	0.056	0.834	0.880	0.860	93404	98002	93979
Permanent wetlands	0.153	0.154	0.195	-0.281	-0.203	0.092	0.320	0.255	0.216	0.582	0.623	0.131	2259	2264	2165
Croplands	0.071	0.056	0.057	-0.014	0.003	0.025	0.072	0.056	0.062	0.725	0.824	0.818	44362	45910	45586
Urban and built-up															
Crop/Natural vegetation mosaic	0.086	0.076	0.080	-0.013	-0.004	0.007	0.087	0.076	0.081	0.731	0.793	0.773	17569	17859	17080
Snow and ice															
Barren/Sparse	0.025	0.025	0.032	0.014	0.018	0.033	0.028	0.031	0.045	0.792	0.804	0.768	62741	61910	61388
Average	0.078	0.066	0.076	-0.032	-0.007	0.031	0.084	0.066	0.082	0.707	0.800	0.775			
Average is based on all sets of observations, not the average of the land covers.															

Table 7.7. SMAP L2SMP Release 3 SMAP-SMOS Assessment (No Flags Applied)

	ubRMSD (m^3/m^3)			**Bias (m^3/m^3)**			**RMSD (m^3/m^3)**			**R**			**N**		
IGBP Class	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
Evergreen Needleleaf forest	0.133	0.120	0.128	0.145	0.168	0.208	0.196	0.207	0.245	0.357	0.357	0.266	132072	132072	132045
Evergreen Broadleaf forest	0.163	0.159	0.161	0.207	0.248	0.276	0.263	0.294	0.319	0.250	0.192	0.108	291546	291546	289344
Deciduous Needleleaf forest	0.079	0.078	0.101	0.002	0.058	0.165	0.079	0.097	0.194	0.430	0.443	0.266	32439	32439	32439
Deciduous Broadleaf forest	0.127	0.123	0.142	0.136	0.160	0.192	0.187	0.202	0.239	0.540	0.536	0.392	40404	40404	40398
Mixed forest	0.134	0.126	0.137	0.133	0.163	0.213	0.189	0.206	0.253	0.391	0.392	0.297	247930	247930	247872

7.5 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 validated release, the goal was to conduct a Stage 2 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 (ubRMSE), bias, and correlation R than the SCA-H or DCA. Differences were relatively small, generally third decimal level. Based on the results, it is recommended that the SCA-V be adopted as the operational baseline algorithm for this release. The overall ubRMSE of the SCA-V is 0.039 m^3/m^3, which is better than the mission requirement.

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 Stage 2 validation by expanding comparison from 15 CVS to over 400 points. The Sparse Network data also allowed the evaluation of performance based on land cover.

In addition, SMAP retrievals were compared globally to SMOS subject to temporal and spatial constraints. This resulted in a very large number of data points that allowed the comparison of results for some land cover-related differences. Overall, the SMAP SCA-V and SMOS were unbiased for non-forested land covers, and SCA-V agreed the best with SMOS. Specific land cover type results indicate the need for a more rigorous evaluation and careful study of different algorithm parameterizations and implementation approaches between SMOS and SMAP. These results further supported the global evaluation needed for Stage 2 validation.

8 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 remaining SMAP primary mission include:

- *Moving toward a Stage 3 validated product.* Stage 3 validation is characterized by a more rigorous analysis and longer time periods: "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."

- *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 (Millbrook, Kuwait, Bell Ville). It is unlikely that any additional sites beyond those already known will be developed and implemented during the remainder of SMAP's primary mission; however, there are a few sites that satisfied the requirements for 9 km validation that could be expanded to 36 km for use with L2SMP if appropriate scaling functions can be developed though field campaigns or modeling.

- *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. Any of the commonly-used dielectric models is highly dependent on the robustness of the data set used in its 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 Version 2 (beta release). 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 spatiotemporal optimization of algorithm parameters have resulted in modest gain 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 2015 and are planned for 2016. Results from these field campaigns will be used in future assessments and algorithm improvements. There are many steps involved in this process: acquisition, quality control, pre-processing, integration of ground observations and precipitation, aircraft soil moisture estimation, model-based mapping, and finally SMAP L2SMP comparisons. 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).

- *Implementing Triple Co-Location as an assessment and algorithm improvement tool.* This technique has been used to assess satellite soil moisture products. Although SMAP is currently implementing a triple co-location analysis, the approach requires a long record of observations (> 1 year) and acquisition of data over multiple seasons to produce meaningful results. It may yet contribute to assessment of SMAP products. It is not clear at this stage how the results will be incorporated into algorithm improvement or assessments.

- *Consider alternative satellite products.* The SMOS intercomparisons provide highly valuable information for assessment and paths for improvement for the L2SMP soil moisture. This is partially due to the fact that both SMOS and SMAP products are derived from L-band radiometers. All of the other satellites which produce soil moisture estimates have issues (differences in microwave frequency, resolution, etc.) that would have to be carefully considered before differences in performance are used as the basis for modifying the SMAP algorithms. Regardless, a more thorough evaluation of SMAP with these alternative satellite products should be completed. Also, as noted in a previous chapter, the ubRMSD are large for SMAP-SMOS. A portion of this difference is attributed to spatial resampling and temporal compositing. It would be desirable to conduct a more thorough analysis at some point in the future.

- *Implementing model-based products as an assessment and algorithm improvement tool.* Model intercomparisons are one of the methodologies proposed for SMAP L2SMP. There are several readily available products that include the GMAO Nature Run, ECMWF, NCEP, and a Canadian Met Office product. One problem faced when using some of these model products is the depth of their surface layer, which is typically thicker than the 5 cm layer assumed by SMAP to apply to the surface satellite retrievals. Preliminary assessments suggest that model responses may be dampened relative to satellite estimates. Some effort is required to further evaluate the use of model products in assessing and validating SMAP products. The greatest contribution that the model-based assessments might make to validation is providing a basis for upscaling several candidate validation sites that are interesting but lack enough points or have an unbalanced distribution of points to qualify as a core site. These potential sites include Tabasco, St. Joseph's, Tonzi Ranch, Valencia, Tereno, Kuwait, Benin, and Ngari.

- *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 should also be done.

- *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 as discussed above, the SMAP 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.

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10 REFERENCES

[1] Chan, S., R. Bindlish, P. O'Neill, E. Njoku, T. Jackson, A. Colliander, F. Chen, M. Mariko, S. Dunbar, J. Piepmeier, S. Yueh, D. Entekhabi, M. Cosh, T. Caldwell, J. Walker, X. Wu, A. Berg, T. Rowlandson, A. Pacheco, H. McNairn, M. Thibeault, J. Martinez-Fernandez, A. Gonzalez-Zamora, M. Seyfried, D. Bosch, P. Starks, D. Goodrich, J. Prueger, M. Palecki, E. Small, M. Zreda, J. Calvet, W. Crow, Y. Kerr. "Assessment of the SMAP Level 2 passive soil moisture product," IEEE Trans. Geosci. Remote Sens., in press.

[2] Science Data Calibration and Validation Plan Release A, March 14, 2014 JPL D-52544

[3] O'Neill, P., S. Chan, E. Njoku, T. Jackson, and R. Bindlish, "Algorithm Theoretical Basis Document (ATBD): L2/3_SM_P," Initial Release, v.3, October 1, 2015. Available at http://smap.jpl.nasa.gov/science/dataproducts/ATBD/

[4] Entekhabi, D., S. Yueh, P. O'Neill, K. Kellogg et al., SMAP Handbook, JPL Publication JPL 400-1567, Jet Propulsion Laboratory, Pasadena, California, 182 pages, July, 2014.

[5] SMAP Level 1 Mission Requirements and Success Criteria. (Appendix O to the Earth Systematic Missions Program Plan: Program-Level Requirements on the Soil Moisture Active Passive Project.), NASA Headquarters/Earth Science Division, Washington, DC, version 5, 2013.

[6] Committee on Earth Observation Satellites (CEOS) Working Group on Calibration and Validation (WGCV): http://calvalportal.ceos.org/CalValPortal/welcome.do and WWW: Land Products Sub-Group of Committee on Earth Observation Satellites (CEOS) Working Group on Calibration and Validation (WGCV): http://lpvs.gsfc.nasa.gov

[7] Dawson, D., SMAP Radiometer Error Budget, SMAP Project, JPL D-61632, Jet Propulsion Laboratory, Pasadena, CA.

[8] Mironov, V. L., L. G. Kosolapova, and S. V. Fomin, "Physically and mineralogically basedspectroscopic dielectric model for moist soils," IEEE Trans. Geosci. Remote Sens., 47(7), pp. 2059–2070, 2009.

[9] Owe, M., De Jeu, R. A. M., and Walker, J. P. "A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index," IEEE Trans. Geosci. Remote Sens., 39(8): 1643–1654, 2001.

[10] Dorigo, W. A., A. Xaver, M. Vreugdenhil, A. Gruber, A. Hegyiova, A. D. Sanchis-Dufau, D. Zamojski, C. Cordes, W. Wagner, M. Drush, "Global Automated Quality Control of In Situ Soil Moisture Data From the International Soil Moisture Network," Vol. 12, No. 3, Vadose Zone J., 2012.

[11] Adams, J. R., McNairn, H., Berg, A. A., and Champagne, C. Evaluation of near-surface soil moisture data from an AAFC monitoring network in Manitoba, Canada: Implications for L-band satellite validation. Journal of Hydrology 521: 82-592, 2015.

[12] Jackson, T. J., Le Vine, D. M., Swift, C. T., Schmugge, T. J., and Schiebe, F. R. "Large area mapping of soil moisture using the ESTAR passive microwave radiometer in Washita'92," Remote Sensing of Environment. 53: 27-37. 1995.

[13] Jackson, T. J., Cosh, M., Bindlish, R., Starks, P., Bosch, D., Seyfried, M., Goodrich, D., Moran, S., and Du, D. "Validation of Advanced Microwave Scanning Radiometer soil moisture products," IEEE Trans. Geosci. Remote Sens., 48: 4256 – 4272, 2010.

[14] Jackson, T. J., Bindlish, R., Cosh, M. H., Zhao, T., Starks, P. J., Bosch, D. D., Seyfried, M., Moran, M., Goodrich, D. C., Kerr, Y. H., and Leroux, D. "Validation of Soil Moisture and Ocean

Salinity (SMOS) soil moisture over watershed networks in the U.S.," IEEE Trans. Geosci. Remote Sens., 50: 1530-1543, 2012.

[15] Jackson, T., Chen, D., Cosh, M., Li, F., Anderson, M., Walthall, C., Doraiswamy, P., and Hunt, E.R. "Vegetation water content mapping using Landsat data derived normalized difference water index (NDWI) for corn and soybean," Remote Sensing of Environment, 92: 475-482. 2004.

[16] Cosh, M., USDA Hydrology and Remote Sensing Laboratory, personal communication, 2015.

[17] Jackson, T., McNairn, H., Weltz, M. A., Brisco, B., and Brown, R. "First order surface roughness correction of active observations for estimating soil moisture," IEEE Trans. Geosci. Remote Sens., 35: 1065-1069, 1997.

[18] Kerr, Y., P. Waldteufel, P. Richaume, I. Davenport, P. Ferrazzoli, and J.-P. Wigneron, "SMOS Level 2 Processor Soil Moisture Algorithm Theoretical Basis Document (ATBD)," Toulouse, France, CESBIO, SM-ESL (CBSA), vol. SO-TN-ESL-SM-GS-0001, v4.a, 2015.