

**Soil Moisture Active Passive (SMAP) Project
Calibration and Validation for the L2/3_SM_P
Beta-Release Data Products
Version 2**

Approved by:

Simon Yueh
SMAP Project Scientist

Date

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Jackson, T.¹, P. O'Neill², E. Njoku³, S. Chan³, R. Bindlish¹, A. Colliander³, F. Chen¹, M. Burgin³, S. Dunbar³, J. Piepmeier², M. Cosh¹, T. Caldwell⁴, J. Walker⁵, X. Wu⁵, A. Berg⁶, T. Rowlandson⁶, A. Pacheco⁷, H. McNairn⁷, M. Thibeault⁸, J. Martínez-Fernández⁹, Á. González-Zamora⁹, M. Seyfried¹⁰, D. Bosch¹¹, P. Starks¹², D. Goodrich¹³, J. Prueger¹⁴, M. Palecki¹⁵, E. Small¹⁶, M. Zreda¹⁷, J. Calvet¹⁸, W. Crow¹, Y. Kerr¹⁹, S. Yueh³, and D. Entekhabi²⁰, November 16, 2015. *Calibration and Validation for the L2/3_SM_P Beta-Release Data Products, Version 2*, SMAP Project, JPL D-93981, Jet Propulsion Laboratory, Pasadena, CA.

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Jet Propulsion Laboratory
4800 Oak Grove Drive
Pasadena, California 91109-8099
California Institute of Technology

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Contributors to this report:

T. Jackson¹, P. O'Neill², E. Njoku³, S. Chan³, R. Bindlish¹, A. Colliander³, F. Chen¹, M. Burgin³, S. Dunbar³, J. Piepmeier², M. Cosh¹, T. Caldwell⁴, J. Walker⁵, X. Wu⁵, A. Berg⁶, T. Rowlandson⁶, A. Pacheco⁷, H. McNairn⁷, M. Thibeault⁸, J. Martínez-Fernández⁹, Á. González-Zamora⁹, M. Seyfried¹⁰, D. Bosch¹¹, P. Starks¹², D. Goodrich¹³, J. Prueger¹⁴, M. Palecki¹⁵, E. Small¹⁶, M. Zreda¹⁷, J. Calvet¹⁸, W. Crow¹, Y. Kerr¹⁹, S. Yueh³, and D. Entekhabi²⁰

¹USDA ARS Hydrology and Remote Sensing Lab, Beltsville, MD 20705 USA

²NASA Goddard Space Flight Center, Greenbelt, MD 20771 USA

³Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109 USA

⁴University of Texas, Austin, TX 78713 USA

⁵Monash University, Clayton, Australia

⁶University of Guelph, Guelph, Canada

⁷Agriculture and Agri-Food Canada, Ottawa, Canada

⁸Comisión Nacional de Actividades Espaciales (CONAE), Buenos Aires, Argentina

⁹University of Salamanca, Salamanca, Spain

¹⁰USDA ARS Northwest Watershed Research Center, Boise, ID 83712 USA

¹¹USDA ARS Southeast Watershed Research Center, Tifton, GA 31793 USA

¹²USDA ARS Grazinglands Research Laboratory, El Reno, OK 73036 USA

¹³USDA ARS Southwest Watershed Research Center, Tucson, AZ 85719 USA

¹⁴USDA ARS National Laboratory for Agriculture and the Environment, Ames, IA 50011 USA

¹⁵NOAA National Climatic Data Center, Asheville, NC 28801 USA

¹⁶University of Colorado, Boulder, CO 80309 USA

¹⁷University of Arizona, Tucson, AZ 85751 USA

¹⁸CNRM-GAME, UMR 3589 (Météo-France, CNRS), Toulouse, France

¹⁹CESBIO-CNES, Toulouse, France

²⁰Massachusetts Institute of Technology, Cambridge, MA 02139 USA

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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 beta release. Note that as opposed to the validated data scheduled for release in 2016, beta quality data have not undergone full validation and may still contain significant errors. 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 meet the criteria established by the Committee on Earth Observing Satellites (CEOS) Stage 1 validation, which supports beta release of the data based on a limited set of core validation sites. The sparse network and SMOS analyses address Stage 2 by expanding to regional and global assessment.

Preliminary analyses showed that a few refinements were required in the passive soil moisture retrieval algorithms. One was related to the physical temperature used for normalizing brightness temperature and another one was the application of the precipitation flag. Both of these modifications involved how the ancillary GMAO (GSFC's Global Modeling and Assimilation Office) model forecast data were used in SMAP processing. In addition, the omega or single-scattering albedos for forest categories were reduced from the prelaunch ATBD values to 0.05 to be consistent with SMOS.

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 the beta release assessment.

The primary assessment methodology was based on CVS comparisons using 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. These analyses indicated that the SCA-V had better unbiased root mean square error (ubRMSE), bias, and correlation R than SCA-H, and SCA-H had better ubRMSE and correlation R than DCA. DCA had the lowest bias of all the algorithms (essentially zero bias). 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 baseline algorithm for the beta release. The overall ubRMSE of the SCA-V is 0.038 m³/m³, which exceeds the mission requirement of 0.040 m³/m³. [Note that the documented mission accuracy requirement is in units of cm³/cm³, which is mathematically identical to m³/m³.]

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 300 sparse network sites mirrored the CVS results. Intercomparisons with SMOS 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 inter-comparisons of SMOS to SMAP retrievals showed good agreement over most land cover types but indicated significant differences over forest covers.

This report notes several limitations in the beta-release calibration which will be addressed in the coming year prior to release of the validated data. These issues include optimization of algorithm parameters, performance over very dense vegetation, and upscaling effects. In addition, the

methodologies will expand prior to validated data release to include nearly double the number of CVS, model-based inter-comparisons, and the results of several intensive field experiments. Despite these remaining areas, the beta-release L2SMP product is of sufficient level of maturity and quality that it can be approved for distribution to and used by the larger science and application communities. This beta release also presents an opportunity to enable users to gain familiarity with the parameters and data formats of the product prior to full validation. It should be noted that this is Version 2 of this report. A correction was made to the validation grid indexing used in Version 1, and the period of analysis was expanded from April 11 – July 14, 2015 to March 31 – October 26, 2015.

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 beta release is described. The approaches and procedures utilized follow those described in the SMAP Cal/Val Plan [1] and Algorithm Theoretical Basis Document for the Level 2 & 3 Soil Moisture (Passive) Data Products [2].

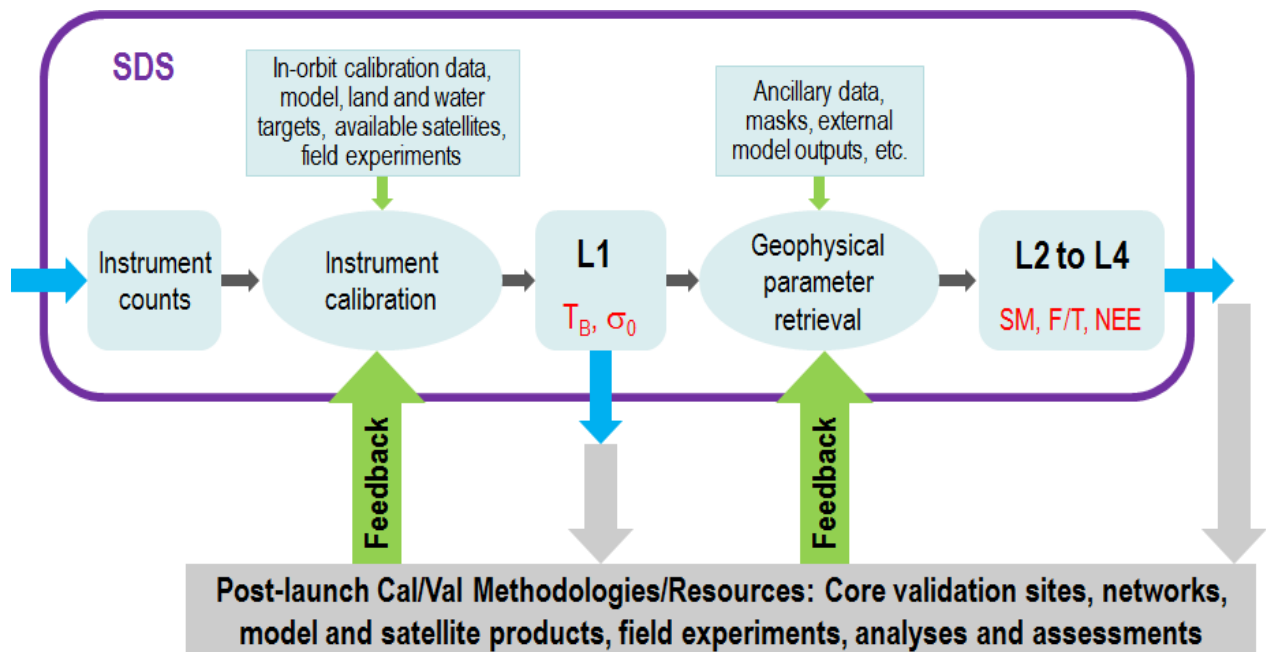


Figure 2.1. Overview of the SMAP Cal/Val Process.

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 [3], 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 ($0.040 \text{ m}^3/\text{m}^3$) that is listed in the Mission L1 Requirements Document [4] for the active/passive soil moisture product.

In order to ensure the public's timely access to SMAP data, before releasing validated products the mission is required to release beta-quality products. The maturity of the products in the beta release is defined as follows:

- Early release is used to gain familiarity with data formats.
- Intended as a testbed to discover and correct errors.
- Minimally validated and still may contain significant errors.
- General research community is encouraged to participate in the quality assessment and validation, but need to be aware that product validation and quality assessment are ongoing.
- Data may be used in publications as long as the fact that the data are beta quality is indicated by the authors. Drawing quantitative scientific conclusions is discouraged. Users are urged to contact science team representatives prior to use of the data in publications, and to recommend members of the instrument teams as reviewers.
- The estimated uncertainties will be documented.
- May be replaced in the archive when an upgraded (provisional or validated) product becomes available.

Due to the quality of the L1B_TB brightness temperatures (T_B) from the SMAP radiometer and the heritage and maturity of passive microwave remote sensing of soil moisture, this beta release of the L2SMP product is closer to a provisional release, which is defined as:

- Incremental improvements are ongoing. Obvious artifacts or errors observed in the beta product have been identified and either minimized or documented.
- General research community is encouraged to participate in the QA and validation, but need to be aware that product validation and QA are ongoing.
- Product may be used in publications as long as provisional quality is indicated by the authors. Users are urged to contact science team representatives prior to use of the data in publications, and to recommend members of the instrument teams as reviewers.
- The estimated uncertainties will be documented.
- Will be replaced in the archive when an upgraded (validated) product becomes available.

In assessing the maturity of the L2SMP product, the L2SMP team also considered the guidance provided by the Committee on Earth Observation Satellites (CEOS) Working Group on Calibration and Validation (WGCV) [5]:

- 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 beta release the L2SMP team has completed Stage 1 and begun Stage 2 (global assessment). The Cal/Val program will continue through these stages over the SMAP mission life span.

3 EXPECTED PERFORMANCE OF L1 RADIOMETER DATA AND IMPACT ON L2SMP

The L2SMP soil moisture retrievals are based on the beta-release version of the radiometer Level 1B and 1C brightness temperature data [6]. A detailed assessment of data quality and calibration is available at NSIDC [7], 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). Global average brightness temperature comparisons over land areas with SMOS are quite favorable indicating less than 1 K (kelvin) mean difference at top of the atmosphere (after Faraday rotation correction was applied). There remain some features of the data that should be considered when using retrieved soil moisture values. First, the radiometer hardware exhibits some calibration drift, which is corrected in the beta-release data to approximately 0.5 K. This drift is assessed using an ocean emissivity model and is corrected by adjusting the radiometer gain. Over brighter land surfaces the effect of the drift should be reduced. Of more interest over land are observed fore-aft differences in L1C_TB likely due to antenna sidelobe contamination and radio frequency interference (RFI). 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. These areas will be the focus of the L1 radiometer Cal/Val activities towards the full validation of the product. Finally, RFI appears to be well filtered by the L1B_TB algorithm in the Americas and Europe; however, there remain areas, particularly in East Asia, where RFI is still challenging. One symptom is larger than expected fore-aft differences in brightness temperature. In summary, the radiometer calibration is fairly stable over time and shows good agreement with SMOS [7]. The noise and geolocation performance meet requirements. Good performance should be expected over homogeneous land surfaces.

Table 3.1. Beta-level Performance of SMAP L1 Radiometer Data

Parameter	Beta-level	Mission Requirement
NEDT	1.1 K	< 1.6 K
Geolocation accuracy	2.7 km	< 4 km
Land SMAP/SMOS comparison (H pol)	-0.54 K	n/a
Land SMAP/SMOS comparison (V pol)	-0.96 K	n/a

Given the baseline error allocation of 1.6 K for a single-look L1B_TB footprint (table above, see also Section 5.4.2, SMAP Radiometer Error Budget, JPL D-61632 [8]) and the current beta-release estimate of 1.1 K, the current L1 radiometer data are expected to provisionally meet the 1.3 K requirement of total radiometric uncertainty in L2SMP's error budget¹, pending the confirmation that all other error terms (i.e., antenna temperature calibration, antenna pattern correction, long-term drift, RFI, and atmospheric correction) in the L1 radiometer error budget have been adequately corrected for according to their respective L1 requirements.

¹An 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). 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.

In addition to its favorable NEDT performance, the current beta-release L1 radiometer data have also demonstrated stable and consistent calibration to within a fraction of a Kelvin against the L-band T_B observations made by the SMOS mission. Because 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), the observed good agreement in T_B between SMAP and SMOS is another indirect indication that the current beta-release SMAP L1 radiometer data have attained sufficient quality to enable passive retrieval of soil moisture to meet the mission accuracy requirement of $0.040 \text{ m}^3/\text{m}^3$ or better.

4 ALTERNATIVE L2SMP ALGORITHMS

The current beta-release L2SMP contains soil moisture retrieval fields produced by the baseline and several option 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 preliminary results from the current L2SMP Cal/Val analyses, the SCA-V algorithm seems to deliver slightly better performance than the SCA-H algorithm, which was designated as the pre-launch baseline retrieval algorithm. For this reason, the SCA-V is designated as the current baseline algorithm for the beta release of L2SMP. Throughout the rest of the entire post-launch Cal/Val period, however, all five algorithms will be continuously assessed; the choice of the operational algorithm for the validated release of the product will be evaluated on a regular basis as analyses of new observations and Cal/Val data become available, and algorithm parameters are tuned based on a longer SMAP radiometer T_B time series record.

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 [2].

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 model².] 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

²Mironov, V. L., L. G. Kosolapova, and S. V. Fomin, “Physically and mineralogically based spectroscopic dielectric model for moist soils,” *IEEE Trans. Geosci. Remote Sens.*, 47(7), pp. 2059–2070, 2009. See also [2].

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_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_B s:

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

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 TB observations. As currently implemented for beta release, the H and V parameters are set the same. During the intensive Cal/Val period leading up to release of the validated 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_B s 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_B s (also expressed in natural logarithm) as follows:

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

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 Φ_{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 APPROACH FOR L2 CAL/VAL: METHODOLOGIES

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. With regard to the CEOS Cal/Val stages, Core Validation Sites address Stage 1 and Satellite and Model Products are used for Stage 2 and beyond. Sparse Networks fall between these two stages.

6 PROCESS USED FOR BETA RELEASE

For Version 1 of this report, in order to provide the beta release data on October 1, 2015 or sooner (one month earlier than originally scheduled), the SMAP L2SMP team chose to define the assessment period as April 11-July 14, 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 selected to allow sufficient time for analysis and reporting in this Beta Release Assessment Report. The current report (Version 2) includes an expanded time period through October 26, 2015 that provides a more robust assessment, especially for North American sites. The team has been conducting assessments on a weekly basis and will continue to do this throughout the intensive Cal/Val phase and beyond.

Weekly reviews of performance based upon CVS, Sparse Networks, and SMOS soil moisture were conducted for a sufficient period of record (more than six months) that captured a range of conditions. These analyses included the intercomparison of three SMAP L2SMP retrieval algorithms, and established consistent levels and patterns of performance. Two algorithm-related actions were taken based upon these performance reviews. First, flags based upon ancillary data (specifically rainfall) were implemented and these data were removed from calculations of performance metrics. Second, retrieval issues were found in arid regions (i.e., non-retrievals in very dry areas). Further investigation indicated that the effective soil temperature being used was not appropriate to the conditions in these areas. As a result, a study was conducted to examine alternative approaches to determination of the effective soil temperature to use in the soil moisture retrievals. This analysis is described in a following section. The resulting effective temperature approach was applied globally (not just in arid regions). In addition, the effective single-scattering albedo for the forested and woody vegetation biomes was reduced from prelaunch ATBD values to be more consistent with SMOS.

Following the modifications noted above, the L2SMP team next reviewed the pre-launch tau-omega parameters used in the retrieval algorithms to determine their suitability for the beta release data set. Several parameter changes were evaluated that might reduce the underestimation bias found in the SCA-H and SCA-V retrieved soil moistures. Preliminary results indicated that some parameter changes did reduce the bias slightly but at the same time increased the ubRMSE. Therefore, the team concluded that more sophisticated and comprehensive calibration and evaluation of the tau-omega parameters are required, which will be completed prior to the L2SMP Validated Data Release in Spring/early Summer, 2016.

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. [10] reported that a mean difference of $0.018 \text{ m}^3/\text{m}^3$ existed between the measurements obtained by inserting a probe 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.

6.1 Effective Temperature

Dynamic surface temperature forecast information is routinely ingested by SMAP from the GMAO GEOS-5 model and processed as an ancillary data input as part of the operational processing of the SMAP passive soil moisture product [2]. The original baseline computation of the effective surface temperature (T_{eff}) consisted of using the average of the GMAO surface temperature (TSURF) and the

GMAO layer 1 soil temperature at 10 cm (TSOIL1). Preliminary analyses showed that a more sophisticated model for computing T_{eff} was required due to non-uniform soil temperature profiles, especially in arid areas, which led to soil moisture retrieval issues. In order to address this problem, several options for T_{eff} were considered and evaluated using SMAP T_B observations along with GMAO soil temperatures for the soil profile [11][12].

The SMAP beta release L2SMP product uses the Choudhury model [11] to compute the effective soil temperature:

$$T_{\text{eff}} = T_{\text{soil_deep}} + C (T_{\text{soil_top}} - T_{\text{soil_deep}}) \quad (3)$$

where $T_{\text{soil_top}}$ refers to the GMAO layer 1 soil temperature at 0-10 cm (TSOIL1) and $T_{\text{soil_deep}}$ refers to the GMAO layer 2 soil temperature at 10-20 cm (TSOIL2). This formulation allows for correct modeling of the deeper sensing depth of emission emanating from deeper in the soil than the surface. C is a coefficient that depends on the observing frequency – for the SMAP L-band beta release data, $C= 0.246$ as given in [11].

This approach to the calculation of T_{eff} was then applied to all regions in SMAP L2SMP soil moisture retrievals, and did minimize the number of non-retrievals due to soil temperature issues.

6.2 Validation Grid (VG)

SMAP provides L2 surface (0-5 cm) soil moisture using the radiometer (passive) data only posted on a 36 km EASE Grid 2.0, using radar (active) data only posted on a 3 km grid, and using combined radiometer and radar (active-passive (AP)) data posted on a 9 km grid. L4 surface and root zone soil moisture (L4_SM) are provided at a 9 km resolution, where the root zone is defined as the 0-100 cm layer.

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 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_B s 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 three standard SMAP Production Grids (SPG) were 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 that would be tied to the existing 3 km standard SMAP Production Grid but would allow the shifting of the 9 and 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).

Computationally the L2 and L3 VG product is the same as the SPG 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 (i.e. water bodies). All of the quantitative analyses and metrics in this Assessment Report are based on results using the 36 km validation grid.

Following the release of the Version 1 report, a glitch in the indexing of the VGs was found that resulted in the *in situ* data being incorrectly matched with a grid cell offset by one grid spacing (36 km) in both directions. This error has been corrected here in Version 2 of the report, and all analyses were repeated with the correct VGs. As previously noted, Version 2 of the report also includes an expansion of the analysis period.

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 beta-release assessment 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 [2]. 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 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 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 this difference needs to be investigated with the SMOS team.

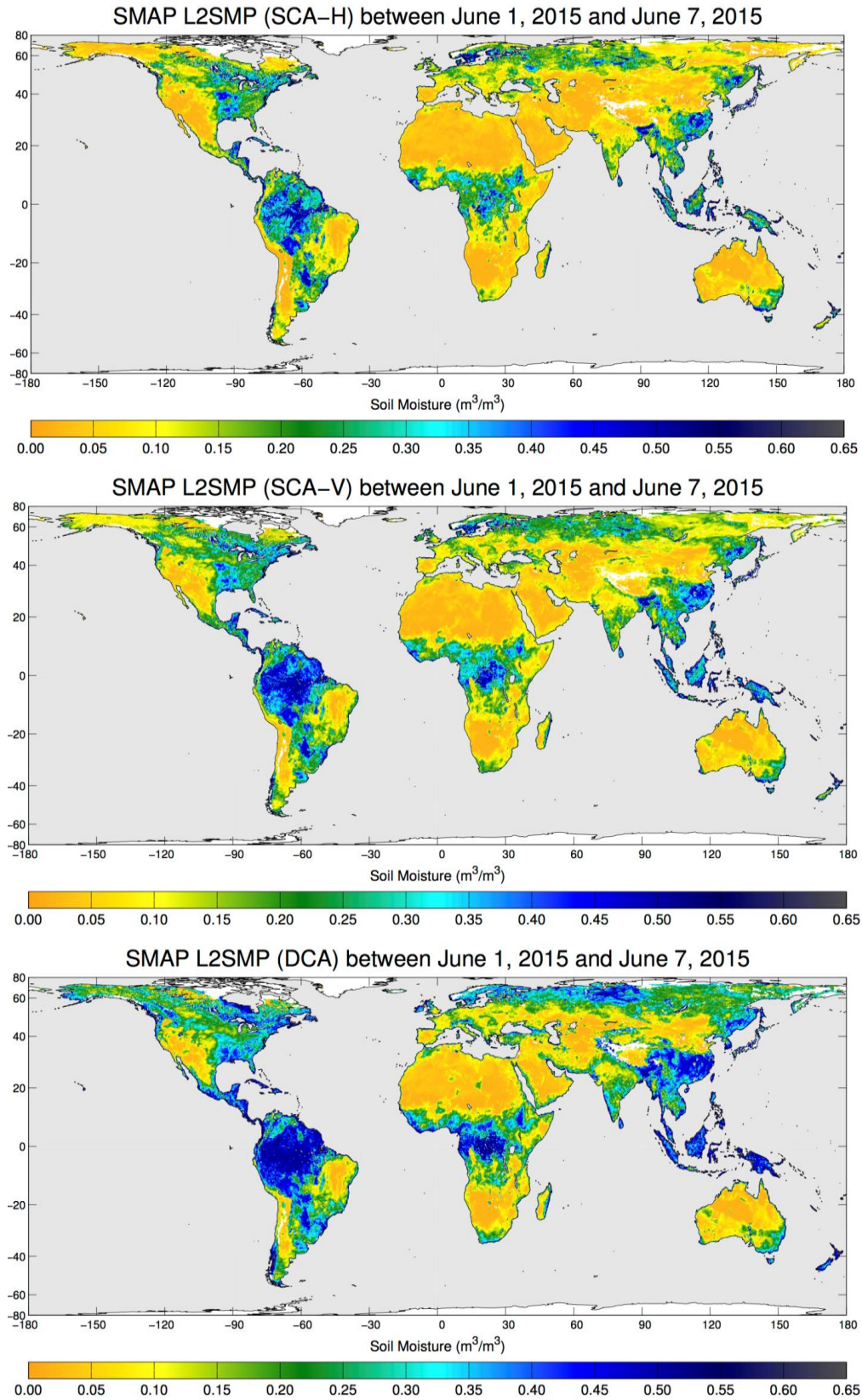


Figure 7.1. SMAP L2SMP global images of soil moisture for three alternative algorithms.

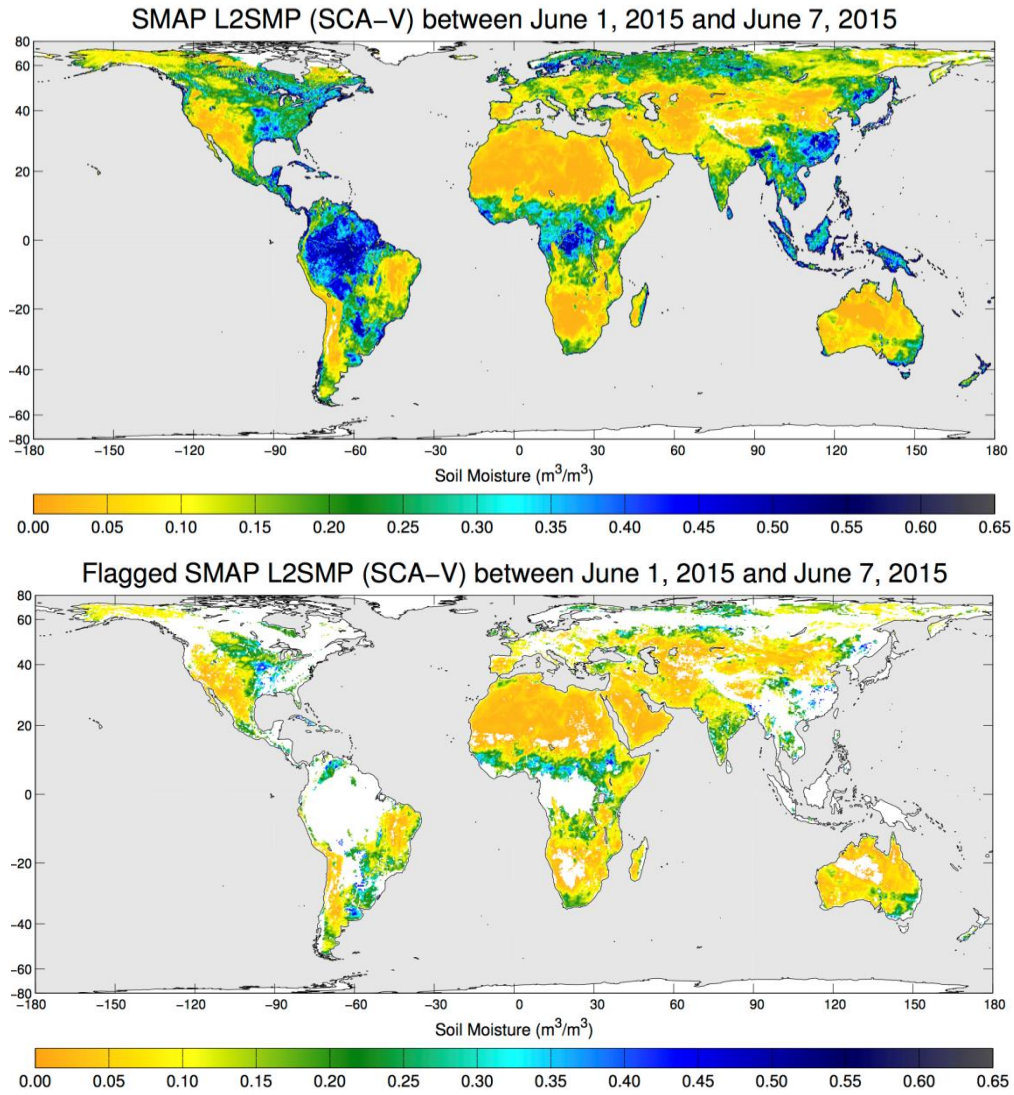


Figure 7.2. SMAP L2SMP global images of soil moisture including (top) or excluding (bottom) flagged data.

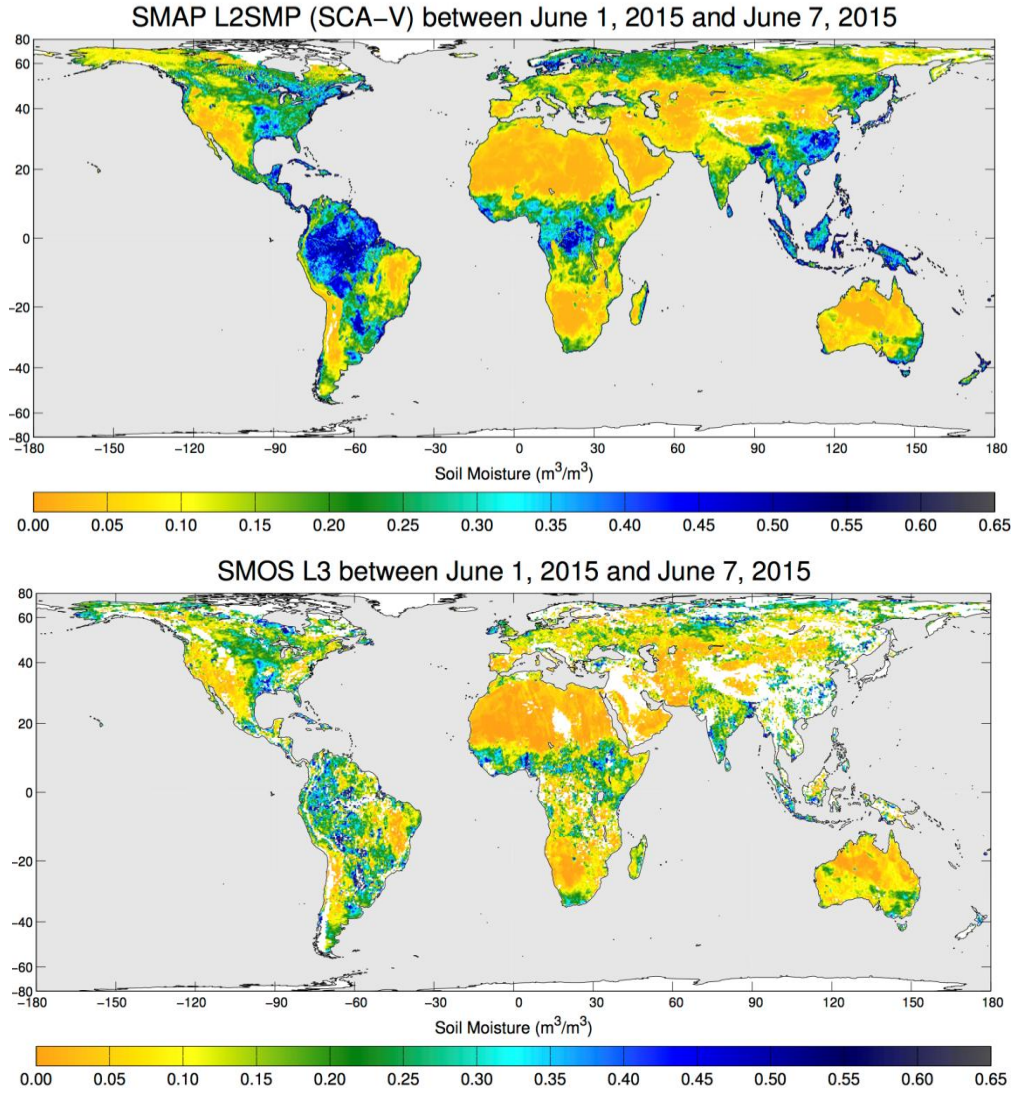


Figure 7.3. SMAP L2SMP and SMOS L3 global images including flagged soil moisture data.

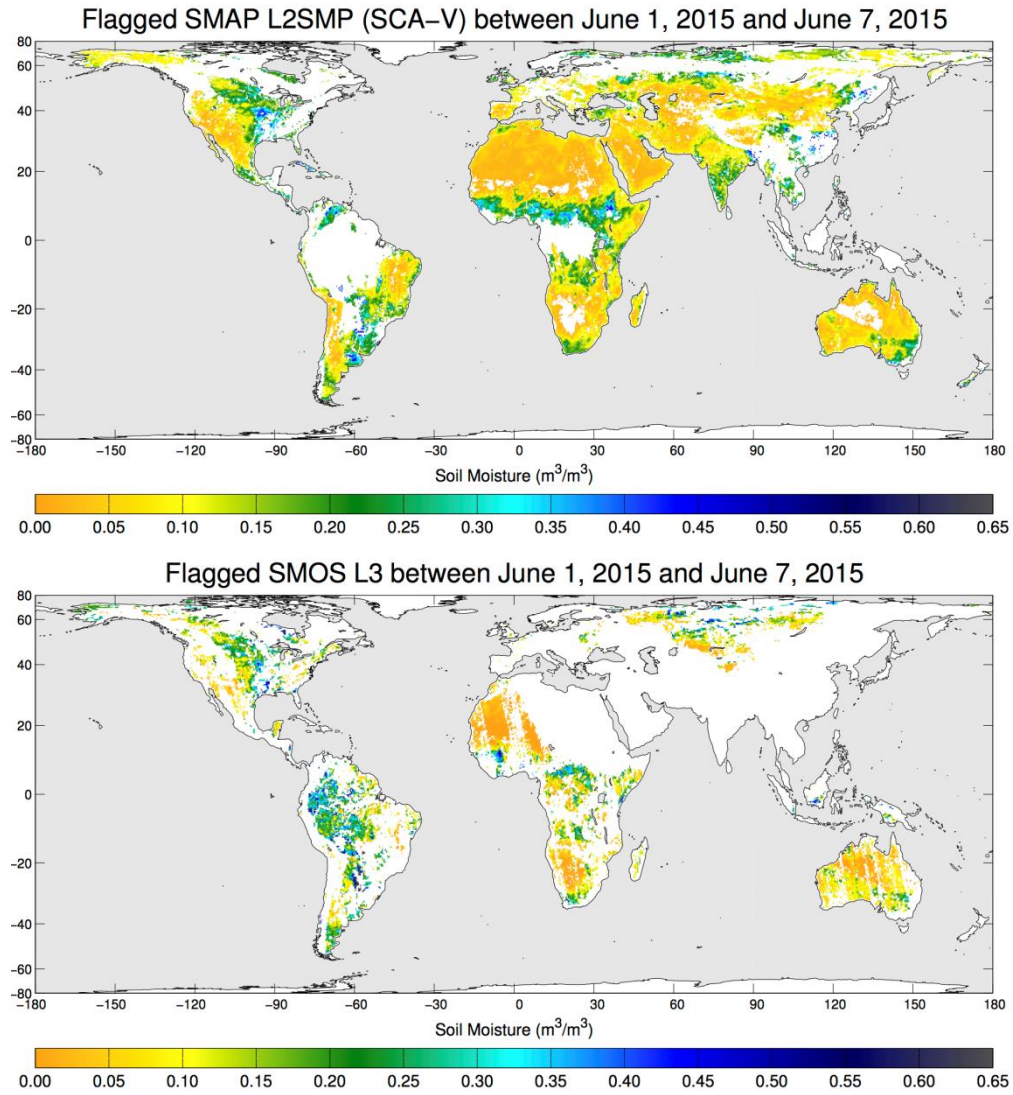


Figure 7.4. SMAP L2SMP and SMOS L3 global images of soil moisture excluding flagged data.

7.2 Core Validation Sites (CVS)

The Stage 1 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.

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 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. 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 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 status of candidate sites is periodically reviewed to determine if they should be classified as CVS. Only the CVS are used in quantitative assessment of algorithm performance for the beta release. The current CVS are marked with an asterisk in Table 7.1. A total of 13 CVS were used in this assessment. Note that two sites were added (changed from candidate to core site) since Version 1 of this report because the correction of the VG removed a water body proximity flag at one site (Carmen) and the longer period of record allowed data from a second site to be used (Reynolds Creek).

The key tool used in L2SMP CVS analyses are the charts illustrated by Figures 7.5-7.8. Each week this chart is updated for each CVS. 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. Several alternative algorithms and the SMOS soil moisture product are also displayed (SMOS v280 was used for March 31-May 4 and SMOS v300 was used for May 5-October 26, 2015). Each CVS is carefully reviewed and discussed by the L2SMP Team and Cal/Val Partners each week. 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 beta-release 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.

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
REMEDIHUS*	J. Martinez	Spain	Temperate	Croplands
Twente	Z. Su	Holland	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

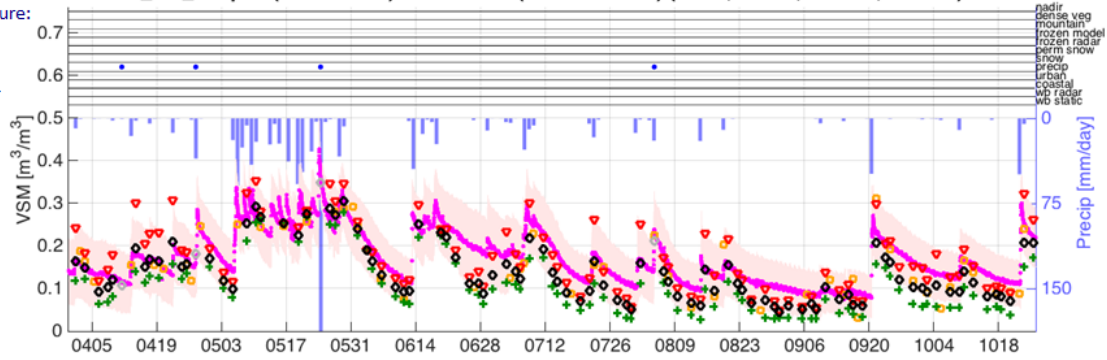
*=CVS used in assessment.

Climate class: Temperate (Cfa)
 Landcover: Grasslands

Little Washita (Core Pixel)

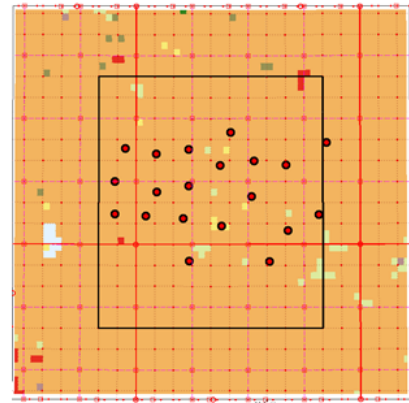
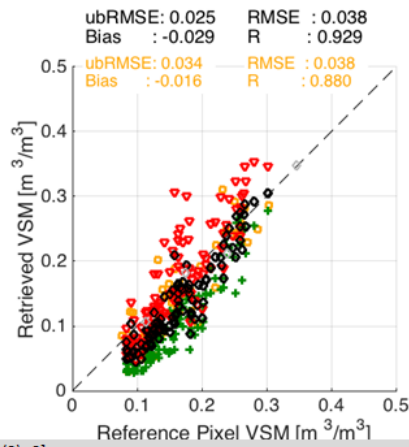
L2_SM_P-Opt 2 (T11880-999): 1602-36-01 (Little Washita) (34.88, -98.09; -2632.5, -1042.5)

Soil texture:
 S-%: 51
 C-%: 16
 BD: 1.44



- In Situ
- ◆ SCA-V
- ◆ SCA-H
- ◆ DCA
- ◆ SMOS SM

Alg	ubRMSE	Bias	RMSE	R
SCA-H	0.025	-0.058	0.063	0.931
SCA-V	0.025	-0.029	0.038	0.929
DCA	0.041	0.007	0.042	0.865



Black: Use recommended [Retrieval Quality Flag bit(0)=0]
 Gray: Retrieval attempted and succeeded but use not recommended [bit(0)=1, bit(1)=0, bit(2)=0]
 Green: Retrieval attempted but failed [bit(0)=1, bit(1)=0, bit(2)=1]

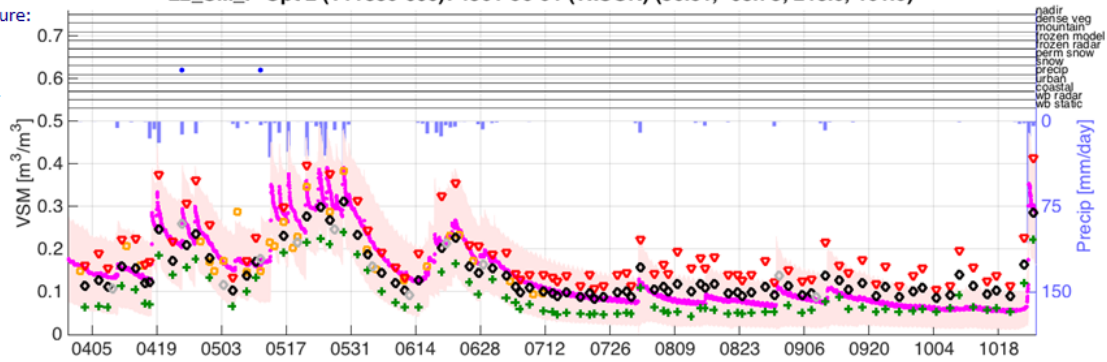
Figure 7.5. L2SMP Assessment Tool Report for Little Washita, OK.

Climate class: Temperate (Cfa)
 Landcover: Grasslands

TxSON (Core Pixel)

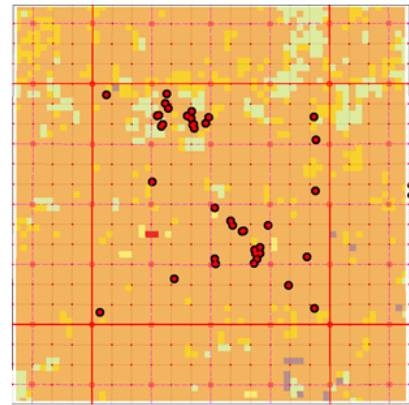
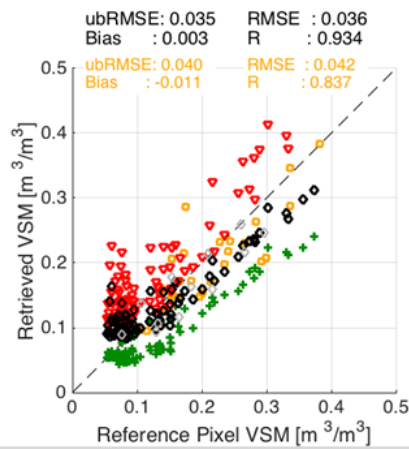
L2_SM_P-Opt 2 (T11880-999): 4801-36-01 (TxSON) (30.31, -98.78; 218.0, 101.0)

Soil texture:
 S-%: 33
 C-%: 33
 BD: 1.42



- In Situ
- ◆ SCA-V
- + SCA-H
- ▲ DCA
- ◻ SMOS SM

Alg	ubRMSE	Bias	RMSE	R
SCA-H	0.037	-0.044	0.058	0.940
SCA-V	0.035	0.003	0.036	0.934
DCA	0.036	0.057	0.067	0.881



Black: Use recommended [Retrieval Quality Flag bit(0)=0]
 Gray: Retrieval attempted and succeeded but use not recommended [bit(0)=1, bit(1)=0, bit(2)=0]
 Green: Retrieval attempted but failed [bit(0)=1, bit(1)=0, bit(2)=1]
 Cyan: Retrieval not attempted [bit(0)=1, bit(1)=1]

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

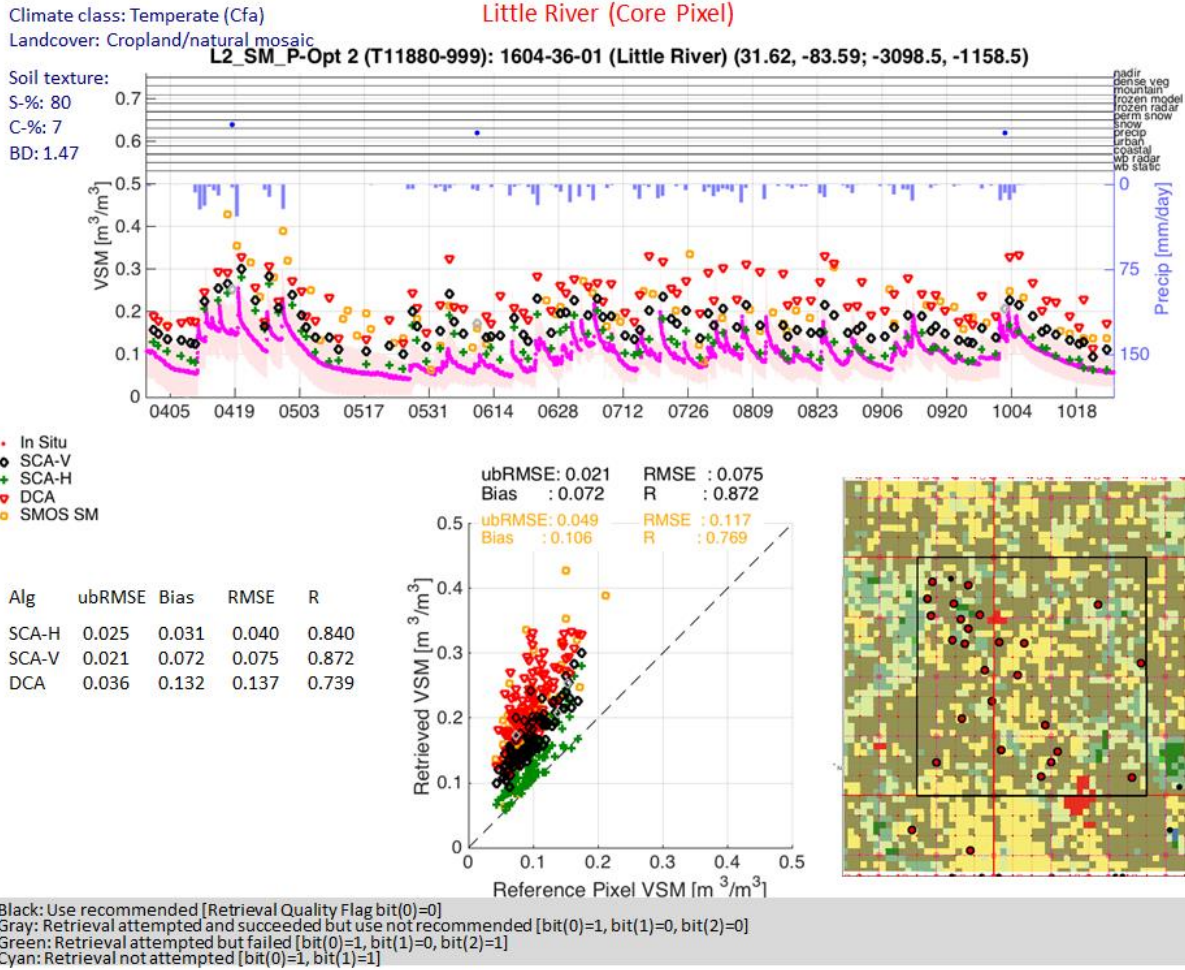


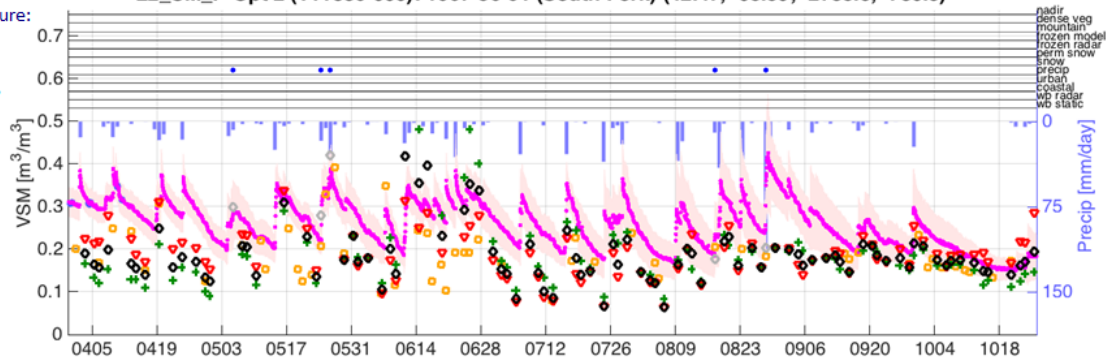
Figure 7.7. L2SMP Assessment Tool Report for Little River, GA.

Climate class: Cold (Dfa)
 Landcover: Croplands

South Fork (Core Pixel)

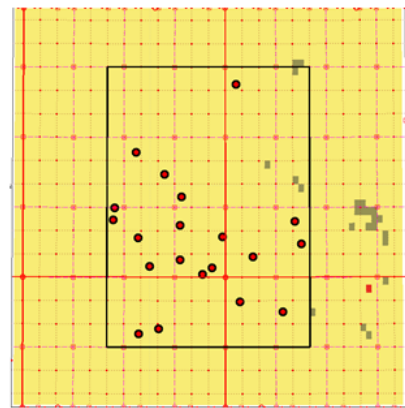
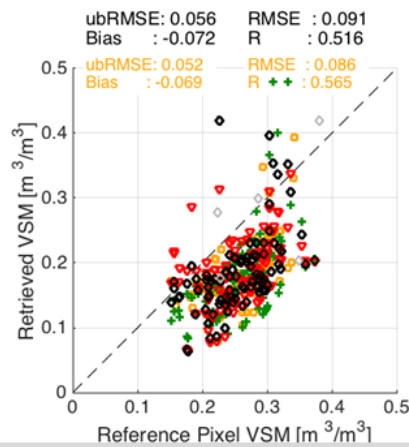
L2_SM_P-Opt 2 (T11880-999): 1607-36-01 (South Fork) (42.47, -93.39; -2783.5, -789.5)

Soil texture:
 S-%: 37
 C-%: 30
 BD: 1.35



- In Situ
- ◆ SCA-V
- + SCA-H
- ▼ DCA
- ◻ SMOS SM

Alg	ubRMSE	Bias	RMSE	R
SCA-H	0.059	-0.075	0.095	0.558
SCA-V	0.056	-0.072	0.091	0.516
DCA	0.054	-0.068	0.087	0.457



Black: Use recommended [Retrieval Quality Flag bit(0)=0]
 Gray: Retrieval attempted and succeeded but use not recommended [bit(0)=1, bit(1)=0, bit(2)=0]
 Green: Retrieval attempted but failed [bit(0)=1, bit(1)=0, bit(2)=1]
 Cyan: Retrieval not attempted [bit(0)=1, bit(1)=1]

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

Table 7.2. SMAP L2SMP Beta Release CVS Assessment

Site name	ubRMSE (m3/m3)			Bias (m3/m3)			RMSE (m3/m3)			R		
	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA	SCA-H	SCA-V	DCA
Reynolds Creek	0.045	0.043	0.058	-0.071	-0.036	-0.016	0.084	0.056	0.060	0.483	0.602	0.576
Walnut Gulch	0.027	0.031	0.045	-0.023	-0.007	0.018	0.036	0.032	0.048	0.581	0.715	0.639
TxSON	0.037	0.035	0.036	-0.044	0.003	0.057	0.058	0.036	0.067	0.940	0.934	0.881
Fort Cobb	0.037	0.032	0.041	-0.077	-0.054	-0.030	0.086	0.062	0.051	0.858	0.881	0.840
Little Washita	0.025	0.025	0.041	-0.058	-0.029	0.007	0.063	0.038	0.042	0.931	0.929	0.865
South Fork	0.059	0.056	0.054	-0.075	-0.072	-0.068	0.095	0.091	0.087	0.558	0.516	0.457
Little River	0.025	0.021	0.036	0.031	0.072	0.132	0.040	0.075	0.137	0.840	0.872	0.739
Kenaston	0.037	0.027	0.041	-0.075	-0.048	-0.004	0.084	0.055	0.041	0.669	0.792	0.699
Carman	0.082	0.061	0.063	-0.088	-0.088	-0.079	0.120	0.107	0.102	0.614	0.677	0.567
Monte Buey	0.041	0.028	0.027	-0.041	-0.019	0.016	0.058	0.034	0.032	0.809	0.886	0.874
REMEDHUS	0.036	0.045	0.057	-0.063	-0.053	-0.042	0.073	0.069	0.071	0.575	0.456	0.332
Yanco	0.055	0.045	0.041	0.024	0.035	0.046	0.060	0.057	0.061	0.943	0.946	0.934
Kyeamba	0.052	0.051	0.033	0.042	0.065	0.062	0.067	0.082	0.070	0.926	0.952	0.940
SMAP Average	0.043	0.038	0.044	-0.040	-0.018	0.008	0.071	0.061	0.067	0.748	0.781	0.719
SMOS Average	0.047			-0.019			0.068			0.751		
Averages are based on the values reported for each CVS												

The key results for this assessment are summarized in the SMAP Average results in Table 7.2. First, all algorithms have about the same ubRMSE, differing by $0.006 \text{ m}^3/\text{m}^3$, and exceed or are very close to the SMAP mission goal of $0.040 \text{ m}^3/\text{m}^3$. 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 DCA being nearly unbiased while SCA-H and SCA-V underestimate the CVS soil moisture. However, the SCA-V bias is also relatively low.

For guidance in expected performance, the SMOS soil moisture products² for each site over the same time period were analyzed and these summary statistics are included in Table 7.2. The results are quite similar to the SMAP results for all metrics. One point to note is that SMOS also has a small underestimation bias. As discussed previously, this is actually something that could be expected when comparing a satellite retrieval to an *in situ* observation at 5 cm. In addition, this assessment is based on a limited time frame. The relative performance of algorithms and products could be different as the record length and seasons captured expands.

Based upon the metrics and considerations discussed, the SCA-V has been selected as the baseline algorithm for the beta release. Prior to the validated release, it is expected that additional investigations will be completed on parameter optimization for all algorithms, additional CVS will be incorporated, and a longer period of observations will be considered which could alter the decision on which algorithm to designate as the SMAP baseline algorithm going forward.

²The SMOS data used are based on v280 (April 11-May 4, 2015) and v300 (May 5-October 26, 2015). Details on these SMOS versions are found in [18].

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.

7.2.1 Little Washita, OK: Benchmark

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 6-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 [13]). 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 very high correlation, 0.929 for DCA-V. 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 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 six months was similar to Oklahoma: dry followed by a very wet May and then an extended drydown.

This site also has a very 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 AMSR-E [14] 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 [15], which are reflected in the results shown in Figure 7.7. SMOS overestimates soil moisture, while the SMAP SCA-H algorithm performs the best. Regardless of the ubRMSE and bias, all algorithms have high correlations. The results for Little River illustrate that there may be inherent performance limitations in some algorithms under specific conditions. These differences between *in situ* observations and different algorithm outputs can challenge the assumptions and premises that have 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 early July corn would have a high VWC ($\sim 3 \text{ kg/m}^2$) while soybeans would be much smaller ($\sim 0.3 \text{ kg/m}^2$) [16].

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 6-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 in [17] 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.

Other explanations that will be investigated in the coming months are changing surface roughness conditions and soil characterization/dielectric models. The divergence of the algorithms and their departure from the *in situ* estimates suggests a fundamental problem that needs to be addressed.

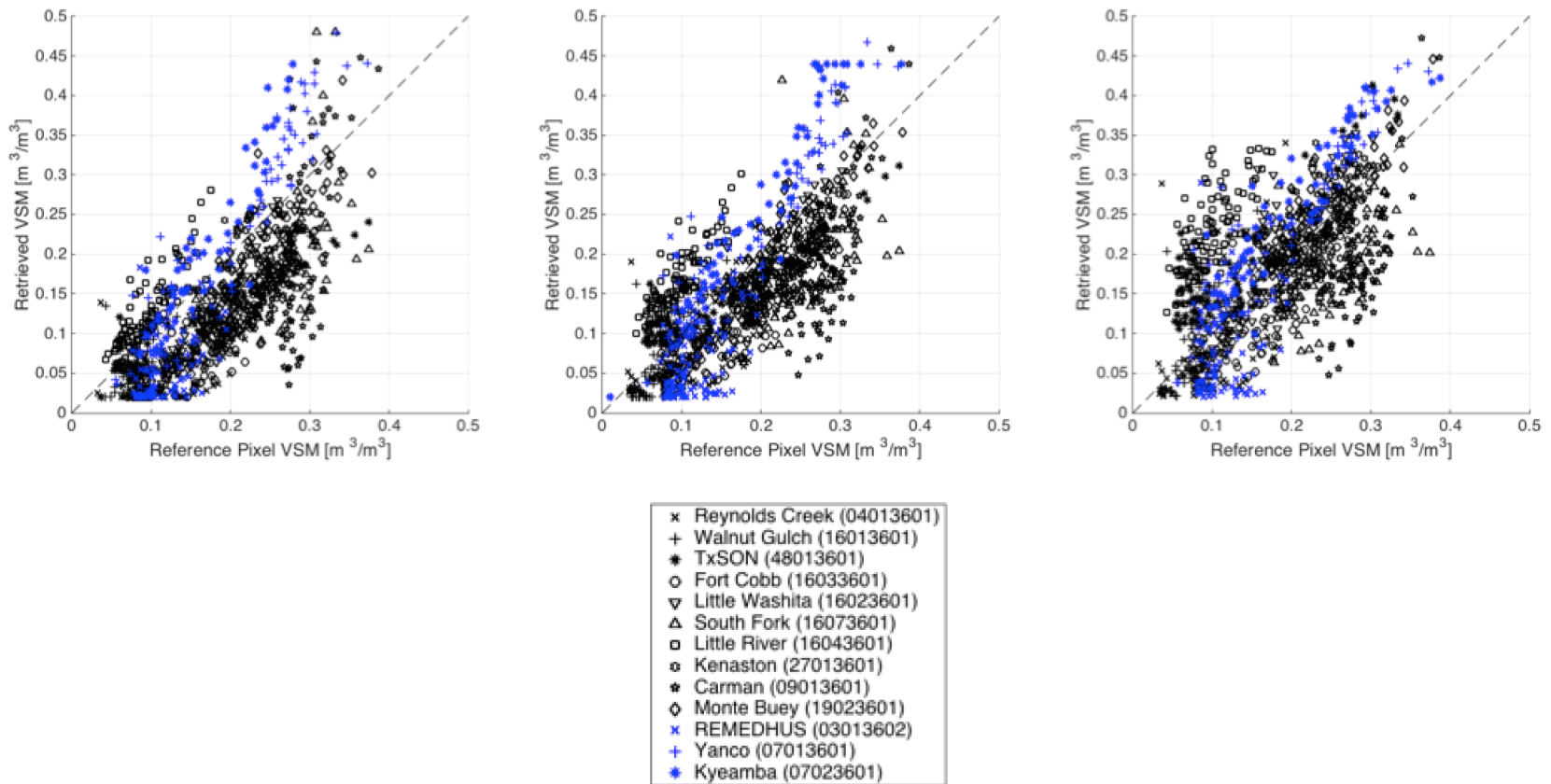


Figure 7.9. Scatterplot of SMAP L2SMP Beta Release CVS Assessment (SCA-H left panel, SCA-V middle panel, and DCA right panel).

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 as well as those planned for the future are listed in Table 7.3.

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 the 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 implementation of this technique will be part of the validated L2SMP product assessment.

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 7.3. Sparse Networks Providing L2SMP Validation Data

Network Name	PI/Contact	Area	Number 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

The sparse network metrics are summarized in Table 7.4 and Figure 7.10. Because of the larger number of sites, it is possible to also examine the results based upon the IGBP land cover classification. The reliability of the analyses based upon these classes will depend upon the number of sites available (N).

Overall, the ubRMSE and bias values are similar to those obtained from the CVS. This result provides additional confidence in the previous conclusions based on the CVS. In addition, the SCA-V has the best overall ubRMSE and correlation while the DCA has the lowest (near zero) bias. These are the same results observed for the CVS.

Interpreting the results based on land cover is more complex. There are no clear patterns associated with broader vegetation types. The ubRMSE values for SCA-V are all between 0.025 and 0.077 m³/m³. The two categories with larger bias values are the Evergreen broadleaf forest and Grasslands. It is not surprising that there would be issues with forests at this stage of validation because they typically have large VWC. In addition, this forest result is based on only 2 sites. The larger ubRMSE and bias for Grasslands needs to be addressed.

SMOS metrics are also included in Table 7.4 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 when partitioned by land cover class. Although the errors for the forest categories are large, the values of N are small and should not dominate the average metrics.

Table 7.4. SMAP L2SMP Beta Release Sparse Network Assessment

IGBP Class	ubRMSE (m ³ /m ³)				Bias (m ³ /m ³)				RMSE (m ³ /m ³)				R				N
	SCA-H	SCA-V	DCA	SMOS	SCA-H	SCA-V	DCA	SMOS	SCA-H	SCA-V	DCA	SMOS	SCA-H	SCA-V	DCA	SMOS	
Evergreen needleleaf forest	0.081	0.077	0.086	0.060	-0.037	-0.001	0.056	-0.079	0.107	0.093	0.114	0.109	0.476	0.515	0.490	0.540	13
Evergreen broadleaf forest	0.066	0.063	0.061	0.073	0.166	0.154	0.108	-0.092	0.181	0.172	0.153	0.190	0.726	0.687	0.466	0.546	2
Deciduous needleleaf forest																	
Deciduous broadleaf forest	0.048	0.047	0.064	0.067	0.004	0.036	0.083	-0.127	0.121	0.109	0.125	0.157	0.622	0.641	0.515	0.488	11
Mixed forest	0.046	0.046	0.063	0.077	0.016	0.050	0.106	-0.082	0.086	0.090	0.137	0.153	0.708	0.703	0.559	0.447	20
Closed shrublands																	
Open shrublands	0.033	0.037	0.053	0.053	-0.048	-0.020	0.014	-0.008	0.066	0.060	0.076	0.075	0.585	0.577	0.561	0.400	47
Woody savannas	0.047	0.047	0.065	0.065	-0.021	0.028	0.108	-0.059	0.099	0.098	0.147	0.114	0.707	0.683	0.486	0.515	24
Savannas	0.027	0.030	0.038	0.047	-0.024	0.002	0.023	-0.005	0.062	0.057	0.070	0.060	0.684	0.620	0.577	0.519	7
Grasslands	0.047	0.048	0.059	0.057	-0.069	-0.038	-0.002	-0.031	0.091	0.077	0.082	0.082	0.708	0.705	0.675	0.642	162
Permanent wetlands																	
Croplands	0.065	0.058	0.064	0.070	-0.037	-0.028	-0.012	-0.041	0.107	0.098	0.101	0.111	0.621	0.624	0.532	0.586	80
Urban and built-up	0.052	0.056	0.068	0.065	-0.019	0.021	0.085	-0.075	0.091	0.098	0.137	0.105	0.394	0.300	0.244	0.411	5
Crop/Natural vegetation mosaic	0.050	0.045	0.056	0.073	-0.029	0.000	0.043	-0.078	0.078	0.070	0.086	0.135	0.675	0.720	0.631	0.560	35
Snow and ice																	
Barren/Sparse	0.023	0.025	0.038	0.050	-0.024	0.004	0.052	-0.004	0.039	0.043	0.077	0.057	0.452	0.429	0.383	0.361	10
Average	0.049	0.048	0.060	0.062	-0.044	-0.016	0.020	-0.042	0.091	0.081	0.095	0.099	0.655	0.654	0.590	0.561	416

Average is based upon all sets of observations, not the average of the land cover category results.

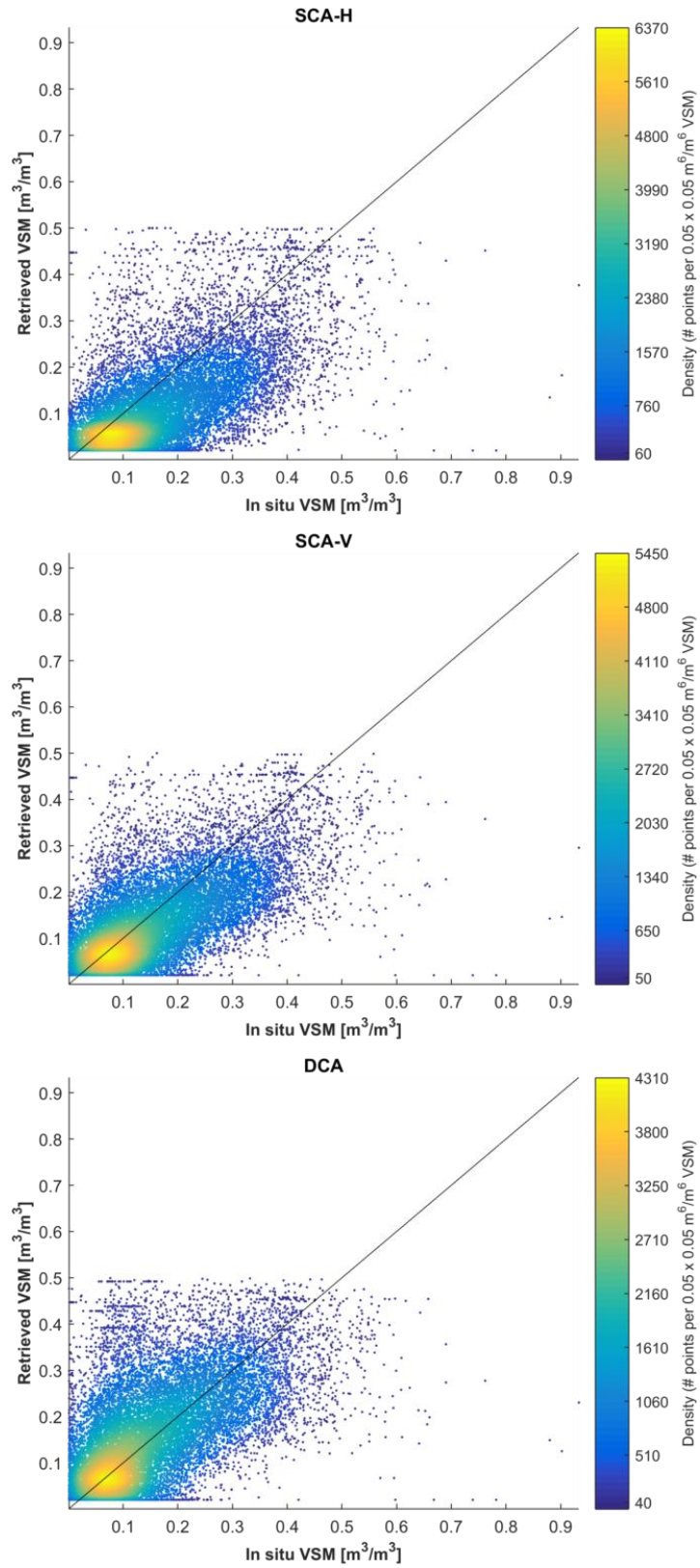


Figure 7.10. Scatterplots of the Sparse Network *In Situ* Observations and SMAP Retrievals.

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 globe 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.
- GCOM-W AMSR2 operates at higher frequencies (X- and C-band) that respond to shallower soil depths and observes at different times of the day (1:30 am/pm), but does have a similar nominal spatial resolution as SMAP.
- 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.

All of these products will be considered as SMAP validation progresses; only SMOS will be utilized for satellite comparisons with SMAP for the beta release assessment in this report.

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. 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 11-May 4) and v300 (May 5-September 8). 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 7.5. 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 Table 7.5 ubRMSD values is that they are larger than those observed 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. These issues will be addressed in more detail prior to the validated release.

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 different implementation or parameterization is being used. A persistent pattern for several classes is also important to examine in more detail. Focusing on SCA-V, the bias values indicate that SMAP predicts lower soil moisture values for most categories than SMOS. The biases are relatively small overall and for most categories; however, the shrubland categories are quite different. The reason for this needs to be explored with a thorough examination of algorithm parameterization used by SMAP and SMOS.

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, the flags were ignored in one analysis. The resulting metrics for the forest categories are shown in Table 7.6. 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. This must be examined in more detail before validated release.

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.

Table 7.5. SMAP L2SMP Beta Release SMAP-SMOS Assessment

IGBP Class	ubRMSD (m ³ /m ³)			Bias (m ³ /m ³)			RMSD (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
Evergreen Needleleaf forest															
Evergreen Broadleaf forest															
Deciduous Needleleaf forest	0.085	0.081	0.081	-0.02	0.032	0.121	0.088	0.087	0.146	0.462	0.541	0.570	285	285	284
Deciduous Broadleaf forest	0.075	0.074	0.072	-0.027	0.005	0.004	0.080	0.074	0.083	0.848	0.850	0.818	58	58	58
Mixed forest															
Closed shrublands	0.075	0.070	0.072	-0.087	-0.043	-0.003	0.115	0.082	0.072	0.486	0.610	0.541	152	161	151
Open shrublands	0.069	0.055	0.066	-0.091	-0.052	0.016	0.114	0.076	0.068	0.557	0.776	0.789	97315	104667	99265
Woody savannas	0.098	0.093	0.107	-0.017	0.023	0.083	0.099	0.096	0.135	0.678	0.734	0.645	29918	30001	29192
Savannas	0.076	0.074	0.081	-0.033	-0.021	-0.015	0.083	0.077	0.082	0.752	0.771	0.723	17975	18897	16319
Grasslands	0.057	0.049	0.052	-0.036	-0.017	0.006	0.067	0.051	0.052	0.827	0.878	0.862	52666	55592	51432
Permanent wetlands	0.150	0.144	0.169	-0.283	-0.205	0.095	0.318	0.250	0.194	0.569	0.608	0.268	1538	1537	1462
Croplands	0.071	0.054	0.054	-0.011	-0.004	0.006	0.071	0.055	0.055	0.744	0.834	0.836	24914	25603	25446
Urban and built-up															
Crop/Natural vegetation mosaic	0.093	0.081	0.082	-0.016	-0.013	-0.009	0.094	0.082	0.045	0.715	0.779	0.764	7690	7685	7436
Snow and ice															
Barren/Sparse	0.028	0.027	0.033	0.013	0.016	0.030	0.031	0.031	0.045	0.757	0.789	0.764	28314	27869	27558
Average	0.081	0.066	0.073	-0.047	-0.023	0.020	0.094	0.070	0.076	0.654	0.797	0.776			
Average is based on all sets of observations, not the average of the land covers.															

Table 7.6. SMAP L2SMP Beta Release SMAP-SMOS Assessment (No Flags Applied)

IGBP Class	ubRMSD (m ³ /m ³)			Bias (m ³ /m ³)			RMSD (m ³ /m ³)			<i>R</i>			<i>N</i>		
	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	0.129	0.119	0.129	0.108	0.132	0.174	0.168	0.178	0.217	0.354	0.358	0.282	95767	95767	95731
Evergreen Broadleaf forest	0.160	0.160	0.170	0.139	0.196	0.244	0.212	0.253	0.297	0.359	0.293	0.153	130359	130359	128228
Deciduous Needleleaf forest	0.080	0.079	0.100	-0.014	0.039	0.132	0.081	0.088	0.166	0.413	0.411	0.256	29250	29250	29250
Deciduous Broadleaf forest	0.122	0.119	0.141	0.092	0.116	0.151	0.152	0.166	0.207	0.576	0.571	0.419	19722	19722	19716
Mixed forest	0.130	0.124	0.137	0.098	0.127	0.176	0.163	0.177	0.223	0.413	0.419	0.335	164268	164268	164199

7.5 Summary

Three alternative L2SMP retrieval algorithms were evaluated using three methodologies in preparation for beta 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 beta release the goal was to conduct a Stage 1 assessment based primarily on CVS comparisons using metrics and time series plots. These analyses indicated that the SCA-V had better unbiased root mean square error (ubRMSE), bias, and correlation R than SCA-H, and SCA-H had better ubRMSE and correlation R than DCA. DCA had the lowest bias of all the algorithms (essentially zero bias); however, the SCA-V bias was only $-0.018 \text{ m}^3/\text{m}^3$. These differences were relatively small, generally third decimal level. Based on the results, it is recommended that the SCA-V be adopted as the baseline algorithm for the beta release. The overall ubRMSE of the SCA-V is $0.038 \text{ m}^3/\text{m}^3$, which exceeds the mission requirement.

Sparse Network comparisons are more difficult due to upscaling but provide many more locations than the CVS. The analyses conducted here supported the conclusion reached in the CVS assessment, thus moving the validation closer to Stage 2. The Sparse Network data also allowed the evaluation of performance based on land cover.

SMAP retrievals were also compared globally to SMOS subject to temporal and spatial constraints. This resulted in a very large number of data points that could also address land cover effects. These inter-comparisons indicated similar performance by some SMAP algorithms for some land cover types, although there was an overall large ubRMSE between the SMOS and SMAP retrievals. They also suggested the need for a more rigorous evaluation and careful study of different algorithm parameterizations and implementation approaches between SMOS and SMAP.

8 OUTLOOK AND PLAN FOR VALIDATED RELEASE

Satellite passive microwave retrieval of soil moisture has been the subject of intensive study and assessment for approximately the past fifteen years. 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. 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 between the beta and validated release include the following:

- *Moving toward a Stage 2+ validated product.* The beta release is limited by the period of record. Six months of data have been utilized in this assessment report. By the time of the validated release in Spring/Summer 2016, there will be a year of SMAP observations covering the full annual cycle in the Northern and Southern Hemisphere. With enhanced inter-comparisons described below, the L2SMP validation should exceed Stage 2 and possibly achieve Stage 3.
- *Increasing the number of CVS.* There are a number of additional sites that may qualify as CVS. Several of these are only awaiting data delivery due to the once-per-year downloading of stations (Mongolia and Tibet). Others need processing by the providers (Twente, Niger, Benin). Several are still under development and may not be available within the time frame of the validated release (Millbrook, Kuwait, Bell Ville). It is unlikely that any additional sites beyond those already known will be developed and implemented; 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.
- *Increasing the number of Sparse Networks.* Efforts are underway to complete the operational acquisition of all the networks listed in Table 7.3. Of these networks, the Oklahoma Mesonet will be of high value to assessments. There are other networks that exist but utilizing these may involve issues that cannot be addressed in the near term. However, these other networks will be considered if they offer a unique resource and require a reasonable effort to integrate.
- *Implementing Triple Co-Location as an assessment and algorithm improvement tool.* This technique has been used to assess satellite soil moisture products. It is currently implemented by SMAP; however, it requires a long record of observations (> 1 year). It may contribute to assessment of the validated product. 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. This is partially due to the fact that both SMOS and SMAP products are derived from L-band radiometers. All of the other satellites have issues that would have to be carefully considered before differences in performance are used as the basis for modifying the SMAP algorithm. Regardless, a more thorough evaluation with these alternative satellites will be conducted prior to validated release.
- *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 these model products is the depth of their surface layer, which is typically thicker than the 5 cm layer used by SMAP. Preliminary

assessments suggest that the model responses may be dampened relative to satellite estimates. Some effort is required to further evaluate this tool and how to utilize it in the validated assessment.

- *Incorporating Field Campaign results into algorithm assessment and improvement.* Several field campaigns will be completed in 2015 that include two SMAPEX experiments in Australia and SMAPVEX15 in Arizona. If these data are to be used in the validated product assessment, the data must be fully processed to provide estimates of surface soil moisture over SMAP L2SMP grids. 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.
- *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. 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 preceding three hours 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. This should be attempted and resolved prior to the validated release. Additionally, a comparison between using GMAO forecast model data and GPM blended satellite data for the SMAP precipitation flag should also be done.
- *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.
- *Optimization of algorithm parameters.* For the beta release the parameter set defined in the ATBD was implemented. Only a minor change to the single scattering albedo of trees was utilized. It is hypothesized that by using time series observations, the algorithm parameters for each grid cell can be optimized, given the unique mix of heterogeneous land covers that is likely present in any given 36-km EASE-Grid 2.0 cell. The improvement in soil moisture retrieval accuracy gained by using these new optimized parameters can be evaluated using data from the *in situ* networks and CVS. In addition, systematic tuning of parameters will be evaluated prior to validated release, as well as the accuracy of flag thresholds and water body corrections.

9 ACKNOWLEDGEMENTS

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