Validation of Advanced Microwave Scanning Radiometer Soil Moisture Products

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***Abstract*—Validation is an important and particularly challenging task for remote sensing of soil moisture. A key issue in the validation of soil moisture products is the disparity in spatial scales between satellite and *in situ* observations. Conventional measurements of soil moisture are made at a point, whereas satellite sensors provide an integrated area/volume value for a much larger spatial extent. In this paper, four soil moisture networks were developed and used as part of the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) validation program. Each network is located in a different climatic region of the U.S., and provides estimates of the average soil moisture over highly instrumented experimental watersheds and surrounding areas that approximate the size of the AMSR-E footprint. Soil moisture measurements have been made at these validation sites on a continuous basis since 2002, which provided a seven-year period of record for this analysis. The National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA) standard soil moisture products were compared to the network observations, along with two alternative soil moisture products developed using the single-channel algorithm (SCA) and the land parameter retrieval model (LPRM). The metric used for validation is the root-mean-square error (rmse) of the soil moisture estimate as compared to the *in situ* data. The mission requirement for accuracy defined by the space agencies is 0.06 m^3/m^3. The statistical results indicate that each algorithm performs differently at each site. Neither the NASA nor the JAXA standard products provide reliable estimates for all the conditions represented by the four watershed sites. The JAXA algorithm performs better than the NASA algorithm under light-vegetation conditions, but the NASA algorithm is more reliable for moderate vegetation. However, both algorithms have a moderate to large bias in all cases. The SCA had the lowest overall rmse with a small bias. The LPRM had a very large overestimation bias and retrieval errors. When site-specific corrections were applied, all algorithms had approximately the same error level and correlation. These results clearly show that there is much room for improvement in the algorithms currently in use by JAXA and NASA. They also illustrate the potential pitfalls in using the products without a careful evaluation.**

***Index Terms*—Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E), passive microwave, soil moisture, validation.**

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I. Introduction

THE ADVANCED Microwave Scanning Radiometer–Earth Observing System (AMSR-E) projects of the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA) were the first satellite programs to incorporate soil moisture as a standard product [1], [2]. In addition to supporting several alternative retrieval algorithms, these projects also initiated validation programs specifically for soil moisture. For soil moisture, these agencies specified an accuracy goal of less than 0.06 m^3/m^3. Validation is a particularly challenging task for microwave remote sensing of soil moisture. The key issue in the validation of soil moisture products is the disparity in spatial scales between satellite and *in situ* observations. Conventional measurements of soil moisture are made at a localized point, whereas satellite sensors provide an integrated area/volume value for a much larger spatial extent. Spatial variations in soil moisture that must be considered within these footprints occur at a variety of scales including the point scale (soil properties), over geographic units (land cover, soils, and topography), and as the result of rainfall events and climate. Land remote sensing has focused on the meter to kilometer scale. For microwave remote sensing, we must consider scales of 1–40 km, which present new challenges.

There were several earlier efforts to generate soil moisture products from other passive microwave satellites; however, all have addressed validation after the fact and have used data sources that were not designed for validating soil moisture estimates from satellite observations. These data sets were sparse (i.e., one point in a footprint), consisted of too short a record, were based on unverified instrumentation, and utilized incompatible measurement depths [3]–[5]. A dedicated soil moisture validation program was one of the key "lessons learned" that we attempted to correct during the AMSR-E project.

There are several algorithms under consideration by NASA and JAXA that had been demonstrated to varying degrees [3], [6]–[10]. Each retrieval algorithm utilizes formulations, parameters, and ancillary data that could not be thoroughly developed and verified until the satellite began providing calibrated data. It is extremely difficult to translate first-principle physics/electromagnetics to the scale of satellite footprints due to the complexity in scaling points to large footprints. Recognizing that validation is a necessity, we are faced with how to approach this challenging problem. The spatial and temporal variability of soil moisture, the large footprint size, and other factors (particularly vegetation) pose significant problems.

It is also important to clarify what the current investigation is addressing—validation of the soil moisture product as defined by the provider. The Committee on Earth Observation Satellites (CEOS) defines validation as the process of assessing by independent means the quality of the data products derived from the system outputs (http://calvalportal.ceos.org/CalValPortal/docs/information/TermsAndDefinitions.pdf). The quality as applied to a satellite product such as soil moisture will be a mission criterion, which, for AMSR-E, was a root-mean-square error (rmse) of 0.06-m^3/m^3 surface soil moisture for areas with vegetation water content < 1.5 kg/m^2 ([1] and http://nsidc.org/data/amsr_validation/pdfs/Version_3_SDV_Plan.pdf). The rmse is also the metric used by the Soil Moisture Ocean Salinity [11] and the Soil Moisture Active Passive [12] satellite missions. As described in a later section, other metrics are also provided.

Our goal in this paper was to provide a close approximation of the soil moisture within the area at the depth measured by low-frequency passive microwave sensors that would result in a robust data set for validating retrieval algorithms. The approach used was to provide standardized, replicated, and verified *in situ* measurements of surface soil moisture over spatial domains that approximated the AMSR-E footprint size. This paper will describe the methodology used to develop and implement this soil moisture validation approach.

The soil moisture networks described here have been in operation since the AMSR-E data start date in June 2002 and now provide a substantial seven-year period of record for validation. Preliminary validation activities have been performed [13]; however, there have been many caveats associated with these due to both minor and major changes in brightness temperature and soil moisture products by NASA and JAXA. Over this period, some of these changes were only implemented from the current point on, and the reprocessing of the entire period of record was postponed. Therefore, some of the earlier validation efforts may not be reliable. At this time, all data sets have been reprocessed. Although there may be changes in the future, both agencies are now supplying these standard products, and it is important that potential users understand the status of these data with respect to validation with ground truth.

II. Key Issues in Soil Moisture Validation

Some of the factors that contribute to the difficulty of validating satellite passive microwave soil moisture products and some reasons why we have to consider ground-based validation as a close approximation and not an absolute include the following.

1) For passive microwave radiometers, the satellite footprint size is ambiguous. It is generally accepted that this is the half-power beamwidth; however, radiation from outside this region can contribute to the signal.
2) Most sensors observe an area that is not a circle, but rather an ellipse, and the satellite track that might cover a specific ground location changes from day to day (not exact repeats). As a result, the center and orientation of the footprint observed changes with every satellite pass: A soil moisture network or a point might be centered in the footprint one day and off center on another day.
3) The depth of soil that contributes to the measured radiation varies with frequency and soil moisture condition (level and profile distribution). Fortunately, soil moistures in adjacent depth levels are highly correlated [14].
4) Passive microwave satellite footprints will contain mixtures of different surface types and soils. Retrievals represent spatial averages over ∼40-km footprints. Nonlinearities in the radiative transfer processes and scattering may give rise to differences between retrieved and true area-averaged quantities [15].
5) The natural soil moisture variability (spatial and temporal), together with the spatial extent of footprints, imposes logistic constraints on replication.

Additional considerations in designing a validation method were developed from review of the approaches that have been tried in the past. Some of these include the following.

1) Traditional sampling programs, such as those described in [16], did not characterize the near surface. These typically had a first depth interval of 10–20 cm, which is well beyond the sampling depth of the satellite sensors, even when considering layer correlation. Using such data for validation requires a strong correlation between the sensor sampling depth and the soil depth measured.
2) Measurements were made using a variety of methods (gravimetric, neutron probe, etc.). These different techniques have differing sampling volumes and accuracies.
3) Typical densities of most networks were (at best) one sample in a footprint, which is not a valid basis of comparison. The densities of some widely used networks that include soil moisture observations are one station per 1600 km^2 (Oklahoma Mesonet), 7500 km^2 (Illinois State Water Survey), and 85 000 km^2 for the Soil Climate Analysis Network (SCAN). It is unlikely that a single point in a 40-km (or even a 5-km)-diameter footprint will be representative of the average conditions. Local (e.g., topography, vegetation, and soils) and regional variability (e.g., precipitation) must be considered. Sometimes, the areal average and the point measurement will have similar trends, which will be discussed in a following section. However, establishing such relationships requires that one obtains actual observational data sets.
4) The temporal frequency of most of the older long-term records is poor, often once every 10–14 days. This results in a sparse validation data set.

TABLE I
USDA ARS WATERSHED CHARACTERISTICS

Watershed	Size (km^2)	Soil Moisture Sites	Climate	Annual Rainfall (mm)	Topography	Land Use
Little Washita, OK	610	16	Sub humid	750	Rolling	Range/wheat
Little River, GA	334	29	Humid	1200	Flat	Row crop/forest
Walnut Gulch, AZ	148	21	Semiarid	320	Rolling	Range
Reynolds Creek, ID	238	19	Semiarid	500	Mountainous	Range

5) Data latency was poor. Few networks provided near-real-time observations.

However, the biggest mistake of the past was the lack of any type of dedicated validation effort during the satellite mission. The AMSR-E programs have recognized this and have incorporated soil moisture validation into their projects. Since the launch of AMSR-E, there have been a few attempts at validation of selected products [17]–[24]. For the most part, these have utilized short-term data sets, limited ground-based sampling, selected algorithms, or preliminary versions of the sensor data and/or algorithms. Here, we have attempted to address each of these issues in our approach and implementation.

III. Development of Watershed Validation Networks

Based upon the previous discussion, we identified the following criteria in designing a validation program for satellite products.

1) Replication/density—multiple measurements within a footprint.
2) Extent—25–50 km, the size of a typical passive microwave footprint.
3) Networks representing a wide range of vegetation/climate conditions.
4) Standard and reliable instrumentation.
5) A 5-cm-depth measurement at all sites, and include at least one full profile in each network site.
6) Temporal frequency of at least hourly.
7) Minimize latency.
8) All data in the public domain.

Cost and infrastructure are additional considerations, particularly if we wish to minimize data latency. Our solution to this was to use existing dense meteorological networks as the backbone of the soil moisture networks.

We choose to build on the experimental watershed network resources of the Agricultural Research Service (ARS) Watershed Research Program (http://ars.usda.gov/Main/docs.htm?docid=9696). These watersheds had previously been selected to represent typical conditions in specific climate regions of the U.S., which addressed our criteria of diverse conditions. We selected four watersheds (Table I and Fig. 1) that were the appropriate size and had the necessary recording and reporting infrastructure to minimize data latency.

To implement this network, additional surface soil moisture and temperature sensors (0–5-cm depth) were installed at and around existing instrument locations in the four ARS watersheds: Walnut Gulch, AZ; Little Washita, OK; Little River, GA; and Reynolds Creek, ID. The vegetation conditions in the selected watersheds are expected to be favorable for AMSR-E-based soil moisture retrieval.

The same type of soil moisture/temperature instrument (Stevens Water Hydra Probe) was used at all sites and watersheds. This is also the same sensor used at all SCAN sites [25]. Each watershed has at least one SCAN site and additional meteorological and hydrological instrumentation. All data collection was initiated prior to the AMSR-E launch in 2002. Since then, a number of investigations have been conducted to verify and calibrate the network sensors and to characterize the scaling behavior and how well the network represents the spatial average.

A key component of both calibration and scaling of the watershed soil moisture networks for satellite validation has been a series of short-term and large-scale intensive field campaigns that have provided a bridge between the point and the footprint scales. As a result of these studies described hereinafter, we have a high degree of confidence that the watershed average soil moisture data being produced by the networks are a reliable representation of the average near-surface condition. The individual sites are presented in more detail, and the related verification activities are described in the following sections.

A. Walnut Gulch, AZ

The Walnut Gulch Experimental Watershed encompasses 148 km^2 in southeastern Arizona that surrounds the historical city of Tombstone. The watershed is representative of approximately 60 million ha (600 000 km^2) of brush- and grass-covered rangeland found throughout the semiarid southwest U.S. Cattle grazing is the primary land use. The climate is classified as semiarid with an annual mean temperature at Tombstone of 17.6 °C and an annual mean precipitation of 324 mm. Precipitation varies considerably both seasonally and interannually. Approximately two-thirds of the annual precipitation occurs as high-intensity convective thunderstorms of limited areal extent. Soils are generally well drained, calcareous, gravelly loams with large percentages of rock and gravel at the soil surface. Soil surface rock fragment cover (erosion pavement) can range from near 0% on shallow slopes to over 70% on very steep slopes. The uppermost 10 cm of the soil profiles contains up to 60% gravel, and the underlying horizons usually contain

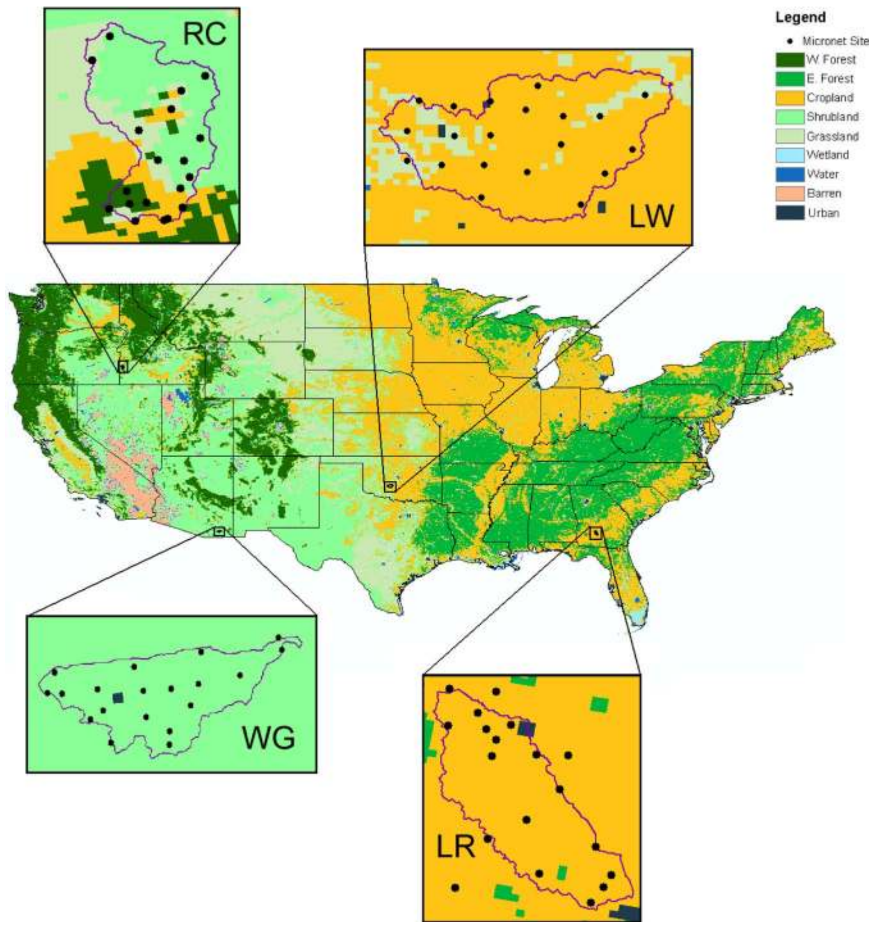

Fig. 1. Location of the validation sites. WG—Walnut Gulch, AZ. LW—Little Washita, OK. LR—Little River, GA. RC—Reynolds Creek, ID. The location of the *in situ* soil moisture sampling sites within the watershed and the general land cover class is also shown.

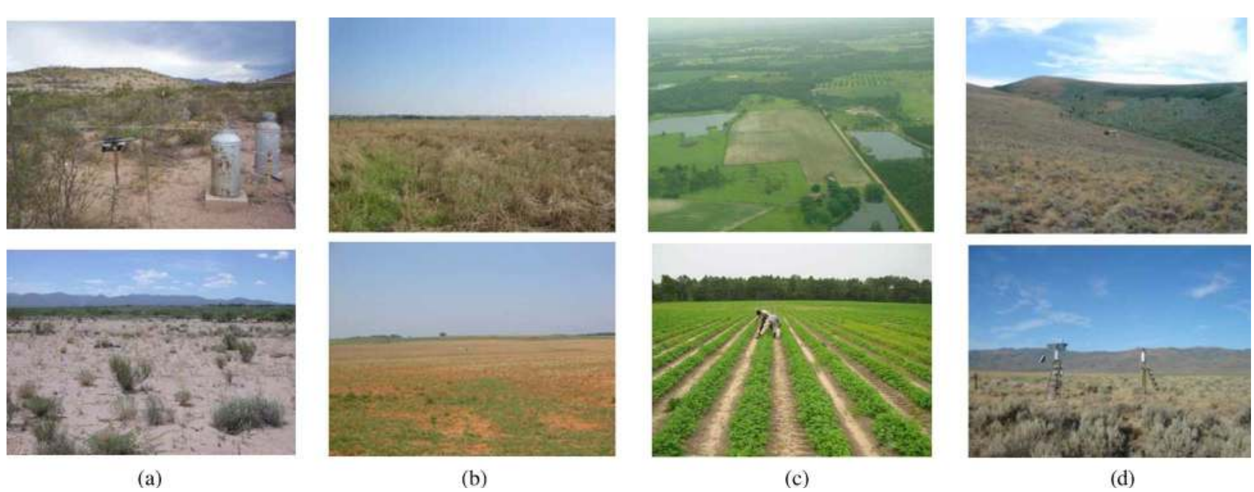

Fig. 2. Representative photographs from (a) Walnut Gulch, AZ, (b) Little Washita, OK, (c) Little River, GA, and (d) Reynolds Creek, ID, showing the land cover conditions in each watershed.

less than 40% gravel. Desert shrubs dominate the lower two-thirds of the watershed, and desert grasses dominate the upper (eastern) third of the watershed. Shrub canopy cover ranges from 30% to 40%, and grass canopy cover ranges from 10% to 80%. The average annual herbaceous forage production is approximately 1200 kg/ha (0.12 $\mathrm{kg/m^2}$). Fig. 2(a) shows landscape conditions in the watershed.

The Walnut Gulch Experimental Watershed is one of the most densely instrumented semiarid watersheds in the world. Rainfall is currently recorded on a continuous basis at 85 locations using digital recording weighing rain gauges. Runoff is measured using a variety of methods from 29 nested watersheds whose drainage areas range in scale from 0.2 to 14 800 ha. In addition, the soils, vegetation, and terrain of the watershed have

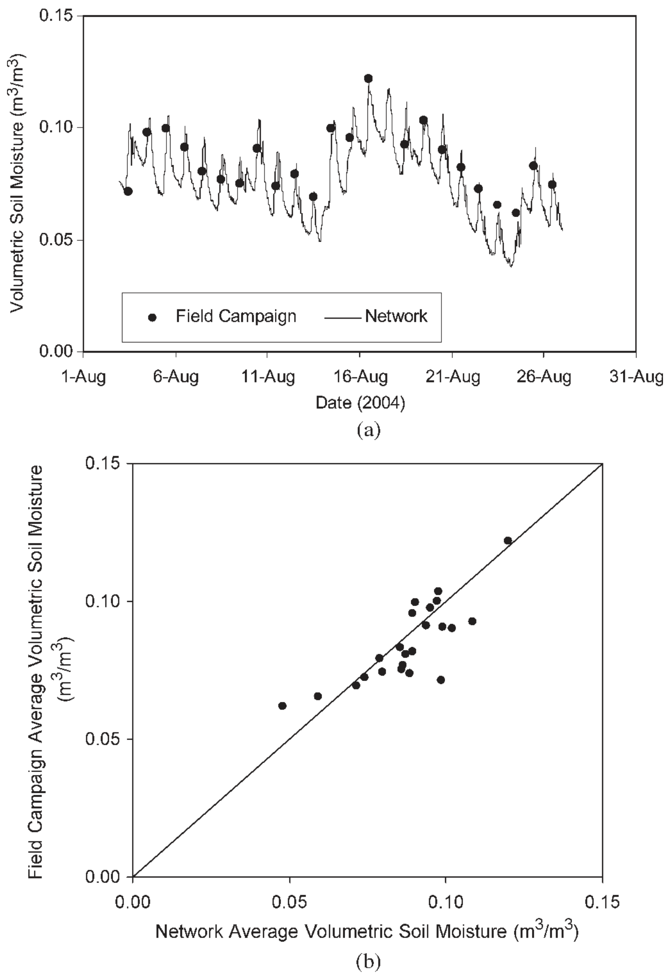

Fig. 3. Comparison of soil moisture averages during the SMEX04 study period. (a) Time series of the geometrically weighted network average and the field campaign results during SMEX04. (b) Comparison of the weighted network average and the higher density field campaign average (bias $= 0.005\ \mathrm{m}^3/\mathrm{m}^3$ and rmse $= 0.010\ \mathrm{m}^3/\mathrm{m}^3$).

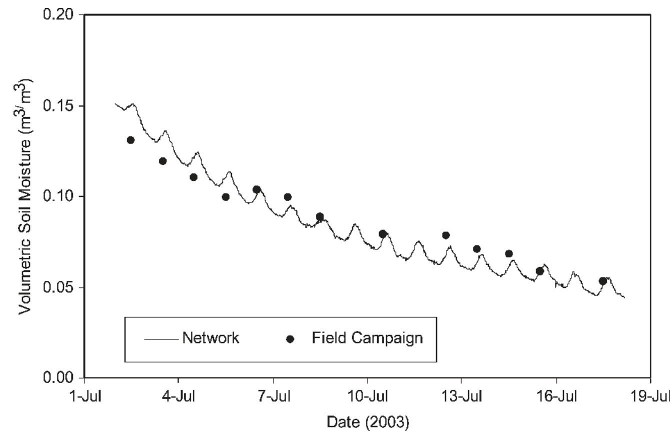

Fig. 4. Time series for the Little Washita Watershed Micronet average versus the SMEX03 field campaign sampling average for the watershed domain (bias $= 0.001\ \mathrm{m}^3/\mathrm{m}^3$, and rmse $= 0.009\ \mathrm{m}^3/\mathrm{m}^3$).

been extensively characterized. Several key microwave remote sensing experiments have been conducted in Walnut Gulch [26], [27]. Most recently, it was the focus of the Soil Moisture Experiment 2004 (SMEX04) [28], [29]. Extensive additional information regarding Walnut Gulch can be found in [30] and at http://www.tucson.ars.ag.gov/dap/.

Surface soil moisture sensors were added to 19 of the rain gauges and also at two sites outside the watershed. These data are transferred via telemetry and the Internet. Periodic gravimetric sampling has been conducted at all sites under diverse moisture conditions to aid in calibration of the *in situ* soil moisture sensors. During the SMEX04 campaign, extensive spatial sampling was conducted to characterize how well the *in situ* sensors represent the domain average soil moisture. A total of 69 samples were taken each day within the watershed on a semiuniform grid, and the average was computed according to Cosh *et al.* [28] to take into account the significant rock fraction present in the study region. When the average of this higher sampling density was compared to the geometrically weighted average from the *in situ* network, the rmse for the network was less than 0.01 $\mathrm{m}^3/\mathrm{m}^3$. Fig. 3(a) shows the time series of the network during SMEX04, and Fig. 3(b) shows a comparison of the weighted network average and the higher density physical sampling average.

B. Little Washita, OK

The Little Washita Watershed has been the focus of extensive soil moisture remote sensing research for over 30 years [31]–[33]. It is located in southwest Oklahoma in the Great Plains region of the U.S. and covers an area of 610 km^2. The climate is classified as subhumid with an average annual rainfall of 750 mm. The topography of the region is moderately rolling with a maximum relief of less than 200 m. Soils include a wide range of textures with large regions of both coarse and fine textures. Land use [see examples in Fig. 2(b)] is dominated by rangeland and pasture (63%), with significant areas of winter wheat and other crops being concentrated in the floodplain and western portions of the watershed area.

At the time we initiated the project, within the watershed, there was a network of 42 meteorological stations, distributed at a 5-km spacing that is called the ARS Micronet. The Micronet provides 5-min measurements of rainfall, air temperature, relative humidity, incoming solar radiation, and soil temperature at 5, 10, 15, and 30 cm below the soil surface. The data are delivered every 15 min via telemetry to a central facility where the data are quality assured and archived. The data are currently accessible via the Internet at http://ars.mesonet.org. Additionally, one SCAN and two Department of Energy Atmospheric Radiation Measurement program sites are located within the watershed (http://www.arm.gov/sites/sgp).

A total of 20 of the Micronet sites were selected for installation of the 5-cm soil moisture sensors. Soil moisture was measured hourly at each of the sites. Many of these also included a surface temperature sensor. During the SMEX03 campaign, large-scale sampling of the Little Washita Watershed was accomplished by sampling a variety of representative fields within the study region each day during an extended drydown [34], [35]. The rmse of the Micronet soil moisture average compared to the field sampling average was less than 0.01 $\mathrm{m}^3/\mathrm{m}^3$. Fig. 4 shows the pattern of soil network moisture during the study period and the field sampling averages. The SMEX03 experiment was uncharacteristically dry, but it is reasonable to assume from these results that the network is a good estimator of the large-scale moisture average.

At the end of 2005, the Micronet in the Little Washita Watershed was transitioned to a new management system, resulting in a reconfigured network with minor interruption in data continuity.

C. Little River, GA

The Little River Watershed is located near Tifton, GA, and has a drainage area of 334 km^2. It was part of the SMEX03 campaign [33] (http://nsidc.org/data/amsr_validation/soil_moisture/smex03/index.html). Due to its southern location, the area experiences long hot humid summers and short mild winters. The average annual precipitation is 1203 mm. The topography is relatively flat, with upland slopes varying from 1% to 5%. The dominant soil type is a sandy loam.

The Little River Watershed is typical of the heavily vegetated slow-moving stream systems in the Coastal Plain region of the U.S. The region is typified by broad floodplains with very poorly defined stream channels and gently sloping uplands. Approximately 36% of the watershed is forested, 40% is for cropland, and 18% is pasture, and the remaining areas are wetlands and residential areas [see Fig. 2(c)]. Major crops in the area are peanuts and cotton. Swamp hardwoods occur along the stream edges and are often accompanied by thick undergrowth forming the riparian vegetation boundary along the stream networks [36].

Within the watershed, there is a network of 35 tipping bucket precipitation gauges recording 5-min cumulative rainfall. The spacing between the precipitation gauges varies from 3 to 8 km. There is one SCAN site located within the watershed. A network of 29 sites was established to continuously monitor soil moisture at 5, 20, and 30 cm. Each station within the Automated NeTwork for Soil-water (ANTS) consists of a data logger, a rain gauge, and three soil moisture probes for measurement of volumetric soil water. Measurements are taken every half hour at the sites to conform to the SCAN data. Calibration efforts are described in [37].

As part of SMEX03, intensive measurements were made for a six-day period in the Little River Watershed to produce a large-scale estimate of the soil moisture in coordination with aircraft measurements and satellite overpasses [38]. After comparing the results from 49 fields within the study domain to the watershed network, the network was found to have a small dry bias ($-0.02\ m^3/m^3$), and it was concluded that the network average would serve as a valuable validation resource for satellite remote sensing.

D. Reynolds Creek, ID

The Reynolds Creek Experimental Watershed is predominantly a rangeland watershed located in the Owyhee Mountains of southwestern Idaho 80 km south of Boise, ID. The 238-km^2 watershed has a total relief of over 1000 m resulting in diverse topography, climate, soils, and vegetation typical of the intermountain west. About 75% of the annual precipitation at higher elevations is snow, whereas less than 25% is snow at lower elevations. Soils range from steep rocky shallow soils in mid elevations to rock-free saline soils in the valley to slightly acid soils in upper elevations. All of the publicly owned land in the watershed, which comprises 77% of the area, is grazed by cattle. Hay production and grazing are the primary land uses on private land. Fig. 2(d) shows typical land cover in the watershed.

Historical monitoring of the watershed, which started in 1961, has included climate, precipitation, snow accumulation and redistribution, snowmelt, frozen soils and frost depth, soil water and temperature, streamflow and sediment yield, and vegetation. Recent improvements to the monitoring network have included installation of a digital telemetry system enabling automated real-time data collection from most of the permanently instrumented sites. Detailed meteorological measurements are collected at 32 sites on the watershed representing a variety of elevations on the watershed. Measurements collected at 15-min intervals at these sites include air temperature, wind speed and direction, relative humidity, solar radiation, and soil temperature [39], [40]. Precipitation is measured at 37 locations.

Profile soil moisture is measured at five sites coincident with meteorological monitoring. Measurements are made biweekly using a neutron probe at 14 different access tubes. The access tubes are over 2 m in length, and measurements are made in 30-cm increments. The record extends back to 1976. Soil temperature profiles are collected hourly at these sites for ten depths between 0 and 180 cm. Snow measurements on the watershed have been made at seven locations on the watershed at two-week intervals from December to May since 1961 [41].

The surface soil moisture network consists of 19 locations. All sites are collocated with existing precipitation gauges for which long-term records are available. All sites currently telemeter the hourly data to the office in Boise, ID, on a daily basis, where the data are evaluated and archived using existing infrastructure. This watershed has been the site of extensive soil moisture sampling in the past [41], [42] although not with the goal of satellite validation. The significant topography and extended snow coverage season limits conducting major field experiments. Investigations into the performance of the soil moisture sensors have been ongoing [43], [44]. However, we must assume that the network average represents the region as a whole based upon the years of study, which have indicated that the physical locations of most of the soil moisture sampling sites have proven to be stable sampling points [41].

IV. Algorithms and AMSR-E Soil Moisture Products

Four soil moisture products derived from AMSR-E data will be compared to the ground-based averages: NASA [10], JAXA [6], [7], single-channel algorithm (SCA) [8], and land parameter retrieval model (LPRM) [45], [46]. Note that all versions used here are those designed to use X-band as the lowest frequency in order to avoid well-known radio-frequency interference issues with C-band observations in some regions, in particular the U.S. [47], [48].

The NASA algorithm has gone through significant modification from its earlier version described in [2]. As currently implemented, it uses normalized polarization ratios (PRs) of the AMSR-E channel brightness temperatures. Vegetation and roughness are accounted for using PRs at 10.65 and 18.7 GHz in empirical relationships. The vegetation/roughness parameter incorporates the effects of vegetation and roughness together, because both have the same functional form (exponential) in their influence on the normalized polarization differences in the simplified model used in the retrieval algorithm. Soil moisture is computed using the deviation of PR at 10.65 GHz from a baseline value [10]. Baseline values are established from the monthly minima at each grid cell. The soil moisture products currently available in the archive are based on variations of the soil moisture algorithm and the brightness temperature products. Here, we extracted the level-2 soil moisture products directly from the data archive (algorithm version B05, data version V10).

In the JAXA algorithm, a forward radiative transfer scheme was used to generate brightness temperatures for a range of parameter values (vegetation and soils) for multiple frequencies and polarizations. Results from synthetic runs were used to create lookup tables for soil moisture that utilize PR at 10.65 GHz and the normalized brightness temperature difference between the 36.5- and 10.65-GHz horizontal channels [6], [7]. The two agencies, namely, JAXA and NASA, calibrate the data independently. Our original intention was to implement the JAXA algorithm on our processor and run it using the NASA level-2 brightness temperatures, which would eliminate differences in the brightness temperature products and their geolocation as sources of error. Although we were able to reproduce the JAXA products fairly well, there were some differences that could not be resolved. As a result, we decided to use the JAXA level-2 soil moisture products (version 4) and extracted these from the archive.

The SCA [8] is based on the radiative transfer equation and uses the available channel that is most sensitive to soil moisture, which, for AMSR-E, is the 10.65-GHz horizontal polarization. The presence of radio-frequency interference at 6.9 GHz has limited the use of these observations in any soil moisture algorithms. Brightness temperature is corrected for the effects of temperature (AMSR-E 36.5-GHz vertical), vegetation (ancillary database derived from Advanced Very High Resolution Radiometer and Moderate Resolution Imaging Spectroradiometer data), roughness and soil texture (static ancillary data sets). The revised AMSR-E level-2 (orbital footprint observations) brightness temperature data (version V10) available from NASA were used as input to the SCA to estimate soil moisture.

The LPRM [45], [46] is a three-parameter retrieval model (soil moisture, vegetation water content, and soil/canopy temperature) for passive microwave data based on a microwave radiative transfer model. It uses the dual-polarized 10.65 GHz data for the retrieval of both surface soil moisture and vegetation water content. The land surface temperature is derived separately from the vertically polarized 36.5-GHz channel. Here, we use the data provided at http://geoservices.falw.vu.nl/adaguc_portal_dev/. This soil moisture is a gridded 0.25° product derived using the NASA gridded brightness temperatures.

V. Results

The soil moisture products described in the previous section were compared to the ground-based soil moisture derived by averaging all points in the watershed at the time closest to that of the overpass. Over a seven-year period of record (actually seven years and two months), this resulted in a large data set (see Table II for the number of observations). The performance of the soil moisture algorithms over the watersheds was evaluated using two different methods. The first method analyzes the rmse and bias. The rmse establishes whether an algorithm can meet the mission performance criterion of 0.06-m^3/m^3 volumetric soil moisture. An algorithm with a smaller rmse and a zero bias is desirable. In addition, for each watershed, a bias correction was applied to compute the standard error of estimate (SEE). A site-specific algorithm correction using a regression equation was also used to correct for both trend and bias errors. Correlation coefficients are also included in this portion of the study. The second comparison involves time-series plots of the observations, which provides some insight into how algorithms perform annually, seasonally, and at various magnitudes of soil moisture. Results for both the descending (1:30 A.M. equatorial overpass time) and the ascending (1:30 P.M.) coverage are included in the figures and tables. The conclusions are similar, and since we anticipate somewhat better performance for the descending coverage due to potentially more uniform near-surface temperature and soil moisture profiles, the discussions will focus on this overpass time.

The first network that will be discussed is the Walnut Gulch Watershed in Arizona, which has very little vegetation [normalized difference vegetation index (NDVI) ~0.16–0.30; also see Fig. 2(a)]. It is expected that this site would involve minimal vegetation corrections, based on our understanding of the effects of vegetation on soil moisture retrieval. Most of the precipitation in this region occurs during the months of July and August. In Fig. 5(a), the observed range of soil moisture is ~0.10 m^3/m^3, which is typical for the sandy and stony soils in this region that have low water-holding capacities. Fig. 5(a) also shows that the NASA product overestimates soil moisture, has a large bias, and exhibits a dampened range as compared to the ground observations. Overall, the NASA algorithm produces unrealistically wet results for this region. The JAXA product is better but still has an overestimation bias. The SCA error level falls below the accuracy requirement and has a low bias. The LPRM has the highest rmse. Neither the NASA nor the LPRM meet the mission accuracy requirement. The SEE values are also included in Table II(a). For all the algorithms, the application of a bias correction reduced the uncertainty in the soil moisture estimates for the Walnut Gulch Watershed. When the regression correction was applied, there was very little change in the SEE for the JAXA, NASA, or SCA beyond the improvement using bias alone. For the LPRM, the use of a regression correction significantly improved the SEE over the bias-only correction. This is associated with the difference in the range of soil moisture values produced by the LPRM and the *in situ* network.

The Little Washita and Little River data [Fig. 5(b) and (c)] both have larger observed ranges of surface soil moisture

TABLE II
SOIL MOISTURE ALGORITHM PERFORMANCE SUMMARY. (a) DESCENDING. (b) ASCENDING

(a)

Watershed	Algorithm	RMSE	Bias	SEE (Watershed Bias Corrected)	SEE (Watershed Regression Corrected)	R	N
Walnut Gulch, AZ	JAXA	0.042	0.033	0.026	0.015	0.717	1587
	NASA	0.069	0.065	0.023	0.020	0.305	1894
	SCA	0.021	-0.008	0.019	0.019	0.495	1757
	LPRM	0.139	0.125	0.061	0.015	0.717	1881
Little Washita, OK	JAXA	0.089	0.043	0.078	0.052	0.343	1695
	NASA	0.054	0.016	0.052	0.052	0.343	1829
	SCA	0.053	-0.017	0.05	0.047	0.528	1668
	LPRM	0.185	0.162	0.089	0.046	0.567	1806
Little River, GA	JAXA	0.088	0.046	0.075	0.044	0.231	1695
	NASA	0.045	0.019	0.041	0.040	0.457	1710
	SCA	0.051	0.034	0.038	0.037	0.590	1647
	LPRM	0.220	0.206	0.077	0.036	0.608	1682
Reynolds Creek, ID	JAXA	0.066	0.045	0.048	0.023	0.219	552
	NASA	0.076	0.072	0.024	0.023	0.220	555
	SCA	0.024	-0.011	0.021	0.021	0.460	554
	LPRM	0.088	0.061	0.063	0.018	0.571	534
RMSE (Root mean square error), Bias, and SSE (Standard error of estimate) are in m^3/m^3. R is the correlation coefficient. N is the number of samples.							

(b)

Watershed	Algorithm	RMSE	Bias	SEE (Watershed Bias Corrected)	SEE (Watershed Regression Corrected)	R	N
Walnut Gulch, AZ	JAXA	0.037	0.030	0.022	0.019	0.534	1629
	NASA	0.063	0.060	0.019	0.020	0.450	1764
	SCA	0.026	-0.015	0.021	0.020	0.444	1757
	LPRM	0.122	0.114	0.043	0.021	0.361	1756
Little Washita, OK	JAXA	0.090	0.054	0.072	0.050	0.429	1700
	NASA	0.058	0.031	0.049	0.048	0.508	1741
	SCA	0.047	-0.015	0.045	0.041	0.676	1814
	LPRM	0.155	0.123	0.094	0.048	0.508	1822
Little River, GA	JAXA	0.059	0.021	0.055	0.043	0.332	1707
	NASA	0.046	0.027	0.037	0.036	0.569	1689
	SCA	0.038	0.018	0.033	0.032	0.673	1661
	LPRM	0.146	0.114	0.091	0.039	0.515	1685
Reynolds Creek, ID	JAXA	0.105	0.079	0.069	0.024	-0.033	509
	NASA	0.076	0.072	0.024	0.023	0.385	588
	SCA	0.026	-0.014	0.022	0.022	0.406	571
	LPRM	0.100	0.091	0.041	0.022	0.363	571

($\sim$0.20 m^3/m^3). Both of these watersheds have moderate vegetation for portions of the year (Little Washita NDVI $\sim$0.25–0.50; Little River NDVI $\sim$0.34–0.55) that may approach levels of vegetation that cannot be reliably accounted for in any of the algorithms. As pointed out earlier, most algorithms providers indicate that accuracy goals are for vegetation water contents < 1.5 kg/m^2. For the Little Washita Watershed, the NASA algorithm performs well in the wetter range but exhibits overestimation bias for dry conditions, resulting in a dampened range of variation in estimated soil moisture [Fig. 5(b)]. The rmse falls in the acceptable range, and the bias is small. In reviewing Fig. 5(b), the JAXA results exhibit some inconsistent behavior; as a result, the rmse and bias are large. The SCA had an acceptable rmse level and the smallest bias for the Little Washita site. As in the case of Walnut Gulch, the LPRM has a high rmse as a result of its large bias. In addition, the LPRM estimates have a different trend, and the scatter is quite large as compared to the *in situ* observations. Based upon these results, the JAXA and LPRM algorithms do not meet the accuracy requirement at this site. The improvements in SEE after removing the bias for all the algorithms, with the exception of the LPRM, were minor because their bias values were low to moderate. The LPRM SEE exhibited a very significant reduction from the rmse; however, the SEE of the LPRM was still larger than the values for the other algorithms. When the regression correction was applied, it had very little impact on the SEE values for the

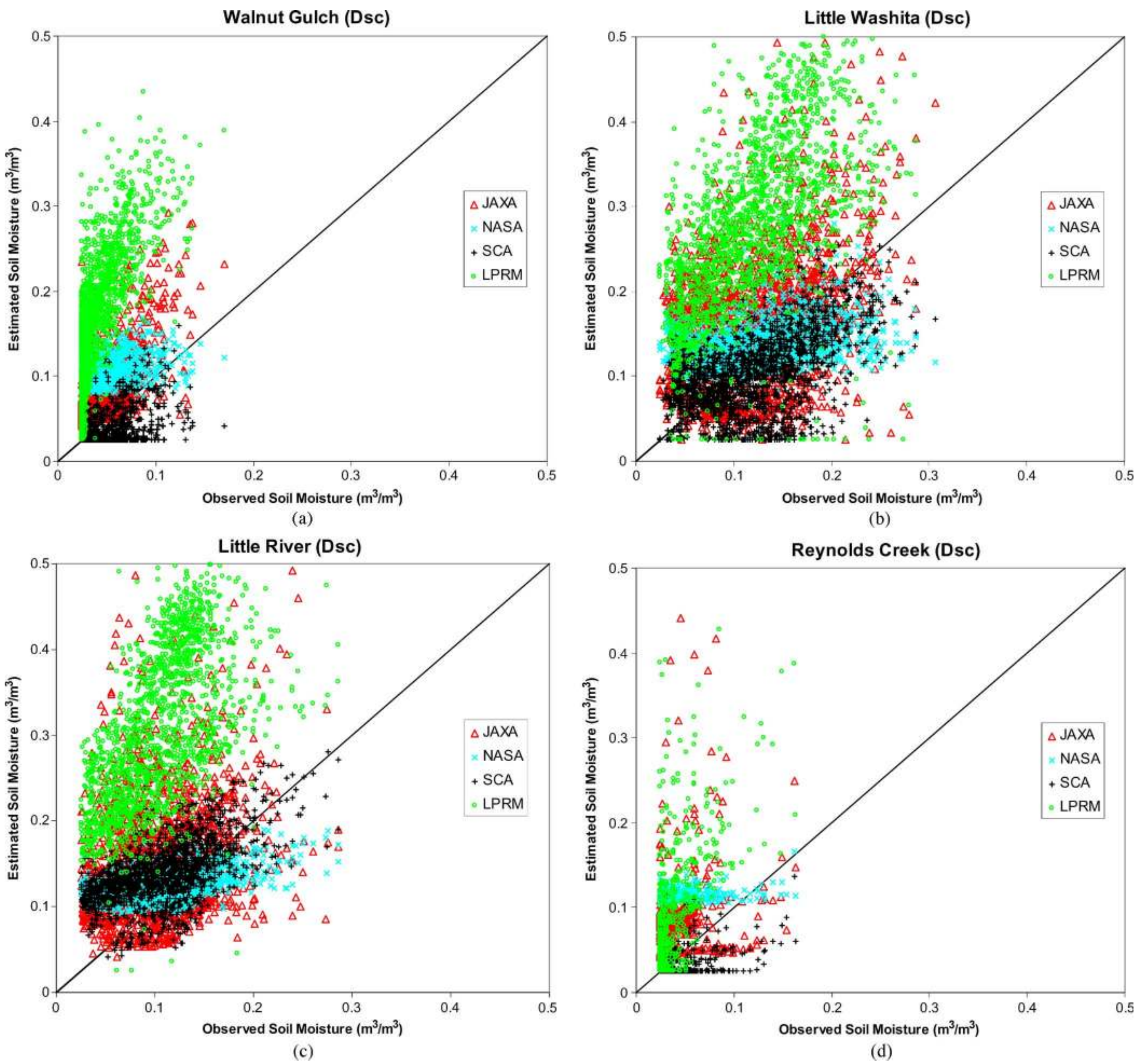

Fig. 5. Comparison of the observed and AMSR-E estimated soil moistures (for descending orbits) from four algorithms for (a) Walnut Gulch, AZ, (b) Little Washita, OK, (c) Little River, GA, and (d) Reynolds Creek, ID.

NASA and SCA algorithms. This correction did significantly improve the JAXA and LPRM SEE values beyond just the bias correction. After this adjustment, all algorithms had the same nominal SEE. This SEE was higher than that found for the Walnut Gulch Watershed and likely reflects the difference in vegetation cover between the two sites; we expect a larger SEE when there is more vegetation.

For the Little River Watershed, the NASA product exhibited very little variation in soil moisture (overestimating dry and underestimating wet conditions) [Fig. 5(c)]. However, it had the best overall rmse, i.e., below 0.06 m^3/m^3, and the lowest bias. The JAXA product had an overestimation bias for dry conditions and a large rmse. The values of these metrics were similar to those found for the Little Washita Watershed. The JAXA algorithm uses a lookup table for estimating the soil moisture based on the vegetation conditions. It is likely that the JAXA errors are associated with the vegetation corrections used. In a recent study [49], the algorithm developers noted this weakness and proposed a modified approach. As in the Little Washita Watershed, the SCA performed well; however, it had a slightly higher bias at this location than any of the other sites. Once again, the LPRM has the highest rmse as a result of its large bias, which, when removed, resulted in a lower but still high SEE. For the Little River Watershed, neither the JAXA nor the LPRM could meet the accuracy requirement. As in the Little Washita Watershed, the bias correction provided an improvement in SEE that was proportional to the bias level of the algorithm, and the regression correction significantly improved the SCA and LPRM SEE values.

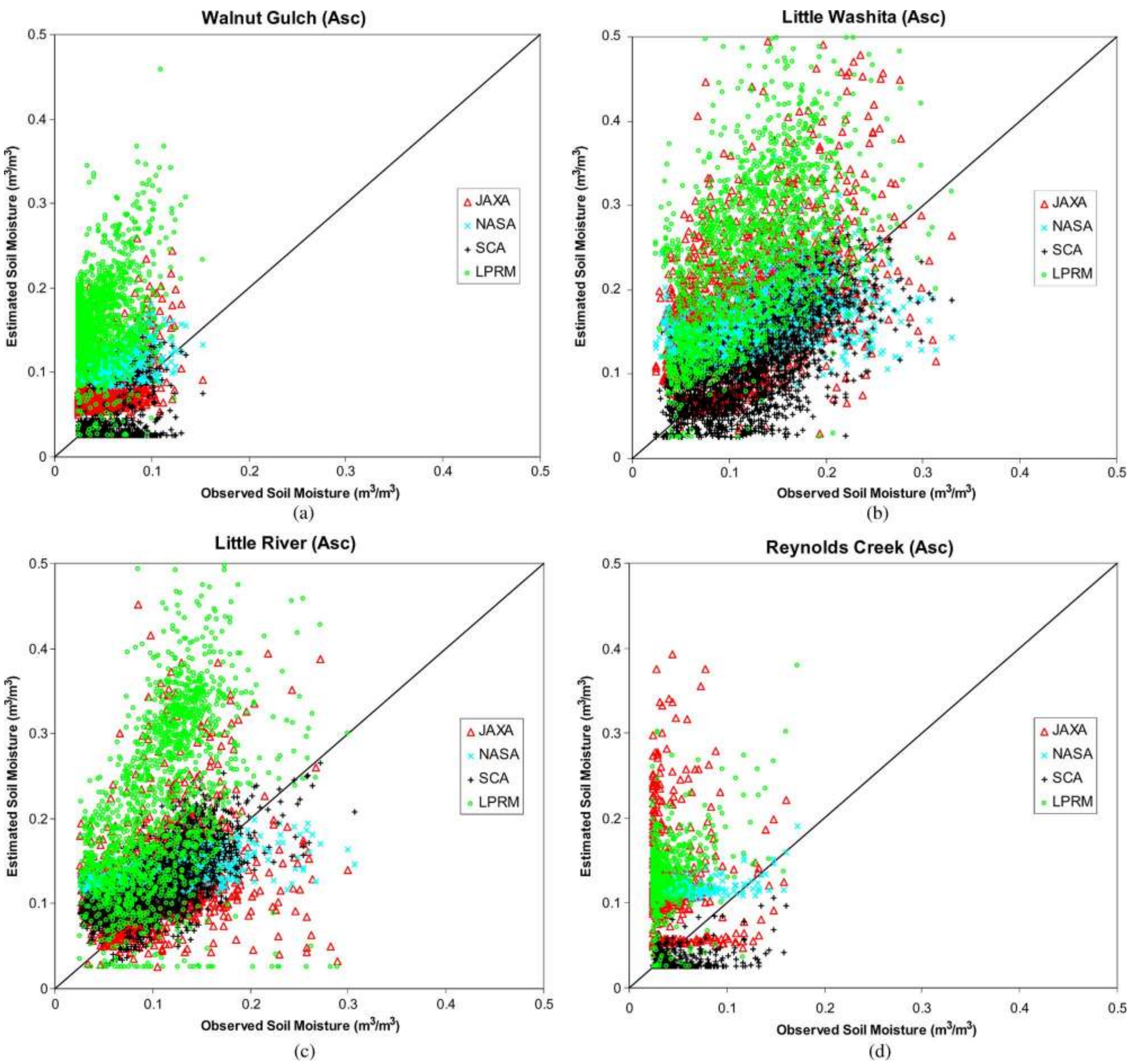

Fig. 6. Comparison of the observed and AMSR-E estimated soil moistures (for ascending orbits) from four algorithms for (a) Walnut Gulch, AZ, (b) Little Washita, OK, (c) Little River, GA, and (d) Reynolds Creek, ID.

Reynolds Creek had moderately low vegetation (NDVI ∼0.26–0.4), and based on this factor alone, we expected that vegetation could reliably be accounted for in AMSR-E algorithms. However, as noted earlier, the watershed has significant topography and presented some difficult restrictions on data use due to the potential presence of snow over an extended portion of the year. To reduce the possibility of snow being present, which the algorithms cannot correct for, all analyses were limited to July through September. This resulted in a smaller set of data and a very small observed range of soil moisture due to limited rainfall in this season. In Fig. 5(d), it is apparent that the NASA product overestimates soil moisture and has a large rmse and a low correlation. The JAXA product is erratic, as compared to the ground observations, which could be due to the use of 36.5-GHz channel to determine the soil moisture. Observations made at 36.5 GHz are very sensitive to the presence of any snow cover. It is possible that, even after limiting the seasonal time window, as described previously, some snow may be present at higher elevations. The JAXA rmse and bias are both large. The SCA performs very well in terms of rmse and bias. The LPRM had the largest rmse with a bias on the order of that found for the NASA and JAXA products. Bias removal significantly improved the NASA algorithm SEE beyond the rmse. Applying the regression correction provided significant improvements in SEE for the JAXA and LPRM algorithms.

As a reminder, the previous discussion focused on the descending overpass data. We separated the descending (Fig. 5) and ascending (Fig. 6) passes because it was expected that the basic assumptions of the retrieval methods are more likely to be satisfied by the nighttime coverage. These include uniformity of the near-surface soil moisture and temperature profiles. The results presented in Table II(a) and (b) indicate that the results

TABLE III
SUMMARY SOIL MOISTURE ALGORITHM PERFORMANCE STATISTICS

Algorithm	RMSE	Bias	SEE (Watershed Bias)	SEE (Watershed Regression)	SEE (Global Bias)	N
JAXA	0.073	0.040	0.060	0.039	0.061	11075
NASA	0.059	0.040	0.037	0.037	0.043	11737
SCA	0.040	-0.002	0.035	0.033	0.040	11429
LPRM	0.159	0.134	0.077	0.035	0.085	11737
RMSE (Root mean square error), Bias, and SSE (Standard error of estimate) are in m^3/m^3. N is the number of samples.						

TABLE IV
SUMMARY SOIL MOISTURE ALGORITHM CORRELATION COEFFFICIENTS (R)

Algorithm	R	R (Global Bias)	R (Watershed Regression)
JAXA	0.556	0.557	0.705
NASA	0.730	0.632	0.739
SCA	0.778	0.746	0.793
LPRM	0.622	0.658	0.773

were about the same order of magnitude and that the best performance was mixed by both site and product.

The overall performance statistics for all watersheds and passes for each algorithm are summarized in Tables III and IV. This includes the overall algorithm rmse, bias, and SEE values for the approaches described by Table II(a) and (b) (watershed-specific/global bias and regression corrections). These statistics are computed by treating all estimates for all watersheds and overpass times as an independent sample of the same population. Based upon these results, we can make the following inferences for the data used in this paper.

1) The NASA and SCA algorithms can provide soil moisture estimates at an accuracy that is lower than the mission rmse requirement of 0.06 m^3/m^3.
2) The SCA provided the lowest rmse and had no bias.
3) Applying a bias correction (specific to the watershed/overpass) improved the performance of all algorithms and lowered the JAXA SEE to 0.06 m^3/m^3.
4) After applying a watershed/overpass-specific regression correction, all algorithms had SEE values below 0.04 m^3/m^3. After making this correction, the difference between algorithm performances was minor.

The LPRM product has a greater dynamic range than the observations or any of the other soil moisture products. It routinely estimates very high soil moisture (greater than 0.4 m^3/m^3) over the validation sites. In other parts of the world, LPRM soil moisture estimates are as high as 0.8 m^3/m^3. These values are unrealistically high and not observed frequently in nature (except during large-scale inundation). Bias removal techniques can only correct for the systematic biases in the algorithm and cannot correct for errors due to different dynamic ranges and trends.

It must be noted that the information to perform either a bias or a regression correction on a footprint or grid basis is not available globally. Therefore, this is useful information for algorithm evaluation and adjustment but cannot be implemented with the operational product.

An alternative bias correction scheme that could be used operationally might be to assume that the data set that is available can be used to represent global conditions and to use a single bias correction value for each algorithm. There are, of course, many variations of this approach that could be used, but this represents the most general approach. From the results listed in Table III, we observed that applying this global bias correction for each algorithm improves the accuracy of all algorithms, except the SCA, which has a near-zero overall bias. After making the correction, all algorithms, except the LPRM (the JAXA algorithm was very close to the target accuracy), can meet the mission requirement of 0.06 m^3/m^3. The NASA and SCA have the lowest and similar SEE values. It is important to note that, when a global bias correction was applied, the increase in SEE over the values obtained using the watershed-pass approach was very small. Of course, a larger set of validation sites and conditions would be desirable, but these results indicate that a first-order correction could be applied to the existing products that would result in an improvement.

Tables II and IV include the correlation coefficients for each algorithm. The comparison of these values on an individual watershed-pass basis (Table II) results in quite different results than when they are computed for each algorithm (Table IV). This is associated with the limited range of conditions observed and, in some cases, the dampened range of response of some algorithms for a specific watershed. Summarizing Table II, for the descending passes, the LPRM has the highest correlations. On the other hand, for the ascending results, the LPRM had some of the lowest values. When the data are composited by the algorithm in Table IV (column 2), all algorithms have a good correlation that results from the larger range of observed and estimated values. The R values for the NASA and SCA decreased after bias removal. The highest correlations were obtained after the regression correction and were quite similar for all the algorithms.

The second method that we used for performance evaluation of the algorithms was analysis of time-series plots. Patterns of Soil moisture patterns may be apparent in time-series analysis that cannot be readily detected in the observed versus predicted plots of Figs. 5 and 6. First, we will discuss the NASA, JAXA, and SCA results and then address the LPRM separately.

The time-series plot for the Walnut Gulch Watershed [Fig. 7(a)] shows a small dynamic range of observed soil moisture (0.15 m^3/m^3). The NASA algorithm consistently overestimates soil moisture in all seasons and fails to capture the dry conditions prevalent in the watershed. The JAXA algorithm compares well to the observed soil moisture, although it tends to overestimate the soil moisture by $\sim$0.02 m^3/m^3. The JAXA algorithm captures the soil moisture dynamics in all seasons. The SCA algorithm compares well to the observations with no significant bias in any season. The SCA ascending retrievals [Fig. 8(a)] are drier than the observations, and the algorithm has a smaller dynamic range for the descending orbits. This result supports the previous discussion on diurnal effects. The ascending orbits have an overpass time of 1:30 P.M. This is also when the soil temperatures are highest and the gradient is strongest.

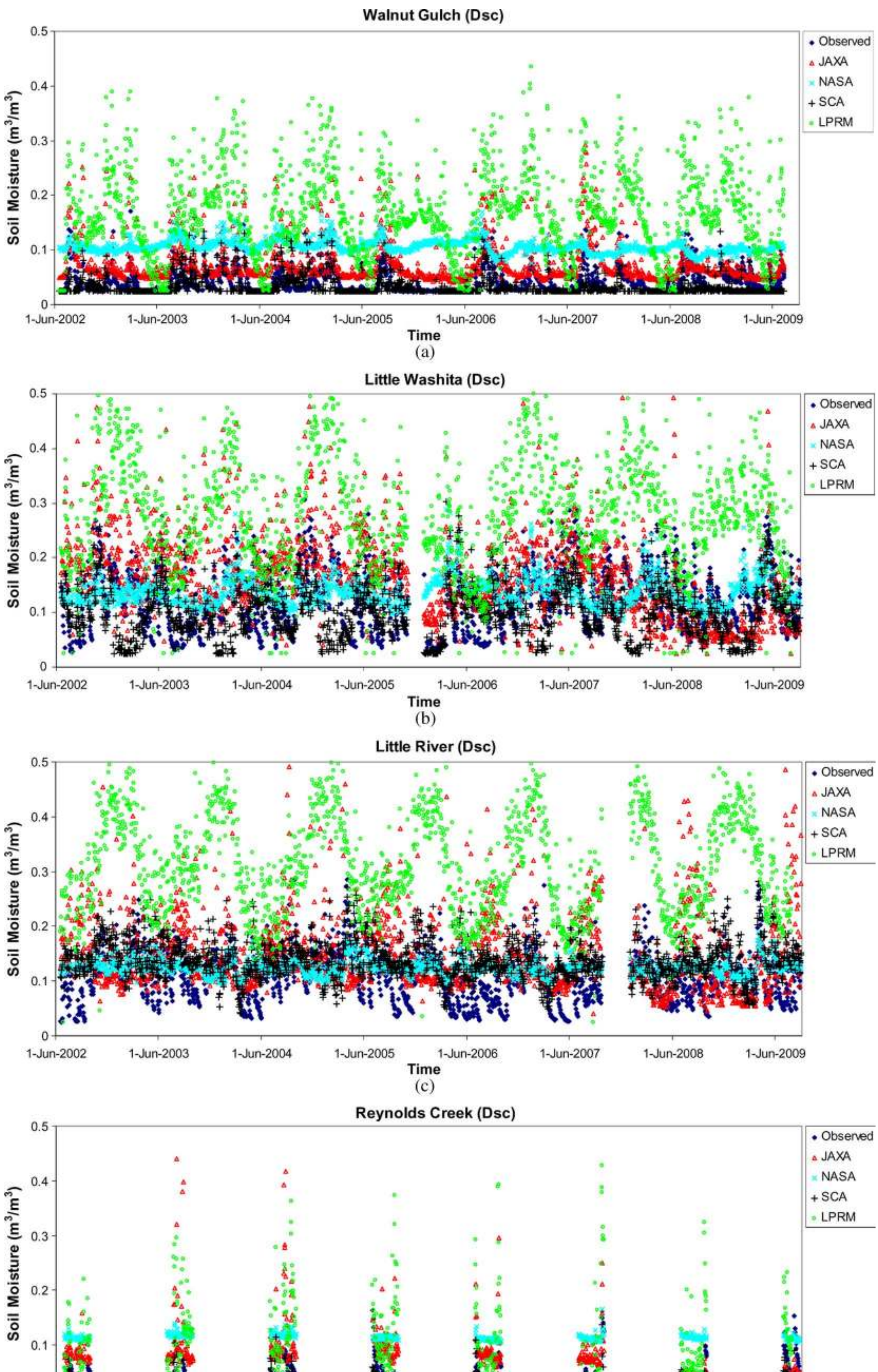

Fig. 7. Plots of the observed and four-algorithm estimated soil moistures as a function of time (for descending orbits) for (a) Walnut Gulch, AZ, (b) Little Washita, OK, (c) Little River, GA, and (d) Reynolds Creek, ID.

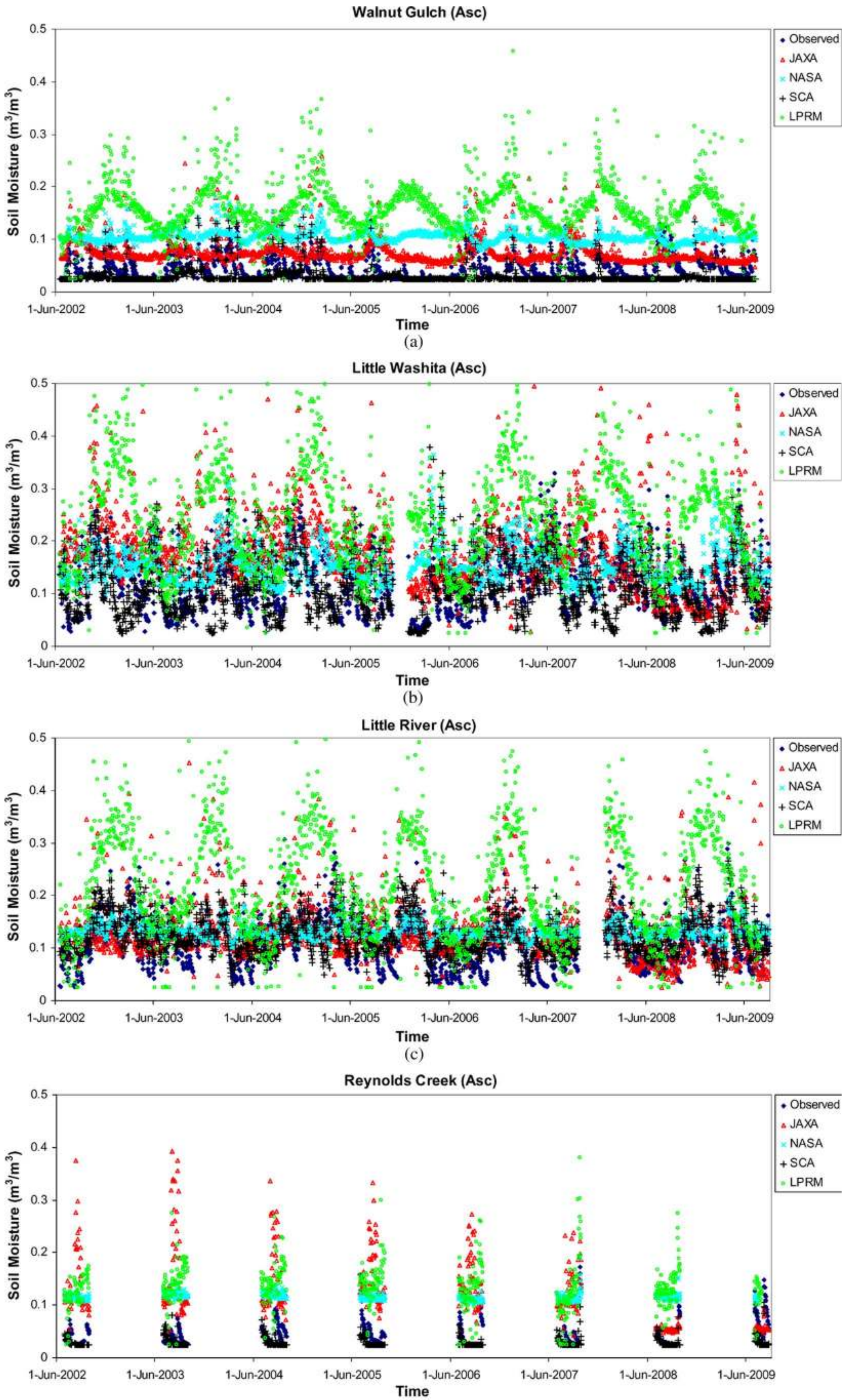

Fig. 8. Plots of the observed and four-algorithm estimated soil moistures as a function of time (for ascending orbits) for (a) Walnut Gulch, AZ, (b) Little Washita, OK, (c) Little River, GA, and (d) Reynolds Creek, ID.

The time-series plots for the Little Washita Watershed and the Little River Watershed [Fig. 7(b) and (c)] exhibit a greater range of observed soil moisture. The NASA algorithm has a smaller range for all the seasons. The NASA algorithm responds to the changes in soil moisture, but the response is dampened as compared to the observations. Again, the NASA algorithm fails to capture the dry conditions in all seasons. The JAXA algorithm exhibits spurious behavior in every season. The range of estimated soil moisture is very high (0.4 m^3/m^3), with some estimates of 0.4–0.5 m^3/m^3. We believe that these are due to the higher amount of vegetation present at these locations. The current JAXA algorithm fails to correctly parameterize the vegetation effects [49].

The time-series analysis [Fig. 7(d)] for the Reynolds Creek Watershed was done only for the months of July to September in order to eliminate the possibility of snow contaminating the footprint. The results reveal a small range and a low level of soil moisture during the summer. The NASA algorithm overestimates soil moisture and fails to capture the dry conditions. The JAXA algorithm also has a positive bias, with some spurious estimates, which may be due to the presence of snow at higher elevations. The SCA captures the dry conditions and performs well.

As noted previously, the time-series behavior of the retrievals from the LPRM was quite different than that of the other algorithms. It is obvious that there are seasonal effects that are impacting the algorithm performance. Errors and bias are largest in winter and lowest in summer. These variations are not consistent with seasonal rainfall or soil moisture. For Little Washita and Little River, the effect could be associated with vegetation growth. However, the pattern is also evident in Walnut Gulch, which has little vegetation. The soil moisture values are different for the ascending and descending overpasses on any given day. The LPRM soil moisture climatology is different for the ascending and descending orbits. It is most likely that the errors are associated with the seasonal temperature cycle.

Based upon the results presented earlier and the mission requirement of rmse $< 0.06\ m^3/m^3$, the NASA and SCA meet or exceed the specified accuracy. The JAXA algorithm performs somewhat better under light-vegetation conditions (AZ and ID), and the NASA algorithm is more reliable when there is moderate vegetation (GA and OK). However, both algorithms have moderate bias in all cases. The SCA algorithm performed best overall with small bias. The LPRM has the largest rmse as a result of the bias and the error pattern over the seasonal cycle, which may indicate a structural problem in the algorithm. A user will have to use site-specific calibration to match the algorithm results to the ground observations.

VI. Summary

Validation of satellite-based soil moisture products is necessary to ensure the quality of information and to provide the user with an assessment of its accuracy and reliability. Retrieval algorithms have inherent limitations resulting from simplifications required for implementation. Soil moisture is particularly difficult to validate due to the mismatch in observing scales of conventional ground-based and satellite observing systems. The issue of spatial scale is common to both current and future satellite missions. In this paper, we developed an approach to validate coarse footprint surface soil moisture retrievals and applied it to the retrieval algorithms that are used to generate the AMSR-E standard products by JAXA and NASA.

Ground-based networks of *in situ* soil moisture sensors were established in four research watersheds. These networks provide estimates of the average soil moisture over the watersheds and surrounding areas that approximate the size of the AMSR-E passive microwave footprint. The watersheds were selected to represent different climatic and vegetation conditions (compatible with the canopy attenuation limitations of X-band). Verification of the sensor measurements and representation of their respective domains were performed through field experiments. These networks have been in operation since 2002, and they provided over seven years of observations for the current analyses.

The NASA and JAXA soil moisture products, along with soil moisture determined via two alternative algorithms (SCA and LPRM), were compared to the network observations. The results indicate that each algorithm has different performance statistics that depend upon the site. Neither of the two standard products, namely, NASA or JAXA, can provide reliable estimates of soil moisture for all of the conditions represented by the test watershed sites. However, the NASA algorithm could meet the accuracy requirement of 0.06 m^3/m^3. The JAXA algorithm performs somewhat better under light-vegetation conditions than the NASA algorithm, and the NASA algorithm is more accurate when there is moderate vegetation. However, both algorithms have moderate to large bias for all the watersheds. The SCA algorithm performed best overall with a very small bias. The LPRM had the largest rmse as a result of the bias and the error pattern over the seasonal cycle, which might indicate a structural problem in the algorithm.

Using a simple bias correction procedure resulted in smaller errors for all algorithms, with the exception of the SCA, which had a near-zero bias. After bias removal, the NASA and SCA algorithms had similar error levels of $\sim 0.04\ m^3/m^3$, and the JAXA algorithm was close to 0.06 m^3/m^3. A second correction scheme using regression for each watershed/overpass significantly improved the JAXA and LPRM SEE values. After this correction, all algorithms had SEE values lower than 0.04 m^3/m^3. These are interesting results but cannot be implemented on an operational basis because the ground data are not available at enough sites to develop a robust technique. After all of the various corrections were applied, the SCA had the best performance for the conditions evaluated here.

There are more advanced techniques that could be used to adjust the algorithm soil moisture products to the observed soil moisture on a watershed and even seasonal basis. These include regression and cumulative distribution function matching, as described in [50]–[52]. However, like the corrections used here, these approaches are site specific and rely on the availability of observations. At this stage, they cannot be used to perform a correction on the entire AMSR-E data set.

Our analysis focused on a basic question, do the soil moisture products meet the agency mission requirement? which was an accuracy of less than or equal to 0.06 m^3/m^3. These results clearly show that there is much room for improvement in many of the algorithms. As noted earlier, each algorithm developer starts from the same basic set of equations, makes numerous assumptions, and applies various parameterizations. These decisions are often based upon limited information. The results presented here suggest that some of these may not be realistic. The fact that some algorithms do perform well presents a challenge to the others to improve.

The validation approach developed here provides a large and representative data set; however, the number of sites and length of record should be expanded. The issues addressed here are common to both current and future satellite missions. Regardless of the degree of difficulty, ground-based sampling must remain a core component of validation.

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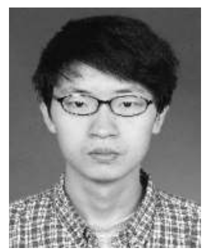

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