A Quasi-Global Evaluation System for Satellite-Based Surface Soil Moisture Retrievals

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Abstract—A recently developed data assimilation technique offers the potential to greatly expand the geographic domain over which remotely sensed surface soil moisture retrievals can be evaluated by effectively substituting (relatively plentiful) rain-gauge observations for (less commonly available) ground-based soil moisture measurements. The technique is based on calculating the Pearson correlation coefficient ($R_{value}$) between rainfall errors and Kalman filter analysis increments realized during the assimilation of a remotely sensed soil moisture product into the antecedent precipitation index (API). Here, the existing $R_{value}$ approach is modified by reformulating it to run on an anomaly basis where long-term seasonal trends are explicitly removed and by calculating API analysis increments using a Rauch–Tung–Striebel smoother instead of a Kalman filter. This reformulated approach is then applied to a number of Advanced Microwave Scanning Radiometer soil moisture products acquired within three heavily instrumented watershed sites in the southern U.S. $R_{value}$-based evaluations of soil moisture products within these sites are verified based on comparisons with available ground-based soil moisture measurements. Results demonstrate that, without access to ground-based soil moisture measurements, the $R_{value}$ methodology can accurately mimic anomaly correlation coefficients calculated between remotely sensed soil moisture products and soil moisture observations obtained from dense ground-based networks. Sensitivity results also indicate that the predictive skill of the $R_{value}$ metric is enhanced by both proposed modifications to its methodology. Finally, $R_{value}$ calculations are expanded to a quasi-global (50° S–50° N) domain using rainfall measurements derived from the Tropical Rainfall Measurement Mission Precipitation Analysis. Spatial patterns in calculated $R_{value}$ fields are compared to regions of strong land–atmosphere coupling and used to refine expectations concerning the global distribution of land areas in which remotely sensed surface soil moisture retrievals will contribute to atmospheric forecasting applications.

Index Terms—Data assimilation, land surface modeling and ground validation, microwave radiometer, soil moisture.

I. INTRODUCTION

A WIDE range of remote sensing retrieval strategies have been applied to routinely estimate surface soil moisture magnitudes from satellite-based instrumentation (see, e.g., [2], [23], [26], [35], and [37]). Most approaches provide soil moisture estimates at a relatively coarse spatial scale (> 10–30 km), and practical difficulties associated with the validation of such coarse-resolution products using ground-based instruments have limited the amount of performance feedback information available to soil moisture algorithm developers concerning the accuracy (and ultimate value) of their products [5], [7], [32]. Relative to ground-based soil moisture probes, ground-based rainfall gauges are inexpensive, easy to maintain, and more readily scalable and have already been widely installed over vast continental regions. For instance, within the contiguous U.S. (CONUS), the number of available rain gauges (∼15 000) [16] is several orders of magnitude greater than the number of operational network stations currently measuring soil moisture (∼200) [19]. Given the obvious connection between rainfall and subsequent soil moisture, it should be possible to leverage relatively abundant rain-gauge observations to indirectly evaluate the accuracy of remotely sensed surface soil moisture retrievals.

Recent work has made substantial progress in this direction. In particular, Crow et al. [7], [8] and Loew et al. [22] develop and/or apply an evaluation approach for surface soil moisture retrievals that effectively substitutes rain-gauge measurements for ground-based soil moisture observations. This approach is based on evaluating the correlation coefficient ($R_{value}$) between antecedent rainfall errors and analysis increments realized during the Kalman-filter-based assimilation of remotely sensed soil moisture products into a water-balance model. Because it does not require ground-based soil moisture measurements, it enables the spatial expansion of potential soil moisture validation locations from localized sites containing sufficiently dense ground-based soil moisture networks (see, e.g., [4], [19], [30], [31], and [36]) to much larger continental-scale regions containing adequate rain-gauge coverage.

Despite this progress, the baseline $R_{value}$ approach (and previous applications of it) have been limited in several important regards. For example, $R_{value}$ calculations have been based on a Kalman filtering methodology to assimilate raw remote sensing retrievals. The reanalysis (i.e., non-real-time) nature of the $R_{value}$ calculation makes the use of a filtering framework potentially suboptimal. Generally, better data assimilation (DA) results can be obtained by implementing smoothing techniques in which model state predictions are updated by both past and future observations [10]. In addition, the assimilation of remotely sensed retrievals possessing a unique seasonal climatology (relative to, for example, the climatology of the assimilation model) can potentially confound the interpretation of $R_{value}$.

This analysis will address these shortcomings by modifying the $R_{value}$ methodology. First, the $R_{value}$ methodology will be altered to operate on an anomaly basis where climatological expectations in soil moisture and precipitation have been

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explicitly removed. This transformation allows $R_{\text{value}}$ to solely reflect the ability of a soil moisture product to capture actual soil moisture anomalies (relative to a given climatology) and not simply mimic seasonal soil moisture cycles. This distinction is critical for key land DA applications, like the initialization of atmospheric prediction models, where the added value of soil moisture remote sensing observations is based on their ability to capture anomalies relative to climatological expectations [9]. Second, because it is essentially a reanalysis-type exercise performed on retrospective data sets, the $R_{\text{value}}$ methodology has been modified to be based on a Rauch–Tung–Striebel (RTS) smoother [27]. The RTS smoother provides a more appropriate estimation methodology for reanalysis-based increments than previous applications of the Kalman filter [10, 11]. These methodological changes enhance the utilization of information embedded in remotely sensed soil moisture products. Consequently, their implementation within the $R_{\text{value}}$ methodology should provide a more robust evaluation of remotely sensed soil moisture products.

In addition to these methodological modifications, this analysis will also expand the manner in which the $R_{\text{value}}$ metric has been applied and verified. To date, $R_{\text{value}}$ results have not been verified through comparison with independent observations nor have they been calculated outside of relatively data-rich areas like CONUS. Crow [7] argues that $R_{\text{value}}$ provides a robust proxy for the correlation of remotely sensed soil moisture products with true soil moisture. However, support for this assertion has been limited to results from synthetic DA experiments in which a number of potential confounding factors (e.g., seasonality, missing data, and/or autocorrelation in retrieval error) are neglected. In order to provide a more credible evaluation, $R_{\text{value}}$-based inferences regarding the accuracy of existing remotely sensed soil moisture products will be compared to analogous inferences obtained from dense ground-based sampling of soil moisture. Finally, using only precipitation data sets from the Tropical Rainfall Measurement Mission (TRMM) Multisatellite Precipitation Analysis (TMPA), an enhanced (and newly verified) $R_{\text{value}}$ algorithm will be applied quasi-globally (50° S–50° N) for the first time using remotely sensed soil moisture data sets from the Advanced Microwave Scanning Radiometer—Earth Observing System (AMSR-E) instrument.

Based on these goals, this paper is organized as follows. Section II reviews the baseline $R_{\text{value}}$ methodology and describes the modifications introduced above. Following a description of watershed study sites in Section III and remote sensing products in Sections IV and V, Section VI presents verification results whereby inferences obtained from the application of the $R_{\text{value}}$ approach are compared to results obtained from dense ground-based soil moisture networks. Sections VII and VIII present a quasi-global scale comparison of $R_{\text{value}}$ results for various AMSR-E soil moisture data products—particularly within land areas identified as regions of strong land-surface/atmosphere coupling by Koster et al. [21].

II. $R_{\text{value}}$ Algorithm

All approaches presented here are based on using daily satellite-based precipitation accumulation estimates ($P_{\text{sat}}$) to derive the antecedent precipitation index (API)

$$API_i = \gamma_i API_{i-1} + P_{\text{sat}}^i$$

where $\gamma$ is the unitless API coefficient and $i$ is a daily time index. Unless otherwise specified, $\gamma$ is assumed equal to a globally constant value of 0.85. Higher quality daily rainfall accumulations derived from the retrospective correction of $P_{\text{sat}}$ using ground-based rain gauges ($P_{\text{gauges}}$) must also be available but are reserved for benchmarking purposes. Values of API and $P$ will be given in units of millimeter water depth.

A. Baseline Approach

The baseline $R_{\text{value}}$ approach in [8] is based on the assimilation of remotely sensed soil moisture retrievals ($\theta_{\text{RS}}$ in volumetric soil moisture units of m$^3$·m$^{-3}$) into (1) using a Kalman filter

$$API_{\text{KF}, i}^+ = API_{\text{KF}, i}^- + K_i [\theta_{\text{RS}, i} - H(API_{\text{KF}, i}^-)]$$

(2)

where $i$ is a daily time index and “−” and “+” denote API values before and after Kalman filter updating, respectively. The observation operator $H$ is a simple time-constant linear function

$$H(API_{\text{KF}, i}^-) = a + bAPI_{\text{KF}, i}^-$$

(3)

whose intercept parameter $a$ (m$^3$·m$^{-3}$) and slope parameter $b$ (m$^3$·m$^{-3}$·mm$^{-1}$) are obtained through a least squares regression of API, calculated via (1) using $P_{\text{gauges}}$ and no Kalman filter updating, against $\theta_{\text{RS}}$. Such regression implicitly assumes that the effective depth of API predictions (determined by the assumed magnitude of $\gamma$) and $\theta_{\text{RS}}$ are approximately equal. Because fitted values of $a$ and $b$ vary according to land cover conditions, this regression must be calculated separately for each geographic domain over which the $R_{\text{value}}$ approach is applied (see Section V for more details).

The Kalman gain $K$ (m$^3$·m$^{-3}$·mm$^{-1}$) in (2) is then given by

$$K_i = bT_{\text{KF}, i}^-/ [b^2 T_{\text{KF}, i}^- + S]$$

(4)

where $T_{\text{KF}, i}^-$ (mm$^2$) is the background error variance in $API_{\text{KF}, i}$ forecasts and $S$ (m$^6$·m$^{-3}$) is the error variance in $\theta_{\text{RS}}$ retrievals. At measurement times, $T_{\text{KF}, i}$ is updated following

$$T_{\text{KF}, i}^+ = (1 - bK_i)T_{\text{KF}, i}^-$$

(5)

Between measurements and the updating of API and $T$ via (2) and (5), $API_{\text{KF}, i}$ is forecasted in time using $P_{\text{sat}}$ and (1). The updated model forecast error $T_{\text{KF}, i}^+$ is also forecasted as

$$T_{\text{KF}, i}^+ = \gamma_i T_{\text{KF}, i-1}^+ + Q$$

(6)

where $Q$ (mm$^2$) relates the variance added to an API forecast as it is propagated from time $i - 1$ to $i$. Values of $Q$ and $S$ are calibrated through the statistical analysis of filter innovations

$$\nu_{\text{KF}, i} = [\theta_{\text{RS}, i} - H(API_{\text{KF}, i}^-)] / (b^2 T_{\text{KF}, i}^- + S)^{0.5}$$

(7)

A properly constructed linear filter should yield a $\nu_{\text{KF}, i}$ time series that is serially uncorrelated [14]. Here, a simple tangent-linear optimization algorithm is used to iteratively vary the $Q/S$ ratio until this constraint is satisfied.
Updates to API given by (2) in the course of assimilating a particular remotely sensed soil moisture product are referred to as “analysis increments”

\[
\delta_{\text{KF}} = API_{\text{KF}}^+ - API_{\text{KF}}^- = K_i \left[ \theta_{\text{RS}} - H \left( API_{\text{KF}}^+ \right) \right].
\]  

If \( \theta_{\text{RS}} \) has appreciable skill in detecting soil moisture temporal variations, values of \( \delta_{\text{KF}} \) will correlate with near-past errors in precipitation anomalies (\( P_{\text{sat}} - P_{\text{gauge}} \)). Following [7], both \( \delta_{\text{KF}} \) and \( P_{\text{sat}} - P_{\text{gauge}} \) are summed within a series of nonoverlapping windows of length \( N \) day(s), and a correlation coefficient is calculated between the \( N \)-day sums of \( \delta_{\text{KF}} \) and \( P_{\text{sat}} - P_{\text{gauge}} \). The negative of this correlation coefficient is referred to as the \( R_{\text{value}} \) metric for a particular \( \theta_{\text{RS}} \) product. Higher \( R_{\text{value}} \) indicates increased efficiency in the filtering of error in API predictions arising from random noise in \( P_{\text{sat}} \) estimates. In this way, the \( R_{\text{value}} \) metric measures the degree to which the assimilation of \( \theta_{\text{RS}} \) adds value to model-based estimates of surface soil moisture—above and beyond the baseline case of simply driving (1) with \( P_{\text{sat}} \). One consequence of this interpretation is that \( R_{\text{value}} \) should have a direct one-to-one relationship with the correlation coefficient between \( \theta_{\text{RS}} \) and true soil moisture [7]. Using the simple modeling approach in (1), we will attempt to verify this relationship and clarify accuracy requirements for \( P_{\text{gauge}} \) measurements forming the basis of the \( R_{\text{value}} \) evaluation approach.

B. Anomaly Modification

Crow et al. [7], [8] use the baseline approach described earlier to generate 1° latitude/longitude \( R_{\text{value}} \) maps, and they argue that these maps constitute a robust proxy for Pearson’s correlation coefficient between \( \theta_{\text{RS}} \) and true soil moisture (as acquired, e.g., from a dense ground-based soil moisture network). Such correlations are sensitive to both the skill of retrievals with regard to short-term soil moisture anomalies and their ability to capture typical soil moisture seasonal cycling. One consequence of this dual sensitivity is that a given soil moisture product can exhibit a relatively high correlation coefficient even if it possesses little or no skill in capturing shorter-term anomalies. Most soil moisture DA systems are based on scaling the observed soil moisture into a model’s unique soil moisture climatology—ideally on a seasonal or monthly basis (see, e.g., [12])—prior to its assimilation. As a result, accurately capturing soil moisture seasonal cycles in a remotely sensed product is of relatively little value. For many DA applications, a more important reflection of product value is skill with regard to detecting soil moisture anomalies relative to an expected annual cycle [9].

To this end, we propose decomposing raw precipitation and soil moisture time series into their climatological and anomaly components

\[
\begin{align*}
\tilde{\theta}_{\text{RS}} &= \theta_{\text{RS}} - \theta_{\text{RS DOY}} \\
\tilde{P}_{\text{sat}} &= P_{\text{sat}} - P_{\text{DOY}} \\
\tilde{P}_{\text{gauge}} &= P_{\text{gauge}} - P_{\text{DOY}}
\end{align*}
\]

where \( \theta_{\text{RS DOY}}, P_{\text{DOY}}^{\text{sat}}, \) and \( P_{\text{DOY}}^{\text{gauge}} \) are climatological expectations for a given day of the year (DOY) and \( \tilde{\theta}_{\text{RS}}, \tilde{P}_{\text{sat}}, \) and \( \tilde{P}_{\text{gauge}} \) are anomalies relative to these expectations experienced on a particular day \( i \). Expectations are calculated by simple linear averaging within a 31-day moving window centered on the particular DOY corresponding to \( i \) and the entire (multiyear) historical data set for each variable.

Because the baseline \( R_{\text{value}} \) analysis in Section II-A is fully linear, raw values of \( \theta_{\text{RS}} \) and \( P_{\text{sat}} \) appearing in (1)–(8) can be substituted with their anomaly equivalents without any loss of validity. In particular, (1) can be modified to produce anomaly API forecasts

\[
\tilde{API}_i = \gamma_i \tilde{API}_{i-1} + \tilde{P}_i^{\text{sat}}
\]

which are then updated using \( \tilde{\theta}_{\text{RS}} \) to produce anomaly analysis increments

\[
\tilde{\delta}_{\text{KF}} = K_i \left[ \tilde{\theta}_{\text{RS}} - H \left( \tilde{API}_{\text{KF}}^- \right) \right]
\]

where \( K \) is based on substituting anomaly-based values of \( T \) and \( S (\tilde{T} \) and \( \tilde{S} ) \) into (4). Analysis increments obtained from (13) and the rainfall anomaly difference \( \tilde{P}_{\text{sat}} - \tilde{P}_{\text{gauge}} \) are both summed within nonoverlapping \( N \)-day windows, and \( R_{\text{value}} \) is estimated from the negative of their Pearson’s correlation coefficient. The process mimics the baseline version perfectly, except that \( R_{\text{value}} \) results now reflect skill in \( \theta_{\text{RS}} \) with respect to only soil moisture anomaly detection.

C. RTS Smoother Modification

The RTS smoother is based on adding a second backward-propagating update to the Kalman filter analysis that incorporates information contained in observations made after the time of update. Because a filter-based update is limited to consider only prior observations, this backward propagation allows for the more efficient use of information embedded in soil moisture retrievals. Furthermore, because our \( R_{\text{value}} \) methodology is essentially a reanalysis-type analysis, there are no practical barriers (e.g., the need for real-time results) to the implementation of a smoothing approach.

After the complete calculation and calibration of Kalman-filter-based increments (now based on climatological anomalies following Section II-B), the RTS smoother propagates information backward in time starting with the final conditions of

\[
\tilde{API}_{\text{RTS}} = \tilde{API}_{\text{KF}}^+ + A_i \left( \tilde{API}_{\text{RTS},i+1} - \tilde{API}_{\text{KF},i+1}^+ \right)
\]

\[
\tilde{T}_{\text{RTS}} = \tilde{T}_{\text{KF}}^+ + A_i^2 \left( T_{\text{RTS},i+1} - \tilde{T}_{\text{KF},i+1}^+ \right)
\]

where

\[A_i = \gamma_i \tilde{T}_{\text{KF}}^+/\tilde{T}_{\text{KF},i+1}^-.
\]
Upon propagation of this second smoothing step, the total analysis increment becomes

\[
\hat{\delta}_{\text{RTS}} = \hat{\delta}_{\text{KF}} + A_i \left( \hat{AP}_{\text{RTS},i+1} - \hat{AP}_{\text{KF},i+1} \right) \tag{19}
\]

where \( \hat{\delta}_{\text{KF}} \) is given by (13). \( R_{\text{value}} \) is then the negative of Pearson’s correlation coefficient between \( \bar{N} \)-day sums of \( \hat{\delta}_{\text{RTS}} \) and \( \bar{\rho}_{\text{sat}} - \bar{\delta}_{\text{range}} \).

### III. Watershed Sites

The \( R_{\text{value}} \) approach described in Section II will be evaluated based on soil moisture and rainfall observations available within three separate U.S. Department of Agriculture (USDA) Agricultural Research Service (ARS) experimental watersheds. Each watershed contains a dense ground-based soil moisture network constructed to facilitate its participation in AMSR-E soil moisture validation activities [19]. As a result, these three watersheds provide an opportunity to assess the performance of the \( R_{\text{value}} \) metric over a range of land surface and climate conditions.

**A. LR, GA**

The 334-km\(^2\) Little River (LR) Experimental Watershed is located in southern Georgia. The USDA-ARS Southeast Watershed Research Laboratory at Tifton, GA, has been collecting hydrologic and climatic data in the watershed since 1968. Land use is a mixture of pasture and forage production, row-crop agriculture (primarily summertime cotton and peanuts), and upland and riparian forests. The watershed topography is characterized by rolling hills and gentle slopes. Climate is humid, with a mean annual precipitation of around 1200 mm—the majority of which occurs during short-duration but high-intensity convective thunderstorms. Rainfall and soil moisture ground data sets are based on measurements made at 29 separate stations within the watershed. For more details on the watershed and its observational networks, see [3], [4], and [19].

**B. LW, OK**

The 611-km\(^2\) Little Washita (LW) Watershed is located in southwestern Oklahoma. The watershed has served as the site for a large number of soil erosion studies since 1936 and hydrological experiments since 1961. Land use is dominated by rangeland and pastures, with significant areas of winter wheat cultivation within the western half of the watershed. The topography is generally flat, with a maximum relief of less than 200 m. Climate is subhumid, with a mean annual precipitation of 760 mm and a mean annual temperature of 16 °C. The watershed experiences strong seasonal variations, with hot and dry summers separated from cold and dry winters by relatively wet periods in the spring and fall. The ground data used here were acquired at 42 rain gauges and 20 soil moisture stations within the study area. Measurements are made as part of the ARS Micronet operated and maintained by the USDA-ARS Grazinglands Research Laboratory in cooperation with Oklahoma State University and the Oklahoma Climatological Survey. For more details on the LW Watershed and these observations, see [1], [5], [19], and http://ars.mesonet.org.

**C. WG, AZ**

The 150-km\(^2\) Walnut Gulch (WG) Experimental Watershed is located in southeastern Arizona. The USDA-ARS Southwest Watershed Research Center in Tucson, AZ, has been collecting rainfall data at the site since 1956 and soil moisture since 1996. Land cover is generally brush and short-grass rangeland. Elevation within the watershed ranges from 1250 to 1585 m above sea level. Located in a semiarid climate zone, the precipitation regime is dominated by the North American monsoon system, with about 60% of the annual rainfall associated with summer convective storms. The mean annual rainfall is 350 mm, and the mean annual temperature is 18 °C. Precipitation data are collected at 82 stations, while the soil moisture is recorded at 19 separate locations. For more details on the WG Experimental Watershed and these observations, see [6], [15], [19], and [29].

### IV. Remote Sensing Data

Remotely sensed soil moisture retrievals are based on five separate products derived from a range of passive microwave brightness temperature \( (T_B) \) observations made by the AMSR-E sensor aboard the National Aeronautics and Space Administration (NASA) Aqua satellite. The AMSR\(^\text{E}_{\text{NASA}}\) product is the official NASA AMSR-E Level 3 soil moisture product [25] derived from application of the dual polarization algorithm described in [23] to H- and V-polarized AMSR-E X-band (10.6-GHz) \( T_B \) observations. The AMSR\(^\text{E}_{\text{USDA}}\) product (developed at the USDA Hydrology and Remote Sensing Laboratory by T. J. Jackson and R. Bindlish) is based on X-band \( T_B \) observations as well but uses the single-channel (H-polarization only) algorithm of Jackson [18]. The AMSR\(^\text{E}_{\text{VU}}\) product (developed at the Vrije University of Amsterdam (VU) by R. M. de Jeu and T. Holmes in collaboration with M. Owe at the NASA Goddard Space Flight Center) applies the algorithm of Owe et al. [26] to dual-polarized C-band (6.9-GHz) \( T_B \) and falls back to X-band \( T_B \) in areas of significant C-band radio-frequency interference (RFI) over the U.S. and Japan [24]. A fourth product (AMSR\(^\text{E}_{\text{SWI}}\)) is based on the application of the soil wetness index (SWI) approach [33] to the AMSR-E \( T_B \) measurements. Here, SWI is simply the difference of AMSR-E H-polarized \( T_B \) observations at 89 and 18.7 GHz. A final soil moisture product (AMSR\(^\text{E}_{\text{COMB}}\)) is obtained from arithmetic averaging of the AMSR\(^\text{E}_{\text{USDA}}, \) AMSR\(^\text{E}_{\text{VU}}, \) and AMSR\(^\text{E}_{\text{NASA}}\) products. To ensure equal weighting, the AMSR\(^\text{E}_{\text{USDA}}, \) AMSR\(^\text{E}_{\text{VU}}, \) and AMSR\(^\text{E}_{\text{NASA}}\) soil moisture products are linearly normalized to the same mean and standard deviation prior to this averaging. For all five products (AMSR\(^\text{E}_{\text{SWI}}, \) AMSR\(^\text{E}_{\text{NASA}}, \) AMSR\(^\text{E}_{\text{USDA}}, \) AMSR\(^\text{E}_{\text{VU}}, \) and AMSR\(^\text{E}_{\text{COMB}}\)), soil moisture retrievals obtained from ascending (1:30 P.M.) and descending (1:30 A.M.) AMSR-E overpasses are analyzed separately.

Two separate satellite-based rainfall data sets produced by TMPA [17] are also utilized. Unless otherwise stated, \( P_{\text{sat}} \) is based on the real-time TRMM 3B40RT product calculated...
using a combination of microwave-only satellite data derived from a number of sensors [17]. In contrast, the TRMM 3B42 product is computed by combining these passive microwave estimates with microwave-calibrated infrared (IR) estimates and a retrospective correction based on monthly rain-gauge data [17]. Our use of the TRMM 3B42 product will vary with context. For the watershed verification analysis in Section VI, it, along with TRMM 3B40RT, will be used for $P_{\text{sat}}$. For the quasi-global analysis in Sections VII and VIII, it will be used exclusively for the benchmark $P_{\text{gauge}}$ rainfall product.

V. APPROACH

The study period for the entire analysis is from February 2, 2002, to December 31, 2007. However, because AMSR-E observations did not become available until June 2002, the first four months of this period are reserved for spinning up the API model. All API modeling is based on a daily time step. Unless otherwise noted, a window length of $N = 5$ days is used, and a minimum threshold of two observations per window is enforced. Time windows failing this threshold are removed from the analysis and not used to calculate $R_{\text{value}}$. Daily TRMM 3B40RT and 3B42 rainfall accumulation estimates are extracted from the quarter-degree latitude/longitude grid box that most closely approximates the spatial extent of each watershed (see Fig. 1). Likewise, retrievals for the five remotely sensed soil moisture products (AMSRE$_{\text{NASA}}$, AMSRE$_{\text{USDA}}$, AMSRE$_{\text{VU}}$, AMSRE$_{\text{SWI}}$, and AMSRE$_{\text{COMB}}$) are extracted from gridded quarter-degree data products for each of the soil moisture data sets. Relative to the LR and LW watersheds, the best quarter-degree grid fit for the WG watershed is still a poor spatial approximation of the actual watershed (Fig. 1). Therefore, for the WG site, a sensitivity analysis was performed to determine the impact of extracting WG AMSRE$_{\text{USDA}}$ and AMSRE$_{\text{NASA}}$ retrievals from individual swath-based footprints instead of a pregridded quarter-degree analysis. Because results from this test indicate little or no impact on subsequent $R_{\text{value}}$ results and some AMSR-E soil moisture products are not readily available in swath format, extraction from quarter-degree gridded data products is retained for our multi-product analysis at the WG site. In addition, to allow for direct comparisons between different soil moisture products, a particular quarter-degree grid (for a given overpass) is included in the analysis only if it contains a viable soil moisture retrieval for all five soil moisture products. As noted previously, retrievals from ascending and descending AMSR-E overpasses are considered separately.

For watershed verification results (Section VI), the API modeling day is defined as the 24-h period starting at midnight Central Standard Time (CST). As noted in Section III, each watershed contains its own dense rain-gauge network. Simple arithmetic averaging is applied to spatially aggregate daily rainfall accumulation values from individual rain gauges within each watershed into a mean daily accumulation for the watershed. These spatially averaged values are then used for $P_{\text{gauge}}$. Based on [19], weighted averages developed through Thiessen polygons are employed to upscale ground-based soil moisture measurements from individual stations to the entire watershed. In order to match AMSR-E overpass times, only ground-based soil moisture observations taken at 1:30 P.M. or 1:30 A.M. local solar time are considered. Due to a disruption in the availability of ground-based soil moisture during late 2007, the watershed analysis in Section VI ended on July 25, August 26, and September 23, 2007, for the WG, LW, and LR watersheds, respectively. Values of $a$ and $b$ in (3) are equal to slope and intercept parameters derived from least squares linear regression of an API time series, derived using $P_{\text{gauge}}$ in (1) and no Kalman filtering updating, to AMSR-E surface soil moisture products. This fitting is based on data from the entire analysis period (2002 and 2007), and separate parameters are obtained for each AMSR-E soil moisture product at every watershed site.

The quasi-global (50° S–50° N) results in Section VII are based on a different temporal and spatial gridding. Prior to any subsequent processing, precipitation and soil moisture remote sensing products are aggregated onto a 1° latitude/longitude spatial grid. Daily precipitation depths $P_{\text{sat}}$ and $P_{\text{gauge}}$ are based on the total rainfall accumulation observed between 12 and 12 UTC, and the soil moisture values for the same day are taken from any ascending or descending AMSR-E retrieval acquired during a period shifted 12 hours into the future (0–24 UTC). This shift is done to maximize the probability that the soil moisture retrieval will occur after a particular rainfall event—as is implicitly assumed in the $R_{\text{value}}$ approach (see Section II). At the global scale, $P_{\text{sat}}$ and $P_{\text{gauge}}$ are always derived from TRMM 3B40RT and TRMM 3B42 results, respectively. Note this difference relative to the watershed approach described before, where both TRMM 3B42 and 3B40RT are used for $P_{\text{sat}}$, and $P_{\text{gauge}}$ is derived from local rain-gauge networks. For the global-scale analysis, parameters $a$ and $b$ in (3) are derived as in the watershed case described earlier except based on linear least squares fitting applied separately to each 1° grid box.
VI. WATERSHED VERIFICATION RESULTS

For the three watersheds described in Section III, Fig. 2 shows \( R_{\text{value}} \) watershed results with Pearson’s correlation coefficients between daily AMSR-E soil moisture products and daily watershed-scale soil moisture estimates obtained from the spatial averaging of high-density soil moisture ground networks. These ground-based correlations, referred to as \( R_{\text{truth}} \), reflect the type of high-quality evaluation that is currently available within only a small number of heavily instrumented watershed sites. The point cloud in Fig. 2 is created by lumping results from all three USDA-ARS watersheds (WG, LW, and LR) and all five AMSR-E soil moisture products (AMSRESWI, AMSRENASA, AMSREUSDA, AMSREVU, and AMSRECOMB). In addition, results are shown for the use of both TRMM 3B42 (open symbols) and TRMM 3B40RT (filled symbols) precipitation products as \( P_{\text{sat}} \). Unless otherwise noted, results are based on implementation of both the anomaly and RTS smoother modifications described in Section II. For consistency with the anomaly-based \( R_{\text{value}} \) calculations, the \( R_{\text{truth}} \) correlation coefficient is also sampled after seasonal cycles have been removed from both the remotely sensed and ground-based soil moisture observations.

The use of TRMM 3B40RT data as \( P_{\text{sat}} \) leads to a high correlation between \( R_{\text{truth}} \) and \( R_{\text{value}} \) (\( R^2 = 0.85 \)), suggesting that \( R_{\text{value}} \) can accurately mimic the correlation-based evaluation of soil moisture products without any reliance on ground-based soil moisture observations (see the filled symbols in Fig. 2). This result verifies the underlying \( R_{\text{value}} \) approach by demonstrating its ability to accurately reproduce validation results obtained from very dense ground-based soil moisture networks. As discussed in Section II, the \( R_{\text{value}} \) results in Fig. 2 are based on a—temporally and spatially constant—choice of \( \gamma = 0.85 \) for API modeling in (1). However, varying \( \gamma \) between 0.80 and 0.90 led to only very minor changes in the observed correlation between \( R_{\text{truth}} \) and \( R_{\text{value}} \).

Despite the obvious simplicity of the API-based modeling approach in (1), the majority of the observed scatter in Fig. 2 appears to be an attributable simple random sampling error and not any underlying incompatibility between \( R_{\text{truth}} \) and \( R_{\text{value}} \). For example, \( 1 \sigma \) sampling uncertainty in the estimated correlation coefficient used for \( R_{\text{value}} \) is responsible for about 75% of the observed root-mean-square (rms) scatter around the TRMM 3B40RT least squares regression line in Fig. 2 [34]. Consequently, it appears unlikely that the observed fit in Fig. 2 can be substantially improved via the application of more complex soil water-balance models. The observed correlations in Fig. 2 are also degraded by the presence of sampling error in the daily watershed-scale soil moisture estimates derived by Jackson et al. [19] from ground-based observations and used here to calculate \( R_{\text{truth}} \). However, structural and sampling uncertainties are likely much larger for \( R_{\text{value}} \) estimates relative to comparably direct \( R_{\text{truth}} \) calculations. Therefore, the presence of significant correlation between independently acquired \( R_{\text{value}} \) and \( R_{\text{truth}} \) in Fig. 2 strongly implies that the ground-based observations of Jackson et al. [19] are accurately representing watershed-scale soil moisture dynamics.

The use of the higher accuracy TRMM 3B42 rainfall product, instead of TRMM 3B40RT, as \( P_{\text{sat}} \) leads to a reduction in calculated \( R_{\text{value}} \) (compare the filled and open symbols in Fig. 2). This reduction reflects the relationship noted by Crow [7], where by higher (lower) accuracy \( P_{\text{sat}} \) rainfall products lead to lower (higher) \( R_{\text{value}} \) magnitudes. Note that \( R_{\text{value}} \) is a metric of added value and can therefore be increased through either of the following ways: 1) the improvement of soil moisture retrievals or 2) the degradation of competing soil moisture estimates obtained from water-balance modeling and remotely sensed rainfall [7]. In Fig. 2, the lower \( R_{\text{value}} \) associated with TRMM 3B42 reflects the fact that a better rainfall product makes it incrementally more difficult for a soil moisture product to provide added skill. In addition, the transition to the TRMM 3B42 product reduces the observed \( R^2 \) correlation between \( R_{\text{truth}} \) and \( R_{\text{value}} \) from 0.85 to 0.66.

As noted previously, the results in Fig. 2 and Table I are based on adopting both the anomaly and RTS smoother modifications discussed in Section II-B and C, respectively. In order to motivate these modifications, Table I presents summary statistics (i.e., the \( R^2 \) between \( R_{\text{truth}} \) and \( R_{\text{value}} \) and the average \( R_{\text{value}} \) calculated across all sites) for analogous results calculated with and without these modifications. For consistency, \( R_{\text{truth}} \) benchmark results are obtained for either raw or anomaly soil moisture times series, depending on whether they are being compared to raw or anomaly-based \( R_{\text{value}} \) results. The raw/KF results in Table I reflect the baseline \( R_{\text{value}} \) approach applied in [7] and [8]. Regardless of whether TRMM 3B40RT or 3B42 rainfall is used as \( P_{\text{sat}} \), the implementation of each modification (alone or in combination) improves the performance of the \( R_{\text{value}} \) metric. Note the clear increase in the \( R^2 \) correlation between \( R_{\text{truth}} \) and \( R_{\text{value}} \) for the fully modified (anomaly/RTS) case relative to the original (Raw/KF) approach used in [7] and [8]. Consequently, modifications to the \( R_{\text{value}} \) methodology described in Section II appear to produce a more reliable evaluation metric.
TABLE I

<table>
<thead>
<tr>
<th>Product</th>
<th>Raw/Anomaly</th>
<th>$R^2$</th>
<th>$R_{value}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>3B42</td>
<td>Raw</td>
<td>0.46</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>Anomaly</td>
<td>0.54</td>
<td>0.29</td>
</tr>
<tr>
<td>RTS</td>
<td>Raw</td>
<td>0.45</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>Anomaly</td>
<td>0.66</td>
<td>0.32</td>
</tr>
<tr>
<td>3B40RT</td>
<td>Raw</td>
<td>0.65</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>Anomaly</td>
<td>0.68</td>
<td>0.51</td>
</tr>
<tr>
<td>RTS</td>
<td>Raw</td>
<td>0.68</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>Anomaly</td>
<td>0.85</td>
<td>0.57</td>
</tr>
</tbody>
</table>

The key to a robust $R_{value}$ approach is reliable even when global rainfall products (and not local rain-gauge observations) are used for $P_{gauge}$. The accuracy of $P_{gauge}$ rainfall pentads relative to the daily rain-gauge-based pentads used for $P_{gauge}$ in Fig. 2.

Reducing the accuracy of $P_{gauge}$ leads to a slightly lower correlation between the calculated $R_{value}$ and observed $R_{truth}$ (compare the closed symbols in Figs. 2 and 3). Nevertheless, a significant level of correlation is retained ($R^2 = 0.78$). This suggests that the $R_{value}$ approach is reliable even when global rainfall products (and not local rain-gauge observations) are used for $P_{gauge}$. In areas of the world in which monthly rain-gauge observations are available for a retrospective correction of satellite-based retrievals, there appears to be a large-enough difference between the accuracy of the TRMM 3B40RT and 3B42 products to calculate a reliable $R_{truth}$. Unfortunately, the results in Fig. 3 provide a lesser guarantee for extremely data-poor areas in which even monthly retrospective rain-gauge correction is difficult and/or impossible to perform. One potential solution in such areas is to use an expanded 30-day window size to maximize the filtering of short-term errors in $P_{gauge}$. However, in the case of Fig. 3, converting from a 5-day to 30-day window size actually reduces the observed correlation between $R_{value}$ and $R_{truth}$ from $R^2 = 0.78$ to 0.61 (not shown). This reduction appears to be in response to the reduced consistency between the (now monthly) temporal support of $R_{value}$ estimates and remaining daily basis of $R_{truth}$. As a result, the use of a five-day aggregation window is retained for all future $R_{value}$ calculations.

Using TRMM 3B42 for $P_{gauge}$ and TRMM 3B40RT as $P_{sat}$, quasi-global (land areas between 50° S and 50° N) $R_{value}$ results are calculated for each of the remotely sensed soil moisture data sets introduced in Section IV. As discussed earlier, high-$R_{value}$ results indicate that a given soil moisture product is contributing to an improved representation of soil moisture anomalies (above and beyond the baseline obtainable using API modeling forced by TRMM 3B40RT rainfall). Fig. 4 shows variations in the average $R_{value}$ performance of various products—grouped according to the lowest frequency AMSRE $T_B$ observation used to create them. Within both CONUS [Fig. 4(a)] and quasi-global [Fig. 4(b)] domains, implementation of the new RTS and anomaly-based approach leads to spatially averaged $R_{value}$ results (indicated by open circles) that gradually rise as $T_B$ frequency falls [Fig. 4(b)]. The slight suppression of AMSRE$_{VU}$ $R_{value}$ results over CONUS (relative to extrapolated expectations for a C-band product) is almost certainly due to C-band (6.9-GHz) RFI considerations that forced Owe et al. [26] to fall back on X-band (10.6-GHz) $T_B$ observations over many parts of the U.S. The relative performance of A.M.- versus P.M.-based retrievals also varies from product to product. Over the quasi-global domains [Fig. 4(a)], daytime P.M. overpasses yield slightly better retrievals for the AMSRE$_{NASA}$, AMSRE$_{USDA}$, and AMSRE$_{SWI}$ products, while nighttime A.M. overpasses are preferable for the AMSRE$_{VU}$ product.

Fig. 4 also shows relative variations in temporally averaged $R_{value}$ associated with different $R_{value}$ methodologies. Over the CONUS domain [Fig. 4(a)], the transition between raw and anomaly-based $R_{value}$ calculations (see Section II-B)
and the subsequent transition from a Kalman filter to an RTS smoother implementation (see Section II-C) consistently increases $R_{\text{value}}$ for all products except AMSRE$_{\text{SWI}}$. At the quasi-global scale [Fig. 4(b)], a consistently positive impact is associated with switching to an RTS smoother; however, the impact of preprocessing data into anomalies is more erratic, with large improvements being noted for some products (e.g., the AMSRE$_{\text{VU}}$ P.M. product) and small decreases for others (e.g., the AMSRE$_{\text{USDA}}$ A.M. and P.M. products). This variable response is tied to the accuracy of each product with regard to representing seasonal soil moisture dynamics. For example, the AMSRE$_{\text{VU}}$ P.M. product has a known problem capturing wet/dry seasonal trends over areas of Africa (T. Holmes, personal communication). Difficulties associated with seasonal cycles can impair the ability of a given product to represent fine-scale temporal soil moisture anomalies. Consequently, implementing the anomaly-based calculation of $R_{\text{value}}$, in which (potentially artificial) seasonal trends are explicitly removed, leads to a large increase in calculated $R_{\text{value}}$. Conversely, because seasonal trends in AMSRE$_{\text{USDA}}$ predictions are relatively more accurate, their removal actually leads to a small decrease in $R_{\text{value}}$. In addition to these differences in performance, the appropriateness of raw versus anomaly-based $R_{\text{value}}$ metrics is dependent on the degree to which capturing seasonal predictions represents an important source of retrieval skill for specific applications. For many DA applications, all soil moisture products (regardless of their accuracy) are preprocessed to explicitly match a land surface model’s individual soil moisture climatology prior to being ingested. Consequently, added value in the assimilation product is derived solely from an improved representation of anomalies relative to this climatology [9]. In these cases, anomaly-based $R_{\text{value}}$ calculations (open circles in Fig. 4) provide a more robust representation of the overall retrieval value by de-emphasizing the accurate representation of a seasonal cycle.

Complete quasi-global 1° imagery is shown in Fig. 5 for A.M. and P.M. retrievals from all AMSRE-E-based soil moisture products except AMSRE$_{\text{COMB}}$. The first-order patterns seen in Fig. 5 reflect the global distribution of vegetation biome types that are amenable to microwave-based soil moisture remote sensing. High skill with regard to anomaly detection (red shading) is clearly evident in lightly-vegetated areas of the western U.S., the Iberian peninsula, the Sahel region of Africa, central Asia, southern Africa, Australia, and the Pampas region of South America. Low skill (blue shading) is identified in the rainforest regions of South America, Africa, and Indonesia, as well as densely vegetated areas in eastern North America.

In addition to these broad geographic patterns, a number of product-to-product differences can be detected. Based only on high-frequency $>10$-GHz $T_D$ measurements, the AMSRE$_{\text{SWI}}$ algorithm demonstrates little added skill outside of sparsely vegetated areas. Much better results are obtained for all other products obtained from lower frequency $T_B$ observations. In particular, the AMSRE$_{\text{USDA}}$ and AMSRE$_{\text{NASA}}$ products use the same AMSRE $T_B$ band (10.6 GHz) but differ in their basis for estimating vegetation canopy opacity. While the single-polarization AMSRE$_{\text{USDA}}$ product requires ancillary vegetation information, typically derived from historical visible and near-IR remote sensing data, to estimate canopy opacity, the AMSRE$_{\text{NASA}}$ products estimate opacity directly from dual-polarization microwave $T_D$ observations. Fig. 5 suggests that, at least for X-band products, the added ancillary data requirements of the AMSRE$_{\text{USDA}}$ product enhance the large-scale accuracy of its A.M. retrievals over Australia and western North America. Likewise, the use of dual-polarized C-band AMSRE $T_D$ appears to provide additional skill to the AMSRE$_{\text{VU}}$ A.M. product (relative to both the X-band AMSRE$_{\text{USDA}}$ and AMSRE$_{\text{NASA}}$ products) in areas of eastern Africa and along a broad swath of Central Asia. Note that the lack of a C-band single-polarization product in the analysis prevents a full examination of dual- versus single-polarization effects on C-band retrievals. In contrast to the product-to-product variations seen in the A.M. products, relatively little difference is observed between the AMSRE$_{\text{USDA}}$, AMSRE$_{\text{NASA}}$, and AMSRE$_{\text{VU}}$ P.M. products—seemingly suggesting that intra-algorithm differences are more pronounced for daytime P.M. retrievals.

Fig. 5 can also be used to examine 1:30 P.M. versus 1:30 A.M. overpass differences for various products. For instance, the
AMSRE_{VU} A.M. product is superior to its P.M. counterpart over arid areas of western North America, north Africa, northeast Asia, and central Australia. Both AMSRE_{VU} and AMSRE_{USDA} products retrieve soil moisture based on surface temperature estimates obtained from 37-GHz AMSR-E T_{B} observations [19], [26]. These surface temperature estimates are prone to error for daytime conditions in arid climates and are likely a significant source of uncertainty in retrievals based on 1:30 P.M. overpasses. Somewhat surprisingly given their similar approach to surface temperature estimation, an analogous A.M./P.M. contrast is not seen for the AMSRE_{USDA} results in Fig. 5. Some care should be taken in interpreting A.M.
versus p.m. overpass differences in Fig. 5 because the temporal support of A.M. and p.m. \( R_{\text{value}} \) results may vary. The clearest example of this is the improved performance of all 1:30 p.m. soil moisture products (relative to their A.M. counterparts) over the Tibetan Plateau (see Fig. 5 to the northeast of India). This difference arises because the AMSRE\textsubscript{VU} and AMSRE\textsubscript{USDA} products provide only very sporadic 1:30 a.m. retrievals in the region, while all four products provide essentially continuous 1:30 p.m. soil moisture estimates. Because the inclusion of a grid cell on a given day requires the availability of retrievals from all products (in order to make product-to-product comparisons as objective as possible), insufficient A.M. data over the region are available to make robust \( R_{\text{value}} \) calculations for any product.

VIII. “HOT-SPOT” COMPARISON

For many weather and climate applications, the value of accurate soil moisture retrievals varies geographically. Recent work using an ensemble of climate models has established the concept of soil moisture “hot spots” where soil moisture information is particularly valuable for predicting long-term precipitation and temperature variability [21]. The existence of such discrete areas implies that, for atmospheric predictability applications, these regions should be disproportionately emphasized when globally evaluating a given soil moisture product. Therefore, a fundamental issue for evaluating soil moisture retrievals is the degree to which areas where remote sensing observations add value spatially correspond to identified hot-spot regions.

Fig. 6 examines this issue by overlaying contour lines for precipitation and temperature hot spots predicted by Koster et al. [21] on quasi-global \( R_{\text{value}} \) results for the AMSRE\textsubscript{VU} A.M. product. The delineated areas represent the target hot spots where enhanced soil moisture information is particularly relevant for temperature and precipitation forecasting applications. Hot spots generally span transitional regions between humid and arid climates [21]. This tendency is clearly illustrated in central/western North America and sub-Saharan Africa. Within these regions, there is a tendency for the AMSRE\textsubscript{VU} A.M. product to perform well on the dry side of the climate transition but less successfully on the corresponding wetter side. Future remote sensing measures acquired at L-band have the potential to penetrate further into wetter (and more heavily) vegetated portions of such climate transects. For all the AMSR-E soil moisture products, Fig. 7 shows mean \( R_{\text{value}} \) results for the following: 1) all global land areas between 50° S and 50° N; 2) only land areas within a precipitation hot spot; and 3) only land areas within a temperature hot spot. \( R_{\text{value}} \) in hot-spot regions tends to be higher than its global average (see, for example, the AMSRE\textsubscript{VU} and AMSRE\textsubscript{USDA} A.M. products). That is, on a globally averaged basis, land cover conditions within hot-spot areas are generally more amenable to soil moisture remote sensing than those outside, and some degree of fortuitous correspondence exists between regions of greatest need and acceptable accuracy for satellite-based surface soil moisture products. However, the \( R_{\text{value}} \) difference between hot-spot and non-hot-spot areas is not observed in the AMSRE\textsubscript{SWI} soil moisture product (Fig. 7). This suggests that new areas of soil moisture retrieval skill for 10.6-GHz retrievals (relative to those already observed at 18.7 GHz) tend to be disproportionately located in hot-spot regions. The prospect of preferentially adding retrieval skill within hot-spot regions remains a key motivator for future soil moisture satellite missions based on even lower frequency \( T_B \) retrievals [13], [20].
Despite these results, it is important to note that the $R_{\text{value}}$ approach is intended to supplement, and not replace, more traditional satellite soil moisture validation activities based on ground-based soil moisture networks. As noted in [7], the $R_{\text{value}}$ metric is blind to bias and/or dynamic range errors and provides only a measure of skill with regard to change detection. While such change-detection skill is frequently cited as the key contribution of remotely sensed soil moisture for many DA activities (see, for example, [9] and [28]), it is not the only metric by which soil moisture products should be validated. In particular, bias and rms error (rmse) calculations must be made versus ground-based observations or through the implementation of an alternative technique designed to recover rmse-type information. A very promising example of such a technique is described by Scipal et al. [32]. In addition, the $R_{\text{value}}$ metric is most properly interpreted as a measure of added skill, which is sensitive to both the inherent accuracy of a soil moisture product and the accuracy of the rainfall estimates driving a competing water-balance-based estimate of soil moisture (Fig. 2). Such relativity is, of course, a limitation for strict validation activities attempting to establish the absolute accuracy of a given soil moisture product. However, evaluation approaches based on measuring the added value of remotely sensed observations relative to some baseline are important for assessing the higher level value associated with a soil moisture product when assimilated into an existing predictive modeling and/or decision support system.

Follow-on plans for this paper include the application of the technique to L-band soil moisture retrievals obtained from the European Space Agency Soil Moisture and Ocean Salinity mission [20] and integrating the approach into validation plans for the upcoming NASA Soil Moisture Active/Passive mission.

IX. SUMMARY

To date, designers of soil moisture remote sensing algorithms have generally lacked the ability to evaluate their products at regional and continental scales. Recent research described in [7], [8], and [22] attempts to develop a DA-based approach that spatially expands the geographic extent of regions in which remotely sensed soil moisture products can be evaluated. In this paper, we do the following: 1) Fundamentally modify the existing $R_{\text{value}}$ approach (Section II); 2) present the first independent verification of its ability to accurately reproduce validation results obtained over highly instrumented watershed sites; and 3) complete a global-scale application of the newly modified and verified approach.

Watershed verification results demonstrate that the $R_{\text{value}}$ metric can effectively mimic correlation-based validation results obtained from dense ground-based soil moisture networks (Fig. 2). In particular, implementation of the methodological modifications introduced in Section II leads to larger $R_{\text{value}}$ magnitudes and a stronger correlation with ground-based validation metrics relative to implementation of the baseline approach in [7] and [8] (Table I). This skill in replicating ground-based validation results remains even after input data access is restricted to only satellite-based rainfall data sets (Fig. 3)—suggesting that the $R_{\text{value}}$ approach can be effectively applied at global scales. The subsequent application over a quasi-global (50°S–50°N) domain using TMPA precipitation data verifies the expected large-scale tendency for soil moisture retrieval skill to increase as $T_B$ frequency decreases (Fig. 4), and it clarifies the global extent of regions in which remote sensing contributes to the detection of soil moisture anomalies (Fig. 5). The spatial correspondence of these areas with regions of strong land–atmosphere coupling is a critical issue for articulating the value of remotely sensed soil moisture retrievals for atmospheric predictability applications. The results here quantify the degree of overlap between the hot-spot regions identified by Koster et al. [21] and those of strong skill for remotely sensed soil moisture products (Figs. 6 and 7).

Fig. 7. Spatial average of $R_{\text{value}}$ for the AMSRE$_{\text{SW1}}$, AMSRE$_{\text{NASA}}$, AMSRE$_{\text{USDA}}$, AMSRE$_{\text{VU}}$, and AMSRE$_{\text{COMB}}$ products for all (circles) land areas between 50°S and 50°N, (squares) land areas within precipitation hot spots, and (crosses) land areas within temperature hot spots.

REFERENCES

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