A Change Detection Algorithm for Retrieving High-Resolution Soil Moisture From SMAP Radar and Radiometer Observations

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Maria Piles, *Student Member, IEEE*, Dara Entekhabi, *Senior Member, IEEE*, and Adriano Camps, *Senior Member, IEEE*

***Abstract*—A change detection algorithm has been developed in order to obtain high-resolution soil moisture estimates from future Soil Moisture Active and Passive (SMAP) L-band radar and radiometer observations. The approach combines the relatively noisy 3-km radar backscatter coefficients and the more accurate 36-km radiometer brightness temperature into an optimal 10-km product. In preparation for the SMAP mission, an observation system simulation experiment (OSSE) and field experimental campaigns using the Passive and Active L- and S-band Airborne Sensor (PALS) have been conducted. We use the PALS airborne observations and OSSE data to test the algorithm and develop an error budget table. When applied to four-month OSSE data, the change detection method is shown to perform better than direct inversion of the radiometer brightness temperatures alone, improving the root mean square error by 2% volumetric soil moisture content. The main assumptions of the algorithm are verified using PALS data from the soil moisture experiments held during June–July 2002 (Soil Moisture Experiment 2002) in Iowa. The algorithm error budget is estimated and shown to meet SMAP science requirements.**

***Index Terms*—Change detection, microwave remote sensing, observation system simulation experiment (OSSE), radar, radiometer, Soil Moisture Active and Passive (SMAP) mission.**

I. Introduction

SOIL moisture is a critical hydrological variable that links the terrestrial water, energy, and carbon cycles. Global and regional observations of soil moisture are needed to estimate the water and energy fluxes at the land surface, to quantify the net carbon flux in boreal landscapes, to enhance weather and climate forecast skill, and to develop improved flood prediction and drought monitoring capability. Active and passive L-band microwave remote sensing provide a unique ability to monitor global soil moisture over land surfaces with an acceptable spatial resolution and temporal frequency [1], [2].

Mapping radars are capable of a very high spatial resolution [$\sim$3 km in case of Soil Moisture Active and Passive (SMAP)] but, since radar backscatter is highly influenced by surface roughness, vegetation canopy structure and water content, they have a low sensitivity to soil moisture under vegetated conditions. Various algorithms for retrieval of soil moisture from radar backscattering have been developed, but they are only valid in low-vegetation water content conditions [3], [4]. In contrast, the spatial resolution of radiometers is typically low ($\sim$40 km), the retrieval of soil moisture from radiometers is well established, and radiometers have a high sensitivity to soil moisture under vegetated conditions [5].

To overcome the individual limitations of the passive and active approaches, the SMAP mission is combining the two technologies. The SMAP mission has been recommended by the NRC Earth Science Decadal Survey Panel for launch in the 2010–2013 time frame [6]. SMAP is based on the NASA Hydros (Hydrosphere State) mission [7] that progressed through Phase A development until it was canceled in 2005 due to NASA budgetary constraints. The SMAP mission payload consists on an approximately 40-km L-band microwave radiometer measuring H, V, and U brightness temperatures and a 3-km L-band synthetic aperture radar sensing backscattering coefficients at hh, vv, and hv polarizations. It will provide global scale land surface soil moisture observations with a three-day revisit time, and its key derived products are the following: soil moisture at 40 km for hydroclimatology, obtained principally from the radiometer measurements; soil moisture at 10-km resolution for hydrometeorology obtained by combining the radar and radiometer measurements in a joint retrieval algorithm; and freeze/thaw state at 3-km resolution from the radar measurements. This paper describes a downscaling algorithm for combining the high radar resolution and the high radiometer accuracy into an optimal blend for the SMAP 10-km soil moisture product.

Change detection techniques have been demonstrated to be able to potentially monitor temporal evolution of soil moisture by taking advantage of the approximately linear dependence of radar backscatter and brightness temperature change on soil moisture change. The feasibility of a change detection approach using the passive and active L- and S-band airborne sensor (PALS) radar and radiometer data obtained during the

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1999 Southern Great Plains Experiment (SGP99) campaign is presented in [8]; a similar approach is used in [9] to downscale PALS data using airborne synthetic aperture radar data from the Soil Moisture Experiment 2002 (SMEX02) campaign. A totally different approach is presented in [10], where a Bayesian method is used to downscale radiometer observations using radar measurements in an Hydros-like simulated environment.

The novel approach presented on this paper is based on change detection and focuses on the idea of considering the surface soil moisture over a sample 10-km region to be composed of weighted averages of the available radar retrievals within that region and the radiometer retrieval within the radiometer footprint containing the 10-km region. The advantage of this approach is that as more radar retrievals are available within the 10-km region, more spatial structure within a radiometer footprint will become evident and, since the collection of 10-km pixels within the larger scale radiometer footprint is constrained to sum to the value indicated by the radiometer retrieval, the high-resolution estimation gracefully keeps the accuracy of the radiometer retrieval.

The theoretical basis and the assumptions behind the change detection algorithm used in this paper are presented in Section II. In Section III, field experiment data from the SMEX02 field campaign is used to validate the algorithm main assumptions. The results of applying the algorithm to a four-month observation system simulation experiment (OSSE) data set are shown in Section IV. The performance of the method is shown in terms of comparison with ground-truth soil moisture data and with the radiometer data resampled to 10 km. An error budget analysis of the algorithm is presented in Section V and, in the final section, the most significant results of the paper are summarized, and the applicability and usefulness of the scheme to future SMAP data on an operational basis are discussed.

II. Change Detection Method

The algorithm presented in this paper is based on the change detection concept. The 40-km radiometer brightness temperatures are combined with the 3-km radar backscatter observations to obtain 10-km soil moisture observations. It assumes in the first place that soil moisture and the log of radar backscatter are linearly related at a 10-km scale (Assumption I)

$$\theta(a,t) = \alpha(a) + \beta(a) \cdot \log\left[\sigma^0(a,t)\right] \tag{1}$$

where a represents the 10-km scale, $\sigma^0(a,t)$ is the radar backscatter aggregated to 10 km at time t and $\theta(a,t)$ is the soil moisture at 10 km at time t. The aggregation could be made in decibels but using this approach the algorithm does not converge for most pixels. Aggregating radar data from fine to medium resolution reduces the noise level in the backscattering coefficient data. The algorithm performance with application at different levels of aggregation needs to be performed with more extensive field experiment data.

We can form time differences to remove the bias term of (1) and space average the result to the radiometer pixel area A of 40 km, which leads to

$$\langle \Delta\theta(a,t) \rangle = \left\langle \beta(a) \cdot \Delta \log\left[\sigma^0(a,t)\right] \right\rangle \tag{2}$$

where $\langle \cdot \rangle$ stands for the spatial average of the a scale pixels contained into the A scale pixels.

At this point, it is assumed (Assumption II) that slope β and backscatter changes are uncorrelated. Hence, the definition of covariance $cov\{x,y\} = \langle xy \rangle - \langle x \rangle \cdot \langle y \rangle$ can be used to write (2) as

$$\langle \Delta\theta(a,t) \rangle = \langle \beta(a) \rangle \cdot \left\langle \Delta \log\left[\sigma^0(a,t)\right] \right\rangle. \tag{3}$$

Finally, it is assumed that variation on vegetation type occur principally at scales larger than A (Assumption III), $\beta(a) = \langle \beta(a) \rangle$, so time differences can be used to write (3) as

$$\theta(a,t) = \theta(A, t - t_{\mathrm{R}}) + \langle \beta(a) \rangle \cdot \Delta \log\left[\sigma^0(a,t)\right] \tag{4}$$

where t_{R} is the revisit time of the observations, three days for the SMAP case.

The radar-radiometer change-detection algorithm can be written as either the radiometer-scale soil moisture retrieval $\theta(A, t - t_{\mathrm{R}})$ updated with moisture change evident in the higher resolution radar back-scatter change as in (4) or, alternatively, the 10-km soil moisture retrieval from the previous algorithm application (orbit pass) $\theta(a, t - t_{\mathrm{R}})$ can be used as the first term. However, this latter approach has the risk of accumulating errors from the relatively more noisy radar measurements.

Equation (4) constitutes the core of the change detection algorithm. It indicates that a soil moisture estimate at scale a and at a given time can be obtained as the previous soil moisture estimate plus a change in soil moisture, which is given by the actual radar estimates and the value of the slope $\langle \beta(a) \rangle$. From (3), the slope can be estimated using regression of radiometer and spatially averaged radar data at scale A. Better slope estimations are obtained with time, since more radar and radiometer observations are available. The first estimates are likely to be noisy due to the high uncertainty on the first calculated slopes. However, when a reasonable number of estimates (on the order of a month) is available, the uncertainty on calculating the slope becomes much lower, leading to robust soil moisture estimations (see Section IV).

III. Test of Assumptions Using SMEX02 Data

A. SMEX02 Description

Experimental data from the soil moisture experiments SMEX02 will be used in this paper to validate the three assumptions of the algorithm. The SMEX02 field campaign was conducted in Walnut Creek, a small watershed in Iowa, between June 25 and July 12, 2002. The PALS sensor was mounted on an aircraft and flown over the SMEX02 region on June 25, 27, and July 1, 2, 5, 6, 7, and 8, 2002, and an extensive data set of *in situ* measurements of volumetric soil moisture, surface and subsurface soil temperature, soil bulk density, and vegetation water content was collected during all the campaign [11]. The PALS coverage during July 1 was partial, and *in situ* sampling was not done on July 2, so data from these two days were not used in this paper. Since the algorithm proposed in this paper is based on the change of soil moisture over

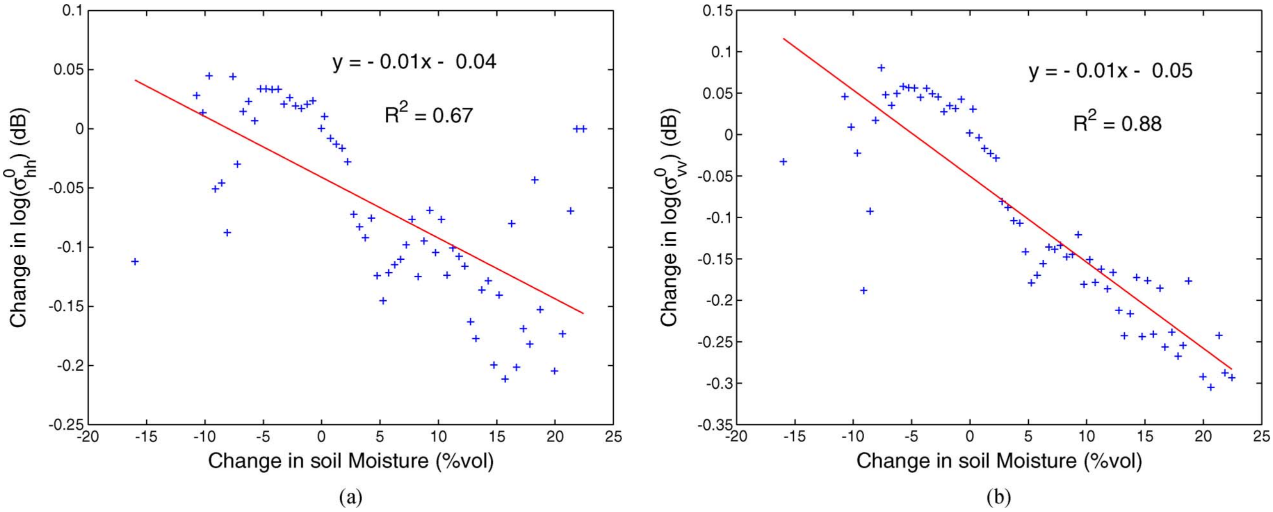

Fig. 1. Change in log of PALS observed L-band radar backscatter at (a) hh and (b) vv polarizations plotted versus change in *in situ* volumetric soil moisture in the 0- to 6-cm soil layer for the period June 25 to June 27 and July 5 to July 7. The change in radar backscatter has been stratified by 0.05% change in volumetric soil moisture.

time, it is not feasible to fully test it with data from aircraft-mounted instruments due to cost limitations. However, L-band PALS data and volumetric soil moisture have been properly used to validate the algorithm assumptions on Section III-B. In addition, SMEX02 experimental data has been used to estimate the algorithm error budget on Section V.

B. Validation of the Assumptions

It was shown in a previous study that for the SMEX02 field experiment PALS L-band brightness temperatures and radar backscatter coefficients were well correlated to soil moisture [12]. To specifically illustrate the correlation between soil moisture and radar backscatter assumed in the algorithm development (Assumption I), in Fig. 1, the change in log of radar backscatter for hh and vv polarizations is compared to the corresponding change in volumetric soil moisture at a resolution of 400 m for the time periods June 25 to June 27 and July 5 to July 7. R^2 values of 0.67 and 0.88 are obtained for hh and vv polarizations, respectively, indicating that radar sensitivity to soil moisture is significant even under the dense vegetation conditions encountered in the SMEX02 experiments with the vegetation water content of corn fields being around 4–5 kg/m^2 [12]. The higher correlation obtained with the radar vertical polarization is consistent with the literature on radar remote sensing of soil moisture.

In order to demonstrate with real data that the algorithm's calculated slope and backscatter changes are uncorrelated (Assumption II), for each day of measurement the slope is calculated using linear regression from (3) and the change in log of radar backscatter is computed. Daily correlations between the slope and the change in radar backscatter indicate values of the order of 10^{-3}, which evidences the validity of the assumption made.

Assumption III in the algorithm formulation states that the slope at 10-km resolution equals the mean of the slope over a 40-km pixel ($\beta(a) = \langle\beta(a)\rangle = \beta(A)$). The spatial resolutions of 400 and 1600 m will be used in this part of the study

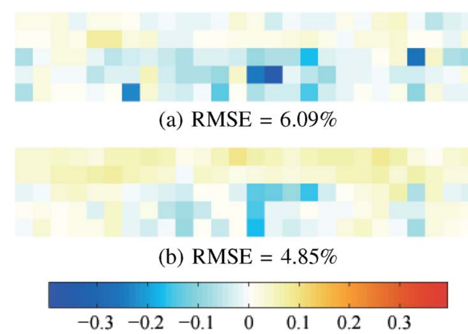

Fig. 2. Error difference between static map of β at 400 m aggregated to 1600 m and directly computed static map of β at 1600-m spatial resolution using radar (a) hh and (b) vv polarizations.

representing a and A, for compatibility with PALS data. As an initial evaluation of this point, for each pixel and for all days of measurement, static maps of β were calculated using linear regressions with brightness temperatures and radar backscatters at 400-m resolution and at 1600 m [(3)]. The 400-m static map of β was then aggregated to 1600 m and compared to the maps of β using aggregated radar and radiometer measurements at 1600 m. Thus, the error difference between the two maps is essentially the error of assuming homogeneity of β. Even though the scale ratios with the PALS data are the same as SMAP radar and radiometer pixels, the absolute scales are clearly different. This mismatch may represent an underestimation of the error due to this assumption. Nevertheless, this represents a preliminary test and more detailed testing using other data sets is needed. The results of the tests on Assumption III are shown in Fig. 2. Results show an acceptable error, greater for horizontal than for vertical polarization. Still, for quantifying the error that this assumption is adding to the retrievals, another experiment has been conducted: From the static map of β at 400 m, the soil moisture estimates for each day are calculated, and the same procedure is followed to retrieve soil moisture estimates from the static map of β at 1600 m. Subsequently, histograms of the difference between the soil moisture retrievals

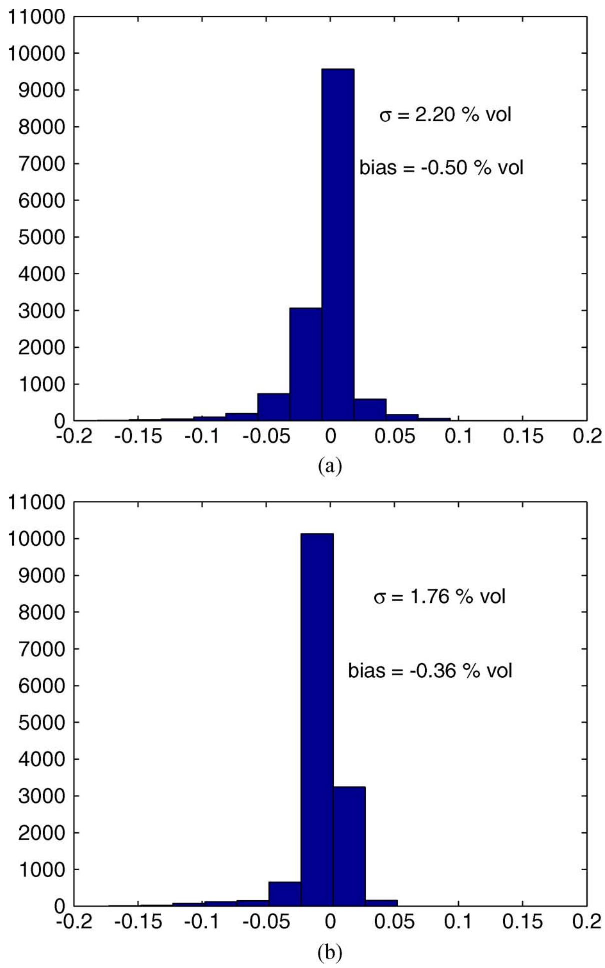

Fig. 3. Histogram of the difference between soil moisture retrieved using static map of β at 400 m and using static map of β at 1600 m for (a) hh and (b) vv polarizations.

acquired using $\beta(a)$ and $\langle\beta(a)\rangle$ are shown in Fig. 3. With an error of $\sim$2%, this third assumption results to be the most critical error source for the algorithm.

The airborne campaign duration is too short and the variability in ground conditions are too limited to fully apply the change detection algorithm. Longer duration data sets with wider range of vegetation conditions are needed. Here, we augment the tests of the algorithm assumptions using airborne field experiment data with tests using synthetic observing system simulation experiments.

IV. Application to OSSE Data

A. OSSE Data Set

The simulated data used in this paper was generated in the Hydros OSSE [13]. The OSSE was designed to mimic as closely as possible the specific Hydros sensor and orbital characteristics and therefore is perfectly valid for SMAP purposes. The experiment was driven by high-resolution land surface geophysical variables generated from a distributed land surface model within the Red-Arkansas river basin. They were used to derive a set of Hydros-like simulated brightness temperatures and radar backscatter cross sections over the area that were then inverted back into soil moisture products using various retrieval algorithms. The OSSE adopts an easily nested fine, medium, and coarse resolution grid of 3, 9, and 39 km, respectively. On this paper, the OSSE resolutions of 9 and 39 km will be used closest to SMAP 10- and 40-km products. Complete OSSE fundamentals and details for radiometer-only soil moisture retrievals are described in [13]. Details regarding the radar and radiometer soil moisture retrievals are provided in [10].

Two sets of OSSE data are used in this paper to reproduce a realistic scenario just after SMAP calibration and validation phase: One month data set is used as background data for the algorithm, representing the data acquired during the commissioning phase; and a four months data set is processed in near real time, simulating the first four months of data obtained in the operational phase, exactly after the commissioning phase. To meet the expected SMAP accuracies, an error of 4% [root mean square error (RMSE)] is added to the radiometer retrievals and the normalized deviation K_{p} of radar backscatters [14] is set to 0.15. Independent noise is added in each measurement channel. Since the three radar polarizations (hh, vv, and hv) can be used independently in the algorithm with different outcomes, the three possible solutions will be analyzed. The simulated data will be used to evaluate the algorithm performance in Section IV-B and to calculate the algorithm error budget in Section V.

B. Results

Sample results of applying change detection to the simulated data (with radar and radiometer noise added) are shown in Fig. 4 for three consecutive days. Comparing with the original soil moisture distributions and the estimates obtained from the radiometer only technique, it can be seen that the active-passive disaggregation algorithm reproduces much of the variability seen in the *in situ* soil moisture images and that these details are not captured by the radiometer only method.

Using the OSSE data sets as described previously, the performance of the change detection method is evaluated by comparing the retrieved soil moisture values of the four months data set with their corresponding original data and with results from the radiometer only or minimum performance product. Minimum performance is obtained by resampling the 40-km radiometer data to 10 km. Fig. 5 shows the spatial distribution of the soil moisture RMSE errors after applying the change detection method and the radiometer only technique. Using the change detection algorithm on the four-month OSSE the RMSE is reduced to 2%, with better results obtained using radar vv polarization. In addition, for a direct comparison with the minimum performance algorithm, the ratio of the change detection RMSE to the minimum performance RMSE is shown in Fig. 6(a)–(c) for hh, vv, and hv polarizations, respectively. In all the areas of the image with a value less than unity, the active–passive approach outperforms the radiometer only technique. Notice that most estimation errors $(\text{value} = 1)$ occur in high vegetated areas where the radar and radiometer soil moisture sensitivity is decreased. In Fig. 7, the algorithm RMSE linear dependence with vegetation water content is shown.

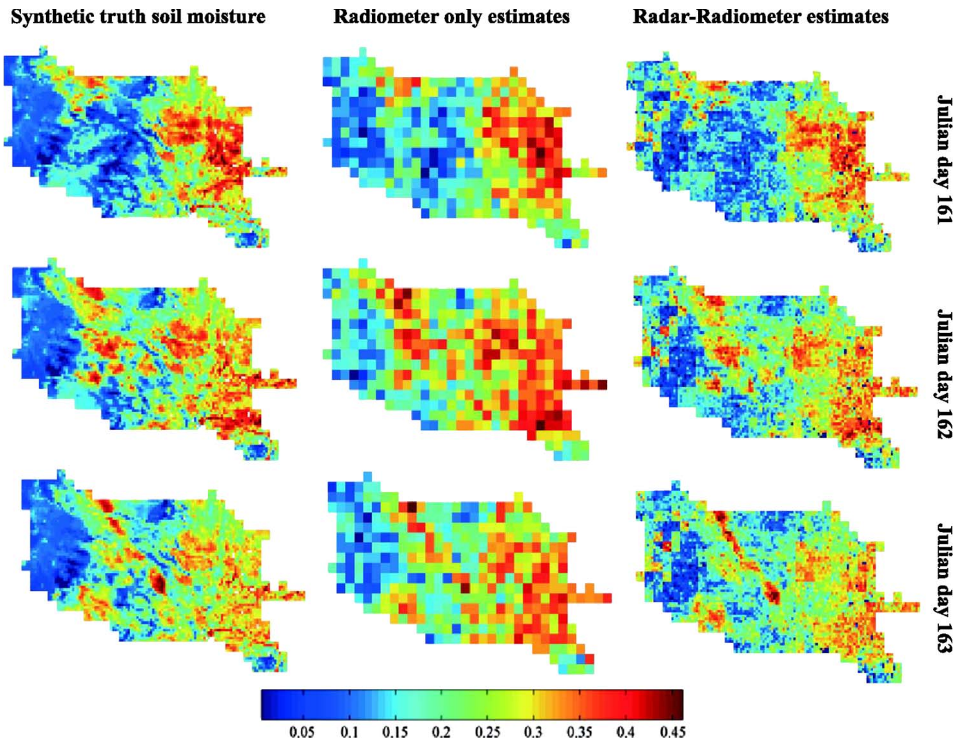

Fig. 4. Sample results (three days) from the OSSE for the comparison of higher resolution (10 km) soil moisture estimates obtained using the active-passive method with synthetic ground-truth soil moisture and with lower resolution (40 km) estimates obtained from a typical radiometer.

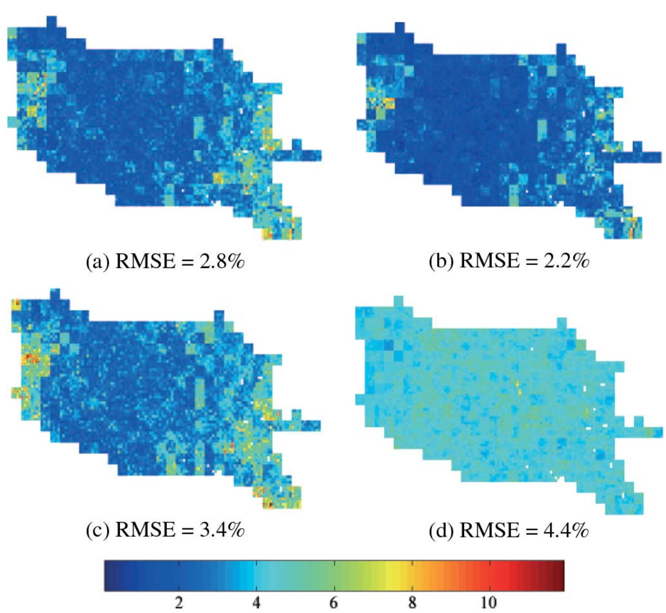

Fig. 5. Spatial distribution of the soil moisture error retrieved using the change detection method with (a) σ^0_{hh}, (b) σ^0_{vv}, (c) σ^0_{hv}, and (d) the radiometer only technique.

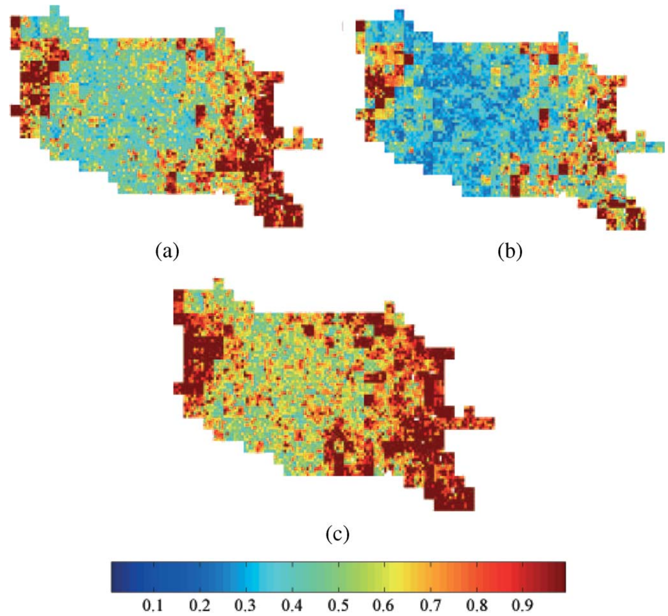

Fig. 6. Ratio of change detection RMSE to radiometer only RMSE using (a) σ^0_{hh}, (b) σ^0_{vv}, and (c) σ^0_{hv}.

A box plot of the slope for each day of the four-month data set is shown in Fig. 8. It can be observed that the uncertainty in the estimation of the slope diminishes with time and that vertical polarization leads to more robust estimates than horizontal and mixed polarizations. Hence, as an alternative to real-time processing, the possibility of monthly reprocessing the data was explored, resulting in marginal improvement. Further studies with real data would be needed to assess the optimal reprocessing time and decide whether the reprocessing is required.

V. Error Budget

An error budget analysis has been performed in order to identify the error sources of the algorithm and fully quantify its performance. The three assumptions made in the algorithm

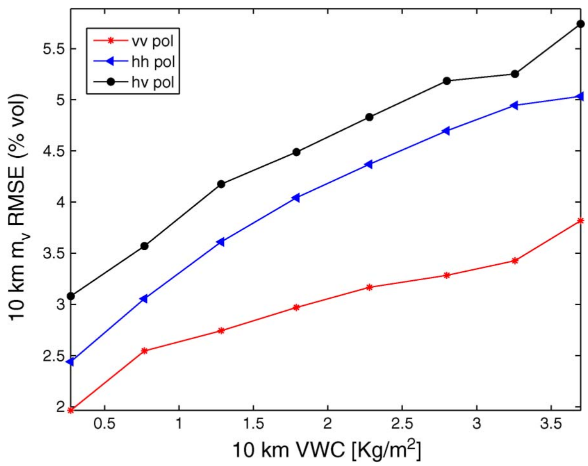

Fig. 7. Plots of change detection RMSE at 10 km stratified by 0.5-kg/m^2 vegetation water content values.

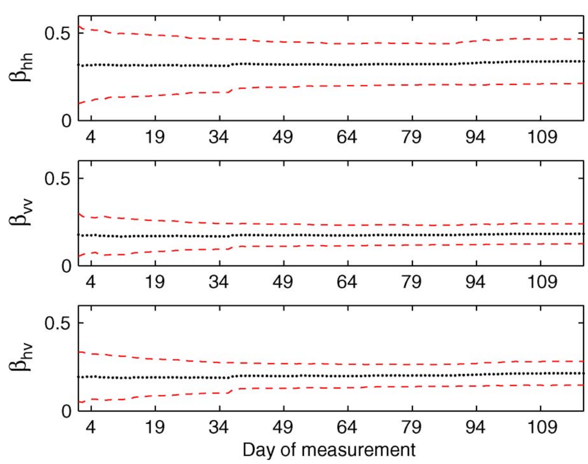

Fig. 8. Plots of the mean slope (in black) and mean slope (in red) $\pm$ the daily slope standard deviation for vv, hh, and hv polarizations, for each day of the four-month OSSE data set.

TABLE I
RESULTS OF THE ERROR BUDGET ANALYSIS (% VOL)

Errors	Horizontal polarization	Vertical polarization
Assumption #1	1.53	1.40
Assumption #2	0	0
Assumption #3	2.20	1.76
RSS	2.68	2.25

formulation have been identified as the three algorithm error sources. The total error has then been calculated as the square root of the sum of the squares (RSS) of these three distinct errors.

To account for Assumption I errors, the algorithm-predicted soil moisture is calculated using linear regression of SMEX02 radar backscatter and soil moisture data [see (1)]. The RMSE between the predicted soil moisture and the ground-truth soil moisture for horizontal and vertical polarizations are presented in Table I. It must be noted that field-sampling errors are inevitably included in the calculations, and they considerably worsen the results. Regarding the errors associated to the Assumption II, the OSSE results in Section IV-B show that the covariance does not affect the retrievals and the error contribution from this source been set to zero. Assumption III-related errors are exactly the values of the standard deviation shown in Fig. 3. This figure shows the difference between the soil moisture retrieved using the slope at scale a and the soil moisture retrieved using the slope at a scale A. Note that Table I represents the algorithm assumptions error and any radiometer error has to be added to the total by RSS.

VI. CONCLUSION

This paper presents a simple and efficient technique to downscale radiometer soil moisture estimates with the use of simultaneous radar observations within an SMAP-like context. The algorithm is based on a change detection scheme that benefits from the synergy of the radar high spatial resolution and the radiometer high accuracy, leading to a balanced product with enough accuracy and spatial resolution to satisfy current meteorology and hydrology needs.

The algorithm has been thoroughly formulated and the assumptions made on the process have been verified using PALS data from the SMEX02 field campaign. In addition, change detection has been successfully applied to a four-month OSSE data producing significantly better results than radiometer only inversions, with a 2% RMSE improvement. Real-time processing of the data has been shown to be feasible having a month of previous observations and, since the algorithm performance improves over time, a monthly reprocessing of the data to improve the estimations' accuracy has been outlined. An error budget analysis of the algorithm estimates a total RSS of 2.68 (% vol) for horizontal polarization and 2.25 (% vol) for vertical polarization, which meet SMAP science requirements for the 10-km product. These results imply that the change detection method presented on this paper is a promising approach to achieving higher resolution and more accurate soil moisture retrievals from future SMAP radar and radiometer observations.

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