A Time-Series Approach to Estimating Soil Moisture From Vegetated Surfaces Using L-Band Radar Backscatter

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***Abstract*— Many previous studies have shown the sensitivity of radar backscatter to surface soil moisture content, particularly at L-band. Moreover, the estimation of soil moisture from radar for bare soil surfaces is well-documented, but estimation underneath a vegetation canopy remains unsolved. Vegetation significantly increases the complexity of modeling the electromagnetic scattering in the observed scene, and can even obstruct the contributions from the underlying soil surface. Existing approaches to estimating soil moisture under vegetation using radar typically rely on a forward model to describe the backscattered signal and often require that the vegetation characteristics of the observed scene be provided by an ancillary data source. However, such information may not be reliable or available during the radar overpass of the observed scene (e.g., due to cloud coverage if derived from an optical sensor). Thus, the approach described herein is an extension of a change-detection method for soil moisture estimation, which does not require ancillary vegetation information, nor does it make use of a complicated forward scattering model. Novel modifications to the original algorithm include extension to multiple polarizations and a new technique for bounding the radar-derived soil moisture product using radiometer-based soil moisture estimates. Soil moisture estimates are generated using data from the Soil Moisture Active/Passive (SMAP) satellite-borne radar and radiometer data, and are compared with up-scaled data from a selection of *in situ* networks used in SMAP validation activities. These results show that the new algorithm can consistently achieve rms errors less than 0.07 m^3/m^3 over a variety land cover types.**

***Index Terms*— Parameter estimation, radar, remote sensing, soil.**

I. Introduction

While the problem of inverting soil moisture from radar backscatter measurements of a bare surface (with little or no vegetation canopy) has been widely studied in the literature [1]–[3], the remote sensing of soil moisture using imaging radars over vegetated terrain remains elusive [4]–[6]. The presence of vegetation significantly increases the complexity of electromagnetic scattering within the observed scene, and scattering from a vegetation canopy can entirely obstruct contributions from the underlying soil surface, thus making soil moisture estimation in the presence of significant vegetation biomass extremely difficult.

Existing approaches to estimating soil moisture under vegetation using radar observations typically rely on a forward model to describe the backscattered signal. While these forward models are becoming increasingly robust, often they assume that the vegetation biomass in the observed scene is known [7]–[11]. In this case, the use of ancillary vegetation information required. Ancillary vegetation information may not be reliable or available during the radar overpass of the observed scene (e.g., due to cloud coverage if vegetation information is derived from an optical sensor). It is, therefore, desirable to develop an estimation technique, which does not require the use of a complicated scattering model or ancillary vegetation information.

The newly proposed estimation technique is most appropriately named the extended alpha method. The alpha approximation serves as the basis for this method and was used to estimate soil moisture conditions reliably for some crop types and vegetation biomass conditions [12]. However, the algorithm was found to be extremely sensitive to optimization constraints. Therefore, the contributions of this paper are an extension of the model to multiple polarization configurations,

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and the incorporation of minimum/maximum inversion bounds from radiometer data. This new version of the algorithm is evaluated here against multiple *in situ* soil moisture data sets, and is designed with Soil Moisture Active/Passive (SMAP) satellite data in mind [10], [11].

This paper is organized as follows. Section II provides an overview of the original alpha approximation soil moisture estimation method and its extension to multiple polarization configurations. Section III discusses two modifications to the alpha method: 1) polarization configuration and 2) the selection of constraints in the constrained linear least-squares optimization. The model is initially tested using airborne radar data concurrent with ground sampling of soil moisture conditions. Section IV describes the measurement-based studies of the extended alpha method using SMAP radar and radiometer data. Section V presents the conclusions and discusses potential future applications.

II. Review of the Alpha Approximation

The alpha method is a change-detection approach to sensing changes in surface soil moisture (through the surface permittivity). The alpha approximation states that ratios between consecutive copolarized radar backscatter measurements can be mapped to changes in soil moisture conditions.

In general, the total PP-polarized (copolarized, i.e., PP is either HH or VV) backscattered normalized radar cross section (NRCS; $\sigma_{PP}^{0\mathrm{tot}}$) of a vegetated soil surface can be expressed as the sum of three terms [7]

$$\sigma_{PP}^{0\mathrm{tot}} = \sigma_{PP}^{0s}\exp(-\tau) + \sigma_{PP}^{0v} + \sigma_{PP}^{0sv}. \tag{1}$$

The first of these terms, σ_{PP}^{0s}, is the surface scattering mechanism, which is modified by attenuation through the vegetation canopy, $\exp(-\tau)$. The second term, σ_{PP}^{0v}, represents direct scattering from the vegetation canopy (volume scattering). The third term, σ_{PP}^{0sv}, is the contribution of interactions between the vegetation canopy and the soil surface. Multiple scattering between from leaves, branches, stalks, and so on within the vegetation canopy at L-band is typically negligible except for the case of thick vegetation, such as corn or woody plants. As a low-order approximation, the alpha method assumes that the second two terms in (1) can be neglected, so that vegetation contributions are treated as strictly multiplicative (attenuation). While this is generally not true, the assumption can hold for certain land cover types, such as cereal crops, grassland, and shrub land. If the vegetation canopy provides a multiplicative contribution which does not significantly change between repeated radar observations, and the underlying soil surface interface can be accurately represented by a first-order scattering theory, such as the small perturbation method (SPM1) or small slope approximation (SSA1), then the ratio of consecutively measured radar backscatter coefficients (observed at times t_1 and t_2) of a natural scene can be approximated as

$$\frac{\sigma_{PP}^{0(t_2)}}{\sigma_{PP}^{0(t_1)}} \approx \left|\frac{\alpha_{PP}^{(t_2)}(\epsilon_s,\theta_i)}{\alpha_{PP}^{(t_1)}(\epsilon_s,\theta_i)}\right|^2 \tag{2}$$

where

$$\begin{aligned}\left|\alpha_{HH}^{(t_i)}(\epsilon_s^{(t_i)},\theta_i)\right| &= \left|\frac{\left(\epsilon_s^{(t_i)}-1\right)}{\left(\cos\theta_i+\sqrt{\epsilon_s^{(t_i)}-\sin^2\theta_i}\right)^2}\right|\\ \left|\alpha_{VV}^{(t_i)}(\epsilon_s^{(t_i)},\theta_i)\right| &= \left|\frac{\left(\epsilon_s^{(t_i)}-1\right)\left[\sin^2\theta_i-\epsilon_s^{(t_i)}\left(1+\sin^2\theta_i\right)\right]}{\left(\epsilon_s^{(t_i)}\cos\theta_i+\sqrt{\epsilon_s^{(t_i)}-\sin^2\theta_i}\right)^2}\right|.\end{aligned} \tag{3}$$

In (2) and (3), $\alpha_{PP}^{(t_i)}$ is the PP-polarized alpha coefficient of the observed scene at time t_i. The alpha coefficient is the first-order scattering amplitude for SPM or SSA [13], [14]. Soil permittivity ($\epsilon_s^{(t_i)}$) information at time t_i can be inverted from the corresponding alpha coefficient, which can be mapped to soil moisture through use of a dielectric mixing model; the Peplinski/Ulaby/Dobson model is used in this paper [15]. It is assumed in (2) that the latency between radar acquisitions ($t_2 - t_1$) is sufficiently small (on the order of one to three days) so that the effects of vegetation growth/decay and surface roughness changes can be neglected. Note that the vegetation water content of the observed scene may still change, e.g., due to rain events and dry-down conditions. Even if the vegetation condition varies appreciably over the time series, the alpha approximation shall hold as long as vegetation changes between consecutive measurements are negligible.

Through the use of a matrix equation, the alpha approximation can be extended to an arbitrary length time-series and multiple polarizations. For a time series N of radar backscatter measurements, the following generalized matrix equation can be constructed:

$$\begin{bmatrix}\boldsymbol{M_{HH}} & \boldsymbol{M_0}\\ \boldsymbol{M_0} & \boldsymbol{M_{VV}}\end{bmatrix}\begin{bmatrix}\left|\alpha_{HH}^{(t1)}\right|\\ \left|\alpha_{HH}^{(t2)}\right|\\ \vdots\\ \left|\alpha_{HH}^{(tN)}\right|\\ \left|\alpha_{VV}^{(t1)}\right|\\ \left|\alpha_{VV}^{(t2)}\right|\\ \vdots\\ \left|\alpha_{VV}^{(tN)}\right|\end{bmatrix} = \begin{bmatrix}0\\0\\ \vdots\\0\\0\\0\\ \vdots\\0\end{bmatrix} \tag{4}$$

where

$$\boldsymbol{M_{PP}} = \begin{bmatrix}1 & -\sqrt{\frac{\sigma_{PP}^{0(t1)}}{\sigma_{PP}^{0(t2)}}} & 0 & \dots & 0 & 0\\ 0 & 1 & -\sqrt{\frac{\sigma_{PP}^{0(t2)}}{\sigma_{PP}^{0(t3)}}} & \dots & 0 & 0\\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots\\ 0 & 0 & 0 & \dots & 1 & -\sqrt{\frac{\sigma_{PP}^{0(N-1)}}{\sigma_{PP}^{0(N)}}}\end{bmatrix} \tag{5}$$

and $\boldsymbol{M_0}$ is an $(N-1)$ by N zero matrix. The unknown α_{PP} coefficient at a given time t_i (which corresponds to permittivity information) is related to the ratio between PP-polarized backscatter measurements taken at times t_{i+1} and t_i. Note that the above-mentioned matrix equation represents an underdetermined system. Thus, a bounded linear least-squares optimization is adopted to approximate (4). Once the α_{PP} coefficients in (4) have been estimated, the complex-valued $\epsilon_s^{(t_i)}$ is inverted for each observation and mapped to soil moisture content using the dielectric mixing model [15]. In the case where multiple polarizations are used, the coefficients are compared with lookup tables of α_{HH} and α_{VV} coefficients in a least-squares sense to derive the soil moisture content for each observation.

The single-polarization version of this algorithm has been tested with tunable upper and lower soil moisture bounds for the 2006 AgriSAR field campaign [12]. The capabilities of the extended alpha method are tested using airborne synthetic aperture radar (SAR) data and SMAP satellite data in the subsequent sections of this paper.

III. On the Selection of Constraints and Polarization Configuration

Since the matrix equation in (4) is not of full rank, a best-fit solution must be derived. A constrained linear least-squares optimization is applied to derive a best-fit solution to the matrix equation. The constraints take the form of hard bounds, which define the minimum and maximum values of the α coefficients. Ideally, these bounds will correspond to the dynamic range of soil moisture for the observed scene over the course of a time series. If these bounds are not chosen carefully, the accuracy of the algorithm degrades significantly. The studies outlined in this section show that it is prudent to constrain this best-fit solution carefully; radiometer-derived soil moisture data have been found to be suitable for this purpose.

Although [12] suggests that HH-polarized radar backscatter is preferred for use in the alpha method, this section suggests that there is little difference in error performance when VV-polarized backscatter is included. Note that VV-polarized backscatter coefficients tend to be stronger than HH backscatter for soil surfaces at oblique incidence [5]. As such, VV-polarized backscatter from soil is less sensitive to system noise, but more sensitive to speckle effects.

The issues of defining minimum and maximum constraints and extending the algorithm to multiple polarizations are explored by using the SMAP Validation Experiment 2012 (SMAPVEX12) field campaign data set, with a focus on high-resolution SAR data provided by NASA-JPL's UAVSAR.

A. Description of the SMAPVEX12 Field Campaign

SMAPVEX12 was carried out in regions surrounding Winnipeg in Manitoba, Canada [16]. Data were collected during a six-week time period over June and July of 2012, which corresponded to the growth season for most local crops. SMAPVEX12 included airborne SAR acquisitions accompanied by ground sampling of soil moisture, surface roughness, and vegetation biomass. The SAR instrument used for this analysis was UAVSAR, which provided multilooked, complex, fully polarimetric strip-map SAR images with 7-m resolution at L-band (1.26 GHz) [17]. In these analyses, the data were not normalized to a single incidence angle; UAVSAR incidence angle data were used independently for each agricultural field examined.

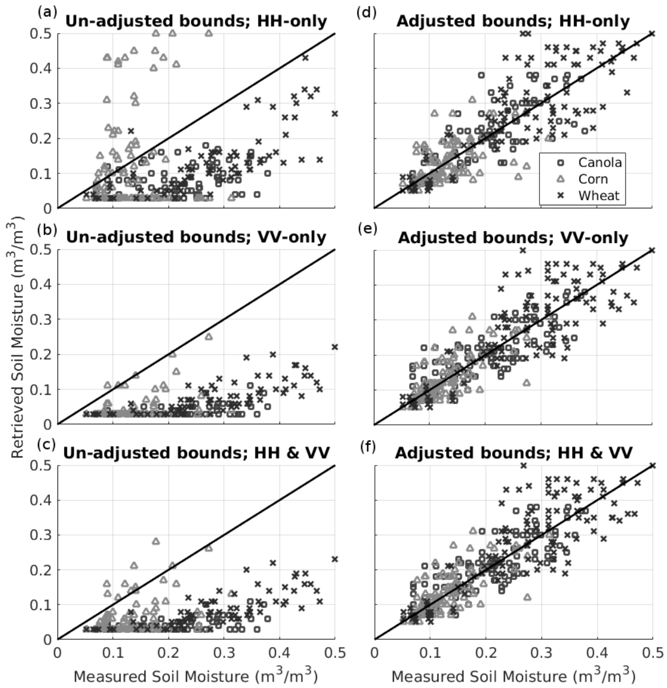

Fig. 1. Performance of the alpha method when applied to a sample of SMAPVEX12 data. (a)–(c) Retrieved versus measured soil moisture using untuned alpha coefficient bounds. (d)–(f) Results using bounds tuned in accordance with surface soil moisture values obtained from dielectric probe measurements. (a) and (d) Results using a time series of only HH-polarized backscatter data. (b) and (e) Results using VV-polarized backscatter data. (c) and (f) Results for the dual-polarization alpha method.

SAR acquisitions were accompanied by extensive ground sampling during the course of the campaign. On days where UAVSAR was flown, ground teams sampled soil moisture conditions in preselected areas (often agricultural fields) using dielectric probes. On off-days, when the airborne instruments were grounded, vegetation biomass was sampled destructively and nondestructively for the same fields in which soil moisture was sampled. Surface roughness for each of the sampled areas was characterized with the use of a pin-profiler.

The data sets acquired during SMAPVEX12 fostered the development of time-series soil moisture retrieval algorithms. A time series of SAR data and ground sampling data was made available for widely varying ground conditions. Over the course of the campaign, many of the sampled fields experienced significant changes in soil moisture as well as vegetation maturity. This extensive data set allowed soil moisture estimation techniques to be tested against a large range of ground conditions.

B. Assessment Using SMAPVEX12 Data

Fig. 1 shows the scatter plots of estimated versus measured soil moisture for several variations of the extended alpha method applied to a sample of SMAPVEX12 / UAVSAR data, using a sliding-window time-series length of eight UAVSAR measurements. This time-series length was selected to remain consistent for each field; some fields only had eight SAR observations with concurrent ground sampling. During this sliding-window implementation, multiple soil moisture estimates are made for some days, but these estimates are treated as independent for the purposes of this error analysis. A total of 13 radar measurements were made for each field over the course of five weeks from June 7 to July 14, 2012. Each field is ground-sampled at 16 discrete points, concurrently with radar overpasses. Radar backscatter values and ground truth measurements are averaged such that one backscatter measurement is obtained for each field. The upper and lower bounds of the HH and VV-polarized α coefficients are derived from the ground-sampled soil moisture data. The algorithm was applied over the course of the growth season of the fields considered in these plots; vegetation water content ranges up to 3.69 kg/m^2 for fully mature canola. The plots in Fig. 1 furthermore show that the soil moisture measurements were sometimes in excess of 0.4 m^3/m^3, in which case a decreased sensitivity in the radar backscatter signature is expected.

In Fig. 1(a)–(c), unoptimized α coefficient bounds were used, which were fixed according to the minimum and maximum sustainable soil moisture conditions, regardless of the area being examined. Fig. 1(d)–(f) shows improved performance with the introduction of tuned bounds which correspond to the minimum and maximum soil moisture values observed by *in situ* dielectric probes over the course of the time series. The tuned alpha coefficient bounds were calculated using (3) according to ground-sampled soil moisture and soil texture data, with the Peplinski/Ulaby/Dobson model [15] used to derive soil permittivity from soil moisture. Note that for both cases, the maximum possible estimated soil moisture allowed by the algorithm was 0.5 m^3/m^3.

Fig. 1 shows the importance of providing the alpha method with reasonable estimates of minimum and maximum soil moisture conditions. Ideally, these minimum and maximum estimates would be provided according to season, since many regions of the world experience wet and dry seasons, which significantly influence the range of soil moisture conditions. During the least-squares optimization technique, it is necessary that the bounds of the α coefficients be tuned in accordance with the dynamic range of soil moisture. This requirement presents a tradeoff: while the algorithm described herein does not require that ancillary vegetation information be provided, some knowledge of the seasonality of soil moisture in the observed scene is required. In this sense, the method is similar to the change-detection approach of [6], which requires knowledge of the NRCSs corresponding to the driest and wettest conditions of the observed scene.

Fig. 1 shows the scatter plots of estimated versus measured soil moisture for the polarization configurations of the extended alpha method for a sample of SMAPVEX12/ UAVSAR data. Each row of plots uses a different polarization configuration to apply the generalized matrix equation in (4). Table I provides the rms error for each polarization configuration, according to crop type. Although [12] encourages the use of HH-polarization only, the results shown in Fig. 1 and Table I demonstrate that the use of VV-polarization provides similar error performance.

TABLE I

ERROR STATISTICS OF ALPHA METHOD APPLIED TO SMAPVEX12 WITH ADJUSTED BOUNDS

Polarization(s)	Bias Error (m^3/m^3)			
	Canola	Corn	Wheat	Total
HH	-0.008	0.000	-0.013	-0.010
VV	0.001	-0.003	-0.004	-0.003
HH & VV	-0.003	-0.003	-0.004	-0.004
	Unbiased RMS Error (m^3/m^3)			
	Canola	Corn	Wheat	Total
HH	0.057	0.051	0.076	0.069
VV	0.049	0.042	0.069	0.061
HH & VV	0.049	0.041	0.069	0.061
	RMS Error (m^3/m^3)			
	Canola	Corn	Wheat	Total
HH	0.057	0.051	0.077	0.069
VV	0.049	0.042	0.069	0.061
HH & VV	0.049	0.042	0.069	0.061
	Correlation Coefficient (R)			
	Canola	Corn	Wheat	Total
HH	0.791	0.557	0.817	0.768
VV	0.803	0.731	0.836	0.813
HH & VV	0.812	0.723	0.836	0.812

IV. Assessment of the Extended Alpha Method Using SMAP Data

A. Overview of SMAP

The SMAP satellite implemented a combined L-band radar (active; 1.26 GHz) and L-band radiometer (passive; 1.41 GHz) system to estimate soil moisture conditions at 5 cm depth globally [18]. SMAP soil moisture products were to be provided at 3-, 9-, and 36-km resolutions, corresponding to the active-only, active/passive, and passive-only moisture estimates, respectively. Unfortunately, the radar stopped working on July 7, 2015 and could not be recovered. However, the algorithm discussed herein makes use of the ten weeks of SMAP radar backscatter data at 3-km resolution collected prior to this failure, together with the SMAP radiometer soil moisture product at 36-km resolution. Each product is gridded to an equal-area projection map known as the EASE-2.0 grid [19].

The SMAP Level-1C radar backscatter product (L1C_s0: Composite Release ID R12170) was provided at a resolution of 1 km after multilooking and spatial averaging. The L1C_s0 backscatter values were further averaged to a resolution of 3 km and organized into a time series to develop the estimates discussed herein [10], [11], [20], [21].

The multilooked 3-km SMAP radar backscatter product (part of the level-2 product [10], [11]) was provided starting on April 25, and continued to be provided until July 7, when the radar high-power amplifier suffered a catastrophic failure [22]. For more detailed information on the SMAP radar, refer to [20] and [21].

The SMAP baseline Level-2 radiometer (passive) soil moisture product (L2_SM_P: Composite Release ID R11340) is used here to constrain radar-derived soil moisture estimates. The baseline L2_SM_P algorithm uses a common approximation to the radiative transfer equation called the $\tau - \omega$ model [23], where the vegetation opacity τ and the scattering albedo ω are computed using lookup tables depending partly on land cover type. For more detailed information on the SMAP L2_SM_P product, refer to [24] and [25].

B. Application of Extended Alpha Method

The algorithm was applied to multilooked, 3-km resolution SMAP radar data, using the SMAP radiometer-derived soil moisture product to constrain radar-derived soil moisture estimates. SMAP data were provided by the National Snow and Ice Data Center. Minimum and maximum soil moisture bounds were derived using the SMAP L2_SM_P product, thereby serving to constrain the radar-derived estimates [24], [25]. The tuned alpha coefficient bounds were calculated using (3) according to the L2_SM_P soil moisture product and ancillary soil texture data, where the Peplinski/Ulaby/Dobson model [15] was used to derive soil permittivity from soil moisture.

When applying the matrix equation in (4) to SMAP radar data, the full time series of radar acquisitions was considered, i.e., one large matrix was constructed which included every radar measurement of the observed scene collected during SMAP radar operation from April 25, 2015 to July 7, 2015 (as opposed to using a sliding time window). Likewise, the L2_SM_P product provided the minimum and maximum soil moisture conditions over this time interval.

C. Comparisons Between Estimates and In Situ Measurements

Four *in situ* networks were used for comparison with soil moisture estimates using the extended alpha method with SMAP data. The Walnut Gulch site, located near Tombstone, AZ, USA, represents a semiarid region characterized by sparse grass and shrubs; the 3-km reference pixel considered here contains three *in situ* stations [26]. The Texas Soil Moisture Observation Network (TxSON) is located west of Austin, TX, USA, and is characterized by mixed rangelands and pastures; the 3-km reference pixel contains seven *in situ* stations [27]. The TxSON network displays a wide dynamic range of soil moisture during the observation period due to the occurrence of multiple rain events at that time. The Yanco (YB7) site, located near Yanco, NSW, Australia, is characterized by grasslands, pastures, and agricultural crops, and was observed during local, dry conditions with one major rain event occurring mid-July; the 3-km reference pixel contains four *in situ* stations [28]. The Kenaston site, located near Kenaston, SK, Canada, is a site characterized predominantly by agricultural crops, and was observed during the beginning of the growth season for many of the local crops; the 3-km reference pixel contains four *in situ* stations [29]. These sites were selected based on the long time series, frequent time sampling (hourly), and dense spatial sampling which they provide. Furthermore, each of these sites has been selected such that effects due to terrain, inland water bodies, radio frequency interference, and urban structures are minimal [30]. Data from measurement stations within each watershed were linearly averaged to the SMAP EASE-2.0 grid 3-km resolution for comparisons with the alpha method applied to SMAP data.

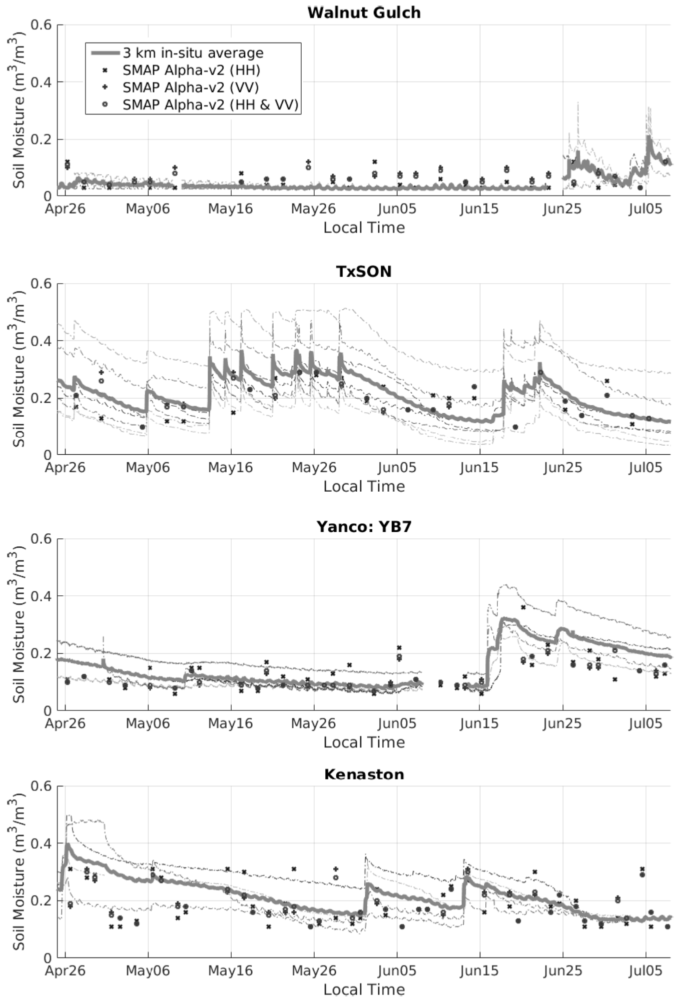

Fig. 2. Comparisons between *in situ* soil moisture data and soil moisture estimates provided by each polarization configuration of the extended alpha method applied to SMAP radar data, with radiometer-based constraints. Each plot represents a 3-km reference pixel from a different site: Walnut Gulch [26] (top), TxSON [27] (second plot), Yanco: YB7 [28] (third plot), and Kenaston [29] (bottom). The markers represent the estimates, with HH-only, VV-only, and dual-polarization algorithms represented by the diagonal crosses, horizontal/vertical crosses, and circles, respectively. The thick lines are a linear average of data from all the stations within a 3-km reference pixel (EASE-2.0 grid map projection [19]). The thin, dotted-and-dashed lines represent *in situ* data from each individual monitoring station. The error statistics for these data are reported in Fig. 3.

The plots in Fig. 2 show extended alpha method soil moisture estimates (for each polarization configuration) and the 3-km *in situ* soil moisture average as a function of time.

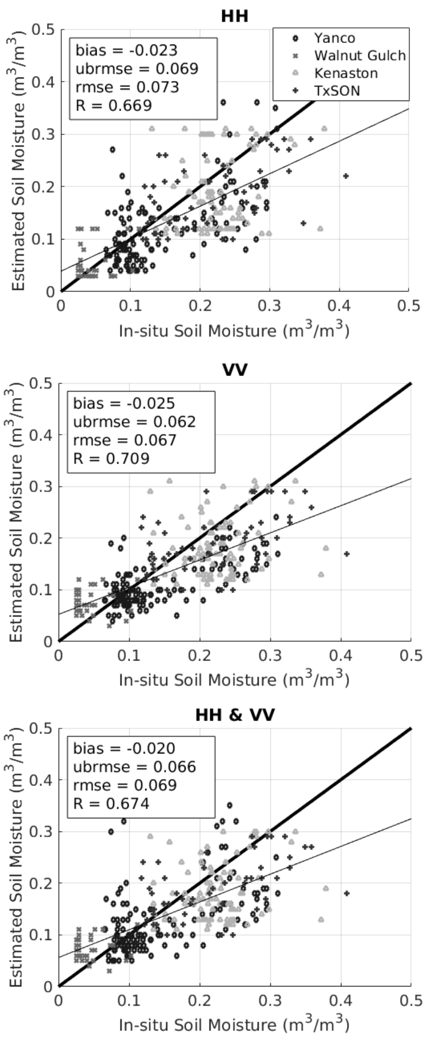

Fig. 3. Estimated versus retrieved soil moisture for each watershed, using the extended alpha method with SMAP data. Each scatter plot corresponds to a different polarization configuration: HH-only (top), VV-only (middle), and dual-polarization (bottom). The data points corresponding to different sites are shown by different data markers. The black thick line is the 1:1 line and the black thin line is a linear regression for all of the data points. Error statistics are shown for all watersheds collectively. The trend of the regression line can be attributed to the decreased sensitivity of radar backscatter to changes in soil moisture for wetter soils, and also to the radiometer-derived constraints placed on the linear least-squares optimization. Note that there are more data markers in this plot than in Fig. 2; all the reference pixels within each watershed are being considered in this plot.

Sample data from each of the four sites considered are represented in Fig. 2, with a reference pixel for each site corresponding to one of the plots. The alpha method algorithm can be seen responding to the rain events characterized by "spikes." The estimation algorithm sometimes incorrectly detects an increase in soil moisture, due to light rain events which do not influence soil moisture at 5 cm depth, and also due to temporal changes in vegetation conditions. Light rain conditions influencing only the soil surface occurred particularly often at the Kenaston site, hence the poor correlation of the algorithm at Kenaston when compared with other sites. The scatter plot in Fig. 3 shows the algorithm performance across all 3-km reference pixels for each *in situ* network considered here. The error performance is similar for each polarization configuration, with the maximum rms error of 0.073 m^3/m^3 being exhibited by the HH-only version.

V. Conclusion

The extended alpha method for estimating surface soil moisture from a time series of L-band radar backscatter measurements has been presented. The algorithm was assessed using measurement data, including airborne SAR measurements and SMAP radar/radiometer data, both of which were concurrent with *in situ* ground sampling. The choice of polarization was found to have little influence retrieval performance, whereas previous studies had hypothesized that HH-polarization would be preferable for use in the alpha method. The extended alpha method was constrained by using the 36-km resolution radiometer soil moisture product delivered by SMAP. Error performance was found to vary by site, but the algorithm's rms error was found to be lower than 0.075 m^3/m^3 rms error for all sites considered. The extended alpha method is therefore attractive for soil moisture remote sensing using L-band radar, due to its ability to track changes in soil moisture even in the presence of significant vegetation. In this paper, the algorithm was shown to be capable of estimating soil moisture for agricultural fields, shrub lands, and pastures, whose vegetation water content ranged up to 3.69 kg/m^2. The algorithm is not expected to work well for more densely vegetated scenes, given that the alpha approximation assumes volume and multiple-bounce scattering phenomena are negligible. Moreover, this algorithm does not need to be supplied with *a priori* vegetation information, but since it is effectively a change-detection approach, it is recommended that it can be supplied with a radiometer estimate which is capable of providing the minimum and maximum expected soil moisture for the area/season of interest.

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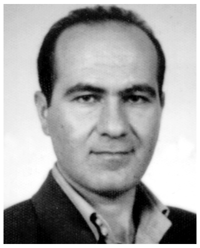

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