An Extension of the Alpha Approximation Method for Soil Moisture Estimation Using Time-Series SAR Data Over Bare Soil Surfaces

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***Abstract*— The objective of this letter is to extend the alpha approximation method, a method proposed by Balenzano *et al.*, for soil moisture retrieval from multitemporal synthetic aperture radar (SAR) data. The original alpha approach requires an initial estimate of the upper and lower bound soil moisture values to constrain the soil moisture retrieval. This letter demonstrates an extension of the alpha approach by employing the juxtaposition method to adaptively set the soil moisture bounds using the absolute radar backscatter values. This extended alpha method was tested using an airborne time series of L-band SAR data and coincident ground measurements acquired during the SMAPEx-3 experiment over bare agricultural fields. The agreement between estimated and measured soil moisture values was within a root-mean-square error of 0.07 cm^3/cm^3 for each of the three polarization combinations used (i.e., HH, VV, and HH and VV). Moreover, inclusion of the two-polarization combination (HH and VV) slightly improved the retrieval performance. The proposed extension to the alpha method makes the most of the information contained in the SAR data time series by using dynamic, spatially explicit soil moisture bounds retrieved from the SAR data themselves.**

***Index Terms*— Bare surface, soil moisture, synthetic aperture radar (SAR), time series.**

I. Introduction

SYNTHETIC aperture radar (SAR) is the most promising option for providing global measurements of near-surface soil moisture at the moderate to high spatial resolution required by hydrological and agricultural applications. However, accurate soil moisture retrieval from SAR backscatter is still an open and challenging task due to the fact that the radar backscatter depends on multiple parameters such as soil dielectric constant (related to soil moisture), surface roughness, and vegetation conditions (e.g., vegetation height, biomass, and canopy structure) [1]. Therefore, soil moisture retrieval from SAR data is an ill-posed problem and requires either *a priori* information on soil and vegetation parameters or multiple-configuration SAR data (i.e., multitemporal, multiincidence angle, multipolarization) to avoid using fewer measurements than the number of unknowns [2], [3].

The availability of missions characterized by short-repeating cycles such as ESA Sentinel-1, JAXA ALOS-2, and CONAE SAOCOM opens possible alternatives for tracking soil moisture changes at a high spatial resolution via change detection methods [4]. The rationale of such methods is that temporal changes of surface roughness, canopy structure, and vegetation biomass take place at longer temporal scales than soil moisture changes [5]. Therefore, time-series SAR data acquired with short repeat cycles are expected to track changes in soil moisture only. A change detection-based method referred to as the alpha approximation method was initially proposed in [5] under a simplified theoretical assumption, being that the ratio of two consecutive backscatter measurements could be approximately represented as the squared ratio of corresponding alpha coefficients. The alpha approximation method has been tested using different SAR data sets at different radar wavelengths (L-, C-, and X-bands [6]–[10]) with soil moisture retrieval accuracy being around 0.05–0.07 cm^3/cm^3.

The alpha approximation method is appealing for soil moisture estimation due to its simplicity, but this approach requires *a priori* information on initial estimates of the upper and lower bound alpha coefficients. Such bounds may be obtained from climate models carried out at coarse scale or calibrated on a specific data set [8]–[12]. However, knowledge of the soil moisture bounds is usually difficult to obtain, thus hampering the estimation of soil moisture.

This letter aims to extend the alpha approximation method by using the absolute backscatter values to first compute the soil moisture bounds. This extended alpha method consists of two steps. The first computes a possible range of soil moisture values for each acquisition date using the juxtaposition method proposed in [13]. The second uses the possible range of soil moisture values to adaptively constrain the soil moisture

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retrieval, as in the original alpha method [5]. This extended method has been tested herein over bare agricultural fields using airborne L-band SAR images.

II. Study Area and Data Set

A. Study Area

A database composed of airborne and ground data collected during the third soil moisture active passive experiment (SMAPEx-3) [14], conducted from September 5 to 23, 2011 in southeastern Australia, has been used for development and testing. The study site is a semiarid agricultural area located in the western plains of the Murrumbidgee catchment near the township of Yanco (Longitude 146°10' E and Latitude 34°50' S). The study area is flat with elevation changes of only a few meters (i.e., negligible geometric distortions of the radar data due to the topographic effects). Of the 72 agricultural paddocks present in the area, 15 fields characterized by bare soils or fallow (i.e., sparse stubble) conditions were studied.

B. SAR Data

The backscatter measurements were acquired by the polarimetric L-band imaging SAR (PLIS) [15] on nine dates (September 5, 7, 10, 13, 15, 18, 19, 21, and 23). PLIS is a fully polarimetric L-band SAR sensor operating at 1.26 GHz. The single-look SAR data with a resolution of approximately 6×0.8 m (range $\times$ azimuth) were multilooked (2×14 in range and azimuth, respectively) to achieve a similar azimuth and range resolution of approximately 12 m and projected to ground coordinates at a spatial resolution of about 10 m. Polarimetric and radiometric calibration of PLIS was accomplished using a distributed forest target in conjunction with six trihedral passive radar calibrators. After calibration, the ratio between co-polarized channels had a mean amplitude of 0 dB and the mean phase difference was of 3° and 6° for left and right antennas, respectively. The absolute and relative calibration accuracies were estimated at 0.9 and 0.8 dB, respectively [14]. The field-averaged backscattering coefficients were calculated by averaging all the pixels completely located within each field, and then used for soil moisture estimation for each field.

C. Field Data

Extensive ground sampling of near-surface (0–5 cm) soil moisture was conducted using portable dielectric probes on a regular grid of locations equally spaced at 250 m. At each location, three soil moisture replicate measurements were taken within a 1-m radius and averaged to characterize small scale soil moisture variability. The volumetric soil moisture at field scale was assumed to be equal to the mean value estimated from the field samples. The volumetric soil moisture values ranged from 0.05 to about 0.40 cm^3/cm^3.

Surface roughness was measured using a custom-built surface profiler consisting of a 1-m-long board with 200 pins spaced at 0.5 cm. Each profile measurement consisted of two 3-m-long surface profiles taken in the north–south and

TABLE I

Summary of Ground-Measured Surface Roughness Parameters

Field #	Radar Inc. Angle (θ)	Row Azimuth Angle	Soil moisture min-max (cm^3/cm^3)	Surface Roughness (cm)			
				Across rows		*Along rows*	
				h_{rms}	*cl*	h_{rms}	*cl*
1	36°	80°	0.14-0.19	6.4	23.0	2.3	8.0
43	24°	20°	0.09-0.39	6.6	22.3	1.1	2.6
51	24°	110°	0.07-0.38	7.6	23.6	1.5	10.8
70	25°	10°	0.12-0.25	5.7	22.5	1.7	5.7
20	19°	0°	0.07-0.20	6.8	18.0	2.2	14.6
79	31°	10°	0.05-0.13	1.3	10.6	1.0	6.9
18	30°	10°	0.05-0.17	-	-	-	-
21	25°	10°	0.07-0.20	-	-	-	-
3	23°	90°	0.22-0.27	-	-	-	-
2	32°	-	0.17-0.21	-	-	-	-
4	30°	-	0.13-0.20	-	-	-	-
144	21°	-	0.16-0.25	-	-	-	-
48	38°	-	0.09-0.12	3.3	15.5	3.3	15.5
49	35°	-	0.08-0.10	4.6	20.8	4.6	20.8
50	30°	-	0.07-0.16	2.1	9.3	2.1	9.3

"-" indicates data not available.

east–west directions, or alternatively in directions parallel and perpendicular to the row direction for ploughed fields. Of the 15 bare soil fields, nine fields had roughness measurements and nine fields presented periodic row structures. For the ploughed fields rows orientation with respect to the north direction were recorded and used to compute the relative azimuth angle between the radar look direction and the row direction. Table I lists the main characteristics of the bare fields used in this analysis.

III. Methodology

A. Alpha Approximation Approach for Soil Moisture Retrieval

When a time series of SAR measurements is available for a bare soil surface, assuming no variation of surface roughness during the radar measurements, the backscatter change is related to soil moisture changes only. Furthermore, the ratio of two consecutive backscatter measurements can be approximately represented as the squared ratio of corresponding alpha coefficients [5]

$$\frac{\sigma_{0,\mathrm{PP}}^{(2)}}{\sigma_{0,\mathrm{PP}}^{(1)}} \approx \left|\frac{\alpha_{\mathrm{PP}}^{(2)}(\varepsilon_s,\theta)}{\alpha_{\mathrm{PP}}^{(1)}(\varepsilon_s,\theta)}\right|^2 \tag{1}$$

where θ is the incidence angle; ε_s is the soil dielectric constant, and PP denotes the polarization (i.e., HH or VV). The alpha coefficient α_{PP} is a function of the dielectric constant ε_s and the incidence angle θ, and given by

$$|\alpha_{\mathrm{HH}}(\varepsilon_s,\theta)| = \left|(\varepsilon_s - 1)/(\cos\theta + \sqrt{\varepsilon_s - \sin^2\theta})^2\right| \tag{2}$$

$$|\alpha_{\mathrm{VV}}(\varepsilon_s,\theta)| = \left|\frac{(\varepsilon_s - 1)(\sin^2\theta - \varepsilon_s(1+\sin^2\theta))}{(\varepsilon_s\cos\theta + \sqrt{\varepsilon_s - \sin^2\theta})^2}\right|. \tag{3}$$

If the ratios between consecutive backscatter values are considered according to (1), N SAR acquisitions result in $N - 1$ equation and N unknown dielectric constants (for the single-polarization case), leading to a system of equations having more unknowns than equations. To solve this

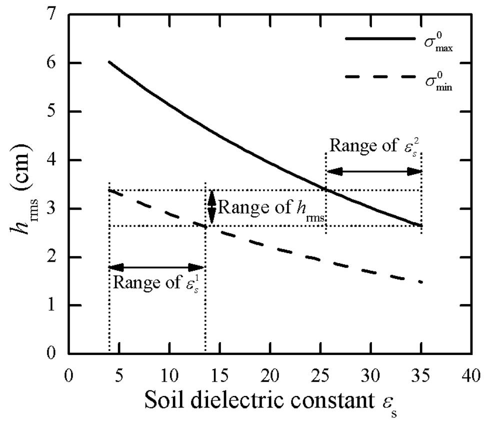

Fig. 1. Ranges of the rms height h_{rms} and the soil dielectric constants ε_s from two SAR measurements. $\sigma^0_{\max}$ and $\sigma^0_{\min}$ represent the maximum and minimum backscatter values, respectively.

underdetermined system of equations, a bounded least-squares optimization is applied [5] to estimate each of the dielectric constant values.

The alpha approximation approach was originally proposed for the single-polarization case [5]. However, it can be easily extended to the dual-polarization case (i.e., HH and VV). Accordingly, N SAR acquisitions result in $2 \times (N - 1)$ equations and N unknown soil dielectric constant values.

B. Determination of Bounds for Least-Squares Optimization

The system of equations constructed using (1) has more unknowns than equations and there exist an infinite number of solutions. Therefore, the solution is found subject to the constraints that $\varepsilon_s^{\min} \le \varepsilon_s \le \varepsilon_s^{\max}$. It has been pointed out that the retrieval accuracy severely relies on the bounds and it is prudent to constrain this best-fit solution carefully [12].

In this letter, the juxtaposition method introduced in [13] is utilized to obtain the upper and lower bounds of the soil dielectric constants from the absolute backscatter values. For a given radar frequency and incidence angle, the measured backscattering coefficient σ^0 can be expressed as a function of only surface root-mean-square (rms) height h_{rms} and soil dielectric constant ε_s, that is

$$\sigma^0 = F(h_{\text{rms}}, \varepsilon_s) \tag{4}$$

where $F(\cdot)$ represents a forward surface scattering model.

According to the juxtaposition method, for a time series of SAR measurements, the minimum possible rms height $h_{\text{rms}}^{\min}$ and the maximum possible rms height $h_{\text{rms}}^{\max}$ can be determined, respectively, by

$$h_{\text{rms}}^{\min} = F^{-1}\left(\sigma^0_{\max}, \varepsilon_s^{\max}\right) \text{ and } h_{\text{rms}}^{\max} = F^{-1}\left(\sigma^0_{\min}, \varepsilon_s^{\min}\right) \tag{5}$$

where $F^{-1}(\cdot)$ indicates the inversion of the forward scattering model; $\sigma^0_{\max}$ and $\sigma^0_{\min}$ represent the maximum and minimum backscattering coefficients in the time-series measurements, respectively; $\varepsilon_s^{\max}$ and $\varepsilon_s^{\min}$ represent the maximum and minimum soil dielectric constants.

Once the possible range $[h_{\text{rms}}^{\min}, h_{\text{rms}}^{\max}]$ of rms height is determined, the possible dielectric constant range $[\varepsilon_s^{\min}(i), \varepsilon_s^{\max}(i)]$ for each acquisition date i can be calculated by inverting the forward scattering model.

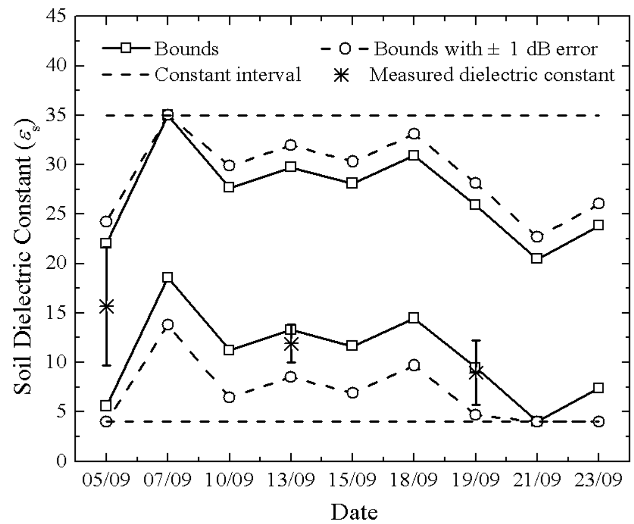

Fig. 2. Range of soil dielectric constant for Field #1. The dashed lines indicate the constant constraint interval while the solid lines with hollow squares indicate the upper and lower bounds computed from the radar backscatter values using the Dubois model. The dashed lines with hollow circles indicate bounds from the Dubois model but with ±1 dB error in backscattering measurements. Stars indicate the ground-measured soil dielectric constants while error bars indicate ± one standard deviation.

As an example, Fig. 1 demonstrates how the ranges of h_{rms} and ε_s are calculated. The Dubois model was chosen as the forward surface scattering model due to its relative simplicity and accuracy [16]. Importantly, the Dubois scattering model includes only two sensitive unknown parameters, i.e., h_{rms} and ε_s. A lookup table technique was utilized to invert the forward Dubois scattering model. The typical range of ε_s was selected as $4 \le \varepsilon_s \le 35$ (approximately corresponding to m_v ranging, at L-band, between 0.04 and 0.50 cm^3/cm^3 as per the soil texture of the study area). The typical range of h_{rms} was selected as 0.3 cm $< h_{\text{rms}} <$ 10 cm, which is wide enough to ensure that it covers all roughness values for the fields analyzed.

IV. Results and Discussion

A. Soil Dielectric Constant Bounds

Fig. 2 demonstrates the upper and lower bounds of dielectric constants (for Field #1) computed using the Dubois model (solid line with squares). To account for the measurement error in radar backscattering coefficients, the bounds with ±1 dB error in radar measurements are also displayed (dashed line with circles). The constant constraint interval (dashed line) for the dielectric constant is set for all acquisitions (i.e., 4 to 35). The ground-measured soil dielectric constant (stars) is presented with ± one standard deviation.

When no *a priori* information on the dynamic range of soil moisture is available, the solution was restricted to the wide range of values of the constraint interval (4 to 35). However, with the help of the juxtaposition method, the possible range of dielectric constant was considerably narrowed so that the bounds could be adaptively adjusted for each acquisition date

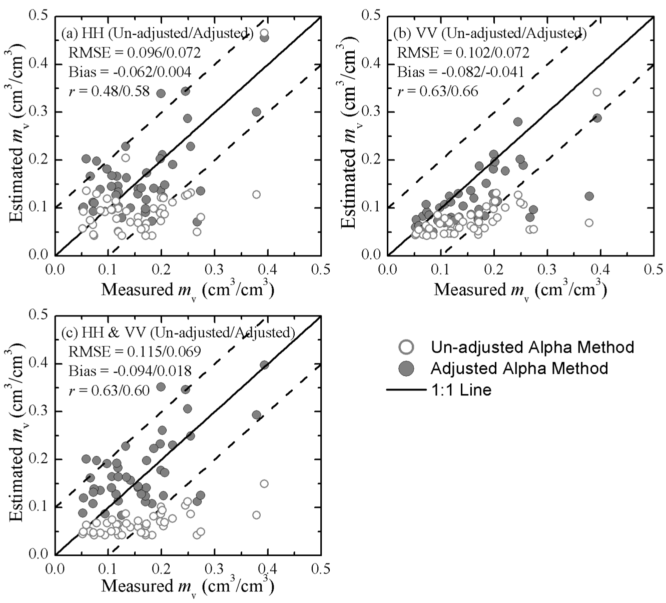

Fig. 3. Scatter plots between estimated and measured soil moisture m_v values obtained by the unadjusted (hollow circles) and adjusted (solid circles) alpha methods for (a) HH polarization, (b) VV polarization, and (c) HH & VV polarizations. The bias, RMSE, and correlation coefficient r values are also displayed for the unadjusted (before the slash) and adjusted (after the slash) alpha methods. The solid line represents the 1:1 line, whereas dashed lines indicate the ± 0.1 cm^3/cm^3 margins.

before least-squares optimization. Since the solution is not unique, narrower range translates into less uncertainty.

B. Soil Moisture Retrieval Results

In this letter, the unadjusted (i.e., original) and adjusted (i.e., with the proposed extension) alpha methods have been tested for three configurations, i.e., two single-polarization (HH or VV) and one dual-polarization configuration (HH and VV). The obtained dielectric constant estimates were converted into volumetric soil moisture using soil-type-specific calibration functions developed for the study area [17]. The validation of soil moisture estimated from different inversion schemes was performed against the ground measurements within each field listed in Table I. Fig. 3 displays the results from the unadjusted (hollow circles) and adjusted (solid circles) alpha methods for the three polarization configurations. Three parameters, namely, rms error (RMSE), mean bias (Bias), and correlation coefficient (r) between the estimated and measured soil moisture m_v values, were also calculated and displayed.

For the unadjusted alpha method, the bounds of the dielectric constant magnitudes have been set as 4 and 35, i.e., the bounds were not adaptively adjusted before least-squares optimization. The soil moisture values were underestimated for all three polarization configurations with bias values varying from -0.094 to -0.062 cm^3/cm^3 and RMSE values varying from 0.096 to 0.115 cm^3/cm^3. More specifically, for the HH polarization, agreement was found between the estimated and measured soil moisture values for relatively dry soils ($m_v < 0.15$ cm^3/cm^3), whereas the retrieved soil moisture was underestimated for wet conditions ($m_v > 0.15$ cm^3/cm^3). For VV-polarization and dual-polarization (HH and VV) cases, a severe underestimation was observed for all soil moisture conditions. It was found that the sensitivity of radar backscattering to dielectric constant was rather strong at low dielectric constant and decreased as the dielectric constant increased [18], so that there is a high possibility that the solutions to the system of equations constructed using (1) locates in the low dielectric constant range. Since many fields observed during this field campaign exhibited particularly high soil moisture content (see Table I), the underestimation of the retrieval scheme is likely associated with the decreased sensitivity of radar backscatter returns to changes in soil moisture. It is interesting to note that the unadjusted alpha method, despite having relatively large RMSE values, exhibited relatively high correlation coefficients (0.48–0.63) with respect to the measured values. This suggested that the alpha method has the potential to achieve decent performance if the systematic bias can be removed.

For the adjusted alpha method, the bounds of the dielectric constant magnitudes were computed from the Dubois model using the juxtaposition method, and were adaptively adjusted before least-squares optimization. The adjusted alpha method showed significant improvements of the retrieval accuracy over the unadjusted alpha method. The RMSE values ranged between 0.069 and 0.072 cm^3/cm^3 while the bias values ranged between -0.041 and 0.018 cm^3/cm^3. In terms of comparison among different polarizations, the three approaches yielded similar results. Inclusion of both polarizations in the retrieval slightly improved the retrieval performance. The retrieval accuracy of the adjusted alpha method is comparable to previous studies [8], [9], [11], [12], in which the soil moisture bounds were adaptively adjusted based on *a priori* information. By contrast, the method analyzed in this letter makes the most use of information contained in the time-series SAR data (both relative change and absolute backscatter values), without any *a priori* information on the surface conditions, making it very appealing for practical estimation of soil moisture under bare surface conditions.

It is important to remember that the Dubois model can solely be applied to estimating soil moisture if dual co-polarized (VV and HH) radar data are available. The results show, however, that only about 45% of the SAR data were successfully inverted (RMSE 0.118 cm^3/cm^3 and bias 0.072 cm^3/cm^3) using the Dubois model itself. The remaining data did not meet the criterion of $\sigma^0_{\mathrm{HH}} \leq \sigma^0_{\mathrm{VV}}$ (as required by the Dubois model) and therefore had no numerical solution. These results are in agreement with the findings in [19]. Since the fields selected in this letter exhibited a wide range of soil moisture and surface roughness conditions (see Table I), and several fields presented row structure, the failure of the Dubois model is likely associated with its restrictive validity range. By contrast, all the SAR measurements could be inverted for soil moisture with the proposed extension of the alpha approximation method, since soil moisture is inverted from temporal changes of radar backscatter rather than absolute backscatter values.

It is worth mentioning that the juxtaposition method was specifically designed to derive the upper and lower bounds of soil dielectric constants before making a retrieval. This method could also be applied for soil moisture estimation with a possibility distribution function. However, the type of possibility distribution function needs to be predefined [13], which requires knowledge of possibility distributions of the rms height and the soil moisture. Therefore, the juxtaposition method with a possibility distribution function was not tested.

It should be noted that the proposed approach was tested over bare soil surfaces. However, this method can be extended to vegetated areas if the effect of vegetation on radar backscatter is carefully corrected [10], which could be done through the water cloud model [20], or polarimetric decomposition of fully polarimetric SAR data [21].

V. Conclusion

This letter proposed an extension of the alpha approximation method for soil moisture inversion which makes use of the information contained in time-series SAR data (both relative change and absolute backscatter values). More specifically, the relative change was used to construct a system of equations to solve for soil moisture while the absolute backscatter was utilized to compute the possible range of soil dielectric constant to constrain the soil moisture retrieval.

The extended alpha method has been applied to time-series L-band SAR data acquired during the SMAPEx-3 campaign over a time span of three weeks in 2011 in southeastern Australia. The results indicate that the overall retrieval accuracy performance is significantly improved when compared to the unadjusted alpha method, without the need of additional *a priori* information on surface parameters. The single-polarization cases (HH or VV) achieved comparable accuracy to the dual-polarization case (HH and VV), with RSME values being about 0.07 cm^3/cm^3. Future steps will be to include vegetation effects and to test using other data sets.

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