Slope-Corrected Vegetation-Corrected Polarimetric Two-Scale Model for Soil Moisture Retrieval

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***Abstract*— We present a method able to retrieve the soil moisture content and the surface roughness of a moderately vegetated soil in a possibly hilly area, from a fully polarimetric SAR dataset. The estimation procedure is based on the prediction of the second order statistics of the scattered field provided by the Slope-Corrected Polarimetric Two-Scale Model combined with a two-component scattering model. The performance of the estimation method is assessed by comparing obtained retrieval results to "in situ" measurements. To this aim, data from AGRISAR 2006 campaign are employed.**

Keywords—SAR Polarimetry; soil moisture retrieval

I. Introduction

Knowledge of soil moisture content is of fundamental importance in many agricultural, hydrological and meteorological applications; for instance, it is an essential piece of information for the prediction of crisis events such as floods and landslides, as well as for water resources management [1]. Therefore, in last decades, ground water content retrieval from multi-angle, multi-frequency or multi-polarization SAR data has been the subject of extensive research. In this framework, recently we proposed a retrieval technique based on an original Polarimetric Two-Scale Model (PTSM) [2-5], able to estimate the volumetric water content of bare soils from polarimetric SAR data in flat areas [2] or also in areas with a significant topography [3, 4], in which case a slope-corrected (SC) PTSM was introduced. In order to further extend the field of application of our retrieval technique to moderately vegetated soils, in [5] we combined the PTSM with a two-component scattering model in order to obtain a modified retrieval algorithm able to remove the (secondary) volume scattering contribution. However, the formulation in [5] only applies to flat terrains with no topography. Conversely, we here present a complete formulation that combines the SC-PTSM to deal with hilly, moderately vegetated terrains.

Accordingly, we compute all the NRCS (Normalized Radar Cross Sections) and the HH-VV correlation by using the SC-PTSM to describe the surface scattering component, and the theoretical model shown in [6] to describe the volume scattering contribution from the vegetation layer which covers the scattering surface. We then show that suitable combinations of the NRCS and HH-VV correlation, that we term "modified co-polarized ratio" and "modified HH-VV correlation coefficient", are related only to the surface parameters (i.e., volumetric contribution cancels out). This allows us to obtain a reasonable estimation of the soil moisture even in hilly, moderately vegetated areas, where the volumetric scattering contribution is non-negligible. We here term this method as slope-corrected, vegetation-corrected PTSM (SC-VC-PTSM).

II. Theory

In this section we provide a theoretical framework to deal with the soil moisture estimation of sloped areas covered by a moderate vegetation layer. To this aim, we consider a two-component scattering mechanism, in which the total scattered power is modeled as composed of independent surface and volume scattering contributions. As regards the former, we model the roughness of the scattering surface through the superposition of two stochastic processes, namely the microscopic roughness and the large-scale roughness [2]. In particular, we assume that within a (multi-look) SAR image resolution cell the slopes (both in azimuth and range directions) of the large scale roughness are stationary Gaussian processes with mean values not forced to be equal to zero [3]. Actually, these assumptions leads to a three scale description of the scattering surface, since macroscopic roughness non-zero mean slopes account for a sloped mean plane due to topographic-scale height variations. The latter are known if a Digital Elevation Model (DEM) of the imaged area is available, as we will here suppose.

Concerning the volume contribution, we model the vegetation layer through a cloud of randomly oriented thin dipoles, whose scattering is described in [6]. Similarly to what was done in [5], we resort to vegetation-independent quantities to estimate the surface parameters.

A. Surface scattering

We consider a soil surface $z(x,y)$ as composed of large-scale variations on which a small-scale roughness $\zeta(x,y)$ is superimposed. We model both large- and small-scale roughness as stochastic processes. The small-scale roughness is described by the set of parameters $\underline{s}$, and here we assume that it satisfies the Small Perturbation Method (SPM) validity range.With regard the large-scale roughness, it is locally treated by replacing the surface with a rough tilted facet, whose slope is the same of the smoothed surface at the center

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of the pertinent facet, so leading to the following analytical expression of the scattering surface:

$$z(x,y) = \tan\omega(x - x_i) + \tan\gamma(y - y_i) + z_i + \zeta(x,y)\ , \qquad (1)$$

where $\tan\omega=a$ and $\tan\gamma=b$ are the local azimuth and range slopes, respectively, and x_i, y_i, z_i are the coordinates of the i-th facet center. Moreover, we assume that the facet slopes along range and azimuth directions, a and b, are independent σ^2-variance Gaussian random variables, whose means μ_a and μ_b represent the topographical features of the scene to be modeled. The randomness of the facet slopes turns into a random rotation β of the local incidence plane and in a stochastic drift of the local angle of incidence ϑ_l around the global angle of incidence (AOI) ϑ. Both these effects, and so the scattering matrix of a generic facet, can be analytically related to the azimuth and range slopes [7]; accordingly, the second order statistics of the filed scattered from a generic tilted rough facet can be expressed as:

$$\left\langle S_{pq} S_{rs}^* \right\rangle_{|\zeta} = k^4 \cos^4 \vartheta_l\, \chi_{pq}(\vartheta_l, \beta)\, \chi_{rs}^*(\vartheta_l, \beta) W(2k \sin\vartheta_l; \underline{s}), \qquad (2)$$

where $k=2\pi/\lambda$ is the wavenumber, $W(\cdot)$ is a polarization-independent function depending on small-scale roughness, p or r and q or s are the polarizations of the incident and scattered field, respectively, and can each stand for H (horizontal) or V (vertical) and $\chi_{pq}(\vartheta_l,\beta)$ ($\chi_{rs}(\vartheta_l,\beta)$) are the elements of the matrix

$$\underline{\underline{\chi}}(\vartheta_l, \beta) = \underline{\underline{R}}_2(\beta) \cdot \underline{\underline{F}}(\vartheta_l, \varepsilon) \cdot \underline{\underline{R}}_2^{-1}(\beta)\ , \qquad (3)$$

wherein $\underline{\underline{R}}_2(\beta)$ is the unitary rotation matrix, accounting for the rotation of the local polarization reference system and responsible of the cross-polarization effect. Finally, here $\underline{\underline{F}}(\vartheta_l, \varepsilon)$ stands for the SPM scattering matrix, whose entries $F_V(\vartheta_l,\varepsilon)$ and $F_H(\vartheta_l,\varepsilon)$ are the Bragg coefficients [2].

According to what is shown in [2, 4], the covariance matrix of the electromagnetic field scattered from the overall surface can be evaluated by averaging over the local slopes the second order statistics of the field scattered from the generic tilted facet, after a second order Taylor expansion around a=0, b=0. Accordingly, the elements of the polarimetric covariance matrix of interest here can be cast in the following way:

$$\begin{cases} \left\langle |S_{VV}|^2 \right\rangle \cong f_S(\varepsilon, \underline{s})\left(1 + \gamma_V(\varepsilon)\mu_b + \underline{\delta}_V(\varepsilon) \cdot \underline{\sigma}^2\right) \\ \left\langle |S_{HH}|^2 \right\rangle \cong f_S(\varepsilon, \underline{s})|\beta(\varepsilon)|^2\left(1 + \gamma_H(\varepsilon)\mu_b + \underline{\delta}_H(\varepsilon) \cdot \underline{\sigma}^2\right) \\ \left\langle |S_{HV}|^2 \right\rangle \cong f_S(\varepsilon, \underline{s})\delta_X(\varepsilon)\left(\mu_a^2 + \sigma^2\right) \\ \left\langle S_{HH} S_{VV}^* \right\rangle \cong f_S(\varepsilon, \underline{s})\beta(\varepsilon)\left(1 + \gamma_{HV}(\varepsilon)\mu_b + \underline{\delta}_{HV}(\varepsilon) \cdot \underline{\sigma}^2\right) \end{cases}\ , \qquad (4)$$

wherein

$$f_S(\varepsilon, \underline{s}) = |S_{VV}|^2_{\substack{a=0 \\ b=0}} = (k\cos\vartheta)^4 W(2k\sin\vartheta; \underline{s})|F_V(\vartheta, \varepsilon)|^2\ , \qquad (5)$$

$\beta(\varepsilon)=F_H(\vartheta,\varepsilon)/F_V(\vartheta,\varepsilon)$, $\delta_X(\varepsilon)=|1-\beta(\varepsilon)|^2/\sin^2\vartheta$, $\underline{\sigma}^2=(\mu_a^2, \mu_b^2, \sigma^2)$ and the full expressions of the other coefficients $\gamma_V(\varepsilon)$, $\gamma_H(\varepsilon)$, $\gamma_{HV}(\varepsilon)$, $\underline{\delta}_V(\varepsilon)$, $\underline{\delta}_H(\varepsilon)$, $\underline{\delta}_{HV}(\varepsilon)$ can be obtained from [2-4]. It is then possible to define the copolarised ratio

$$CP = \frac{\left\langle |S_{HH}|^2 \right\rangle}{\left\langle |S_{VV}|^2 \right\rangle} \cong |\beta(\varepsilon)|^2 \left[1 + \gamma_{CP}(\varepsilon)\mu_b + \underline{\delta}_{CP}(\varepsilon) \cdot \underline{\sigma}^2\right]\ , \qquad (6)$$

and the *HH-VV* correlation coefficient

$$CORR = \frac{\left|\left\langle S_{HH} S_{VV}^* \right\rangle\right|}{\sqrt{\left\langle |S_{HH}|^2 \right\rangle \left\langle |S_{VV}|^2 \right\rangle}} \cong 1 + \gamma_{CORR}(\varepsilon)\mu_b + \underline{\delta}_{CORR}(\varepsilon) \cdot \underline{\sigma}^2\ , \qquad (7)$$

where the expressions of $\gamma_{CP}(\varepsilon)$, $\gamma_{CORR}(\varepsilon)$,$\underline{\delta}_{CP}(\varepsilon)$, $\underline{\delta}_{CORR}(\varepsilon)$ can be obtained by using (4), expanding the ratios in (6) and (7) in Taylor series, and dropping terms of order higher than two. Dependence on small-slope roughness cancels out in *CP* and *CORR*, so that from these two equations ε (and hence soil moisture) and σ of bare soils can be retrieved, as shown in [4].

B. Volume scattering

Concerning the volume scattering, we assume that the vegetation layer that covers the scattering surface can be modeled by a cloud of randomly oriented thin dipoles. According to what shown in [6], i.e. assuming a uniform distribution for the dipole orientation angle, we get that the only non-null elements of the covariance matrix are:

$$\begin{cases} \left\langle |S_{VV}|^2 \right\rangle = \left\langle |S_{HH}|^2 \right\rangle = f_V(\underline{u}) \\ \left\langle |S_{HV}|^2 \right\rangle = \left\langle S_{HH} S_{VV}^* \right\rangle = f_V(\underline{u})/3 \end{cases}\ , \qquad (8)$$

where $f(\underline{u})$ is a function of the set of parameters $\underline{u}$ describing the dipole cloud (i.e., vegetation), whose expression is of no concern here.

C. SC-VC-PTSM

As noted in [5], if we assume that the scattering area does not contain trees, so that the double-bounce scattering component is negligible, and, moreover, that the volume and surface scattering mechanisms give rise to independent contributions, we can express the covariance matrix of the sloped rough and moderately vegetated surface as the sum of the elements of eqs. (4) and (8). Accordingly, in this case CP and CORR also depend on $f(\underline{u})$, and hence on vegetation parameters, and the problem is underdetermined. However, we note that the cross-polarised channel return can be used to cancel out the volumetric contribution. This leads to define a "modified co-polarized ratio"

$$CP_{\text{mod}} = \frac{\left\langle |S_{HH}|^2 \right\rangle - 3\left\langle |S_{HV}|^2 \right\rangle}{\left\langle |S_{VV}|^2 \right\rangle - 3\left\langle |S_{HV}|^2 \right\rangle} \cong \qquad (9)$$

$$\cong |\beta(\varepsilon)|^2 \left[1 + \left(\gamma_{CP}(\varepsilon) + \gamma_{CP\text{mod}}(\varepsilon)\right)\mu_b + \left(\underline{\delta}_{CP}(\varepsilon) + \underline{\delta}_{CP\text{mod}}(\varepsilon)\right) \cdot \underline{\sigma}^2\right]$$

and a "modified *HH-VV* correlation coefficient"

$$CORR_{\mathrm{mod}} = \frac{\left|\left\langle S_{HH} S_{VV}^{*} \right\rangle - \left\langle \left|S_{HV}\right|^{2} \right\rangle\right|}{\sqrt{\left(\left\langle \left|S_{HH}\right|^{2} \right\rangle - 3\left\langle \left|S_{HV}\right|^{2} \right\rangle\right)\left(\left\langle \left|S_{VV}\right|^{2} \right\rangle - 3\left\langle \left|S_{HV}\right|^{2} \right\rangle\right)}} \cong \tag{10}$$

$$\cong 1 + \left(\gamma_{CORR}(\varepsilon) + \gamma_{CORR\mathrm{mod}}(\varepsilon)\right)\mu_b + \left(\underline{\delta}_{CORR}(\varepsilon) + \underline{\delta}_{CORR\mathrm{mod}}(\varepsilon)\right)\cdot \underline{\sigma}^{2}$$

where the expressions of $\gamma_{CP\mathrm{mod}}$, $\gamma_{CORR\mathrm{mod}}$, $\underline{\delta}_{CP\mathrm{mod}}$, $\underline{\delta}_{CORR\mathrm{mod}}$ can be obtained by using (4) and (8), expanding the ratios in (9) and (10) in Taylor series, and dropping terms of order higher than two. Notice that CP_{mod} and $CORR_{\mathrm{mod}}$ do not depend on small-scale roughness and on volume scattering, so it is possible estimate ε and σ from the ratios defined in (9) and (10) following the procedure described in [4], but building up modified copol-correlation charts instead of copol-correlation charts. Finally, note that the modified correlation coefficient is not restricted to be smaller than unity.

III. RETRIEVAL RESULTS

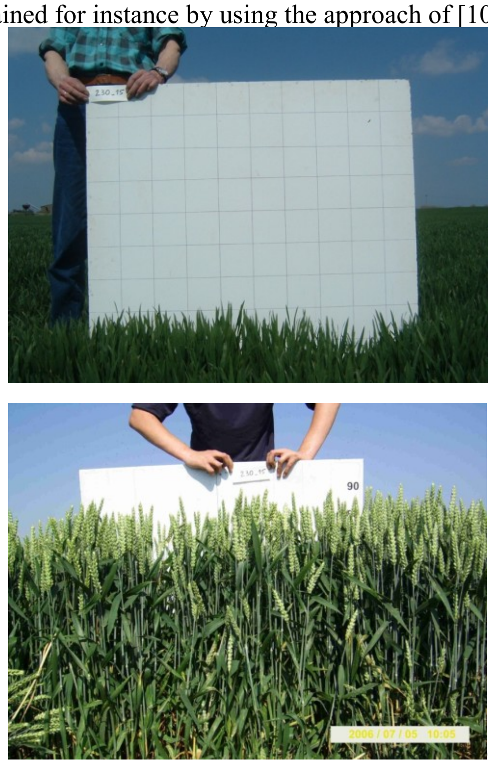
In this paper we evaluate the retrieval results obtained with SAR data acquired in the framework of the 2006 AgriSAR campaign [8]. In this context multifrequency SAR, optical and ground data over a whole vegetation-growing period were acquired in the site of Demmin in northern Germany. In particular, in this study we use L-band quad-polarimetric SAR data acquired by the DLR airborne experimental SAR (E-SAR) system.

Simultaneously to SAR acquisitions, a wide set of ground data was collected, regarding vegetation phenology, terrain conditions, precipitations and volumetric soil moisture. In particular, the soil water content was measured with different techniques (i.e., time-domain reflectometry, gravimetric and capacitive measurements) and different time-sampling scenarios (intensive campaigns over many fields, weekly measures on a limited set of fields, and via continuous measurements stations over few fields). The area of interest is characterized by the presence of several crops types: in this work we studied the soil moisture behavior of fields presenting different types of crops, namely sugar beet, wheat, winter barley, winter rape, grassland, and maize.

The retrieval procedure was applied on the available geocoded L-band quad-polarimetric images. We use here both East-West and North-South SAR passes. The original pixel spacing of the data is 2 m x 2 m and, following a preliminary multilook step, it is degraded to 20 m x 20 m. As explained in the previous section, in order to account for a sloped mean plane due to the non-null topography of the scene, knowledge of the slopes of the area is necessary. We use here the available DEM (obtained through X-band SAR interferometry [8]) to evaluate the slopes, which must be re-projected in the azimuth-range reference system, see (1). The area is characterized by altitude variations of less than 50 m, with slopes enclosed in the range [−15°, 15°]. Once the topographic-scale slopes of the area are available, we can use the expressions in (9) and (10) to estimate ε and σ following the procedure described in [4]. Finally, the retrieved values are converted into volumetric moisture m_v using the mixing model in [9], considering that the soil in the Demmin area consists mostly of loamy sand, with percentages of sand and clay of 68% and 7%, respectively [8].

We show separate results for two different periods. In the first period (April-May 2006) vegetation was mostly in an early stage of growth and its height was moderate/low, while in the second one (June-July 2006) the various crop types were in an advanced stage of growth, presenting significant heights in most cases. As an example, in Fig. 1 (a) and (b) photos of the same field acquired in the two periods are presented, testifying to a huge increase in vegetation height.

In Fig. 2 the results relevant to the first period are reported. In order to evaluate the effects of the proposed slope and vegetation corrections, in Fig. 2 (a) we present the scatterplot of the m_v values retrieved via the original CP-CORR method of [4] vs. ground-measured data, while in Fig. 2 (b) the SC-VC-PSTM-based estimates are presented. Looking at the scatterplots the positive effects of the applied corrections can be appreciated: actually, the standard technique of [4] provides in most cases strongly overestimated values, whereas the proposed SC-VC-PSTM approach provides good estimates of m_v, as it can be also quantitatively assessed through the indexes reported in the captions. In Fig. 3 the results relevant to the second period are reported. Again, comparison of the results in Fig. 3 (a) and (b) shows a significant enhancement of the estimates obtained by SC-VC-PSTM with respect to the standard CP-CORR method of [4]. However, in this case it is clear that the retrieval procedure provides bad estimates of m_v, irrespective of the considered model. This result is not surprising: in fact, from Fig. 1 (b) it is evident that in that period the considered fields are very vegetated, and surface scattering is not dominant, so that a simpler surface scattering model can be used, whereas more complex volumetric and double-bounce scattering models would be needed. This could be obtained for instance by using the approach of [10].



(a)

(b)

Fig. 1. Photos relevant to the Demmin field 230 (wheat field) on May 3 2006 (a) and July 5 2006 (b).

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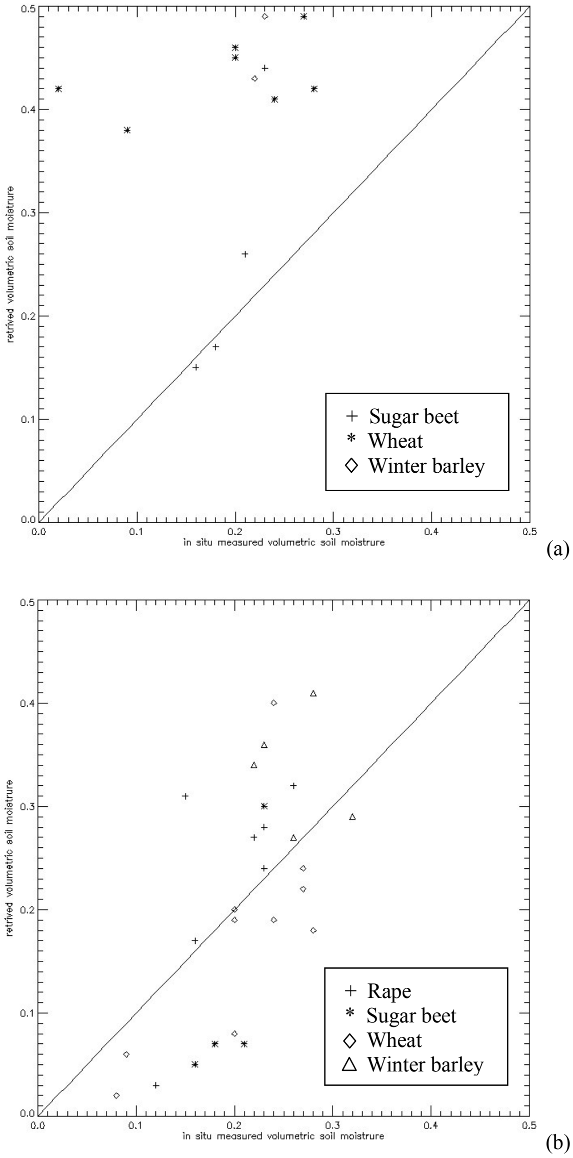

Fig. 2 Scatterplot of the retreived volumetric soil moisture vs. ground-measured data (April-May period): (a) original *CP-CORR*-based estimates; (b) SC-VC-PSTM-based estimates. For (a) the mean error is 0.19, the rms error is 0.22, and the correlation coefficient is 0.29; for (b) the mean error is 0.001, the rms error is 0.088, and the correlation coefficient is 0.66.

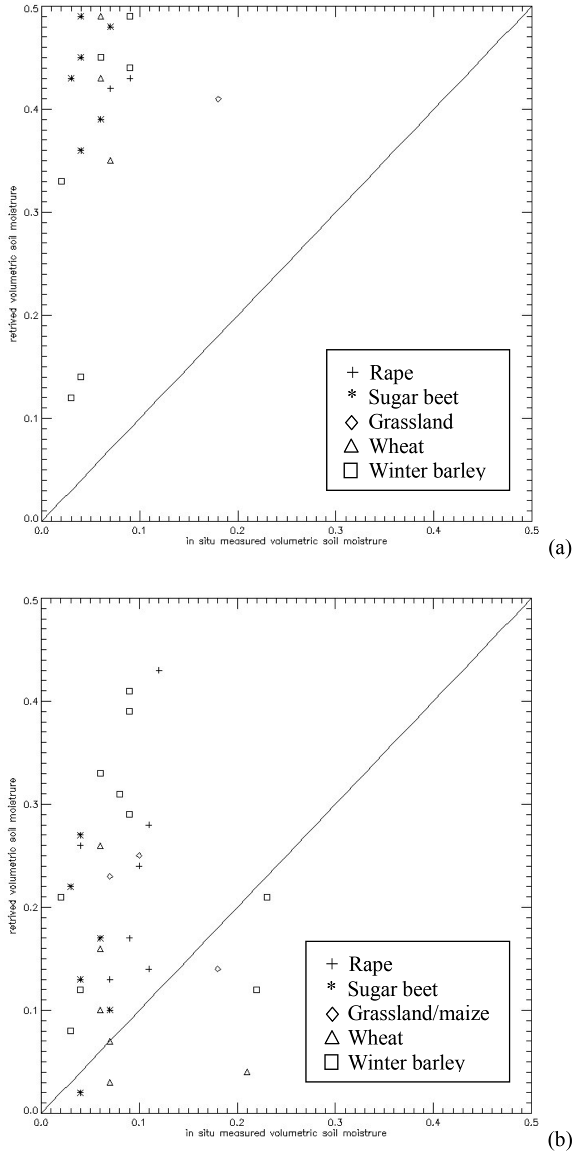

Fig. 3 Scatterplot of the retreived volumetric soil moisture vs. ground-measured data (June-July period): (a) original *CP-CORR*-based estimates; (b) SC-VC-PSTM-based estimates. For (a) the mean error is 0.33, the rms error is 0.35, and the correlation coefficient is 0.33; for (b) the mean error is 0.11, the rms error is 0.16, and the correlation coefficient is −0.02.