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POLARIMETRIC TWO-SCALE MODEL FOR SOIL MOISTURE ESTIMATION FROM HYBRID COMPACT POLARIMETRY SAR DATA

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ABSTRACT

Hybrid compact polarimetric (CP) SAR systems present significant advantages with respect to fully polarimetric (FP) ones, in terms of hardware simplification and better attainable resolution and coverage. Retrieval of soil moisture is a classical application of FP SAR data: in this context, advanced model-based techniques have been proposed to support microwave data inversion. In this paper, we present a new approach for soil moisture retrieval from CP data, based on the use of the Polarimetric Two-Scale Model (PTSM), which has been originally proposed in support of soil moisture retrieval from FP data. Obtained results are validated using simulated CP data relevant to the AgriSAR campaign test sites and compared with FP PTSM-based retrieval results.

***Index Terms*—** SAR, compact polarimetry, soil moisture retrieval

1. INTRODUCTION

Retrieval of soil moisture from Synthetic Aperture Radar (SAR) data has been the object of considerable research and, in this context, polarimetric data has attracted significant attention in the last couple of decades [1]-[5]. Several model-based approaches have been proposed over the years. First efforts were focused on modeling the surface scattering component only [1]-[3]; then, refined models were developed to account for the volume and double-bounce components, thus habilitating the estimation of soil moisture also in moderately vegetated areas [4]-[5]. Most of these models require fully polarimetric (FP) measurements and exploit all the elements of the FP covariance matrix.

However, FP systems present well-known drawbacks, in terms of hardware complexity and limited coverage and resolution. Therefore, recently significant research efforts were devoted to the analysis and development of compact polarimetric systems, with several spaceborne hybrid compact polarimetric (CP) SAR sensors launched in the last years, such as the Indian RISAT-1, the Canadian RCM, and the Argentinian SAOCOM-1. With respect to FP systems, CP systems are not able to measure the complete scattering matrix, thus calling for the development of ad hoc soil moisture retrieval approaches. Indeed, several techniques have been proposed in the literature (e.g., [6]-[8]), usually based on the joint use of suitable CP parameters and surface scattering models. In many cases, the X-Bragg model is used to account for surface scattering [7]-[8]. Since the retrieval is usually based on the inversion of the surface scattering component, it is reasonable to expect that soil moisture retrieval could benefit from a more accurate modeling of this scattering component.

In this paper we propose to model surface scattering using the Polarimetric Two-Scale Model (PTSM) [2]-[3], which has been demonstrated to be more accurate than X-Bragg, since it accounts not only for the random rotation of the incidence plane around the line of sight, as X-Bragg does, but also for the random variation of the local incidence angle, which is, conversely, neglected by X-Bragg. Based on the obtained PTSM expressions of the entries of the CP covariance matrix, we then develop an effective retrieval method, based on the definition of suitable CP parameters. The proposed method is then tested on suitable AgriSAR test sites and compared with FP retrieval results. In particular, sparsely vegetated measurement sites are considered here, for which the surface scattering component can be considered to be definitely dominant. In order to extend the method to the case of non-negligible vegetation cover, the surface component should be preliminarily isolated, e.g. using existing CP decomposition approaches [9], which is object of current research.

2. THEORY

We first recall how the covariance matrix elements of CP data can be expressed in terms of those of the FP one. Then, we use PTSM to obtain meaningful expressions of these elements.

2.1. Hybrid compact polarimetry

CP SAR systems transmit circular polarized fields and receive the two orthogonal polarized horizontal (H) and vertical (V) fields. Therefore, considering right circular polarization (R), the elements of the CP scattering matrix can be related to those of the FP scattering matrix as follows [6]:

$$S_{RH} = S_{HH} - jS_{VH} \quad (1)$$

$$S_{RV} = -jS_{VV} + S_{HV} \;. \quad (2)$$

It is possible to obtain the expression of the elements of the CP covariance matrix in terms of the FP scattering matrix elements using (1) and (2)

$$\langle|S_{RH}|^2\rangle = \langle|S_{HH}|^2\rangle + \langle|S_{HV}|^2\rangle \quad (3)$$

$$\langle S_{RH}S_{RV}{}^*\rangle = j(\langle S_{HH}S_{VV}^*\rangle - \langle|S_{HV}|^2\rangle) \quad (4)$$

$$\langle|S_{RV}|^2\rangle = \langle|S_{VV}|^2\rangle + \langle|S_{HV}|^2\rangle \quad , \quad (5)$$

where $\langle\cdot\rangle$ stands for statistical mean and * for complex conjugate. Reflection symmetry has been assumed, implying zero correlation between copolarized (copol) and crosspolarized (crosspol) returns [6]: this assumption holds with very good approximation in the case of scattering from isotropic rough surfaces [10].

2.2. Polarimetric two-scale model

We here limit our attention to sparsely vegetated areas and, hence, we assume a dominant surface scattering component, so that the returns can be modeled using the PTSM [2]-[3], which provides expressions for the elements of the FP covariance matrix. According to PTSM, the soil surface is modeled as a collection of randomly tilted rough facets, with facets' roughness representing the small-scale surface roughness, whereas facets' random slope the large-scale one. Large- and small-scale roughness are modeled as independent stochastic processes. Facet slopes *a* and *b* along azimuth and range directions are assumed to be independent σ^2-variance Gaussian random variables, whose means are assumed to be zero, in view of the flatness of the areas considered in the experiments. The small-scale roughness is modeled as a zero-mean band-limited fractional Brownian motion (fBm) stochastic process, characterised by its Hurst coefficient H_t (with $0 < H_t < 1$) and by its height standard deviation s_0, which is assumed to be small compared to the electromagnetic wavelength λ, so that the validity limits of the Small Perturbation Method (SPM) are satisfied. According to PTSM, the entries of the covariance matrix of the overall surface can be obtained averaging the elements of the covariance matrix of the tilted rough facets over *a* and *b*, after a second-order expansion around *a*=*b*=0. Substituting these expressions in (3)-(5) leads to

$$\langle|S_{RH}|^2\rangle \cong s_0^2 f_s(\varepsilon,H_t)|\beta_r(\varepsilon)|^2\left[1+\left(\delta_H(\varepsilon)+\frac{\delta_X(\varepsilon)}{|\beta_r(\varepsilon)|^2}\right)\sigma^2\right] \quad (6)$$

$$\langle S_{RH}S_{RV}{}^*\rangle \cong js_0^2 f_s(\varepsilon,H_t)\beta_r(\varepsilon)\left[1+\left(\delta_{HV}(\varepsilon)-\frac{\delta_X(\varepsilon)}{\beta_r(\varepsilon)}\right)\sigma^2\right] \quad (7)$$

$$\langle|S_{RV}|^2\rangle \cong s_0^2 f_s(\varepsilon,H_t)\left[1-\big(\delta_V(\varepsilon)-\delta_X(\varepsilon)\big)\sigma^2\right] , \quad (8)$$

where

$$f_s(\varepsilon,H_t) = k^4\cos^4\vartheta\,|F_V(\vartheta,\varepsilon)|^2 W_n(2k\sin\vartheta\,,H_t) \;, \quad (9)$$

ϑ is the incidence angle, $k=2\pi/\lambda$ is the wavenumber, $W_n(\cdot)$ is the normalised power spectral density of the small-scale roughness, whose expression is reported in [2], $F_V(\vartheta,\varepsilon)$ and $F_H(\vartheta,\varepsilon)$ are the Bragg coefficients for vertical and horizontal polarizations, that depend on the soil relative permittivity ε,

$$\beta_r(\varepsilon) = \frac{F_H(\vartheta,\varepsilon)}{F_V(\vartheta,\varepsilon)} \quad (10)$$

$$\delta_X(\varepsilon) = \frac{|1-\beta_r(\varepsilon)|^2}{\sin^2\vartheta} \quad (11)$$

$$\begin{cases} \delta_V(\varepsilon) = 2\mathrm{Re}\left\{\frac{1-\beta_r(\varepsilon)}{\sin^2\vartheta}\right\} - \frac{C_2^{VV}(\varepsilon,H_t)}{f_s(\varepsilon,H_t)} \\ \delta_H(\varepsilon) = 2\mathrm{Re}\left\{\frac{1-\beta_r(\varepsilon)}{\beta_r(\varepsilon)\sin^2\vartheta}\right\} + \frac{C_2^{HH}(\varepsilon,H_t)}{|\beta_r(\varepsilon)|^2 f_s(\varepsilon,H_t)} \\ \delta_{HV}(\varepsilon) = \frac{1-\beta_r(\varepsilon)}{\beta_r(\varepsilon)\sin^2\vartheta} - \frac{1-\beta_r^*(\varepsilon)}{\sin^2\vartheta} + \frac{C_2^{HV}(\varepsilon,H_t)}{\beta_r(\varepsilon)f_s(\varepsilon,H_t)} \end{cases} \quad (12)$$

$$C_2^{pq}(\varepsilon,H_t) = \frac{1}{2}\frac{\partial^2\left(W_n k^4\cos^4\vartheta F_p(\vartheta,\varepsilon)F_q^*(\vartheta,\varepsilon)\right)}{\partial a^2}\bigg|_{a=b=0} + \frac{1}{2}\frac{\partial^2\left(W_n k^4\cos^4\vartheta F_p(\vartheta,\varepsilon)F_q^*(\vartheta,\varepsilon)\right)}{\partial b^2}\bigg|_{a=b=0} \quad , \quad (13)$$

with *p* and *q* that can each stand for H or V. Full analytical expressions of the derivatives in (13) are reported in [2].

3. RETRIEVAL METHOD

Retrieval of soil moisture via PTSM can be implemented through the joint use of copol ratio and copol correlation coefficient [3]. Their use is justified by the fact that the dependence from the small-scale roughness cancels out in the ratios, which are only dependent on ε and σ. Therefore, if we reasonably neglect the imaginary part of the soil dielectric constant, this makes possible to retrieve σ and ε (and, hence, the soil moisture) from FP data (actually, even from dual-pol HH-VV data).

However, the abovementioned quantities cannot be measured by CP systems. Therefore, we propose here to use the following ratios (limiting to the same second-order expansion considered by the PTSM) in support of soil moisture retrieval:

$$\frac{\langle|S_{RH}|^2\rangle}{\langle|S_{RV}|^2\rangle} \cong |\beta_r(\varepsilon)|^2\left[1+\left(\delta_{\mathrm{copol}}(\varepsilon)+\delta'_{\mathrm{comp}}(\varepsilon)\right)\sigma^2\right] \quad (14)$$

$$\frac{|\langle S_{RH}S_{RV}{}^*\rangle|}{\sqrt{\langle|S_{RH}|^2\rangle\langle|S_{RV}|^2\rangle}} \cong 1-\left(\delta_{\mathrm{corr}}(\varepsilon)+\delta''_{\mathrm{comp}}(\varepsilon)\right)\sigma^2 \;, \quad (15)$$

Figure 1: Optical image of the considered area, with indication of the field identification number.

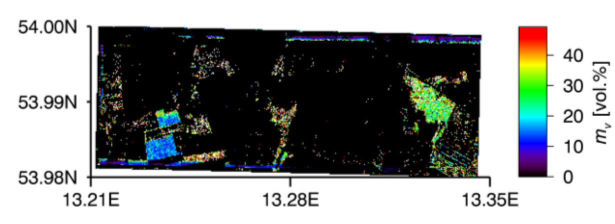
where

$$
\begin{cases}
\delta_{\text{copol}}(\varepsilon) = \delta_H(\varepsilon) + \delta_V(\varepsilon) \\
\delta'_{\text{comp}}(\varepsilon) = \frac{1-|\beta_r(\varepsilon)|^2}{|\beta_r(\varepsilon)|^2}\delta_X(\varepsilon) \\
\delta_{\text{corr}}(\varepsilon) = \frac{1}{2}\delta_H(\varepsilon) - \frac{1}{2}\delta_V(\varepsilon) - \text{Re}\{\delta_{HV}(\varepsilon)\} \\
\delta''_{\text{comp}}(\varepsilon) = \frac{\delta_X(\varepsilon)}{2}\frac{|1+\beta_r(\varepsilon)|^2}{|\beta_r(\varepsilon)|^2}
\end{cases} . \tag{16}
$$

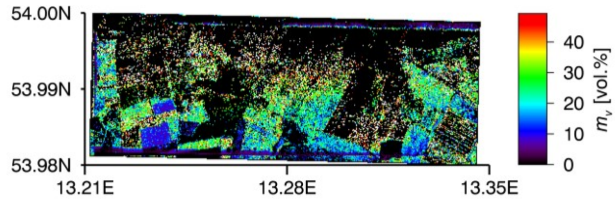
It is worth noting that (14) and (15) differ from the FP copol ratio and correlation coefficient, respectively, for the presence of the non-null terms $\delta'_{\text{comp}}(\varepsilon)$ and $\delta''_{\text{comp}}(\varepsilon)$ [3]. Equations (14)-(16) can be used for the retrieval of σ and ε from measurements exactly in the same way described in [3] for the retrieval of σ and ε from measured copol ratio and correlation coefficient. In fact, in both cases it is possible to build up numerical look-up tables parameterized by the dielectric constant ε and the large-scale roughness rms slope σ. Accordingly, the same automatic estimation algorithm as in [2]-[3] can be devised.

4. EXPERIMENTAL RESULTS

We consider L-band SAR data acquired by the DLR airborne experimental SAR (E-SAR) system over the site of Demmin in northern Germany, during the whole vegetation growth cycle in the year 2006 [11]. They refer to an agricultural scenario with several different crop types, see Fig. 1, where the considered fields are highlighted with their identification numbers. Field conditions significantly change from the times of the first acquisitions to those of the latest ones, moving from scarcely, to moderately, and finally to very vegetated fields. In the framework of the AgriSAR campaign, in correspondence with SAR acquisitions a wide set of ground data was collected, regarding vegetation phenology, terrain conditions, precipitations, and volumetric soil moisture [11]. Based on photos and descriptions available in [11], here we focus on two fields, namely corn field 222 and sugar beet field 460, which are bare in correspondence of the first acquisition in April 2006, and on the subset of acquisitions for which vegetation height is lower than 10 cm, i.e. the first six acquisition dates for field 222 and the first five for field 460.



(a)



(b)

Figure 2: Soil moisture maps retrieved for the date of April 19, 2006 (black pixels: parameter not retrieved): (a) FP; (b) CP.

Starting from the measured values of the FP scattering matrix and using (1)-(2), we simulate the CP scattering matrix elements, which are then used to evaluate measured values of the ratios in (14) and (15). The retrieval procedures are performed after application of a spatial multilook leading to a final pixel spacing of 20 m × 20 m. Estimation maps of the volumetric soil moisture have been obtained from the soil permittivity maps through the Hallikainen mixing model [12] (average values of percentages of sand and clay can be derived from data in [11] and they are about 68% and 7%, respectively). One example of soil moisture maps is provided in Fig. 2, both for FP retrieval in Fig. 2 (a) and for CP retrieval in Fig. 2 (b). In general, a higher inversion rate is observed for CP data. However, note that most of the fields are significantly vegetated at the time of acquisition, so that the high inversion rate does not necessarily correspond to accurate soil moisture retrieval results in these fields.

In Figs. 3 and 4 quantitative results of soil moisture estimation are provided for fields 222 and 460, respectively. For the corn field 222 FP and CP results are quite similar and they are in good agreement with the ground truth, being within the ±30% variation region for almost all the considered dates. Note that good retrieval results are obtained up to a vegetation height of 10 cm. Moving to the sugar beet field 460 the agreement between FP and CP results worsen, with CP data providing mostly underestimated soil moisture, especially for growing vegetation. In general, FP results better fit ground measurements, even if CP estimates seem to roughly follow the ground truth soil moisture temporal variations. It is worth noting that from the field pictures provided in [11] some tillage patterns can be appreciated, with tillage activity being dependent on the type of crop. This may significantly impact, in a crop-dependent fashion, on the

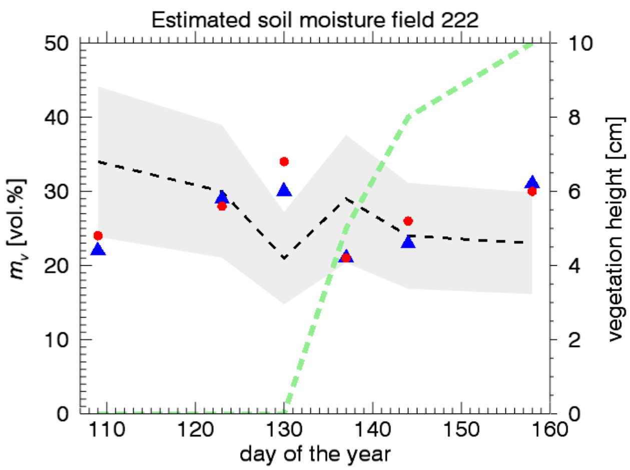


Figure 3: Estimated average soil moisture over corn field 222 inverted from simulated CP data (red circle) and FP data (blue triangle). The in situ estimated soil moisture (as taken from [11]) is indicated by the black dashed line and the ±30% variation region is highlighted in gray. Vegetation height is indicated by the green dashed line.

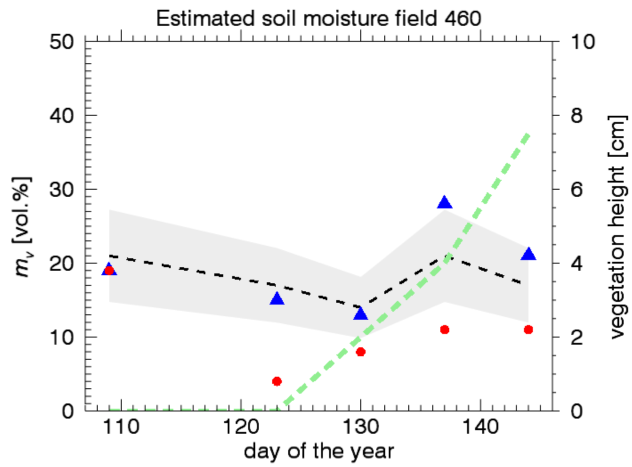


Figure 4: Estimated average soil moisture over sugar beet field 460 inverted from simulated CP data (red circle) and FP data (blue triangle). The in situ estimated soil moisture (as taken from [11]) is indicated by the black dashed line and the ±30% variation region is highlighted in gray. Vegetation height is indicated by the green dashed line.

reflection symmetry assumption made in the derivation of the presented model [10], and, hence, on the estimation results.

5. CONCLUSION

A novel approach for the estimation of soil moisture from CP data based on the inversion of the surface scattering component modeled via PTSM has been presented in this paper. Suitable CP measurables have been identified in support of inversion. Future research paths will focus on the extension of the proposed approach to moderately vegetated soils and on the possibility to account for anisotropic surfaces, frequently encountered in agricultural sites due to the occurrence of tillage activities.

6. REFERENCES

[1] I. Hajnsek, E. Pottier, S. R. Cloude, "Inversion of surface parameters from polarimetric SAR", *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 4, pp. 727–744, Apr. 2003.

[2] A. Iodice, A. Natale, D. Riccio, "Retrieval of Soil Surface Parameters via a Polarimetric Two-Scale Model", *IEEE Trans. Geosci. Remote Sens*., vol. 49, no. 7, pp. 2531–2547, July 2011.

[3] A. Iodice, A. Natale, D. Riccio, "Polarimetric Two-Scale Model for Soil Moisture Retrieval via Dual-Pol HH-VV SAR Data", *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 11, no. 3, pp. 1163–1171, June 2013.

[4] T. Jagdhuber, I. Hajnsek, K.P. Papathanassiou: "An Iterative Generalized Hybrid Decomposition for Soil Moisture Retrieval Under Vegetation Cover Using Fully Polarimetric SAR", *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 8, no. 8, pp. 3911–3922, 2015.

[5] G. Di Martino, A. Iodice, A. Natale, D. Riccio, "Polarimetric Two-Scale Two-Component Model for the Retrieval of Soil Moisture under Moderate Vegetation via L-Band SAR Data", *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 4, pp. 2470–2491, Apr. 2016.

[6] J. D. Ouellette *et al.*, "A Simulation Study of Compact Polarimetry for Radar Retrieval of Soil Moisture," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 9, pp. 5966–5973, Sept. 2014.

[7] G. G. Ponnurangam, T. Jagdhuber, I. Hajnsek, Y. S. Rao, "Soil Moisture Estimation Using Hybrid Polarimetric SAR Data of RISAT-1," *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 4, pp. 2033–2049, Apr. 2016.

[8] N. Bhogapurapu, S. Dey, A. Bhattacharya, C. López-Martínez, I. Hajnsek, Y. S. Rao, "Soil Permittivity Estimation Over Croplands Using Full and Compact Polarimetric SAR Data," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1-17, 2022, Art no. 4415917.

[9] S. Dey, A. Bhattacharya, D. Ratha, D. Mandal, A. C. Frery, "Target Characterization and Scattering Power Decomposition for Full and Compact Polarimetric SAR Data," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 5, pp. 3981–3998, May 2021.

[10] G. Di Martino, A. Iodice, D. Riccio, "Closed-Form Anisotropic Polarimetric Two-Scale Model for Fast Evaluation of Sea Surface Backscattering", *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 8, pp. 6182–6194, Aug. 2019.

[11] "AGRISAR 2006 Agricultural Bio-/Geophysical Retrievals from Frequent Repeat SAR and Optical Imaging", Final Report, Jan. 2008.

[12] H. T. Hallikainen, F. T. Ulaby, M. C. Dobson, M. A. El-Rayes and L. K. Wu, "Microwave dielectric behavior of wet soils - Part I: Empirical models and experimental observations", *IEEE Trans. Geosci. Remote Sens.*, vol. 23, pp. 25–34, Jan. 1985.