Soil Moisture Estimation Under Low Vegetation Cover Using a Multi-Angular Polarimetric Decomposition

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Abstract—The estimation of volumetric soil moisture under low agricultural vegetation from fully polarimetric synthetic aperture radar (SAR) data at L-band using a multi-angular polarimetric decomposition is investigated. Radar polarimetry provides the framework to decompose the backscattered signal into different canonical scattering mechanisms referring to scattering contributions from the underlying soil and the vegetation cover. Multi-angular observation diversity further increases the information space for soil moisture inversion enabling higher inversion rates and a stable inversion performance. The developed approach was applied on the multi-angular L-band data set acquired by German Aerospace Center’s ESAR sensor as part of the OPAQUE campaign in 2008. The obtained results are compared against ground measurements collected by the OPAQUE team over a variety of vegetated agricultural fields. The validation of the estimated against ground measured soil moisture results in an root mean square error level of 6–8 \% including all test fields with a variety of crop types.

Index Terms—Multi-angular model-based decomposition, polarimetric SAR, soil moisture.

I. INTRODUCTION

Soil moisture is a key parameter in hydrological modeling recognized by the Global Climate Observing System as an emerging essential climate variable. It affects a variety of hydrological processes like infiltration, percolation, evapotranspiration, and run off. The systematic monitoring of soil moisture with a high spatial and temporal resolution is today a challenge concerning the configuration and implementation of an adequate observation system as well as concerning the development of a robust inversion/estimation methodology [1]–[5].

This paper focuses on the second challenge by means of synthetic aperture radar (SAR) remote sensing. Until recently, single-polarization SAR data at shorter wavelengths (C-band) were mostly used for soil moisture inversion with some success over bare fields [6]. However, the performance of these approaches is strongly compromised by the presence of vegetation. Moreover, the fact, that agriculture fields are most of the year covered by vegetation, makes the development of a distinct approach essential [7]. A promising solution for air- or space-borne applications is the use of fully polarimetric SAR at lower frequencies that allows penetration into vegetation and provides an observation space enabling the interpretation and decomposition of different scattering contributions. Indeed, polarimetric decomposition techniques have been successfully developed and used to “filter” the disturbing vegetation contribution and enable the estimation of the moisture content on the isolated ground components.

Freeman and Durden [8] proposed in 1998 a model-based polarimetric decomposition for forest vegetation, which interprets the measured polarimetric signature of each resolution element in terms of different scattering contributions (surface, dihedral, and vegetation volume). Since then, polarimetric decomposition techniques have been further developed and refined. Based on the idea of separating scatterers by their polarimetric properties, Yamaguchi et al. [9], Arii et al. [10], and Neumann et al. [11], [12] introduced a more detailed description of the vegetation volume component. More recent decompositions compensate for azimuthal rotations to minimize the cross-polarization component [13]. While most effort was set on forest application, the work on agricultural vegetation is rather limited. In 2009, Hajnsek et al. [14] investigated the implementation of polarimetric decomposition techniques at L-band for soil moisture retrieval under agricultural vegetation cover. The analysis along a whole growing cycle showed the importance to account for the surface roughness in the decomposition process for soil moisture retrieval and revealed the limitations arising by the insufficient modeling and removal of the volume (vegetation) component.

Multi-angular inversion approaches for soil moisture have been proposed at C-band in [15]–[21] by means of single- or multi-polarization data. However, the change of conditions in the time between the acquisitions limits to a certain extent the information content of the observable space and hampers a rigorous soil moisture retrieval. Srivastava et al. investigated...
the potential of multi-polarization data (HH/VV and VV/VH) [22]–[24], acquired at different incidence angles and at different dates. They established empirical relations for soil moisture estimation in the presence of vegetation and surface roughness by exploiting multi-angular acquisitions based on backscattering coefficients, but without using the full polarimetric information for the separation of different scattering components.

In this paper, fully polarimetric decomposition techniques are combined with multi-angular acquisitions to develop a physically based decomposition algorithm for soil moisture inversion over bare and vegetated soils. For the analysis, quasi-simultaneously acquired multi-angular fully polarimetric data at L-band are used.

Our approach is introduced in Section II. A sensitivity analysis with respect to angular diversity is given in Section III. Section IV introduces the experimental data of the OPAQUE campaign. The application of the developed approach on the experimental data is described in Section V together with a detailed validation with ground measurements. Finally, in Section VI, potentials and limitations of the proposed approach are discussed, and conclusions are drawn.

II. THEORY OF MULTI-ANGULAR POLARIMETRIC DECOMPOSITION AND INVERSION FOR SOIL MOISTURE

Polarimetric decomposition techniques provide a framework to decompose the backscattered signature into different canonical scattering mechanisms related to scattering contributions of the ground (surface and dihedral component) and vegetation cover (volume component) [25]–[27]. In this sense, the underlying soil scattering can be separated from the vegetation scattering, and the soil moisture \((mv)\) can be inverted using established inversion models.

However, the results in Jagdhuber et al. [28] indicated that the performance of model-based decompositions is limited to a certain range of local incidence angles (\(\sim 20^{\circ} \) to \(\sim 70^{\circ}\)). Outside this local incidence angle (AOI) range, the inversion often leads to non-physical results. In order to increase the inversion rate(s) and to avoid non-physical results, different ranges of AOIs obtained from additional acquisitions performed at different flight headings can be used (Fig. 6). The availability of such multi-angular data requires an optimized multi-angular polarimetric decomposition and inversion scheme as shown in Fig. 1 and described in the following.

A. Processing Scheme for Bare Surfaces

In a first step, an eigenvalue decomposition is applied providing polarimetric entropy \((H)\) and mean scattering alpha angle \((\overline{\alpha})\) values. For this, the coherency-matrix \([T]\) is formed and decomposed into its eigenvalues \(\lambda\) and normalized eigenvectors \(e\), in which \(T^*\) denotes the transpose conjugate [25], [27]:

\[
[T] = \lambda_1 \cdot e_1 \cdot e_1^T + \lambda_2 \cdot e_2 \cdot e_2^T + \lambda_3 \cdot e_3 \cdot e_3^T. \tag{1}
\]

The scattering entropy \(H\) and the mean scattering alpha angle \(\overline{\alpha}\) are calculated with the probabilities \(P\) and \(n = 3\) (for mono-

\[
H = \sum_{i=1}^{n} -P_i \log_P P_i, \quad P_i = \lambda_i / \sum_{j=1}^{n} \lambda_j \tag{2}
\]

\[
\overline{\alpha} = \sum_{i=1}^{n} P_i \cdot \arccos (|e_{i1}|), \quad e_i = [e_{i1} \ e_{i2} \ e_{i3}]^T. \tag{3}
\]

Using the extended Bragg (X-Bragg) model of [29], the range of entropy and alpha values for surface only scattering is determined for each local incidence angle up to a maximum \(mv\) of 50 vol\%. Areas within this \(H/\alpha\)-range are considered as “non-vegetated” bare soil areas and are inverted by using the X-Bragg inversion approach [29]. The obtained \(\varepsilon_s\) values are converted into \(mv\) by applying the universal transformation polynomial of Topp et al., which is valid for a variety of soil texture classes [30]. For the proposed approach, only the real part of the dielectric constant is retrieved, referred as dielectric constant \(\varepsilon\) in the following.

B. Processing Scheme for Vegetated Surfaces

For areas outside the X-Bragg \(H/\alpha\)-range, a scattering scenario consisting of ground and vegetation components is assumed, and the model-based three component decomposition is applied. The approach is described in detail in Appendices A and B, and a shortened version follows. The coherency matrix \([T]\) is decomposed into a depolarizing (rank-3) surface

\[
\begin{align*}
&\text{SOIL MOISTURE INVERSION WITH} \\
&\text{THE EIGEN-BASED DECOMPOSITION} \\
&\text{FOR BARE SOIL} \\
&\text{EXTRACTION OF} \\
&\text{EIGENVALUES/EIGENVECTORS} \\
&\text{CALCULUS OF} \\
&\text{POLARIMETRIC ENTROPY} \\
&\text{AND MEAN SCATTERING} \\
&\text{ALPHA ANGLE} \\
&\text{INVERSION USING} \\
&\text{THE X-BRAGG MODEL} \\
&\text{TOTAL} \\
&\text{SOIL MOISTURE} \\
&\text{OF BARE AND} \\
&\text{VEGETATED SOILS} \\
&\text{FOR 1, 2 OR 3 ACQUISITIONS} \quad \text{GO}
\end{align*}
\]

\[
\begin{align*}
&\text{SOIL MOISTURE INVERSION WITH} \\
&\text{THE EIGEN-BASED DECOMPOSITION} \\
&\text{FOR VEGETATED SOIL} \\
&\text{EXTRACTION OF} \\
&\text{VOLUME POWER} \\
&\text{CORRECTION OF VOLUME POWER} \\
&\text{CALCULUS OF} \\
&\text{DOMINANT GROUND COMPONENTS} \\
&\text{INVERSION dominant} \\
&\text{ground components} \\
&\text{1 ACQUISITION} \\
&\text{FIRST, SECOND, THIRD} \\
&\text{2 ACQUISITIONS} \\
&\text{FIRST, SECOND, THIRD} \\
&\text{3 ACQUISITIONS} \\
&\text{FIRST, SECOND, THIRD}
\end{align*}
\]

---

**Fig. 1. Processing scheme and inversion procedure for \(mv\) form bare and vegetated soils based on a multi-angular polarimetric decomposition (AOI = local angle of incidence).**
scattering component \([T_{XB}]\), a deterministic (rank-1) dihedral scattering component \([T_{AD}]\), and a generalized (rank-3) volume scattering component \([T_{GV}]\) as in (4), shown at bottom of page. In this case, both components, the surface \([T_{XB}]\) and the dihedral \([T_{AD}]\), carry information about the ground.

\([P_{\kappa}]\) describes the propagation through the vegetation layer. In the case, where the eigenpolarizations of the medium are the H and V polarizations, \([P_{\kappa}]\) becomes [27]:

\[
[P_{\kappa}] = e^{-j\left((\kappa_{H}+\kappa_{V})h_{v}\right)} = \begin{bmatrix} 1 & 2(\kappa_{H} - \kappa_{V}) & 0 \\ 2(\kappa_{H} - \kappa_{V}) & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.
\] (5)

\([P_{\kappa}]\) is a function of the vegetation height \(h_{v}\), the local incidence angle \(\theta\) as well as \(\kappa_{H}\) and \(\kappa_{V}\), which are the complex propagation wavenumbers of the eigenpolarizations representing both, attenuation (imaginary part of \(\kappa\)) and phase shifts (real part of \(\kappa\)). The differential wavenumber \(\kappa_{D} = \kappa_{H} - \kappa_{V}\) includes differential attenuation and differential phase shifts.

\(mv\) can be inverted after removing the vegetation component \([T_{GV}]\). The volume component \([T_{GV}]\) is modeled as a cloud of uniformly shaped dipoles with a certain orientation angle distribution, which defines the \([T_{GV}]\)-matrix in terms of a vertically \([T_{VV}]\), horizontally \([T_{HV}]\), or randomly \([T_{RV}]\) oriented volume matrix:

\[
\begin{align*}
\text{General volume} & : [T_{GV}] = f_{v} \begin{bmatrix} C_{1} & C_{4} & 0 \\ C_{4} & C_{2} & 0 \\ 0 & 0 & C_{3} \end{bmatrix}, \\
\text{Vertically oriented volume} & : [T_{VV}] = f_{v} \frac{1}{30} \begin{bmatrix} 15 & 5 & 0 \\ 5 & 7 & 0 \\ 0 & 0 & 8 \end{bmatrix}, \\
\text{Horizontally oriented volume} & : [T_{HV}] = f_{v} \frac{1}{30} \begin{bmatrix} 15 & -5 & 0 \\ -5 & 7 & 0 \\ 0 & 0 & 8 \end{bmatrix}. \\
\end{align*}
\] (6)

The derivation of the different volume components is given in Appendix A, while the theoretical background can be found in [14], [31], and [32]. For a randomly oriented volume \([T_{RV}]\), it applies that \(\kappa_{H} = \kappa_{V}\) and \(\kappa_{D} = 0\). In this case, \([P_{\kappa}]\) reduces to a complex scalar expressing a polarization-independent attenuation and phase shift. For horizontally/vertically oriented volumes, it applies that \(\kappa_{H} \neq \kappa_{V}\) and \(\kappa_{D} \neq 0\). In this case, the volume acts like a polarization filter distorting the surface \([T_{XB}]\) and the dihedral \([T_{AD}]\) scattering signatures.

For reflection symmetric scatterers, the measured coherency matrix \([T]\) provides five independent observables. For a determined inversion problem, it is therefore necessary to predetermined the volume orientation \((C_{1} - C_{4})\), the surface roughness depolarization \((\psi)\), and the propagation parameters of \([P_{\kappa}]\).

In order to select the orientation of the vegetation volume, the approach provided by Yamaguchi et al. [9] is adopted. Accordingly, the co-polarization power ratio is used for the discrimination of horizontally, vertically, or randomly oriented vegetation [cf. (6)].

Further differential propagation effects within the oriented vegetation volumes \([T_{VV}],[T_{HV}]\) are neglected, which is a rather strong assumption associated with a certain estimation error. However, the increasing complexity of the inversion problem, if differential propagation is included, combined with the fact, that we consider rather low vegetation layers (with heights well below 1 m) at a low-frequency-like L-band, makes this assumption reasonable at least for weak differential propagation effects. Instead, a mean attenuation common to all polarizations is accounted in the formulation of the surface and dihedral components in the next section.

Having defined the volume orientation, the volume component \(f_{v}\) is extracted by solving (4) (cf. Appendix B-2). To account for negative scattering power(s) for one (or both) ground components, the volume component \(f_{v}\) is corrected using an eigen-based approach as proposed in [27] and [33] (cf. Appendix B-3). The dominant of the two ground components is then determined by using the criteria proposed in Freeman and Durden [8] (cf. Appendix B-4). Finally, the ground components (surface and dihedral) are estimated by solving the remaining equations in (4) (cf. Appendix B-5).

### C. Inversion Schemes for Soil Moisture

For the inversion of \(mv\), both ground components (surface, dihedral) are used. The inversion for a single quad-pol acquisition case was successfully demonstrated in Jagdhuber et al. [28] and is described in the following.

#### Single-Angular Inversion for Soil Moisture: The surface component \([T_{XB}]\) is modeled by the X-Bragg model, as shown in (4), (7)–(10), which can be understood as an extension of the small perturbation method (SPM) to higher roughness scales [29]. According to [29], the conventional SPM is extended by an azimuthal symmetric roughness term generated by the width \(\psi\) of an angular distribution of facets that introduces depolarization and a cross-polarized signal due to soil roughness. The \(\psi\)-term can be retrieved from the following relation [34], [35]:

\[
\psi = \pi/2 \cdot (1 - |\gamma_{RPLL}|)
\] (7)
where

\[
\gamma_{RRL} = \frac{\langle S_{RR} \cdot S_{LL}^* \rangle}{\sqrt{\langle |S_{RR}|^2 \cdot |S_{LL}|^2 \rangle}}. \tag{8}
\]

\(\lambda_{RRL}\) is the polarimetric circular coherence. \(S_{RR}\) and \(S_{LL}\) are the scattering coefficients in the right-circular and the left-circular copolarization, respectively.

The surface scattering model additionally includes the surface scattering intensity \(f_s\) and the ratio of the surface scattering mechanism \(\beta\) \cite{14,28}:

\[
f_s = \frac{L^2}{2} |R_h + R_v|^2 \quad \text{and} \quad \beta = \frac{R_h - R_v}{R_h + R_v}. \tag{9}
\]

While \(f_s\) rises with increasing soil moisture content due to higher backscattering intensity, the behavior of \(\beta\) as a function of the dielectric constant of the soil (i.e., of increasing soil moisture) is shown in Fig. 2. Both parameters are functions of the horizontal \((h)\) and vertical \((v)\) Bragg coefficients \((R_h, R_v)\) and of a parameter \(L_s\), which accounts for soil roughness and vegetation attenuation \cite{14}

\[
R_h = \frac{\cos \theta - \sqrt{\varepsilon_s - \sin^2 \theta}}{\cos \theta + \sqrt{\varepsilon_s - \sin^2 \theta}},
\]

\[
R_v = \frac{(|\varepsilon_s| - 1) (\sin^2 \theta - \varepsilon_s (l + \sin^2 \theta))}{(|\varepsilon_s| \cos \theta + \sqrt{\varepsilon_s - \sin^2 \theta})^2}. \tag{10}
\]

The Bragg coefficients depend on the dielectric constant of the soil \(\varepsilon_s\) and the local incidence angle \(\theta\). Hence, the X-Bragg surface component \([T_{XH}]\) can be inverted for \(mv\) by using the ratio \(\beta\) \cite{14}, which has the advantage that all mean attenuation effects are cancelled out and no bias occurs on the \(mv\) retrieval for randomly oriented vegetation cover. The presence of volume orientation introduces an additional HH-VV imbalance, which is not accounted for by our model (cf. Section II-B), and introduces an additional estimation error.

The dihedral component \([T_{AD}]\) is modeled as a Fresnel reflection of the soil \((s)\) and the stem of the plant \((t)\) by means of \(\alpha\) and \(f_d\), which represent the dihedral scattering intensity and the ratio of the dihedral scattering mechanism, respectively \cite{14,28}:

\[
\alpha = \frac{R_{s,h} R_{t,h} - R_{s,v} R_{t,v} e^{i \phi}}{R_{s,h} R_{t,h} + R_{s,v} R_{t,v} e^{i \phi}},
\]

\[
f_d = \frac{L_d}{2} \left| R_{s,h} R_{t,h} + R_{s,v} R_{t,v} e^{i \phi} \right|^2. \tag{11}
\]

The parameters are functions of the horizontal \((h)\) and vertical \((v)\) Fresnel coefficients \((R_{s,v}, R_{s,h}, R_{t,v}, R_{t,h})\)

\[
R_{t,h} = \frac{\cos \theta_i - \sqrt{\varepsilon_i - \sin^2 \theta_i}}{\cos \theta_i + \sqrt{\varepsilon_i - \sin^2 \theta_i}},
\]

\[
R_{t,v} = \frac{\varepsilon_i \cos \theta_i - \sqrt{\varepsilon_i - \sin^2 \theta_i}}{\varepsilon_i \cos \theta_i + \sqrt{\varepsilon_i - \sin^2 \theta_i}}. \tag{12}
\]

Fig. 2. Surface component \(\beta\): (top) Variation of \(\beta\) with dielectric constant of the soil \(\varepsilon_s\) for different local incidence angles \(\theta\); (bottom) maximum \(|\beta|\) difference \(|\beta|_{max} = |\beta_{\theta} - \beta_{\theta'}|_{cal}\) as function of the local incidence angle \(\theta\) for different values of \(\varepsilon_s\) (Diamond = 5, Asterisk = 10, Triangle = 20, Plus = 30, Square = 40).

where \(i \in \{t, s\}\). Both, \(\alpha\) and \(f_d\), contain a phase difference \(\phi\) and depend on the local incidence angle \(\theta_s = \theta\) (and \(\theta_t = (\pi/2) - \theta\)) and the dielectric constant of the surface \(\varepsilon_s\) and the trunk \(\varepsilon_t\) \cite{14}. While \(f_d\) increases with increasing soil moisture content due to higher backscattering intensity, \(\alpha\) is decreasing with increasing soil moisture content (cf. Fig. 3). The vegetation/roughness attenuation term \(L_d\) is accounted assuming \cite{28}:

\[
L_d = e^{-1/(\mu_{max} - \mu_{min})} \quad \text{with} \quad \mu_{max} = \frac{\lambda_1}{f_v}, \quad \mu_{min} = \frac{\lambda_2}{f_v}. \tag{13}
\]

In (13), \(\mu_{max}\) and \(\mu_{min}\) represent the maximum and minimum ground-to-volume ratios, expressed by the eigenvalues of the ground component matrices \((\lambda_1, \lambda_2)\) and the volume power \(f_v\). Furthermore, \(L_d\) represents a mean attenuation loss and does not incorporate differential attenuation from different polarizations. After estimation of \(\varepsilon_s\), it is converted into \(mv\) by using the universal polynomial of Topp et al. \cite{30}, which is valid for a variety of soil texture classes.
The dielectric constant of the soil $\varepsilon_s$ is obtained from the surface component by comparing $\beta^m$, i.e., the modeled values for a given local incidence angle $\theta^d$, and $\beta^d$, the value obtained from the decomposition of the data

$$\varepsilon_s = \min \left( \sum_{n=1}^{k} |\beta^m_n(\theta^d_n, \varepsilon_s) - \beta^d_n| \right)$$  (14)

where $n$ are the individual acquisitions. If $\beta^d$ is not included in the range of modeled $\beta^m$, the result is considered as nonphysical and is set invalid.

For the inversion of the dihedral component, the dielectric constant of the soil $\varepsilon_s$ has to be inverted simultaneously with the dielectric constant of the trunk $\varepsilon_t$ (that is also assumed to be the same for all acquisitions) as they are linked within the Fresnel coefficients. Therefore, $\alpha$ and $f_d$ (after correction of vegetation/roughness attenuation by $L_d$) are utilized in a combined approach to retrieve $\varepsilon_s$ and $\varepsilon_t$

$$\varepsilon_s, \varepsilon_t = \min \left( \frac{\sum_{n=1}^{k} |f^m_n(\theta^d_n, \varepsilon_s, \varepsilon_t) - f^d_n|}{\sum_{n=1}^{k} |\alpha^m_n(\theta^d_n, \varepsilon_s, \varepsilon_t) - \alpha^d_n|} \right)$$  (15)

where $f^m$ and $\alpha^m$ represent the modeled values, while $f^d$ and $\alpha^d$ are the values obtained from the decomposition of the data. If $f^d$ and $\alpha^d$ are not included in the range of modeled $f^m$ and $\alpha^m$, the result is considered as nonphysical and is set invalid. The retrieval of $mv$ from the dielectric constants of the soil $\varepsilon_s$ is the same as for the single image case. In a last step, the estimated $mv$ from the vegetated surfaces and the bare surfaces are combined. For pixels where more than one $mv$ result from the different methods is present, the average is taken.

The proposed multi-angular, fully polarimetric decomposition technique for soil moisture inversion combines incidence angle and polarimetric diversity to achieve a soil moisture retrieval, which is robust for a variety of vegetation cover without the need of a priori information and/or model calibration. The major difference to other proposed approaches in [15]–[24] is the application of polarimetric decomposition techniques to separate the vegetation layer contribution and to isolate the ground scattering contribution used for an unbiased retrieval of the soil signature for inversion.

### III. Model Sensitivity Analysis on Angularity

The sensitivity analysis of the X-Bragg model inversion with respect to the local incidence angle is given in [29]. Accordingly, the sensitivity to $mv$ increases at shallower incidence leading to better conditions for $mv$ inversion in the far range regions ($\theta > 40^\circ$), which may be confined by a reduced SNR level. At steeper incidence angles ($\theta < 30^\circ$), the sensitivity of the model degrades leading to unfavorable conditions for $mv$ inversion. The surface parameter $\beta$ [see (9)] and the dihedral parameter $\alpha$ [see (11)] are plotted in Figs. 2 and 3 as function of the dielectric constant of the soil $\varepsilon_s$ for different local incidence angles. The sensitivity of $\beta$ to $\varepsilon_s$ is increasing at shallower local incidence (cf. Fig. 2 upper plot). This becomes also clearly visible on the lower plot in Fig. 2, where the

**Multi-Angular Inversion for Soil Moisture:** In the case of a multi-angular inversion, each acquisition geometry $k$ provides a set of $\alpha$, $\beta$, and $f_d$ values that has to be inverted for $mv$ in a multi-acquisition inversion scheme. For quasi-simultaneously acquired scenes, it is appropriate to assume the same dielectric constant of the soil and the trunk for all acquisitions. In contrary, vegetation (e.g., orientation) and roughness conditions may be different as agricultural fields are tilled and planted in different row directions with respect to the sensor trajectory. The simplifying assumption of a random vegetation volume that appears the same in all acquisitions has been proven to be insufficient to describe the data set (cf. Fig. 7). Thus, in order to incorporate a variety of cultivation practices and vegetation diversity, a separate decomposition of the volume and the roughness influence on each scene is performed as described before.

The inversion of the multi-angular cases ($k = 2, 3$) is carried out using minimum pixel-by-pixel operators for the surface and dihedral scattering component in the following way (cf. [36]).
maximum $|\beta|$ difference ($|\beta|_{\text{max}} = |\beta_0 - \beta_{\text{IR}}|_{\text{max}})$ is plotted for different $\varepsilon_s$-levels. The behavior is even more distinct under wet soil conditions ($\varepsilon_s > 20$). Hence, surface $\text{mv}$ inversion benefits from shallow local incidence angles.

The contour plots in Fig. 3 display the variation of the parameter $\alpha$ as function of the dielectric content of the soil $\varepsilon_s$ and of the trunk $\varepsilon_t$ for different local incidence angles $\theta$. For the steep local incidence angle of 30$^\circ$ (top of Fig. 3), the sensitivity to the dielectric properties of the trunk $\varepsilon_t$ is higher than for the dielectric properties of the soil $\varepsilon_s$.

The sensitivity to $\text{mv}$ decreases for wetter soil conditions. The situation changes beyond 45$^\circ$ local incidence. In the case of 60$^\circ$ local incidence the dihedral parameter $\alpha$ is more sensitive to the dielectric properties of the soil $\varepsilon_s$ than to the dielectric properties of the trunk $\varepsilon_t$. This is particularly true for higher moisture levels of the trunk component (cf. Fig. 3 bottom plot).

Thus, the optimum sensitivity of the dihedral parameter $\alpha$ for the dielectric constant of the soil $\varepsilon_s$ is also given at shallow local incidence angles. The $f_v$-parameter is not further considered due to its small (compared to the parameters $\alpha$ and $\beta$) variation with local incidence angle (cf. [14]).

In Fig. 4, the error of the surface soil moisture inversion caused by an increasing amount of vegetation volume (i.e., volume power $f_v$) is presented for a local incidence angle range from 25$^\circ$ to 55$^\circ$.

For all three volume orientation cases (vertical, horizontal, random), the error is smaller at shallow local incidence angles (e.g., bottom plot of Fig. 4). This behavior is particularly pronounced for the horizontally oriented volume (solid line in Fig. 4) case due to the negative $T_{12}$-$T_{21}$-elements. However, this advantage vanishes, when due to the longer propagation path through the vegetation layer attenuation decreases the effective ground components.

The incidence angle dependency is very weak for the surface soil moisture inversion with an increase of soil roughness as shown in Fig. 5.

Therefore, the trend of the deviation for an $k_s$-range from 0 to 0.3 (validity range of the surface scattering model) stays almost constant for the complete local incidence angle range from 25$^\circ$ to 55$^\circ$ (the lines for 25$^\circ$ and 40$^\circ$ are almost overplotted), which indicates almost no dependency on the local incidence angle.

The fact that gentle terrain variations are sufficient to lead to unfavorable local incidence angle range conditions, where the surface and/or dihedral parameters are less sensitive to $\text{mv}$, motivates a multi-angular approach. This should enable higher inversion rates and higher estimation accuracy compared to the single acquisition case.

IV. EXPERIMENTAL DATA OF THE OPAQUE CAMPAIGN

The OPAQUE campaign was conducted in May 2008 in the Weißeritz catchment area near Dresden, Germany [37]. OPAQUE stands for operational discharge and flooding predictions in head catchments and is a project performed by the University of Potsdam, the German Research Center for Geosciences, the University of Stuttgart, and the German Aerospace Center. The identification of critical catchment states caused by saturated top soil layers for an improvement of flood forecasting and hazard warning is one of the main project objectives.

During the campaign, L-band fully-polarimetric SAR data were acquired by German Aerospace Center’s (DLR’s) airborne E-SAR sensor along three different flight headings. In Fig. 6, the three acquisitions are combined in an RGB-composite and are labeled as “master” (m), “opposite” (o), and
Fig. 5. Error of the dielectric constant ($\Delta \varepsilon_s$) for the inversion of the surface component $\beta$ as function of the increasing surface roughness $k_s$ for $25^\circ$ (solid), $40^\circ$ (dash-dot-dotted) and $55^\circ$ (dashed) local incidence angle (input $\varepsilon_s = 20$).

Fig. 6. RGB composite of the three different incidence angle acquisitions in HH-polarization for L-Band (R: Master, G: Opposite, B: Perpendicular); red frame indicates the overlapping area of the three flight strips.

TABLE I
FIELD MEAN VALUES OF in situ MEASUREMENTS: SOIL MOISTURE ($m_v$), STANDARD DEVIATION OF $m_v$($\Delta m_v$)FOR EACH FIELD, VEGETATION HEIGHT (HEIGHT), AND WET BIOMASS (BIOMASS) (WT = WINTER TRITICALE, WB = WINTER BARLEY, WR = WINTER RYE, WW = WINTER WHEAT, SO = SUMMER OAT, − = NO MEASUREMENT).

<table>
<thead>
<tr>
<th>Fields</th>
<th>$m_v \pm \Delta m_v$ [vol.%]</th>
<th>Height [cm]</th>
<th>Biomass [kg/m$^2$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>WT</td>
<td>19.4 ± 3.5</td>
<td>23.0</td>
<td>0.39</td>
</tr>
<tr>
<td>WB</td>
<td>11.8 ± 3.0</td>
<td>24.4</td>
<td>0.66</td>
</tr>
<tr>
<td>WR</td>
<td>19.9 ± 3.3</td>
<td>17.4</td>
<td>0.15</td>
</tr>
<tr>
<td>WW</td>
<td>16.9 ± 2.7</td>
<td>14.0</td>
<td>0.24</td>
</tr>
<tr>
<td>SO</td>
<td>22.7 ± 2.8</td>
<td>6.75</td>
<td>-</td>
</tr>
</tbody>
</table>

For the soil moisture measurements at 0–5 cm depth, “ThetaProbe ML2×” Frequency Domain Reflectometry (FDR) probes were used. The $m_v$ value at each measurement location was obtained by averaging three individual measurements (cf. Table I for field mean values).

The standard deviation ($\Delta m_v$) of all measurements within each of the five test fields indicates a variation of 12–25% of the measured $m_v$, which cannot be allocated to topographic variations and might be due to the local moisture variability within the fields. In Table I also, the mean height and the mean wet biomass of the vegetation cover are presented.

V. POLARIMETRIC DECOMPOSITION AND
SOIL MOISTURE INVERSION

The proposed multi-angular polarimetric decomposition and soil moisture inversion algorithm was applied on the OPAQUE data set. The three flight headings allow seven different inversion configurations incorporating one, two, or three acquisitions.

In Fig. 9, the local incidence angle for each acquisition (master, opposite, perpendicular), the normalized power components of the model-based decomposition, the results of the inverted $m_v$ for the seven different incidence angle configurations, and a land use map including references for the test fields are shown. The area common to all acquisitions is indicated by the red frame.

Due to the complex local topography caused by the river morphology, the local incidence angle covers a wide range of values; from almost perpendicular until grazing (see first column of Fig. 9). The influence of the topography on the three scattering mechanisms can be seen by comparing the local incidence angle maps with the decomposition results (see Fig. 7 as well as second column of Fig. 9). In regions with steep local incidence surface scattering (blue colored in the second column of Fig. 9) dominates, while for shallower local incidence dihedral scattering (red colored in the second column) emerges, sometimes even on the same type of land use (e.g., white frame in Fig. 9—grass land).

The results of the model-based decomposition (second column in Fig. 9) appear plausible and physically meaningful, when compared against the land use information, which is in accordance with the results in Hajnsek et al. [14]. The flexibility, provided by the selection of the decomposition components (cf. Fig. 1), is important for fitting the variety of scattering scenarios in the scene, as shown in Fig. 7. Most of the agricultural fields show randomly oriented vegetation over dominant surface scattering in all the three acquisitions. This is a strong indication for negligible differential attenuation effects within the agricultural fields and fits to the vegetation measurements stating an emerging vegetation layer with heights smaller than 25 cm.

The analysis of the distribution of decomposition method together with the land use information, both shown in Fig. 7, indicates a meaningful selection of the volume orientation by the approach of [9], even under low vegetation conditions. The separation into vegetated and non-vegetated areas by the $H/\alpha$-criterion assists here, in order to classify the ground-dominant pixels to diminish wrong estimations in the vegetation

“perpendicular” (p). Simultaneously, soil moisture and vegetation parameters (vegetation height, biomass, and phenology) were measured on selected test fields covering different vegetation types (winter triticale, winter barley, winter rye, winter wheat, summer oat). A summary of the measurements for the different test fields is shown in Table I.
volume orientation. However, the analysis of the decomposition methods and of the surface ground-to-volume ratios from the decomposition (not shown in the manuscript) state a distinct influence of the low vegetation layer on the polarimetric signature, which has to be removed for vegetated soils before moisture inversion. Focusing on $m v$ (third to fifth column of Fig. 9), the achieved results range from 0 vol.% to 50 vol.%.

Non-invertible pixels, e.g., in the forested areas in the upper right corner of Fig. 9 are masked white. $m v$ inversions based on a single acquisition (see third column) are characterized by low inversion rates at steep local incidence angles ($\theta < 25^\circ$).

Emphasizing this effect, the distribution of the surface scattering component $\beta$ against the local incidence angle $\theta$ is shown exemplarily for the “master” and the “perpendicular” acquisition in Fig. 8, where the analysed $\beta$ values are taken from the overlapping region (red box) shown in Fig. 9. The upper boundary (corresponding to dry soil: $\varepsilon_s = 2$) and the lower boundary (corresponding to wet soil: $\varepsilon_s = 41$) for the modeled $\beta$ values from (9) and (10) are overplotted. All $\beta$ values extracted by the model-based decomposition, which are located within the two bounds, can be inverted for soil moisture.

Accordingly, a predominant proportion of the $\beta$ values in Fig. 8 matches the surface scattering model, particularly at shallower incidence angles ($\theta \geq 30^\circ$). However, $\beta$ values outside the bounds of the surface scattering model are not invertible and are considered as non-physical results (white areas in soil moisture images of Fig. 9).

Figs. 8 and 9 confirm both, the insensitivity of the model (cf. Fig. 2) as well as the impact of vegetation (cf. Fig. 4) at steep incidence angles as predicted by the sensitivity analysis.
In this sense, the limitations of a single-angular approach for soil moisture inversion are evident in the third column of Fig. 9. The advantage of the multi-angular approach regarding the inversion rate becomes clear in the fourth and fifth columns of Fig. 9. An analysis of the inversion results for \( m \) on the overlapping areas (red box) shows a significant increase of the inversion rates when moving from simple single-angular to multi-angular approaches (cf. Table II). For a single acquisition in a single-angular configuration, an inversion rate of about 30–50\% is achieved, whereas for two acquisitions in a bi-angular configuration, the rate rises to about 55–65\%. Finally, using all three acquisitions, i.e., in a tri-angular configuration, an inversion rate of about 70\% is reached.

In Table III, the different local incidence angles for the test fields (summer oat, winter triticale, winter barley, winter rye, and winter wheat) are shown on a field scale. The local incidence angle over the fields varies between 23.4\(^\circ\) and 58.6\(^\circ\). The field measurements in Table I indicate a dry weather period, with soil moisture values between 11.8 vol.\% and 22.7 vol.\% for all test fields.

The vegetation is at this time in its emerging stage with a maximum height of 24 cm, except for the summer oat field.
which is almost bare (cf. Table I). This low vegetation layer on the fields in spring is in many cases insufficient for a detection as “vegetated area,” when applying the $H/\alpha$ preselection described in Section II, but it is sufficient to bias the X-Bragg inversion results, when the areas are considered as bare. Therefore, the three component model-based decomposition is also applied to those areas, which are classified in the first step as bare surfaces and the surface component is used to estimate $mv$.

A. Validation of Soil Moisture Inversion

The obtained $mv$ results for each of the seven different incidence angle configurations are validated against the ground measurements. The estimated $mv$ values have been averaged within a $13 \times 13$ box centered at the sampling points leading to 169 samples for a pixel resolution of $2 \times 2$ m. To avoid outliers only boxes with at least 70% invertible pixels have been considered (cf. Fig. 10).

In Fig. 11(a)–(h), scatter plots display the comparison of measured to estimated $mv$ for the different configurations. Additionally, the root mean square error (RMSE) is given in Table IV for all investigated fields and all configurations. The RMSE values range from 4.41 vol.\% to 10.33 vol.\%, while a minimum of five pairs of measured and inverted $mv$ has been used. Fields with a low inversion rate ($< 5$ valid samples) have been discarded (cf. Fig. 10). The winter wheat field is such an example, where the steep local incidence angle of 26.6° in the case of a single-angular inversion using the “opposite” acquisition makes the $mv$ inversion impossible. This is also the reason, why the validation of the $mv$ retrieval from a single-angular configuration (master, opposite, perpendicular) cannot be performed for all fields as evident in Figs. 9 and 11(a)–(c).

The multi-angular configurations provide higher inversion rates and lead to continuous $mv$ patterns, even for high validation requirements (70% box coverage for a valid inversion result).

Considering the mean RMSE over all fields the best performance and the highest inversion quality is obtained for the triangular configuration (m-o-p): A mean RMSE of 5.85 vol.\% and a mean STDDEV of 9.47 vol.\% have been achieved (cf. Fig. 11(d) and (h) and Tables IV and V).

For the bi-angular approaches, the mean RMSE values lie between 5.95 vol.\% and 8.13 vol.\%, while for the single-angular approaches, the mean RMSE is in all cases higher than 6.17 vol.\%. The results confirm a mean RMSE for the different approaches in the range of 6–8 vol.\% and a mean of STDDEV between 10 and 11 vol.\%, that becomes slightly better for the case of the tri-angular inversion below 6 vol.\% (RMSE) and below 10 vol.\% (mean of STDDEV) (cf. Fig. 11 and Tables IV and V).

On the field scale, the results of the winter rye field indicate the highest stability with a RMSE below 6.5 vol.\% for all configurations, primarily because of the moderate to shallow local incidence (33.9°, 35.2°, 52.9°), which is favorable for $mv$ retrieval (cf. Section III).

Also, the winter wheat field with 58.6° local incidence for the “master” acquisition yields a favorable RMSE of 4.52 vol.\% due to an inversion dominated by the bare soil method (using $H - \alpha$ and the X-Bragg model) under predestinate shallow incidence angle conditions (cf. Section III).

The summer oat field shows a RMSE of 8.55 vol.\% due to an underestimation of $mv$ for the “master” acquisition, which is caused by the very steep local incidence angle of 23.4°. It is of interest, that, even if the vegetation layer is weak (6.5 cm vegetation height), the inversion using the bare soil approach fails because of the steep local incidence angle.

The winter triticale and the winter wheat field are located in the far range with 53.5° and 55.5° of the “perpendicular” acquisition and exhibit the highest variability with an RMSE of more than 9.5 vol.\%. The local incidence angle range allows a $mv$ inversion, but for these fields, the $mv$ retrieval with the “perpendicular” acquisition leads to an overestimation. One reason might be the low vegetation layer of 14–23 cm, which causes valid results for bare soil inversion on some parts of the fields misinterpreting low vegetation for roughness. The same problem is occurring for the winter barley field with a local incidence angle of 43.4° and a vegetation height of 24.4 cm resulting in an RMSE of 9.75 vol.\%. A second reason might be the poor roughness estimation of the surface component (cf. Fig. 5), which appears highly rough for the winter triticale and the winter wheat field in the “perpendicular” acquisition scenario. This might be caused by the shallow incidence combined with the presence of a low vegetation layer and a specific orientation of the soil furrows. So far, neither the bare soil inversion nor the model-based inversion works sufficiently well. In this case, angular diversity is not helping (cf. Fig. 5 for insensitivity of roughness on multi-angularity).

VI. DISCUSSION AND CONCLUSION

A multi-angular polarimetric decomposition and inversion technique for $mv$ retrieval has been proposed and demonstrated on fully polarimetric L-band data acquired by DLR’s airborne E-SAR sensor within the OPAQUE campaign conducted in May 2008 in the Weißeritz catchment area near Dresden, Germany. The obtained results indicate a significant rise of inversion rate from 30% for the single-angular case to 70% for the tri-angular case. The results demonstrate that topographic effects caused by local slopes can be compensated, if more
Fig. 11. (a)–(h). Scatter plots of measured to estimated soil moisture values in vol.% for the different incidence angle scenarios including all investigated fields (w = winter, s = summer) (dashed lines indicate the ±10 vol.% interval). (a) master (m) acquisition; (b) opposite (o) acquisition; (c) perpendicular (p) acquisition; (d) m-o-p configuration; (e) m-p configuration; (f) m-o configuration; (g) o-p configuration; (h) field mean value of soil moisture for one field from m-o-p configuration (gray bars indicate the standard deviation of the estimates and the measurements).
than a single acquisition is used in the mv inversion. The performed sensitivity analysis indicates a higher sensitivity to the ground scattering components (surface, dihedral) at higher local incidence angles. The estimated mv values were validated against ground measurements from FDR, remote sensing (RD), and field tests with different crop types. The mean RMSE of the mv retrieval with the different incidence angle configurations indicates a stable inversion for the majority of configurations resulting in an error level of approximately 6–8 vol.% (level of mean STDDEV 10–11 vol.% with a slight improvement for the tri-angular approach incorporating three acquisitions (master-opposite-perpendicular) with a mean RMSE of 5.9 vol.% (mean STDDEV of 9.5 vol.%).

The availability of more acquisitions in the mv retrieval does not imply automatically a better performance given by a decrease in RMSE. This might be due to the assumptions made to obtain a determined inversion problem. The roughness term ($\psi$) and the estimation of the orientation of the volume component inside the model-based decomposition [$T_{GV}$] using the power ratio $P_r$ as well as the bare soil classification with the $H - \alpha$ criterion are estimated for each acquisition separately. This can lead to a reduced quality of the results for certain ranges of local incidence angles on natural media due to model insensitivities (cf. Section III). Moreover, the elongated ray path through the vegetation layer for large local incidence angles increases the influence of the vegetation volume and the ground scattering components. Hence, the quality of an inversion with a combination of two or three scenes for a multi-angular approach can be affected by the validity of the underlying assumptions on each of the single scenes.

This explains also why the incorporation of more than one scene in the algorithm is not necessarily resulting in an accuracy improvement of the mv estimation. For example, the configuration using the “opposite” and the “perpendicular” acquisition in a bi-angular approach obtains a mean RMSE of 8.15 vol.%, which is distinctly higher than utilizing only the “master” acquisition with 6.17 vol.% of mean RMSE. The configuration of ascending and descending acquisitions (i.e., master-opposite) appears more favorable than the configuration with perpendicular headings (i.e., opposite-perpendicular) considering equivalent local incidence angle conditions for both configurations (cf. Table III). This can be caused on the one hand by the fact that the effective soil roughness as well as the orientation distributions of the vegetation in agriculture appear different at orthogonal (perpendicular) headings and on the other hand by the effect that in the ascending-descending configuration, the low performing near range inversion from the one acquisition is outperformed by the well performing far range inversion from the opposite acquisition. Therefore, an ascending-descending combination of fully polarimetric acquisitions seems to be suited for space-borne applications.

Finally, the proposed approach combines for the first time polarimetric decomposition techniques with the concept of multi-angularity. This adds up to a major increase in inversion rate for mv estimation and a stable inversion quality over all investigated test fields for the majority of incidence angle configurations. Remaining uncertainties of the developed approach have to be addressed in the future. However, a polarimetric inversion model has to compromise between the degrees of freedom in the modeling of the single scattering components (increasing the number of variables) and the observation space available. In agricultural areas, a generalized inversion model is important that allows accounting for the volume as well as the ground complexity being at the same time invertible without a priori knowledge. Thus, the incorporation of a depolarizing surface component accounting for surface roughness induced cross polarization and the inclusion of a flexible volume component considering different phenological stages are essential. Differential propagation through the vegetation volume has not been considered in the proposed approach, as it plays a negligible role in the phenological stage of emerging vegetation. In addition, it increases significantly the complexity of the inversion problem making it practically unsolvable, if only polarimetric acquisitions are available. Therefore, an extension to polarimetric interferometric techniques may be a possible solution together with a validation campaign during the maturity stage of the vegetation growth cycle [38].

### APPENDIX

#### A. Modeling of Vegetation Volume Component

Three different orientation cases are modeled in order to characterize a specific vegetation volume with the volume component [$T_{GV}$]: Random orientation, horizontal orientation,
and vertical orientation. For modeling a randomly oriented volume of dipoles \([T_{RV}]\), the orientation distribution results in a distribution width of \(\Delta \tau = 2\pi\) and a probability density function (pdf) of \(p(\tau) = 1/(2\pi)\) within \(0 < \tau < 2\pi\). For modeling an oriented volume of dipoles \([T_{VV}], [T_{HV}]\), the orientation distribution shows a distribution width of \(\Delta \tau = \pi\). For vertical orientation the pdf as \(p(\tau) = (1/2) \sin \tau\) is defined within \(0 < \tau < \pi\), whereas for horizontal orientation, the pdf as \(p(\tau) = (1/2) \cos \tau\) within \(-\pi/2 < \tau < \pi/2\) is used. Finally, the volume coherency matrices shown in (6) are obtained.

**B. Three-Component Model-Based Decomposition**

In the following paragraphs, the single steps for the model-based three-component decomposition are described in more detail.

1) **Estimation of Vegetation Volume Orientation:** The orientation of the vegetation volume is estimated by a power ratio \(P_v\) of the vertical divided by the horizontal copolarizations (cf. [9])

\[
P_v = 10 \cdot \log \left( \frac{|S_{VV}|^2}{|S_{HH}|^2} \right) \quad (16)
\]

where

\[
P_v < -2 \text{ dB} \quad \text{vertically oriented dipoles: } [T_{VV}]
\]
\[-2 \text{ dB} < P_v < 2 \text{ dB} \quad \text{randomly oriented dipoles: } [T_{RV}]
\]
\[P_v > 2 \text{ dB} \quad \text{horizontally oriented dipoles: } [T_{HV}]
\]

Depending on the result of (16) the respective vegetation volume \([T_{VV}], [T_{RV}], [T_{HV}]\) is allocated to \([T_{GV}]\). As \(P_v\) is estimated before separation of the volume and the ground components, the influence of the underlying soil conditions can bias the volume orientation estimation, if the volume conditions are nondominant. However, in this case, the volume intensity \(f_v\) should be also considerably reduced in order to limit this disturbing effect.

2) **Extraction of Volume Power:** After retrieval of the appropriate volume matrix, the linear system of equations in (4) is solved analytically for the volume parameter \(f_v\), whereas (7) and (8) are used for the calculus of \(\psi\). It is important to note that \(f_v\) is calculated differently according to the volume orientation and the scattering dominance. Since the dominance criterion is only known in a later step of the algorithm, both \(f_v\) values, from surface and from dihedral dominant cases, have to be calculated until the scattering dominance is determined.

3) **Correction of Volume Power:** A remaining coherency matrix \([T_{RemV}]\) is calculated as displayed in (17) by the subtraction of the respective volume component \([T_{GV}]\) from the acquired SAR data and solved for its three eigenvalues (cf. [33]). The three eigenvalue equations are set to zero and solved for \(f_v\)

\[
[T_{RemV}] = \begin{bmatrix}
T_{11} & T_{12} & 0 \\
T_{12} & T_{22} & 0 \\
0 & 0 & T_{33}
\end{bmatrix} - f_v \begin{bmatrix}
C_1 & C_4 & 0 \\
C_4 & C_2 & 0 \\
0 & 0 & C_3
\end{bmatrix}.
\quad (17)
\]

These solutions for \(f_v\) are compared with the extracted \(f_\text{v}\) of the previously calculated three component decomposition to find the minimum \(f_\text{v}\) value. This minimum \(f_\text{v}\) will be used in a later step to subtract the corrected and selected volume component from the measured coherency matrix \([T]\) for the retrieval of the ground scattering components (surface and dihedral).

4) **Estimation of Scattering Dominance:** The scattering dominance is estimated by a criterion defined by Freeman and Durden to set the parameter \(\alpha\) or \(\beta\) in the non-dominant case to zero [8], [39]. Subsequently, the system of equation for the model-based decomposition is uniquely determined and can be solved for the ground components [8], [14], [39].

5) **Calculation of the Ground Components:** After the estimation of the scattering dominance, the before corrected and selected volume component \(f_v\) is subtracted from the measured SAR data and, according to the scattering dominance, the dominant ground components (surface dominant: \(f_s, \beta, f_d\), dihedral dominant: \(f_d, \alpha, f_s\)) for each pixel are calculated. Finally, the dominant ground components (surface or dihedral) can be inverted for \(mv\) for each pixel (cf. Section II).

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