IMPROVEMENT OF VEGETATION PARAMETER RETRIEVAL FROM POLARIMETRIC SAR INTERFEROMETRY USING A SIMPLE POLARIMETRIC SCATTERING MODEL

Maxim Neumann¹, Laurent Ferro-Famil¹, and Andreas Reigber²

¹SAPHIR Team, IETR, Université de Rennes 1, France, Email: maxim.neumann@univ-rennes1.fr
²German Aerospace Center (DLR), Microwave and Radar Institute, Wessling, Germany

ABSTRACT

This paper concerns vegetation parameter retrieval from polarimetric interferometric SAR (PolInSAR) data. A two–component polarimetric interferometric model, designed for geophysical parameter retrieval, is presented for volumetric media over ground. It is based on a scattering model based polarimetric decomposition and the random volume over ground (RVoG) PolInSAR inversion technique. For forest vegetation observed at L–band, this model accounts for the ground topography, canopy layer and total tree heights, wave attenuation in the canopy, tree morphology in the form of orientation distribution and effective shapes of the branches, surface scattering contribution, and double–bounce ground–trunk interactions. A parameter retrieval framework is developed for repeat–pass acquisitions which aims to estimate and to compensate temporal decorrelation. The parameter estimation performance is evaluated on real airborne L–band SAR data. The contributions of the ground and the vegetation are separated to permit further analysis of ground properties and canopy layer morphology.

1. INTRODUCTION

Polarimetric SAR Interferometry (PolInSAR) provides strong means for vegetation parameter retrieval as it is sensitive to the vertical structure and the physical characteristics of the scattering media. In this paper, we seek to combine polarimetric model–based decompositions [1–3] with PolInSAR random volume over ground (RVoG) parameter inversion techniques [4–6]. The goal of this approach is to model separately ground and volume contributions, in order to enhance the estimation of structural vegetation parameters, and to permit the retrieval of morphological vegetation parameters as well as ground parameters under the vegetation for further analysis.

The presented PolInSAR model is intended for single– and multi–baseline repeat–pass acquisitions, and the temporal behavior of the coherence is analyzed with the goal to develop a parameter retrieval framework which is robust against temporal decorrelation. Initial results based on simulated data and neglecting temporal decorrelation were already presented in [7].

In the next section, a polarimetric and interferometric model [8, 9] for a vegetated area is briefly presented. In section 3, the vegetation parameter retrieval problem is discussed in terms of the inverse theory, and a parameter retrieval framework is presented. In section 4, the model and the parameter retrieval approaches are evaluated using real airborne SAR data, acquired by the German Aerospace Center’s E–SAR system at L–band.

2. MODEL

A simplified forest model, consisting of a single homogeneous canopy layer above the ground, is shown in Fig. 1. The canopy layer fills a fraction $r_c$ of the total vegetation height. The main scattering contributions explicitly denoted are surface, volume and double–bounce. In this section, a general polarimetric and interferometric model is developed and presented, starting with the characterization of the vegetation.

2.1. Vegetation Characterization

A simplified volumetric vegetation layer can be characterized by a cloud of scattering particles whose electromagnetic properties are governed by the probability density functions (PDF) of their positions, shapes, sizes, dielectric constants, tilts, and orientations in the polarization plane. The single particle scattering properties are
assumed to be independent of position and polarization orientation. Under the hypothesis that particles have an axis of symmetry, one may represent the average particle backscattering matrix after projection into the polarization plane in the eigenpolarization basis by

\[
E \{ \mathbf{S} \} = \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix} = \frac{a + b}{2} \begin{bmatrix} 1 + \delta^* & 0 \\ 0 & 1 - \delta \end{bmatrix}
\]

(1)

where \(E \{ \} \) implies expectation value operation, \(^*\) is the complex conjugate operator, and

\[
\delta = \left( \frac{a - b}{a + b} \right)^* \quad (2)
\]

is the particle anisotropy, which describes the scattering properties of an average particle, as perceived by the radar, independently of orientation and scattered power. The average backscattering matrix at a given polarization orientation angle \(\psi\) is given by

\[
E \{ \mathbf{S}(\psi) \} = \mathbf{R}^T_{S(\psi)} E \{ \mathbf{S} \} \mathbf{R}_{S(\psi)} = \begin{bmatrix} \cos \psi & \sin \psi \\ -\sin \psi & \cos \psi \end{bmatrix} \quad (3)
\]

where \(\mathbf{R}_{S(\psi)}\) is a rotation matrix for the polarization orientation angle change.

The particle anisotropy characterizes the effective shape of the average particle in dependence of the particle and background permittivities. If the particle permittivity is similar to the background permittivity (i.e., air), the particle anisotropy tends towards 0 independently of the real shape of the particle [10]. If the permittivities are significantly distinctive, one can make the following predictions about the effective particle shapes, assuming simple ellipsoid particles: as \(|\delta| \to 0\), the average effective particle shape approaches an isotropic sphere/disk, whereas for \(|\delta| \to 1\) the effective shape tends towards a dipole. If the phases of the scattering coefficients \(a\) and \(b\) are similar, then \(\delta\) is a function only of their moduli. Then, in the line of sight direction, the particle axis of symmetry tends to be horizontal if \(\text{Re}\ \delta > 0\) and vertical if \(\text{Re}\ \delta < 0\), with respect to the polarization basis of the particle scattering amplitude matrix. The interpretation of \(\delta\) becomes more complex when the phases of \(a\) and \(b\) diverge.

The imaginary part of the forward scattering amplitude matrix determines the extinction \(\tau\) inside the vegetation layer [11]. The scatterers are assumed to be uniformly distributed inside the layer.

The particle orientation angles \(\psi\) in the polarization plane are assumed to follow a unimodal circular distribution \(p_\psi(\psi, \kappa)\) and to be independent from other vegetation characteristics. Under the central limit theorem condition, given a large number of scatterers, the orientations of these scatterers are normally distributed, and follow the circular normal distribution (also known as the \textit{von Mises} distribution) [12] which is the circular analogue of the Gaussian distribution:

\[
p_\psi(\psi, \kappa) = \frac{e^{\kappa \cos(2(\psi - \tilde{\psi}))}}{\pi I_0(\kappa)}, \quad \kappa \in [0, \infty] \quad (4)
\]

where \(\kappa\) is the degree of concentration (analogous of the inverse of the standard deviation), \(\tilde{\psi} \in [-\pi, \pi]\) is the mean orientation angle, and \(I_0(\kappa)\) is the modified Bessel function of order 0. For the sake of interpretation, the normalized degree of orientation randomness \(\tau\) is introduced by

\[
\tau = I_0(\kappa)e^{-\kappa}, \quad \tau \in [0, 1] \quad (5)
\]

As \(\tau \to 0\) the volume becomes strongly aligned in the preferred polarization orientation direction, whereas for \(\tau \to 1\) the particle orientations become completely random. Note that the degree of orientation randomness becomes meaningless for (effectively) isotropic scatterers (\(\delta = 0\)).

2.2. Polarimetry

Second-order scattering statistics for random media can be better represented in the Pauli matrix basis. Assuming reciprocity, the scattering vector and the coherency matrix are given in the Pauli basis by

\[
k = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{hh} + S_{vv} \\ S_{hh} - S_{vv} \end{bmatrix}, \quad \mathbf{T} = E \{ k k^\dagger \} \quad (6)
\]

where \(^\dagger\) is the Hermitian operator.

In analogy to the Freeman–Durden model [1], the coherency matrix under the modeled assumptions can be decomposed into

\[
\mathbf{T} = f_s \mathbf{T}_s + f_d \mathbf{T}_d + f_v \mathbf{T}_v = f_g \mathbf{T}_g + f_v \mathbf{T}_v \quad (7)
\]

where the individual coherency matrices are normalized with reference to the \(E \{|S_{hh} + S_{vv}|^2\}\) terms, so that \(f_{s/d/v}/\delta\) are equal to these power values. For simplicity, the surface and the double–bounce terms are summed to a single ground contribution, since this combination does not restrict in any way the retrieval of vegetation parameters. In the general case, the ground coherency matrix can be represented in the ground eigenpolarizations by a reflection symmetric form

\[
\mathbf{T}_g = \begin{bmatrix} 1 & \beta^* & 0 \\ \beta & 0 & 0 \\ 0 & 0 & \beta \end{bmatrix} \quad (8)
\]

consisting of 4 polarimetric degrees of freedom (\(\beta \in \mathbb{C}, \beta_{22}, \beta_{33} \in \mathbb{R}\)).

Using (3), the normalized first–order coherency matrix of a single particle is given by

\[
\mathbf{T}_v(\psi) = \mathbf{R}_{T(2\psi)} \begin{bmatrix} 1 & \delta & 0 \\ \delta^* & |\delta|^2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{R}_{T(2\psi)}^* \quad (9)
\]

where

\[
\mathbf{R}_{T(2\psi)} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos 2\psi & \sin 2\psi \\ 0 & -\sin 2\psi & \cos 2\psi \end{bmatrix} \quad (10)
\]
is the rotation matrix for coherency matrices. Since the particles are homogeneously distributed in the canopy layer, the volume component coherency matrix can be obtained by integration of these individual coherency matrices over the orientation angles:

\[
T_v = \int_{-\pi/2}^{\pi/2} p_\psi(\psi) T_v(\psi) d\psi = \\
\int_{-\pi/2}^{\pi/2} p_\psi(\psi) \begin{bmatrix}
1 & \delta \cos 2\psi & \delta \sin 2\psi \\
\delta^* \cos 2\psi & |\delta|^2 \cos 2\psi & |\delta|^2 \sin 2\psi \\
-\delta^* \sin 2\psi & -|\delta|^2 \cos 2\psi \sin 2\psi & |\delta|^2 \sin^2 2\psi
\end{bmatrix}
\]

where the integration is performed element-wise. The solution is in general non reflection symmetric. However, since \( p_\psi(\psi) \) is a circular pdf, symmetric around the mean vegetation orientation \( \tilde{\psi} \), one can rotate the polarization orientation angle by \( \tilde{\psi} \) to obtain a reflection symmetric form. Equation (11) can be integrated over all elements to obtain the coherency matrix for a volumetric vegetation layer under reflection symmetry

\[
T_v = R_{T(2\tilde{\psi})} \begin{bmatrix}
1 & g_c \delta^* \frac{(1+g_c^2)}{2} |\delta|^2 & 0 \\
g_c \delta \frac{(1+g_c^2)}{2} |\delta|^2 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix} R_{T(2\tilde{\psi})}^T
\]

where the values of \( g \) and \( g_c \) are obtained using trigonometric and integral identities (def. 9.6.19 on p. 376 in [12]) which result in

\[
g = \int_{-\pi/2}^{\pi/2} p_\psi(\psi) \cos 4\psi d\psi = \frac{L_2(\kappa)}{I_0(\kappa)}
\]

\[
g_c = \int_{-\pi/2}^{\pi/2} p_\psi(\psi) \cos 2\psi d\psi = \frac{I_1(\kappa)}{I_0(\kappa)}
\]

where \( I_n \) are modified Bessel functions of \( n \)-th order.

Equation (12) represents the most general form of direct volume backscattering from a simple homogeneous layer using a circular unimodal orientation angles distribution.

In the reflection symmetric form (neglecting \( \tilde{\psi} \)) the polarimetric properties of this component are determined by three real valued parameters: the magnitude and phase of particle anisotropy, and the degree of orientation randomness.

In order to rotate the whole coherency matrix \( T \) into a reflection symmetric form requires the normal vector of the ground terrain to be in the plane of the volume eigen-polarizations, so that both surface and volume share a common eigenpolarization basis (same azimuthal orientation). If this assumption is valid, one might also be able to estimate the terrain slopes under vegetation based on polarimetry only, as it is done for bare surfaces for instance in [13].

2.3. Polarimetric Interferometry

The expectation value of the single–baseline PolInSAR coherency matrix under polarimetric stationarity [14] and reciprocity conditions is given by

\[
T_0 = E \left\{ k_0 k_0^\dagger \right\} = \begin{bmatrix} T & \Omega \\ \Omega^T & -T \end{bmatrix}, \quad k_0 = \begin{bmatrix} k_1 \\ k_2 \end{bmatrix}
\]

where \( k_1, k_2 \) are scattering vectors describing the same scene, but from slightly different incidence angles and possibly different times. The wave interferometric properties are characterized (after appropriate pre-processing) by the vertical wavenumber

\[
k_z = 2k_0 \frac{B_\perp}{R_0 \sin \theta_0}
\]

where \( k_0, B_\perp, R_0, \theta_0 \) are the wavenumber, the effective (perpendicular) baseline, the slant range distance, and the incidence angle, respectively. The temporal baseline, the time period between the acquisitions, is called \( B_t \). The main PolInSAR observable is the complex coherence, which can be computed by

\[
\gamma(\omega) = \frac{\omega^4 \Omega \omega^T}{\omega^T T \omega}
\]

where \( \omega \) is a projection vector determining transmit and receive polarizations at the baseline ends.

In analogy to the polarimetric model of \( T \) in (7), the interferometric behavior of the main scattering contributions from a layer of random volume vegetation over the ground can be modeled by a linear combination of polarimetric interferometric cross–correlation matrices.

\[
\Omega = f_\gamma T_\gamma + f_\nu T_\nu
\]

If all decorrelation sources are polarization independent (which is in general not true, but is a simplifying approximation), then (18) can be expressed by

\[
\Omega = f_\gamma T_\gamma + f_\nu T_\nu
\]

where \( \gamma_\gamma, \gamma_\nu \) are the coherence terms associated with the two scattering components.

In the considered repeat–pass acquisition mode, surface scattering volume coherence is equal to double–bounce scattering volume coherence expression which makes the summation of both components possible. After conventional PolInSAR data processing (calibration, coregistration, spectral range filtering, flat earth removal, etc.), these coherences can be expressed by

\[
\gamma_\gamma = e^{i \omega_0 \gamma_{sys}}
\]

\[
\gamma_\nu = e^{i \omega_0 \gamma_{temp} t z}
\]

\( \gamma_{sys} \) depends in general on the acquisition system and data processing characteristics, whereas \( \gamma_{temp} \) describes the temporal change which either requires appropriate models or needs to be estimated from the data. In this work, both of these decorrelation sources are approximated by polarization independent real–valued terms which only degrade the coherence magnitude without affecting the interferometric phase.
The volume coherence $\gamma_z$ for vegetation with the canopy layer extending to a fraction $r_v$ of the total vegetation height $h_v$, as shown in Fig. 1, is given by

$$\gamma_z = e^{ik_v(1-r_v)h_v} \int_0^{r_vh_v} e^{i \kappa_3 z} e^{-\sigma(z,v)z} dz$$

(22)

where $\sigma$ is the extinction in dB/m of the volume layer.

In general, in presence of orientation effects in the volume, extinction becomes polarization dependent and needs to be given in the eigenpolarizations [4, 8, 15]. However, for the scenario considered in this paper, that is, forest parameter retrieval at L-band in repeat pass acquisitions, the degree of orientation randomness is very high, the mean extinction is low, and, hence, interferometry is hardly sensitive to extinction, and even less to the polarization dependent variation of extinction. Therefore, to keep the model and the parameter retrieval framework simple, extinction is approximated in this work by a polarization independent scalar value. However, the full polarimetric interferometric model with extinction and refractivity differences in the volume layer is derived in [8].

2.4. Multiple Baselines

The single–baseline PolInSAR model can be readily scaled to multiple baselines, given $n$ data acquisitions:

$$T_{3n} = E \{ k_{3i} k_{3j} \} = \begin{bmatrix} T & \cdots & \Omega_{1n} \\ \vdots & \ddots & \vdots \\ \Omega_{1n} & \cdots & T \end{bmatrix}, \quad k_{3i} = \begin{bmatrix} k_1 \\ \vdots \\ k_n \end{bmatrix}$$

(23)

where every baseline $i-j$ ($i,j \in [1,n]$) and every cross–correlation matrix $\Omega_{ij}$ are characterized by a distinctive vertical wavenumber $k_{eij}$ and a temporal baseline $B_{eij}$. The acquisition of more observables can enhance the retrieval of modeled parameters. However, with every baseline, two parameters are added to the model: the ground reference phase $\phi_{0ij}$, and the temporal canopy decorrelation $\gamma_{temp_{ij}}$, which are both in general unknown $a$ priori.

In a similar manner, multi–angular, multi–altitude, multi–frequency models can be constructed, where in dependence of the acquisition properties, the polarimetric coherency matrices $T$ will be different.

3. VEGETATION PARAMETER RETRIEVAL

Vegetation parameter retrieval can be understood as an inverse problem [16] as outlined in Fig. 2.

3.1. Data Observables

The data observables are represented by the estimates of the polarimetric coherency matrix and the cross–correlation matrix:

$$d = \{ T, \Omega \}$$

(24)

The initial estimate of $T_n'$ is obtained by averaging (also called multi–looking) of data samples using $L$ looks:

$$T_n' = \frac{1}{L} \sum_{i=1}^{L} \kappa_{0i} \kappa_{0i}^\dagger$$

(25)

A maximum likelihood estimator for the polarimetric stationary form of the polarimetric coherency matrix is given by [14]:

$$\hat{T} = \frac{\hat{T}_{11} + \hat{T}_{22}}{2}$$

(26)

Most vegetated areas exhibit reflection symmetry with respect to the vertical incidence plane, and the eigenpolarizations are given by the H–V polarization basis. However, in presence of azimuth slopes of the terrain, the polarization orientation angle might be different and need to be estimated for instance from a DEM (digital elevation model), or directly from polarimetry [13].

The final estimator of the single–baseline PolInSAR coherency matrix with reciprocity, reflection symmetry and polarimetric stationarity assumptions is given by

$$T_6 = \begin{bmatrix} A & D + iE & 0 \\ D - iE & B & 0 \\ 0 & 0 & C \end{bmatrix}$$

(27)

where the individual observables are explicitly denoted by capital letters. Therefore, the set of independent observables for a single–baseline coherency matrix under the named assumptions contains 15 real–valued elements [17]: 1 for the backscattered power, 4 for polarimetry, and 10 for polarimetric interferometry. These are the 10 additional parameters from interferometry, which enable us to construct more complex, but still invertible, polarimetric models for the ground and vegetation components. With the help of interferometry we seek to separate two coherency matrices which should be representable for the ground and the volume contributions. At the same time, the coherences, which separate these two components, permit to estimate structural vegetation parameters and the degree of temporal decorrelation.
3.2. Model Parameters

With reference to Fig. 2, the set of modeled parameters for a single–baseline scenario is given by

\[ m = \{ \psi, f_g, \text{Re} \beta, \text{Im} \beta, \beta_{22}, \beta_{33}, f_v, \text{Re} \delta, \text{Im} \delta, \tau, h_v, r_h, \sigma, \gamma_{sys}, \gamma_{temp}, \phi_0 \} \]  

(28)

These are 16 real–valued model parameters, as presented in the previous section, which determine the modeled PolInSAR coherency matrix \( T_0 \). One degree of freedom, \( \psi \), is used to rotate the coherency matrix into reflection symmetric form, which leaves 15 degrees of freedom. Of the remaining parameters, the first 9 determine the polarimetric properties, whereas the last 6 determine the interferometric properties of the model.

The critical point of the whole parameter retrieval framework is to estimate the interferometric structural parameters correctly. With the knowledge of acquisition system properties, \( \gamma_{sys} \), which is usually dominated by thermal decorrelation, will be assumed to be known \textit{a priori}. Hence, \( \phi_0 \) is estimable from \( \gamma_v \).

However, \( \gamma_v \), a complex–valued term, still depends on additional 4 parameters, \( h_v, r_h, \sigma \) and \( \gamma_{temp} \). Since in the data we can estimate only \( \gamma_v \), that provides only two degrees of freedom (\( |\gamma_v|, \arg \gamma_v \)), the parameters \( h_v, r_h, \sigma \) and \( \gamma_{temp} \) are ambiguous in a single–baseline acquisition and need further examination.

In addition, the magnitude of \( \gamma_v \) cannot be used for structural parameter estimation since it is perturbed by the unconstrained temporal decorrelation \( \gamma_{temp} \). Therefore, the retrieval of \( h_v, r_h \) and \( \sigma \) needs to be performed solely on the phase of \( \gamma_v \).

3.3. Parameter Retrieval Framework

The direct model \( G(m) \), that is related to the forward problem in Fig. 2, is given by

\[ d = G(m) \iff \begin{cases} 
T = f_g T_g(\beta, \beta_{22}, \beta_{33}) + f_v T_v(\delta, \tau) \\
\Omega = f_g' T_g'(\beta, \beta_{22}, \beta_{33}) \gamma_0(\phi_0, \gamma_{sys}) + f_v' T_v'(\delta, \tau) \gamma_v(\phi_0, \gamma_{sys}, \gamma_{temp}, h_v, r_h, \sigma) 
\end{cases} \]  

(29)

where the individual terms are given by equations in section 2.

The inverse model can be represented as a minimization problem, subject to a set of constraints \( e \):

\[ m = G^{-1}(d) \iff m = \arg \min_{m \in \mathcal{M}} \| d - G(m) \| \]  

(30)

The norm \( \| \cdot \| \) is given by the \( L_2 \) vector norm of the argument (root mean square misfit minimization). \( G^{-1} \) is a multi–dimensional non–linear optimization problem with local minima and possibly non–physical solutions. The set of constraints \( e \) is provided to enforce physically reasonable solutions. It proved useful to include into \( d \), next to the elements of the PolInSAR coherency matrix, several coherence values with distinctive polarizations to enhance the sensitivity of the parameter retrieval method to structural parameters.

While the problem formulation is straightforward, finding a solution is an art in itself. Using brute–force optimization might lead to undesirable results, and a physically refined approach is recommended (in the manner of [6]). A possible multi–stage parameter retrieval framework for a multi–baseline data set is presented below:

Initial Processing

i. SAR image preprocessing: data generation, calibration, coregistration, range spectral filtering, flat earth removal, topography removal, multi–looking operation.

ii. Estimation of the reflection symmetric and polarimetric stationary form.

iii. Estimation of thermal decorrelation and possibly other system decorrelation sources, as for example the coherence bias [18] in case of low number of looks.

Parameter retrieval

1. Determine the linear structures of the PolInSAR coherence sets. Independently for every baseline:

   (a) Fit a line \( L_i \) through the PolInSAR coherence set, in analogy to the \textit{three–stage inversion process} [6].

   (b) Determine the ground phase \( \phi_0 \).

2. Determine the degree of orientation randomness in the data.

For all baselines simultaneously:

   (a) Find \( \delta', \tau', f_g', f_v', \beta', \beta_{22}', \beta_{33}' \) which minimize (30), neglecting for the moment the structural parameters, and only enforcing all \( \gamma_{gi}, \gamma_{vi} \) to be on the lines \( L_i \).

   (b) Keep only \( \tau = \tau' \) for future computation.

3. Determine the structural parameters and temporal decorrelation together with other remaining parameters:

   (a) Find common \( h_v, \sigma, r_h \) as well as \( \delta, f_g, f_v, \beta, \beta_{22}, \beta_{33} \) and the baseline dependent \( \gamma_{temp} \), which approximate the linear structure of the coherences and the polarimetric coherency matrix.

4. If the retrieved parameters are physically not meaningful, either restart using different initialization, or mark this pixel as non–inverted and continue.

For step 1.a) we propose to use the eigenvalues of the contraction matrix \( \Pi \)

\[ \Pi = T^{-\frac{1}{2}} \Omega T^{-\frac{1}{2}} \]  

(31)
to estimate the linear structure of the coherences. The line function is estimated in polar coordinates.

Step 1.b) is very important as errors in determining all ground phases correctly will result in erroneous parameter retrieval. Used criteria for identifying the ground phase [6]: (1) polarimetric ordering of coherences, (2) maximal phase distance between the ground and the volume coherence. Other criteria are possible.

Step 2) has been introduced to make the procedure more robust. Theoretically, after step 2) the structural parameters can be directly retrieved from $\gamma_{0i}$, but using the full parameter inversion in step 3) (except $\tau$) provides possibility of further fine-adjustment.

The Nelder–Mead simplex method [19] is used for the optimization problems in steps 2.a) and 3.a), which does not guarantee the optimal solution, but which, even with repeated trials, is computationally effective. The usage of a more sophisticated optimization method, like simulated annealing or genetic algorithms, would provide better results but the computation cost will be enormous in this case.

4. EXPERIMENTAL RESULTS

The application of the developed parameter retrieval method is conducted on real SAR data from a mountainous temperate forested region in the south of Germany, near the city of Traunstein (Fig. 3). Approximate ground truth data is available for 20 validation stands covering 123 hectares, which are delimited in Fig. 3 and their main characteristics are presented in Table 1. These individual stands were delineated in order to achieve high homogeneity in terms of tree species, height, biomass, and growth stadium [20]. The forest stands can in general be characterized as mixed forests. Table 1 presents the dominant tree species in the order of dominance. The species shortcuts have the following meanings: Fi=Nor spruce, Ki=Scots pine, Ta=white fir, La=Eur. larch, Bu=Eur. beech, Es=ash, Ah=maple, Ei=oak, Bi=birch. 17 of the 20 stands are dominantly coniferous, and only 3 stands are dominated by deciduous trees, as denoted in the type column. The average tree heights of the evaluation stands range between 12.46 and 36.10 meters with spatial variations inside of the stands of up to 8.6 meters.

Fully polarimetric and interferometric data at L-band have been acquired by the German Aerospace Center (DLR)'s E–SAR sensor in 2003 in a repeat–pass configuration. The acquisition times and nominal baselines of the four data sets used in this study are presented in Table 2. Further acquisition system characteristics are shown in Table 3.

To guarantee good estimates of the covariance matrices and the coherences, the first series of tests is conducted using 1800 looks, which, with the given slant range and azimuth resolutions correspond to an area of 0.25 ha (slant range geometry). 1800 looks can be obtained by a $15 \times 15$ boxcar averaging of the data after an $8 \times$ multi-look in the azimuth. 3 baselines are used: 1–2, 1–3 and 1–4. The system coherence, which includes thermal,
Table 3. Characteristics of the SAR imagery.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelength</td>
<td>23 cm</td>
</tr>
<tr>
<td>Polarizations</td>
<td>HH, HV, VV, VH</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>100 MHz</td>
</tr>
<tr>
<td>Altitude (above ground)</td>
<td>3 km</td>
</tr>
<tr>
<td>Slant range resolution</td>
<td>1.5 m</td>
</tr>
<tr>
<td>Azimuth resolution</td>
<td>95 cm</td>
</tr>
<tr>
<td>Incidence angles</td>
<td>25°–56°</td>
</tr>
</tbody>
</table>

Table 4. A priori and optimization constraints.

<table>
<thead>
<tr>
<th>A priori constraints</th>
<th>Optimization constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{sys} = 0.96$</td>
<td>$0.2 \leq m_V \leq 0.98$</td>
</tr>
<tr>
<td></td>
<td>$0 \leq</td>
</tr>
<tr>
<td></td>
<td>$0 \text{dB/m} \leq \sigma \leq 0.4 \text{dB/m}$</td>
</tr>
<tr>
<td></td>
<td>$0.4 \leq r_h \leq 1$</td>
</tr>
<tr>
<td></td>
<td>$0.25 \leq \gamma_{temp} \leq 1$</td>
</tr>
<tr>
<td></td>
<td>$5 \text{m} \leq h_v \leq 45 \text{m}$</td>
</tr>
</tbody>
</table>

mis-coregistration, mis-calibration and other decorrelation sources, as well as possible temporal decorrelation of the ground contributions is set a priori to 0.96 independently of the polarization.

Further constraints, used to regularize the parameter retrieval method to deliver physically reasonable solutions and to avoid local minima, are presented in Table 4.

Figs. 4.(a) and (b) show the ground-truth forest heights and the estimated heights. Fig. 5 represents the forest heights and the individual canopy layer depths for the 20 evaluation stands. The red line in this plot represents the ground-truth height. The green line represents the estimated heights, whereas the lengths of the error bars are given by the standard deviations. The brown line delimits the canopy layer from the non-canopy layer above the ground, and represents the canopy-fill-factor, normalized to the total vegetation height. In average, the forest height is underestimated by 1.6 meters, the average absolute error is 3.97 meters, the average root mean square error (RMSE) is 4.97 meters, and the standard deviation of height estimation is 4.33 meters. It is interesting to see that the lowest height error (-32cm, RMSE: 1.5m; stand 2) corresponds to the only forest stand which is dominated by a single tree species without other significant species.

The highest error corresponds to stand number 20. The forest heights seems to be underestimated by over 5 meters with RMSE of 7.75 meters. Observing the intensity image, one can see that this evaluation stand is not as homogeneous as the ground truths indicate. It is very likely that between the forest inventory in 1998, on which base the evaluation stands have been defined, and the date of radar data acquisition in 2003, there have been significant changes in the spatial structure of this stand. It seems likely that the “ground-truth” measurements do not correspond to the true forest height of this stand, which appears to be quite heterogeneous. This emphasizes again the capability of radar remote sensing for quantitative vegetation monitoring and parameter retrieval on spatial and temporal scales not achievable by other means.
Fig. 6 presents the estimated ground–to–volume power ratios $P_g/P_v$ for all forest stands ranging approximately between 0.1 and 0.3, where

$$P_g = f_g \text{trace} T_g, \quad P_v = f_v \text{trace} T_v$$

(32)

Fig. 7 shows the relative ground scattering components in the Pauli basis for all evaluation stands. Although surface and double–bounce terms are larger, the cross–polar component is significant, too.

The images and the graphs of the estimated temporal decorrelation are shown in Fig. 8. The three baselines (1–2, 1–3, 1–4) have nominal perpendicular baselines of 5, 10 and 0 meters, and temporal baselines of 10, 20 and 60 minutes. Over these short temporal periods, the number of minutes between the acquisitions is not authoritative. The temporal decorrelation of the volume at these scales is mostly caused by wind which is non–stationary, neither temporally nor spatially. As it can be seen, in average the temporal decorrelation is between 0.5 and 0.95.

In [9], the estimated vegetation parameters related to plant morphology, the degree of orientation randomness and particle scattering anisotropy, are presented and discussed.

5. CONCLUSION

This paper has presented a model to characterize polarimetric interferometric radar response from vegetation.
The model consists of volume and ground contributions for a PolInSAR repeat-pass configuration. The ground component accounts for surface and double-bounce scattering contributions. For the volume component, a simple polarimetric model has been derived. Modeled as a cloud of discrete particles, it takes into account vegetation morphology in the form of effective particle anisotropy and orientation distribution. The von Mises distribution has been recognized as the expected orientation angles distribution of vegetation particles, and a closed form solution for the volume coherency matrix has been presented.

The repeat-pass acquisition of the data requires the adaptation of the parameter retrieval framework to temporal decorrelation. Temporal decorrelation is a significant error source for vegetation parameter estimation at L-band, caused on the given short temporal scale (minutes to hours) mostly by wind. The strategy to estimate the degree of temporal decorrelation, as presented in this paper, is based on the assumption that in ensemble average, temporal decorrelation does not affect the coherence phase, but only degrades the magnitude. Since the temporal decorrelation can be different in every baseline, the coherence magnitude of the volume component is contaminated and can hardly be used for the estimation of structural parameters. These parameters need to be estimated based on the phase measurements only. However, having estimated the structural parameters it is as well possible to estimate the degree of temporal decorrelation.

In this paper, first preliminary results on real SAR data have been presented which illustrate the potential of the developed model and parameter retrieval approach. However, further studies need to be conducted for evaluation and validation purposes.

REFERENCES