Interpretation and Analysis of Polarimetric L-Band E-SAR-Data for the Derivation of Hydrologic Land Surface Parameters

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Abstract – This paper evaluates the use of polarimetric L-band Synthetic Aperture Radar (SAR) information for applied derivation of important hydrologic parameters. In most cases empirical relationships between SAR-data and water cycle components are investigated as a first step towards hydrological information extraction. In this study the use of polarimetric parameters for hydrological modelling is analysed. Furthermore, the dependency of the polarimetric parameters from the local incidence angle are investigated.

I. INTRODUCTION

Hydrological applications, i.e. physically-based, distributed hydrological modelling, require spatial input for parameterisation and validation of water cycle components. Active microwave remote sensing research in particular has shown the potential of multi-frequency and polarimetric SAR data to retrieve a variety of useful information such as land cover, vegetation parameters and soil moisture [4,6]. Especially the use of polarimetric parameters (alpha, entropy, anisotropy, lambda 1-3, alpha 1-3) as derived from L-band SAR using the Cloude-decomposition [1] algorithm have been found to be useful in land surface parameter estimation, since they allow a very detailed description of the radar wave-surface interaction including the phase information.

The investigations in this study are part of a research project called PHYMO funded by the German Science Foundation, which focuses on the derivation of land surface information from SAR data for the parameterisation of water balance and solute transport models. It is based on investigations using airborne experimental SAR (E-SAR) data from the German Aerospace Center (DLR).

The testsite of the study, the catchment of the drinking water reservoir Zeulenroda, suffers from intensive nutrient leaching from agricultural areas. Therefore remote sensing based water balance studies including sophisticated simultaneous ground truth data are of superior importance. The investigations could also be seen as basic hydro-application research for future spaceborne polarimetric L-Band sensors (ALOS, TerraSAR, etc.).

II. PREPROCESSING

A. Polarimetric SAR Data Decomposition

The SAR data recorded from the German Aerospace Center included X-band (co-polarised, single pass interferometry) and L-band (full polarimetric).

For the decomposition after Cloude [1] the complex L-band information is utilized. That means, the polarisations HH, VV and either HV or VH enter the decomposition algorithm. Thus, the backscatter is separated into three eigenvalues and three eigenvectors. These six parameters provide the input for computing the parameters alpha (α), entropy (H) and anisotropy (A). The α-angle has a range of values between 0 and 90. It indicates the backscattering mechanism. The entropy indicates the dominance of one (H near 0) or more backscattering mechanism (H = 1, if the portion of every scattering process is equal). Both explained parameters enclose the entropy-alpha-feature space, were different land uses appear in different regions of the diagram (see “Fig. 3”). This aspect was successfully used by Hellmann et al. [4] for a land use classification. The anisotropy provides a value which indicates the distribution of the second and third eigenvalue. It becomes 0, if both scattering mechanism are of an equal proportion.

The application of the decomposition algorithm on geocoded single look complex (SLC) data can be considered as feasible, since the results showed only negligible differences to the results achieved from original SLC data.

B. Local Incidence Angle Normalization

All radar intensities (βₐ in dB) showed a significant dependency on the local incidence angle (LIA) as is presented exemplarily in “Fig. 1” for short vegetation/bare soil. In this diagram the intensity is plotted against the related local incidence angle (450 pixel in the case of this study).

For classification procedures or other comparative interpretation of SAR data this dependency needs to be normalised. In this study a simple linear regression model was used to overcome this problem. With equation (1) the disturbing effect could be taken out.

new intensity = β₀ + D – (m · LIA + n) (1)
In this equation \((m)\) and \((n)\) are the parameters of the respective regression line and \((D)\) is the mean intensity of the analysed pixels.

\[
y = -0.27x + 4.67 \\
R^2 = 0.55
\]

Fig. 1. Dependency of backscatter intensity from the local incidence angle for short vegetation/bare soil

Analogue to “Fig. 1” the dependency of the polarimetric parameters from the local incidence angle was investigated using a simple linear regression analysis. This examination was done separately for the classes smooth surface (seedbed), rough surface (ploughed fields) and forest. The results show a strong dependency for most of the polarimetric parameters for rough surfaces, while smooth fields indicate only a weak relationship. The correlation between the polarimetric parameters and the local incidence angle for the class forest shows mainly intermediate values. The dependencies in numbers are presented in “Table 1”, were \((m)\) and \((n)\) are the parameters of the respective regression line and \((R^2)\) is the squared coefficient of correlation. The number of included picture elements lies between 200 and 250.

<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>DEPENDENCY OF POLARIMETRIC PARAMETERS FROM LIA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>smooth surfaces</td>
</tr>
<tr>
<td>(m)</td>
<td>(n)</td>
</tr>
<tr>
<td>(a_1)</td>
<td>-0.003</td>
</tr>
<tr>
<td>(a_2)</td>
<td>0.003</td>
</tr>
<tr>
<td>(a_3)</td>
<td>0.001</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>0.220</td>
</tr>
<tr>
<td>(\lambda_1)</td>
<td>22.01</td>
</tr>
<tr>
<td>(\lambda_2)</td>
<td>62.28</td>
</tr>
<tr>
<td>(\lambda_3)</td>
<td>-1146</td>
</tr>
<tr>
<td>(H)</td>
<td>0.009</td>
</tr>
<tr>
<td>(A)</td>
<td>0.011</td>
</tr>
</tbody>
</table>

“Fig. 2” shows the analysed correlation for the alpha angle. While the correlation between LIA and alpha angle for the class forest is negligible, a very strong dependency was found for rough surfaces. The low correlation for forest may be due to the predominant volumetric scattering. For rough surfaces the prevalent scattering mechanism shifts from dipole scattering to surface scattering with an increasing local incidence angle. An inverse, but much less significant correlation was found for smooth surfaces.

Fig. 2. Dependency of alpha angle values from the local incidence angle

III. RESULTS

A. Land use classification

For the segmentation of the SAR scene into several land use classes the level approach as suggested in [2, 5] was applied. The first level distinguishes the classes forest/settlement, water/shadow and short vegetation/bare soil. At the first level an unsupervised classification (isodata-clustering) was applied. For this step all 5 intensities were used.

At the second level the classes forest/settlements and low vegetation/bare soil were subdivided into their components. In both cases a supervised maximum likelihood classification was applied. To separate low vegetation (grasslands, field grass) and bare soil, only the X-band information was used. For most hydrological modelling approaches a further separation is of no use, since the crops are changing usually every year.

To separate settlements and forest a texture analysis had to be applied since the spectral information of the intensity images was insufficient. The mean Euclidian distances provided the most useful texture parameter. They were calculated for all intensities and for the difference image L-HH minus L-HV. This approach led to a distinct separation of the level one class forest/settlements. The usual post processing refined the achieved result.

The land use classification at the second level distinguishes the classes settlements, forest, water/shadow, bare soil and short grass like vegetation (grassland, field grass etc.). For several numbers specifying the classification accuracy see “Table 2”.

The presented land use classification is based on intensity images. The integration of polarimetric parameters show some problems. They arise from the overlapping of the polarimetric parameters within entropy-alpha-feature space for different land uses (see “Fig. 3”). However, the results concerning the separation of short
vegetation/bare soil are promising. They will be further investigated, including the fuzzy logic algorithm presented by [4].

### Table 2

<table>
<thead>
<tr>
<th></th>
<th>Producers accuracy [%]</th>
<th>Users accuracy [%]</th>
<th>Class proportion [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Settlements</td>
<td>93,98</td>
<td>81,25</td>
<td>3,86</td>
</tr>
<tr>
<td>Forest</td>
<td>98,99</td>
<td>99,68</td>
<td>27,40</td>
</tr>
<tr>
<td>Water/ shadow</td>
<td>95,71</td>
<td>98,98</td>
<td>1,87</td>
</tr>
<tr>
<td>Grassland</td>
<td>89,26</td>
<td>73,10</td>
<td>16,52</td>
</tr>
<tr>
<td>Bare soil</td>
<td>95,81</td>
<td>98,29</td>
<td>50,35</td>
</tr>
<tr>
<td>Total accuracy</td>
<td>96,11</td>
<td></td>
<td>100,00</td>
</tr>
</tbody>
</table>

Kappa coefficient 0.93

**Fig. 3. Entropy-alpha-feature space**

### B. Empirical relationships between SAR parameters and soil moisture/surface roughness

Soil moisture estimations using polarimetric SAR data have been carried out several times (i.e. [3]). To explore the information content concerning soil moisture of all SAR parameters (intensities, polarimetric parameters, principal components) a linear regression analysis was applied for every field separately using LIA-normalized data due to obvious surface roughness differences. The most distinct correlation was found for the eigenvalues one and three, the principal components one and three and for the intensities L-VV and L-HV. Furthermore a relationship between surface roughness and the content of soil moisture information in the SAR data was determined. A particular high correlation was found for fields characterised by a middle surface roughness, e.g. shallow ploughed fields. A weaker correlation was determined for very rough fields, while smooth areas did not show a significant correlation between polarimetric parameters and measured soil moisture. Soil moisture maps were created by combining the radar parameters with a high content of soil moisture information. Thus, the noise could be reduced and the inherent soil moisture information was intensified. The correlation between field measured soil moisture and soil moisture achieved from combined SAR Data is expressed by a number of $r = 0.85$ for the field with the best conformity.

The SAR parameters, which contain the surface roughness information differ from the relevant parameters for soil moisture. These are mainly the eigenvectors one and two, the alpha angle and the first eigenvalue. The correlation between the field measured RMS-heights and the RMS-heights achieved from SAR Data is expressed by a number of $r = 0.62$ for the whole test site.

A significant conformity between radar parameters and autocorrelation lengths could not be verified.

### IV. Conclusions

This study gives an idea of the practical relevance of SAR data for the parameterisation of hydrological models. Particularly, the polarimetric parameters include a significant amount of soil moisture and surface roughness information. Several approaches designed for the extraction of hydrological relevant information from SAR data were discussed.

The polarimetric parameters, which were derived from geocoded and original SLC data, proved to be more or less affected by the local incidence angle. The significance of this correlation differs from surface roughness and land use.

### References


