A knowledge – based classification method for polarimetric SAR data

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ABSTRACT

Full polarimetric data can define the scattering behavior of land use/cover through several approaches. Several classification methods have been proposed based on analysis methods. These classification methods are based on the backscattering mechanisms which are extracted using a single decomposition method. The objectives of this work are a) the investigation of the different polarimetric analysis methods; b) the interpretation of the images resulting from polarimetric analysis; c) the development of an object – oriented classification method based on polarimetric analysis imagery and the comparison of this method with the H/a and the H/a Wishart classification methods respectively.

Keywords: Polarimetry, Pauli analysis, Freeman- Durdan analysis, Entropy/a/Anisotropy, object – oriented classification

1. INTRODUCTION

Classification of land use/cover using full polarimetric SAR data is one of the most important applications of radar Polarimetry. Full polarimetric SAR data can define the scattering behavior of land use/cover, thus giving better land use/cover classification results than single – channel SAR. Different methods have been proposed to analyse polarimetric SAR data such as the a) Pauli method analysis (Papathanassiou, 1999), b) Cloude – Pottier method analysis which produces the Entropy, a Angle and Anisotropy images and other derivatives (Pottier, Lee, 1999), c) the Freeman – Durdan method which produces the Double Bounce, Surface and Volume images (Freeman, Durdan, 1998), d) analysis to Sphere, Diplane and Helix (Hellmann 1999), e) analysis based on the Huynen parameters (Titin-Schnaider, 1999), f) decomposition based on different combinations of entropy and anisotropy (Pottie r, Lee, 1999). In addition, several supervised and unsupervised classification methods have been proposed in order to classify polarimetric SAR data, including a) Entropy/a/Anisotropy classification (Cloude, Pottier, 1997), b) supervised Wishart classification (Lee, Grunes, Ainsworth, Du, Schuler, Cloude, 1999), c) unsupervised Entropy/a Wishart classification (Lee, Grunes, Ainsworth, Du, Schuler, Cloude, 1999), d) unsupervised Lee classification based on the Freeman – Durdan analysis method (Lee, Grunes, Pottier, Ferro-Famil, 2004), e) physical classification (Ferro-Famil, Pottier, Lee, 2002) and f) unsupervised classification based on polarimetric components and absolute amplitude (Smith,van den Broek, Dekker, 1998). Most classification methods are based on the backscattering mechanisms which are extracted using a single decomposition method.

The aim of this study is to investigate polarimetric SAR data analysis methods, interpret the scattering mechanisms of the land uses in the study area; develop a knowledge – based classification method for polarimetric SAR data and finally compare the classification results with the results produced by the H/a and the H/a Wishart classification method.

The full polarimetric SAR data, which are used in this work, are from the Oberpfaffenhofen area, in Germany approximately 25 kilometers southwest of Munich, around the German Aerospace Centre (DLR).

Processing and classification of the data are implemented using a) the RAT software (free software available on the Internet), b) the eCognition software (object – oriented image analysis software).
2. POLARIMETRIC SAR DATA ANALYSIS METHODS

2.1 Pauli analysis method

Pauli analysis is one of the basic SAR polarimetric data analysis methods. In this method, the 3X3 coherency matrix $T$ is decomposed to three independent matrices, whereby each matrix represents a single scattering process. These matrices constitute the Pauli base which is related to the physics of wave scattering (Papathanassiou, 1999):

$$\Psi_p = \left\{ \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \right\}$$  \hspace{1cm} (1)

The corresponding scattering vector is then:

$$P_k = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{hh} + S_{vv} \\ S_{hh} - S_{vv} \\ 2S_{hv} \end{bmatrix}$$  \hspace{1cm} (2)

This method interprets the isotropic surface scattering mechanism (odd bounce), the isotropic dihedral (even bounce) and 45° tilted dihedral (45° titled even bounce) scattering mechanisms. The Pauli components are computed as follows:

Pauli1 = $S_{hh} - S_{vv}$  \hspace{1cm} (3)
Pauli2 = $2S_{hv}$
Pauli3 = $S_{hh} + S_{vv}$

2.2 Cloude – Pottier analysis method

This analysis method is based on the decomposition of coherency matrix to eigenvectors ($e_i$) and eigenvalues ($\lambda_i$). Important parameters can be derived based on the Cloude – Pottier decomposition. Entropy ($H$) is defined by the logarithmic sum of the eigenvalues (Pottier, Lee, 1999):

$$H = -R_1 \log_3 P_1 - P_2 \log_3 P_2 - P_3 \log_3 P_3 \text{  Where  } P_i = \frac{\lambda_i}{\sum_{j=1}^{3} \lambda_j}$$  \hspace{1cm} (4)

This parameter is an indicator for the number of effective scattering mechanisms, whereby $H = 0$ belongs to deterministic scattering and $H = 1$ to totally random scattering. Anisotropy ($A$), the second physical feature, describes the proportions between the secondary scattering mechanisms:

$$A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3}$$  \hspace{1cm} (5)

A only yields additional information for medium values of $H$. A high $A$ signifies that besides the first scattering mechanism only one secondary process contributes to the radar signal. A low $A$ signifies that, both secondary scattering processes play an important role. Another polarimetric parameter is alpha ($\alpha$), which represents the type of scattering mechanism and ranges between 0 and 90°. It is evaluated as:

$$\alpha = p_1\alpha_1 + p_2\alpha_2 + p_3\alpha_3$$  \hspace{1cm} (6)
Thereby $\alpha = 0$ indicates surface scattering. As $\alpha$ increases, the surface becomes anisotropic. An $\alpha$-value of 45° represents a dipole. If $\alpha$ reaches 90°, the scattering process is characterized by double bounce interactions.

2.3 Freeman – Durdan analysis method

This analysis method (Freeman and Durdan, 1998) is particularly well adapted to the study of vegetated areas and relies on the conversion of a covariance matrix to a three-component model (PolSARpro guide). The results of this decomposition are three coefficients corresponding to the weights of different model components. A 3x3 covariance matrix $C_3$ may be decomposed to a sum of 3 components, corresponding to volume scattering, surface scattering and double bounce scattering.

$$[C_3] = f_v[C_3]_v + f_s[C_3]_s + f_d[C_3]_d$$  \hspace{1cm} (7)

The volume scattering component is obtained by averaging an oriented dipole canonical covariance matrix $U_3(\phi)$ over a constant distribution of the azimuthal orientation angle between -180° and 180°.

$$[C_3]_v = U_3(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}^{-1} = \begin{bmatrix} 1 & 0 & 1/3 \\ 0 & 1/3 & 0 \\ 1/3 & 0 & 1 \end{bmatrix}$$  \hspace{1cm} (8)

The surface scattering term is directly parameterized using the first order Sinclair matrix of a horizontal rough surface.

$$[S] = \begin{bmatrix} R_h \\ 0 \\ R_v \end{bmatrix} \Rightarrow [C_3]_s = \begin{bmatrix} \beta^2 & 0 & \beta \\ 0 & 0 & 0 \\ \beta & 0 & 1 \end{bmatrix}$$  \hspace{1cm} \text{Where } \beta = \frac{R_h}{R_v} \in \mathbb{N}$$  \hspace{1cm} (9)

$R_h$ and $R_v$ are the reflection coefficients for horizontal and vertical polarization, respectively. The double bounce scattering term is built from the Sinclair matrix of a Fresnel double bounce reflection.

$$[S] = \begin{bmatrix} e^{i2\gamma_v}R_{gv}R_{iv} \\ 0 \\ e^{i2\gamma_h}R_{gh}R_{ih} \end{bmatrix} \Rightarrow [C_3]_d = \begin{bmatrix} \alpha^2 & 0 & \alpha \\ 0 & 0 & 0 \\ \alpha & 0 & 1 \end{bmatrix}$$  \hspace{1cm} \text{Where } \alpha = e^{i2(\gamma_h - \gamma_v)} (R_{gh}R_{ih}/R_{gv}R_{iv})$$  \hspace{1cm} (10)

$R_h$ and $R_v$ are the reflection coefficients of the vertical surface (e.g. the trunk) for horizontal and vertical polarization, respectively; $R_{gh}$ and $R_{gv}$ are the Fresnel reflection coefficients of the horizontal surface (the ground) and $\gamma$ are complex.

2.4 Sphere/Diplane/Helix analysis method

This decomposition method is based on the transformation of the linear basis $hv$ (h = horizontal, v = vertical) of polarimetric SAR data to circular base $rl$ (r = right hand circular, l = left hand circular), (Hellmann, 1999):
This method interprets the scattering mechanisms sphere, diplane and helix. The components of this method are computed as follows:

\[ S_{rr} = iS_{hv} + \frac{S_{hh} + S_{vv}}{2} \]  
(11)

\[ S_{II} = iS_{hv} + \frac{S_{hh} - S_{vv}}{2} \]  
(12)

\[ S_{rl} = iS_{hh} + S_{vv} \]  
(13)

The coherency matrix \( T \) can be written using the parameters of the Mueller matrix as follows (Schnaider, Palaiseau, 1999):

\[
\begin{bmatrix}
2A_0 & C - iD & H + iG \\
C + iD & B_0 + B & E + iF \\
H - iG & E - iF & B_0 - B
\end{bmatrix}
\]  
(10)

The scattering mechanisms that are interpreted using the diagonal elements of the coherency matrix are volume, surface and double bounce. In the case of volume scattering, parameter \( B_0 - B \) increases considerably but never dominates other diagonal elements. In the case of surface scattering, parameter \( 2A_0 \) is dominant but parameter \( B_0 + B \) can have significant values. In the case of double bounce scattering, the parameter \( B_0 + B \) is dominant but parameter \( 2A_0 \) can have significant values.

2.5 Decomposition using the diagonal elements of the coherency matrix

The examination of the different images corresponding to the different combinations of entropy and anisotropy leads to the following remarks:

1. The \((1-H)(1-A)\) image corresponds to the presence of a single dominant scattering process (low entropy and low anisotropy with \( \lambda_2 \approx \lambda_3 \approx 0 \)).
2. The \(H(1-A)\) image characterizes a random scattering process (high entropy and low anisotropy with \( \lambda_1 \approx \lambda_2 \approx \lambda_3 \)).
3. The \(HA\) image indicates the presence of two scattering mechanisms with the same probability (high entropy and high anisotropy \( \lambda_3 \approx 0 \)).
4. The (1-H)A image corresponds to the presence of two scattering mechanisms with a dominant process (low to medium entropy) and a second one with medium probability (high anisotropy with $\lambda_3 \approx 0$).

3. INTERPRETATION OF ANALYSIS IMAGES

The analysis methods described in the previous section were implemented and several images resulted. Based on them, normalized images were produced for comparison purposes. For each land use category, i.e. forest, grass, buildings and airway, representative samples were selected on the normalized images and the minimum value, the maximum value, the average and the standard deviation were calculated. At first glance it is observed that the Pauli and Sphere/diplane/helix decomposition methods yield images with higher values than the other decomposition methods. In all the produced images, the categories with the highest values are those of the buildings and forest. Grass and airways present significantly lower values. Diagrams with the average values of the scattering mechanisms for each land use, were drawn.

3.1 Interpretation of the images produced by Pauli decomposition method

As shown in figure 1, forest presents medium values in the images resulting from Pauli decomposition method. However, all scattering mechanisms: surface (hh+vv), dihedral (hh-vv) and dihedral 45° tilted (2hv) are involved in this category. The dihedral 45° tilted scattering mechanism and the dihedral scattering mechanism produced by the interaction between ground, leaves, and the tree trunks are the dominant mechanisms. The surface scattering mechanism produced by ground has smaller contribution.

For the grass category, all scattering mechanisms present low values. The dominant are those of the dihedral scattering mechanism, produced by the interaction between the ground and grass, and surface produced mainly by the ground.

Buildings present very high values. The dihedral scattering mechanism produced by the interaction between the ground and buildings is the main mechanism of this category with very high values. The surface scattering mechanism produced by the roofs of buildings follows.

Airway presents very low values. The dihedral scattering mechanism, produced by the interaction between the surface of the airway and the grass along the two sides of the airway present the highest values.

Pauli method can efficiently contribute to the classification of forest and buildings.

![Figure 1: The average values of pixels in the major land use categories.](image)

3.2 Interpretation of the images produced by Freeman – Durdan decomposition method
As shown in figure 2, forest presents medium values on the images resulting from Freeman – Durdan decomposition method. However, all scattering mechanisms, Double Bounce (DB), Volume (V) and Surface (S) are involved in this category. The volume scattering mechanism produced by forest canopy is the dominant mechanism, having higher values than other land uses. The surface scattering mechanism produced by the ground and the double bounce scattering mechanism produced by the interaction between the ground and the tree trunks have minor contribution.

For the grass category, all scattering mechanisms present very low values. The dominant is that of the double bounce scattering mechanism, produced by the interaction between the ground and grass. Surface produced mainly by the ground, and volume scattering mechanisms follow. The double bounce scattering mechanism produced by the interaction between the ground and buildings present very high values in the building category. The surface and volume scattering mechanisms have low values relatively to the double bounce mechanism.

Airway presents very low values and almost equal. The double bounce scattering mechanism, produced by the interaction between the surface of the airway and grass along the two sides of the airway, has significant values. The surface scattering mechanism produced by the surface of the airway follows.

Using this decomposition method, forest and buildings can be distinguished but grass and airways cannot be discriminated.

![Figure 2: The average values of pixels in the major land use categories.](image)

### 3.3 Interpretation of the images produced by Sphere/diplane/helix decomposition method

As shown in figure 3, forest presents medium values in the images resulting from the sphere/diplane/helix decomposition method.
All scattering mechanisms sphere, diplane and helix are involved in this category. The helix scattering mechanism produced by the interaction between ground, leaves, and tree trunks are the dominant mechanism. The diplane scattering mechanism, which pronounces strict dihedrals, and the sphere scattering mechanism produced by ground have smaller values.

Grass presents low values and almost equal. The dominant scattering mechanism is that of the sphere scattering mechanism produced mainly by the ground or the leaves. The helix and diplane scattering mechanisms, produced from the interaction between the ground and grass present smaller values.

In the building category the diplane scattering mechanism produced from the interaction between the ground and buildings has very high values. The sphere scattering mechanism produced by the building roofs and helix scattering mechanism present medium and approximately equal values.

Airway presents very low values. The helix scattering mechanism that pronounces dihedrals with various orientations is the dominant. The diplane scattering mechanism produced by the interaction between the surface of the airway and grass along the two sides of the airway, follows. This decomposition can efficiently contribute to the classification of the grass and building categories.

3.4 Interpretation of the images produced by diagonal elements of the coherency matrix

As shown in figure 4, forest presents medium values in the normalized images resulting from diagonal elements of coherency matrix. All the scattering mechanisms surface scattering ($2A_0$), dihedral scattering ($B_0 + B$), and volume scattering ($B_0 - B$) are involved in this category. Although volume scattering, produced by canopy of the forest, is not dominant in the original images resulting from this decomposition method, a significant increment of the parameter $B_0 - B$ is observed, making it dominant, when normalization is applied. Consequently, like in the Volume (V) normalized image produced by Freeman – Durdan analysis, the regions with volume behavior (forest) not only have increased values relatively to other land uses, but also the volume scattering is dominant in these regions. The dihedral scattering mechanism produced by the interaction between ground and tree trunks has also significant values. The contribution of surface scattering mechanism produced by the ground is minor.

Grass presents very low values. The dihedral scattering mechanism, produced from the interaction between the ground and vegetation is the dominant. The surface scattering mechanism produced mainly by the ground follows.

The dihedral scattering mechanism produced by the interaction between ground and buildings present very high values in the building category. The surface scattering mechanism follows with medium values.
Airway presents very low values. The dihedral scattering mechanism, produced by the interaction between the surface of the airway and the grass along the two sides of the airway, has significant values. The surface scattering mechanism produced by the surface of the airway follows.

Like the Freeman – Durdan decomposition method, this method is more effective for forest and buildings discrimination.

### 3.5 Decomposition methods and objects scattering behavior

The above interpretation indicates that the number of the revealed backscattering mechanisms increases if all decomposition methods are used. Images produced by Freeman – Durdan decomposition method and diagonal elements of the coherency matrix only yield similar backscattering mechanisms. Even according to these methods, objects’ scattering behavior differs if analysis is implemented in not normalized images. Consequently, every method can efficiently contribute to the identification of the land use categories and a classification method based on all the images produced by the above decomposition methods, could improve the classification performance. Based on the above analysis, the scattering mechanisms with the highest values, for each category, are listed below:

1. **Forest**
   - High values
   - Helix $2hv$ (Dihedral $45^\circ$ tilted) V (Volume) $Bo - B$ (Volume)

2. **Grass**
   - High values
   - Sphere $hh-vv$ (Dihedral) DB (Dihedral) $Bo + B$ (Dihedral)

3. **Buildings**
   - High values
   - Diplane $hh-vv$ (Dihedral) DB (Dihedral) $Bo + B$ (Dihedral)

4. **Airway**
   - High values
   - Helix $hh-vv$ (Dihedral) DB (Dihedral) $Bo + B$ (Dihedral)

### 4. THE KNOWLEDGE BASED CLASSIFICATION METHOD

A knowledge based classification method has been developed in the e-Cognition environment (eCognition User Guide 2000). The software introduces a new classification technology called ‘Object Oriented Image Classification’ in which homogeneous image objects in any chosen resolution are extracted and subsequently classified by means of fuzzy logic. The basic strategy is to build up a hierarchical network of image objects, which allows the representation of image information content at different resolutions (scales) simultaneously. By operating on the relations between networked objects, it is possible to classify local context information. The method developed requires three main steps for its implementation: multi-scale segmentation, knowledge base construction and classification.

The data which participate in the classification method are: 1) images from the diagonal elements of the coherency matrix, 2) Freeman – Durdan analysis images, 3) Cloude – Pottier analysis images (entropy, $\alpha$ angle and anisotropy), 4) analysis images from different combinations between entropy and anisotropy, 5) Pauli image analysis and 6) sphere/diplane/ helix analysis images.

#### 4.1 Multi-scale segmentation

The segmentation used is a bottom-up region merging technique starting with one-pixel objects. It creates image objects at several scales, as similar pixels at each level are aggregated to segments. Depending on the task, a trade-off between spectral and spatial homogeneity is possible. The spectral criterion is the change in heterogeneity that occurs when merging two image objects as described by the change of the weighted
standard deviation of the spectral values regarding their weightings. The spectral values used for the calculation of heterogeneity can be different channel values of an image, or spectral values of more than one images. The shape criterion is a value that describes the improvement of the shape with regard to two different models describing ideal shapes (compactness and smoothness).

A ‘merging cost’ is assigned to each possible combination. These costs represent the degree of fitting. For a possible combination the merging cost is evaluated and the merging is fulfilled, if the cost is smaller than a given threshold. The procedure stops when there are no more possible combinations. A small heterogeneity threshold permits fewer merges than a larger one. Therefore the size of the resulting image objects will grow with the heterogeneity threshold value. Due to this property, the threshold is called scale parameter (eCognition User Guide 3 2000).

Many tests were made in order to get the best segmentation using different segmentation settings and layers. The aim of the different tests was to get regular objects, preserving at the same time the edges between different land uses. Two segmentation levels were finally implemented, using the following input data: 1) Freeman – Durdan analysis images, 2) entropy and α angle, 3) Pauli analysis images and 4) sphere/diplane/helix analysis images. The segmentation settings of the two levels are shown in table 2:

<table>
<thead>
<tr>
<th>Level 1</th>
<th>heterogeneity</th>
<th>shape</th>
<th>scale</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>color</td>
<td>shape</td>
<td>compactness</td>
</tr>
<tr>
<td>1</td>
<td>0.7</td>
<td>0.3</td>
<td>0.9</td>
</tr>
<tr>
<td>2</td>
<td>0.6</td>
<td>0.4</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Table 2: The settings of the two segmentation levels.

After multi-segmentation, image objects are available on two levels. The first level contains objects of small size. These objects are joined in much bigger objects. However, some objects with high contrast especially in the town are preserved. Aggregation of pixels to image objects has two major advantages, 1) only a reduced number of class assignments have to be performed and 2) features – only available or more meaningful for objects – can be evaluated for classification (Benz, Pottier, 2000).

4.2 Knowledge base development

Based on objects, several features can be derived, such as values presented in the decomposition images which indicate scattering mechanisms, perimeter, complexity, texture, etc. The knowledge base which is created from them uses a fuzzy based logic in order for objects to be classified. Categories to be classified are: forest, airport, town, and vegetation.

The main characteristics of the forest are the high values of the volume scattering mechanism, dihedral 45° tilted (2hv) and cross-polarized (hv) component due to forest canopy, and the high entropy (H) values because of random scattering. Therefore, rules for forest classification were based on the images: hv, H, B0- B and V.

The main characteristic of the airport is very low backscattering due to the reflection of the signal from the airway surface. The orientation of the airway and the airport’s fence play an important role in classification. Thus the “main direction” feature is also included in the set of rules. Eight groups of rules were formed to classify the airport. The different sets of rules, rely on the facts that: 1) there are airport components which only form dihedral scattering, components which only produce surface mechanism, and components which produce both dihedral and surface mechanisms. The helix scattering mechanism that pronounces the simultaneous presence of dihedrals with various orientations is also dominant, 2) the orientation of dihedrals plays a significant role in their classification.

The town category is quite complicated as it includes several land uses, such as roads, buildings and trees. Therefore we used two subcategories, one for roads and one for buildings and trees. The main characteristics of the road subcategory are the surface scattering mechanism produced by the surface of the roads and the dihedral scattering mechanism produced by the interaction between the surface of the roads
The main characteristics of buildings/trees subcategory are the very high values of the surface scattering mechanism produced by the floors of the buildings or by the ground and the very high values of the dihedral scattering mechanism produced by the interaction between the ground and the buildings or the trunks of trees. Moreover the Volume backscattering mechanism is presented in trees and buildings which are not aligned to radar look direction. Thus the images $2A_0$, $B_0 + B$, and $V$ participated in the rules of this category. The “area” feature also helps in the setting of the rules. Further discrimination between buildings and trees was based on the “neighborhood” feature since the subcategory buildings/trees includes groups of trees which are present in the forest.

For the vegetation category, low values are observed for the surface and dihedral scattering mechanisms. This category includes three subcategories: vegetation 1, vegetation 2, and grass.

The vegetation 1 subcategory includes vegetation in its first growth stage. Its main characteristics are the low values of the $\alpha$ angle (isotropic surface) and entropy. This shows that the main scattering mechanism in this subcategory is the surface. Images $a$, $H(1-A)$, and $HA$ participated in the setting of rules.

The vegetation 2 subcategory includes vegetation in its mature stage. Its main characteristics are medium values of the $\alpha$ angle and entropy, because of the presence of three scattering mechanisms, the surface scattering mechanism produced by the ground, Helix scattering mechanism (many dihedrals) and dipoles produced by the interaction between stem and leaves with different orientation. Images $a$, $A$, $(1-H)(1-A)$, $HA$, $H$, and Helix participated in the setting of rules.

The third subcategory concerns grass. Entropy takes low values and the $\alpha$ angle take medium to high values. High values of the image $A(1-H)$ are observed because two scattering mechanisms appear. The dominant scattering mechanism is surface produced by the ground, and “dipoles” is the secondary one.

4.3 Classification scheme

Three classification levels are used to classify different land uses. The classification of the different categories and subcategories is performed in the second segmentation level. The hierarchy of the categories and subcategories in three classification levels is shown in figure 5:

![Figure 5: The hierarchy of the categories and subcategories in three classification levels.](image)

The classification results produced based on the rules of the knowledge base are shown in figure 6:
Figure 6: Classification of land uses.
The forest is shown in dark green color, airway in magenta, buildings in red, roads in brown, vegetation 1 in yellow, vegetation 2 in olive-green, and grass in green color.

4.4 H/α and H/α Wishart classification

For evaluation purposes we also implemented the H/α classification and the H/α Wishart classification method, using the Radar Tools (RAT) software. Their results are shown in figure 7 and 8 respectively:

Figure 7: H/α classification of land uses.

Figure 8: H/α Wishart classification of land uses.

4.5 Evaluation of the results

Using some test regions the classification accuracy for different land uses and overall accuracy can be calculated for each classification method. Table 3 shows the classification accuracy of the three classification methods for each land use:

<table>
<thead>
<tr>
<th>Land use</th>
<th>Knowledge based classification</th>
<th>H/α classification</th>
<th>H/α Wishart classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>forest</td>
<td>98%</td>
<td>52%</td>
<td>100%</td>
</tr>
<tr>
<td>buildings</td>
<td>95%</td>
<td>0%</td>
<td>91%</td>
</tr>
</tbody>
</table>

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Table 3: Classification accuracy for each land use in the three classification methods.

<table>
<thead>
<tr>
<th>Land Use</th>
<th>H/α Classification</th>
<th>H/α Wishart Classification</th>
<th>Knowledge Based Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>airport</td>
<td>86%</td>
<td>70%</td>
<td>0%</td>
</tr>
<tr>
<td>vegetation-1</td>
<td>70%</td>
<td>100%</td>
<td>83%</td>
</tr>
<tr>
<td>vegetation-2</td>
<td>75%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>grass</td>
<td>100%</td>
<td>95%</td>
<td>100%</td>
</tr>
<tr>
<td>roads</td>
<td>77%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>trees</td>
<td>100%</td>
<td>100%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Overall classification accuracy for the developed classification method, H/α classification and H/α Wishart classification are 94.5%, 66.4% and 54.6% respectively. It is shown that the knowledge based classification method has the highest performance. Moreover, in table 3, we observe that by the proposed method, more land uses were discriminated. In fact, vegetation was discriminated in three subcategories. Roads are also discriminated. All categories were classified with very high accuracy, except for categories vegetation-1 and vegetation-2 and roads. Parts of roads are confused with airways. The reduced accuracy in vegetation categories is due to the various rate of vegetation growth, even within the same field.

5. CONCLUSIONS

In this study, an investigation of the various polarimetric analysis methods was first performed. Based on this, a knowledge based classification method for the classification of the various land uses was developed. This method relied on the integration of the information provided by all the analysis decomposition methods of the polarimetric SAR data. Thus, the classification method was proved very efficient in discriminating land use categories and subcategories with high accuracy. Information provided by Cloude – Pottier analysis and the images produced by different combination of entropy and anisotropy were crucial for the determination of the number of the scattering mechanisms which participated in the classification rules. Features provided by Freeman, Pauli, and other analysis methods, efficiently attributed the scattering mechanisms and contributed significantly to classification performance. Among these methods, the Freeman analysis proved very efficient, for the discrimination of objects which mainly present Volume backscattering mechanism. The use of additional features, such as length/width, area, neighborhood, also improved classification performance. The comparison of the knowledge based proposed method with H/α and H/α Wishart classification methods indicated increased performance of the former in terms of accuracy and potential number of categories discriminated.

6. ACKNOWLEDGEMENTS

The authors are grateful to Dr J. Moreira (DLR) who kindly provided the E-SAR polarimetric data and Berlin University of Technology for the free software Radar Tools (RAT).

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