Land Cover Classification using Polarimetric SAR data

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ABSTRACT

In this paper we demonstrate and validate the benefit of polarimetry for land cover classification. The performance of supervised and unsupervised algorithms are presented. Two data sources are used: DLR -ESAR L-Band data of Alling, Germany and JPL AIRSAR L and C Band data of Flevoland, The Netherlands. Both datasets have comprehensive ground truth and this is used as validation. Confusion matrices are presented and conclusions about the best frequency and polarisation combinations to use are drawn.

1 INTRODUCTION

Over the last 20 years there has been considerable progress in the application of multi-polarimetric data to land observation. There have been three complementary lines of development in the following areas:

- Polarimetric radar data collection and calibration.
- Techniques for describing polarimetric radar signatures.
- Classification of polarimetric radar imagery.

The authors conducted a literature review for land applications of polarimetric SAR covering the period 1989 to November 2001. The objective was to support a critical review of polarimetric classification techniques for agriculture and land cover applications. Key events during this period are stated and briefly summarised below.

The status of polarimetric measurements in 1990 is comprehensively described in the book by Ulaby and Elachi [1]. This publication shows that there is considerable potential in polarimetric radar data, but that the techniques for extracting information had not yet been developed. The fundamental issues to be resolved were in the following areas:

- Definition of the features derived from the polarimetric signatures that contain the information relevant to classification.
- Determination of the feature statistics for use in the development of maximum likelihood classifiers.
- Speckle reduction techniques that do not destroy the inter channel relationships in polarimetric data in terms of phase and amplitude.

The polarimetric properties of natural objects can be described in terms of the co-polar and cross-polar response diagrams [1]. However these diagrams are not unique and not amenable to simple comparison or for use as a characteristic measurement.

Initially researchers experimented with many features (such as channel intensity, channel ratios, channel phase difference etc.). The feature combinations that best suited their requirement were found by experiment [e.g. 2] This procedure can however lead to practical sets of features for specific applications. [3].

In 1994 Lee [4] used Wishart statistics to describe the statistical variation of the amplitudes of the terms of the covariance matrix of polarimetric data. This allowed a maximum likelihood classification scheme to be developed using averaged covariance matrices.

The difficulty in the general discrimination between different crop types led Ulaby to adopt a systematic hierarchical classification scheme [5], however this approach was not developed further.

A new type of general approach was required that could utilise all the polarimetric information, this came through theoretical developments in radar polarimetry.

Techniques for the interpretation of polarimetric signatures have been the subject of considerable research. There are two signature categories in practical applications, determined by whether the scattering objects are stochastic or deterministic. Natural scenes consist of areas containing scatterers of a similar type for example, fields and forests. The stochastic scattering characteristics of these scenes are described by averages of second order parameters, such as the covariance matrix. This is in contrast to man made objects with discrete scatterers, such as ships, that are best characterised at a pixel level.

Cloude and Pottier [6] found that polarimetric characteristics of stochastic can be described principally in terms of two parameters H (entropy) and alpha, that respectively describe the type and purity of scattering mechanisms. An additional parameter, A (anisotropy), provides further information on the number of scattering components. Using physical arguments the H and alpha parameters can be used to provide a basis for a direct classification of polarimetric data [7]. The A parameter can be used to provide further class refinement [8].

There are two approaches to scene classification: unsupervised or supervised. The supervised approach requires ground truth. However it may lead to ambiguities because the scene characteristics required by the analyst may not necessarily be supported by the properties of the data. Unsupervised classification leads to an understanding of the class separability in the scene that is supported by the polarimetric signatures of the data. A difficulty with unsupervised classification is that convergence depends on the initial seeding of candidate classes. A way to seed the candidate classes is to use class centres defined by the H alpha properties of the data [9].

To improve class definition the statistical variation in stochastic data due to speckle needs to be reduced. A fundamental problem with speckle reduction techniques that use averaging, is the reduction of resolution and the attendant smearing of line features in the data. In [10] Lee overcame this by using an adaptive windowing technique allowing line features to be preserved. This technique is applied in conjunction with other analysis processes [e.g. H alpha analysis].

Lee et al [11] showed that by the use of supervised classification and a Wishart classifier, high classification accuracies for various land cover types could be obtained. This approach could also be modified in a consistent way, for the classification of partially polarimetric data. Good results were reported, this led to the recommendation of this technique for evaluation in this study, together with the unsupervised method [8].

In addition, a method that is based on the manual selection of feature vectors was evaluated on a subset of the Flevoland dataset. This work is presented in a separate paper [12].

2 SAR IMAGE AND GROUND TRUTH DATA

This paper presents the results from two scenes: Alling, Germany and Flevoland, The Netherlands. Fully polarimetric SAR and comprehensive ground truth data of these scenes was available. These data are briefly summarised in Table 1. At least 3 fully polarimetric images at each frequency, at each site were analysed. However, in this paper it is only feasible to show a representative sample of the results.

Test site	Radar Frequency	Sensor	Acquisition Date	Summary of ground truth
Alling, Germany	L	DLR E-SAR	March 2000 July 2000	Detailed crop cover, crop height, planting density, meteorological data, corner reflectors, IKONOS image
Flevoland, The Netherlands	L, C	JPL AIRSAR	July 1991	Detailed information on crop type

Table 1- SAR data and ground truth

All SAR data was supplied calibrated. However, calibration checks were performed before data processing. For all datasets the inter-channel power imbalance was less that 0.2 dB and inter-channel phase imbalance was less than 3 degrees.

Figure 1 (left) shows an L Band polarimetric colour composite for the Alling scene. This image was acquired by the DLR E-SAR system in July 1999. The polarisations are colour-coded as shown above the image. The resolution of the image is approx. 2m in range and azimuth.

Figure 1 (right) shows a subset of the ground truth for the same area. In this image, the *crop types* have been displayed in different colours. Many other parameters (such as crop height, planting density, soil surface roughness, soil moisture) are also available in this ground truth set. However, in this study, we have used the *landcover type* for classifier training (if required) and the validation of the classifications.

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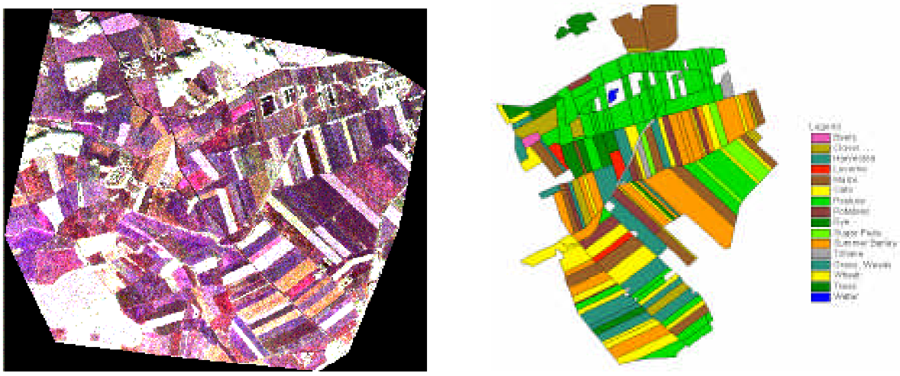

Figure 1 Band multiple polarisation colour composite of Alling (left), Crop type ground truth (right)

Figure 2 (left) shows an L Band polarimetric colour composite for Flevoland, The Netherlands. This image was acquired by the JPL AIRSAR system in summer 1991. The figure also shows the land cover ground truth for the same area. In this ground truth map, the land cover types have been displayed in different colours. No ground truth was obtained for black areas.

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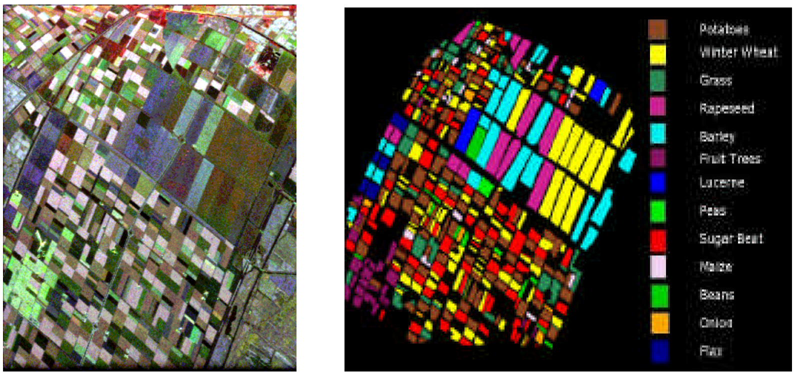


Figure 2 Multiple polarisation composite of Flevoland scene (left). Crop type ground truth (right)

3 SOFTWARE DEVELOPMENT AND DATA PROCESSING

To perform the classification several software modules were developed. These included:

- Data import and export for DLR E-SAR, JPL AIRSAR data
- Polarimetric speckle reduction using edge enhanced windows
- Entropy, alpha, anisotropy Polarimetric decomposition
- Wishart Classification - automatic seeding from H/α and H/α/A space (Unsupervised classification)

- Classification using Wishart statistics, with manual seeding (Supervised classification)

Details of the classification algorithms used can be found in [11]. The data processing chain is shown below. During the study, several classifications were attempted using 5 by 5, 7 by 7, 9 by 9 and 11 by 11 pixel windows for speckle filtering. A 7 by 7 window was found to give good speckle reduction without significant degradation in image resolution. For the results that are shown in this paper, the 7 by 7 speckle filtering window was used.

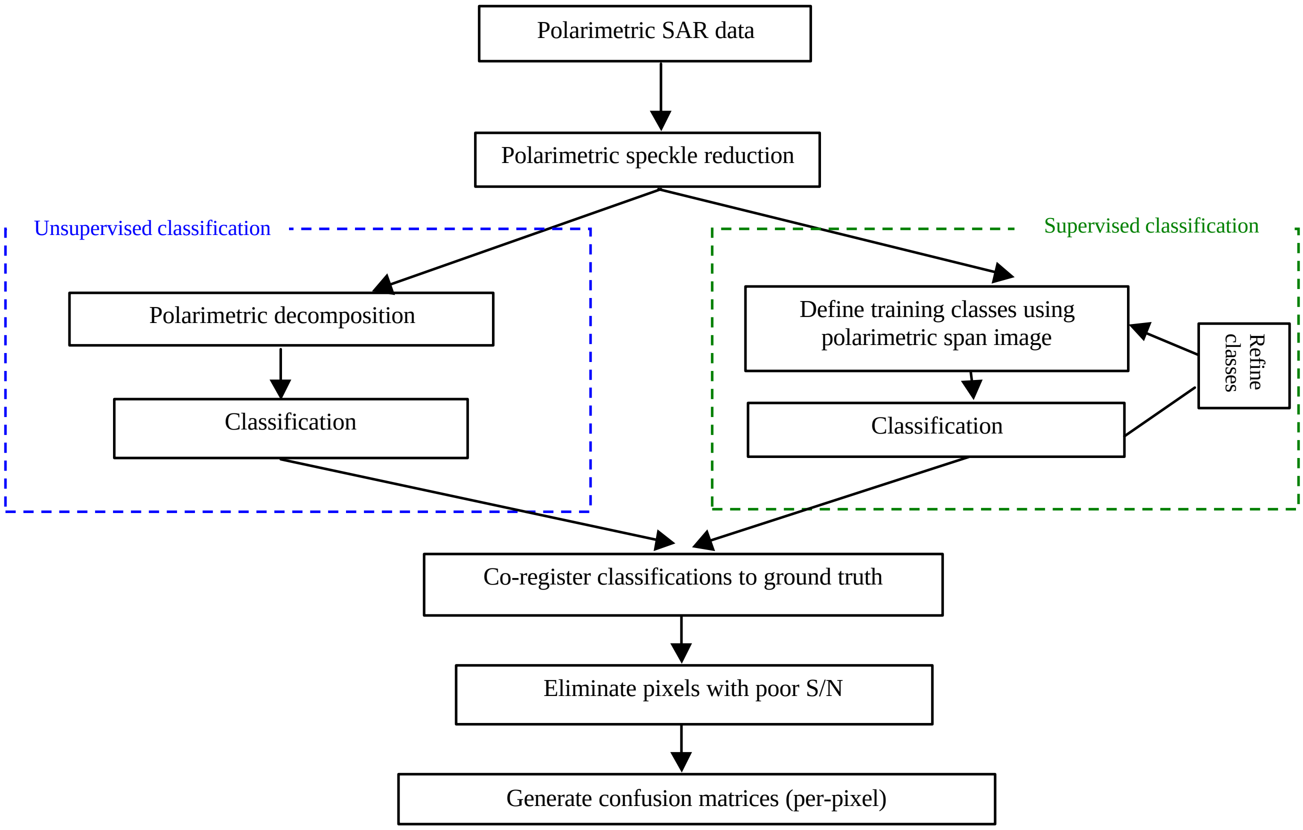


Figure 3 – Data processing chain

In order to take account of pixels that have poor signal to noise values, a mask was applied before the generation of the confusion matrices. The poor S/N areas mainly consisted of wide roads and still water.

4. RESULTS

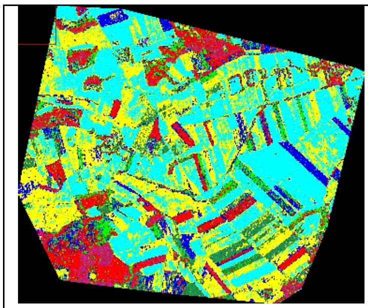
In this section, the classification results are presented. However, when looking at the results it is important to note the information in the next two paragraphs concerning the colours assigned to classes in the classified images.

The unsupervised classifications have been derived purely from the statistics of the data. They have not been seeded in any way by the ground truth. The number of classes that are obtained is therefore not the same as the number of classes in the ground truth. This means that, although the unsupervised classifications have been assigned colours for visualisation purposes, the colours that are displayed in the unsupervised classifications **do not** correspond to the colours in the ground truth image.

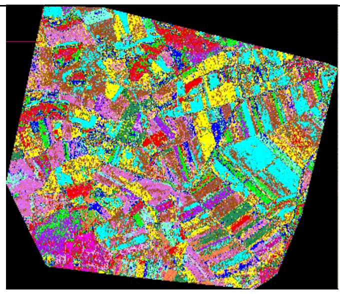
However, for the supervised classifications, a training set is produced for *each* ground truth class. As each land cover type in the ground truth is assigned a training set, the classification will produce the same number of classes that are in the ground truth. This means that it is possible to assign the same colour map to the classification and to the ground truth.

Alling, Germany

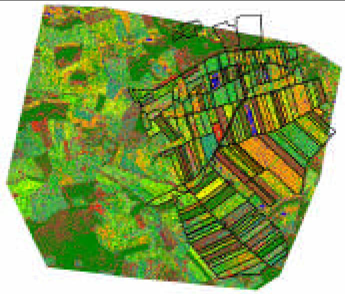
Figure 4 shows the classification results at L Band.for Alling. Tables 2- 4 show the confusion matrices for the Alling classifications shown in figure 4.



Entropy-alpha seeded unsupervised classification



Entropy-alpha-A seeded unsupervised classification



Supervised classification

Ground truth

Figure 4 – L Band classifications – Alling scene

All confusion matrices were computed on a per-pixel basis. The ground truth is represented in columns, the radar classifications are in rows. The values in the confusion matrices are percentages with respect to the ground truth data. This means that, if we take Table 2 as an example, 27% of the pixels that were weeds (in the ground truth) have been assigned to class 1. In this scheme, the sum of each column in the confusion matrix is 100%.

Class	Beets	Clover	Harvested	Lucerne	Maize	Oats	Pasture	Potatoes	Rye	Sugar	Barley	Tritikale	Weeds	Wheat	Forest
1	0	0	0	0	16	0	0	10	0	0	0	0	27	0	51
2	0	0	4	1	55	0	0	43	0	0	0	0	42	0	14
3	2	6	6	34	24	0	0	44	1	1	1	4	5	4	5
4	94	69	14	31	1	44	49	0	39	50	11	80	22	62	1
5	1	13	25	0	0	55	45	0	58	48	86	15	0	32	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25
8	1	10	48	31	0	0	4	1	0	0	0	0	1	0	0
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Table 2 – L band H-alpha –seeded classification confusion matrix

Class	Beets	Clover	Harvested	Lucerne	Maize	Oats	Pasture	Potatoes	Rye	Peas	Barley	Tritikale	Weeds	Wheat	Forest
1	0	0	0	0	2	0	0	13	0	0	0	0	0	0	40
2	0	0	4	0	14	0	0	55	0	0	0	0	6	0	16
3	0	1	3	27	10	0	0	26	1	0	1	2	0	1	3
4	39	29	13	5	0	3	36	0	23	23	5	47	14	9	1
5	0	3	12	0	0	0	8	0	0	4	37	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22
8	1	6	45	7	0	0	1	1	0	0	1	1	2	0	0
9	0	0	0	0	31	0	0	1	0	0	0	0	50	0	7
10	0	0	5	5	32	0	0	2	0	0	0	0	17	0	0
11	22	25	3	19	7	0	4	0	2	8	1	9	10	9	1
12	32	20	0	19	1	47	3	0	14	20	5	23	1	46	0
13	2	12	13	1	0	50	37	0	58	45	49	18	1	33	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2
16	4	3	3	17	0	0	11	0	0	0	0	0	0	1	0
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Table 3 – L band H-alpha-A –seeded classification confusion matrix

	Beets	Clover	Harvested	Lucerne	Maize	Oats	Pasture	Potatoes	Rye	Peas	Barley	Tritikale	Weeds	Wheat	Trees
Beets	**28**	15	1	6	0	2	5	0	3	5	0	8	3	5	0
Clover	8	**9**	7	21	2	0	4	1	1	0	0	2	1	2	0
Harvested	4	5	**18**	1	0	4	17	1	9	3	0	8	3	2	0
Lucerne	4	8	5	**24**	3	1	3	7	3	6	0	11	5	4	3
Maize	0	1	2	4	**33**	0	1	20	1	1	0	1	43	2	13
Oats	2	3	1	1	0	**38**	2	0	12	7	0	4	0	11	0
Pasture	12	12	4	3	0	2	**18**	1	9	9	7	12	5	5	0
Potatoes	1	1	22	9	20	0	2	**47**	1	1	1	2	3	1	12
Rye	11	10	6	3	1	15	12	1	**25**	19	17	9	3	22	0
Peas	9	7	1	8	1	8	2	0	4	**7**	2	5	2	15	0
Barley	2	8	14	1	0	3	18	0	13	13	**60**	6	1	5	0
Tritlake	6	5	1	3	1	6	6	0	6	3	3	**14**	2	6	0
Weeds	7	10	13	9	2	3	6	3	3	6	2	9	**8**	7	0
Wheat	7	7	1	5	0	17	4	1	10	20	7	9	2	**13**	0
Trees	0	0	3	1	36	0	1	18	1	0	0	1	20	0	**71**
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Kappa value = 0.24

Table 4 - Supervised classification confusion matrix

Flevoland, The Netherlands

Figure 5 shows the classifications for Flevoland at L and C band. The confusion matrices are shown in Tables 6-11.

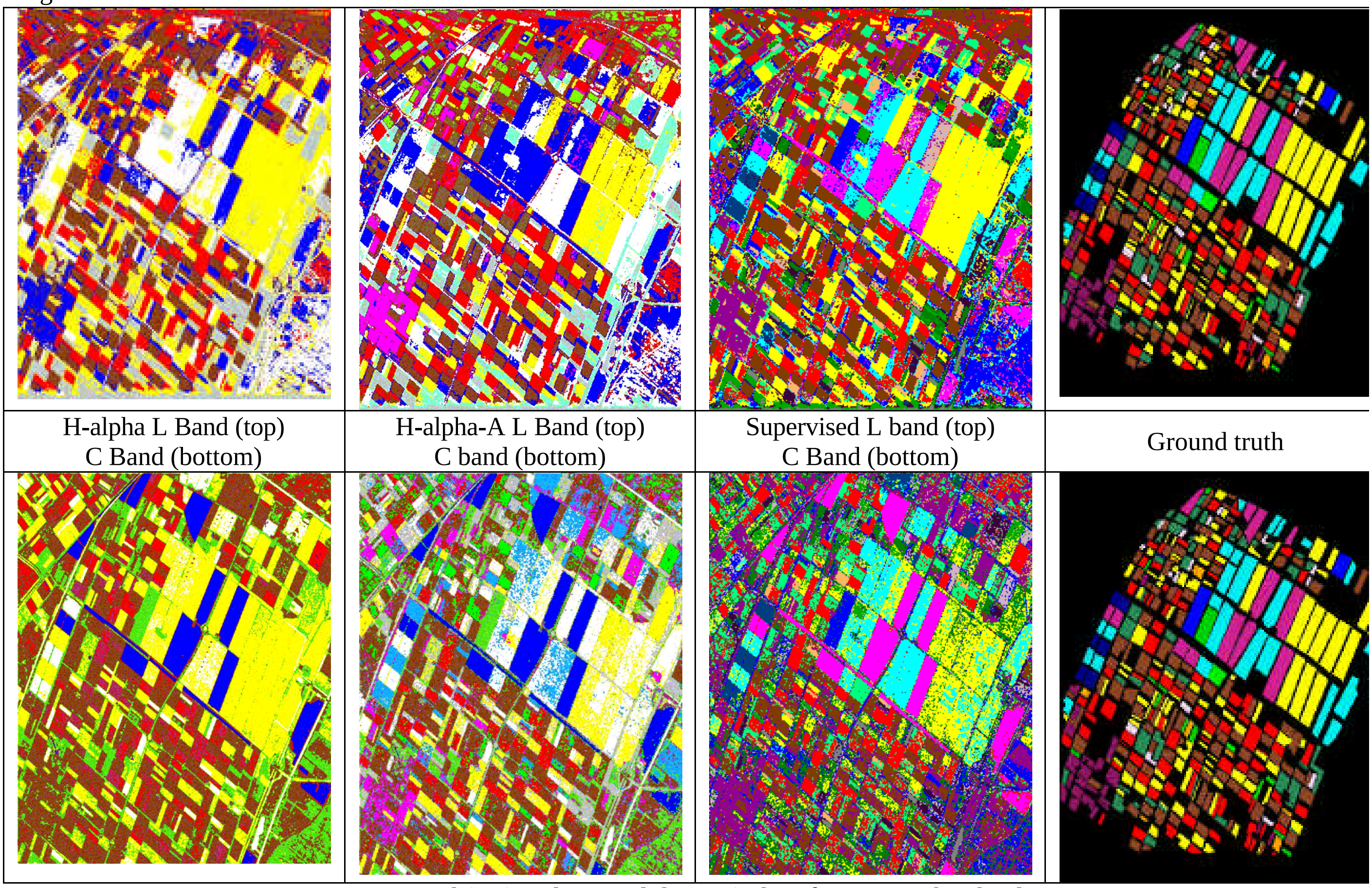


Figure 5 – L-Band (top) and C-Band (bottom) classifications –Flevoland

Class	Potato	Beet	Wheat	Grass	Maize	Rapeseed	Barley	Trees	Onion	Bean	Pea	Flax	Lucerne	Road	Canal
1	3	14	0	2	42	55	1	70	61	1	5	1	1	27	0
2	54	5	0	2	28	12	0	7	0	0	10	0	0	1	0
3	0	0	8	44	4	0	2	0	0	33	0	0	19	0	100
4	2	3	1	9	2	30	70	1	27	45	12	53	67	45	0
5	0	3	80	33	11	1	26	8	3	9	4	45	13	11	0
6	37	1	0	0	7	0	0	10	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	3	74	10	10	5	0	1	4	8	13	68	1	0	16	0
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Table 6 – L Band H-alpha classification confusion matrix

Class	Potato	Beet	Wheat	Grass	Maize	Rapeseed	Barley	trees	Onion	Bean	Pea	Flax	Lucerne	Road	Canal
1	3	2	1	2	19	57	1	2	50	1	4	1	14	31	0
2	46	1	0	2	27	10	0	0	0	0	11	0	0	1	0
3	0	0	0	13	0	0	0	0	0	29	0	0	0	0	100
4	0	1	0	3	0	24	37	0	20	41	0	8	54	9	0
5	0	1	4	26	9	0	20	6	2	5	0	47	10	5	0
6	34	1	0	0	7	2	0	2	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	3	72	2	9	4	1	1	3	6	12	61	1	1	27	0
9	0	2	0	0	21	5	0	84	14	0	7	0	0	1	0
10	1	18	0	1	5	1	0	0	1	1	3	0	0	0	0
11	0	0	10	35	5	0	3	0	0	5	0	0	22	0	0
12	1	2	1	6	2	1	38	1	6	5	12	42	1	25	0
13	0	1	81	4	0	0	0	1	0	1	1	0	0	0	0
14	11	0	0	0	1	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Table 7 – L Band H-alpha-A classification confusion matrix

Class	Potatoes	Beet	Wheat	Grass	Maize	Rapeseed	Barley	trees	Onion	Beans	Peas	Flax	Lucerne	Road	Canal
Potatoes	**90**	2	0	1	28	9	0	1	0	0	1	0	0	0	0
Beets	4	**77**	1	9	5	2	1	3	13	12	2	2	0	37	0
Wheat	0	2	**82**	22	9	1	4	4	1	7	6	0	9	1	0
Grass	0	0	0	**23**	0	0	0	0	0	1	0	0	3	0	2
Maize	0	0	0	1	**26**	15	0	0	9	0	0	0	0	7	0
Rapeseed	1	0	0	1	0	**55**	4	0	9	15	0	0	1	7	0
Barley	0	1	1	6	0	0	**70**	1	3	20	0	7	0	15	0
Trees	1	6	0	1	4	9	0	**80**	5	0	0	0	0	4	0
Onion	0	1	0	1	13	5	3	4	**36**	1	1	0	0	5	0
Beans	0	0	3	10	0	0	2	0	0	**14**	0	0	1	0	11
Peas	0	9	10	2	3	1	0	4	6	1	**67**	0	0	1	0
Flax	0	0	0	4	1	0	3	1	0	1	0	**86**	0	0	0
Lucerne	2	3	1	4	4	4	8	0	17	10	22	1	**67**	22	0
Road	0	0	2	16	6	0	5	2	0	3	0	3	18	**0**	0
Canal	0	0	0	0	0	0	0	0	0	15	0	0	0	0	**87**
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Kappa index = 0.59

Table 8 – L Band Supervised classification confusion matrix

Class	Potatoes	Wheat	Grass	Rapeseed	Barley	Trees	Lucerne	Peas	Beets	Maize	Beans	Onion	Flax	Canal	Road
1	0	0	0	94	0	0	0	0	0	0	0	0	0	0	1
2	1	2	0	1	5	30	35	0	3	19	0	3	0	0	5
3	2	27	0	3	54	9	2	27	2	34	4	18	71	0	33
4	84	17	81	0	1	1	0	3	47	2	5	34	3	0	0
5	10	39	2	1	5	3	1	69	6	11	12	34	18	0	51
6	1	9	0	0	34	34	48	0	7	7	0	5	6	0	10
7	1	2	0	0	2	21	14	0	2	25	0	1	2	0	0
8	1	4	17	0	0	1	0	0	35	1	79	5	0	100	0
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Table 9 – C Band H-alpha classification confusion matrix

Class	Potatoes	Wheat	Grass	Rapeseed	Barley	Trees	Lucerne	Peas	Beets	Maize	Beans	Onion	Flax	Canal	Road
1	0	0	0	94	0	0	0	0	0	0	0	0	0	0	0
2	0	1	0	2	4	21	20	0	1	33	0	2	0	0	5
3	1	19	0	0	50	5	1	4	0	26	4	6	28	0	18
4	13	22	3	0	1	1	0	0	11	1	17	22	2	0	1
5	3	29	0	0	3	2	1	62	2	10	35	14	9	0	44
6	1	8	0	0	35	19	55	0	4	9	1	4	5	0	10
7	1	3	0	0	3	48	21	0	6	7	0	3	1	0	1
8	0	0	0	0	0	0	0	0	25	1	0	1	0	100	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	1	11	0	3	3	3	1	28	4	8	31	20	50	0	13
13	34	0	85	0	0	0	0	2	43	1	1	5	0	0	0
14	46	3	11	0	1	1	0	1	3	3	8	16	2	0	0
15	0	1	0	0	1	1	0	2	0	1	2	5	2	0	8
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Table 10 – C Band H-alpha-A classification confusion matrix

Class	Potatoes	Beet	Wheat	Grass	Maize	Rapeseed	Barley	trees	Onion	Beans	Peas	Flax	Lucerne	Road	Canal
Potatoes	**67**	41	1	4	13	2	0	2	2	5	11	0	2	1	0
Beets	7	**49**	0	2	8	2	0	0	0	8	4	0	0	0	0
Wheat	0	0	**50**	1	0	0	0	0	2	12	0	0	0	0	0
Grass	0	0	13	**39**	8	0	0	7	1	2	0	8	0	39	0
Maize	3	3	0	4	**32**	0	0	14	9	1	0	0	9	1	0
Rapeseed	0	0	0	0	1	**80**	0	0	0	1	0	0	0	1	0
Barley	0	0	0	3	0	0	**71**	1	4	21	0	2	0	5	0
Trees	3	2	21	29	10	1	1	**71**	4	6	0	7	14	38	0
Onion	0	1	0	2	23	12	1	0	**29**	2	3	0	0	1	0
Beans	0	0	3	3	0	0	2	1	0	**1**	0	0	0	5	0
Peas	17	1	7	5	3	1	2	2	8	1	**64**	1	16	8	0
Flax	0	0	0	2	1	0	1	0	0	0	0	**82**	0	1	0
Lucerne	1	1	3	1	0	1	21	0	41	26	18	0	**57**	0	0
Road	0	0	1	3	0	0	0	1	0	12	0	0	0	**0**	0
Canal	0	0	0	0	0	0	0	0	0	4	0	0	0	0	**100**
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Kappa Value=0.51

Table 11 – C Band Supervised classification confusion matrix

5 DISCUSSION

Unsupervised classifications

Analysis of the unsupervised classifications and their associated confusion matrices shows that the automatically radar-derived classes do not correlate well with the land cover classes that are in the ground truth.

For the 8-class entropy-alpha-seeded classification, many of the ground truth land cover classes are fused into a common radar class, with the other radar classes only scarcely populated. This occurs in both the Alling and the Flevoland scenes. For example, consider the Alling data. In table 2, the radar-derived classes 4 and 5 (cyan and yellow respectively in Figure 4) contain approximately 65% of the data. The confusion matrix shows that classes 4 and 5 contain almost every type of crop that is recorded in the ground truth. Some of these crops are structurally distinct. For example, the highest populations in class 4 are: wheat, tritikale, beets and clover. Figure 6 shows photographs of these crops. The photographs were taken at the time of SAR imaging.

Wheat	**Tritikale**	**Clover**	**Beets**

Figure 6 – Alling Landcover at time of imaging

The 16-class H-alpha-A seeded unsupervised classifications appear to be *visually* better, but when compared rigorously to the ground truth, there is not a significantly improved correlation between the radar classification and the land cover ground truth. It was found that, as was the case with the H-alpha classification, structurally different types of landcover were merged into a single radar class (eg class 4 in Table 3). Other classes, such as classes 1,2,3, 13 and 14 also contain mixtures of significantly different types of landcover.

Supervised classifications

The supervised classifications were better for landcover discrimination than the unsupervised classifications. It was found that the Flevoland data produced much better results than at Alling. One reason for this may be because the fields in Flevoland are very large – this allowed larger training areas to be defined for Flevoland than for Alling.

For Alling, trees (71%) and barley (60%) were classified most accurately. Peas (7%), weeds (8%), wheat (13%) and clover (9%) were classified least accurately. This was consistent for a number of other classifications of the Alling scene using different datasets (not shown in this paper). In the case of clover, the low classification accuracy could be because a small training area was necessary due to the limited amount of clover in the ground truth.

For Flevoland, at L band, potatoes (90%), beets (77%), wheat (82%), barley (70%), trees (80%), flax (86%) and canal (87%) were classified most accurately. Grass (23%), beans (14%), road (0%), maize (26%) were classified least accurately. Although road classification was consistently poor, this can partly be explained by the very small size of the training area that was used, and the fact that the road training sample was contaminated by the response from fields that were directly adjacent to the road.

For Flevoland at C band, the classification accuracy for most crops either remains the same or decreases when compared to the L band result. This is reflected in a lower kappa value (0.51) for the C band classifications.

However, there are some crops that are classified better at C Band – rapeseed and grass classification was improved by over 15% compared to L band.

6 SUMMARY

Unsupervised and supervised classification using Wishart statistics was performed on L and C Band polarimetric SAR data of Alling, Germany and Flevoland, The Netherlands. The classifications were validated using comprehensive landcover information, obtained at the time of SAR imaging. The unsupervised classifications were seeded using entropy, alpha and anisotropy information. The supervised classifications were seeded manually by the user using ground truth information.

The unsupervised classifications did not map uniquely to the desired land cover classes. It was found that many landcover classes were fused into just a few radar-derived classes. It was also found that landcover types that are structurally very different were fused into the same radar class.

The supervised classifications at L band performed as well as or better than at C band for the majority of the land cover classes. The kappa measure for the Flevoland L band supervised classification (0.59) was significantly higher than the kappa measure for Alling L Band (0.24). However, in general it was found that the classification performance was lower than has been reported by other groups [11].

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