CROP CLASSIFICATION WITH MULTITEMPORAL POLARIMETRIC SAR DATA

Shaun Quegan[(1)] , Thuy Le Toan[(2)], Henning Skriver[(3)], Jose Gomez-Dans[(1)], Maria Carmen Gonzalez-Sampedro[(4)], and Dirk H. Hoekman[(5)]

[(1)]*University of Sheffield, Hicks Bldg, Hounsfield Rd, Sheffield S3 7RH, United Kingdom. Email: s.quegan@shef.ac.uk*
[(2)]*CESBIO, 18 ave. Edouard Belin, 31401 Toulouse, France. Email: thuy.letoan@cesbio.cnes.fr*
[(3)]*Technical University of Denmark, Building 348, DK-2800 Lyngby, Denmark. Email: hs@oersted.dtu.dk*
[(4)]*Faculty of Physics, Dr Moliner 50, E-46100 Burjassot, Valencia, Spain. Email: mcgonzal@uv.es*
[(5)]*Wageningen Agricultural University, Nieuwe kanaal 11, 6709 PA Wageningen, Netherlands. Email: Dirk.Hoekman@users.whh.wau.nl*

Abstract

Multitemporal measurements gathered by EMISAR over the Foulum (Jutland) test site and AirSAR over the Wageningen test site provide an unrivalled opportunity to examine the factors affecting classification of northern European agricultural crops using both polarimetric and multitemporal information. Data analysis, guided by physical principles, has been used to investigate those polarimetric features most adapted to separating different classes of crops (with the emphasis on C band data). This has led to a hierarchical approach in which broad classes (e.g., spring vs. winter crops) are successively subdivided into more specific classes using the most appropriate polarimetric features. This direct scheme has been linked to statistical methods in order to permit adaptivity of the decision boundaries. Its performance is compared with data-driven methods as a function of the temporal evolution of the crop state.

1 INTRODUCTION

Growing crops display a wide range of canopy geometries and shapes of plant components. From the radar point of view, this means that different crops distribute the dielectric material of which they are made differently in space: their architectures vary significantly. Some crops (or at least some of their components) show strongly preferred orientations, such as the stalks or ears of cereals. The importance of SAR polarimetry in crop classification arises principally because polarisation is sensitive to orientation. Hence it provides a means to distinguish crops with different canopy architectures. Detailed explanation of how this occurs is not straightforward, since the polarimetric response is determined by both attenuation and scattering processes, and these in turn depend on the probing frequency and the incidence angle as well as plant properties. In addition, the scattering mechanisms can vary with depth in the crop canopy, particularly between the response of the canopy itself and soil response.

Despite the recognised potential, studies in crop classification and in crop parameter retrieval have been limited for a number of reasons:

- The available SAR datasets have been few in number and rarely accompanied by adequate ground data;
- Many of the datasets came from just a few campaigns covering a fairly limited range of conditions, which are often not ideal for studying backscatter from crops (for example, the 1994 SIR-C mission produced data from April and October, times which are unsuitable for assessing crop conditions in Northern Europe);
- Multitemporal polarimetric data have not been widely available;
- The experimental nature of the datasets, limited in time and geographical extent, has made them of marginal interest in developing applications, with much greater emphasis, particularly in Europe, on exploiting multitemporal satellite data.

A further issue is the immaturity of the necessary data analysis methods. The first half of the 1990's saw numerous papers dealing with crop classification methods using polarimetry. Very high classification accuracies were reported. However, in all cases these were isolated studies with no consolidation and no extensive assessment. This strongly affects the significance of the conclusions of studies which attempted to assess the value of polarimetric and multi-frequency data.

It is against this background that the present study is set. It will use both thorough analysis of datasets available to the study team, and detailed test of classification methods to demonstrate the use of polarimetry in crop and land cover classification.

2 SAR AND GROUND DATASETS

This study uses an EMISAR dataset from Foulum (Denmark) and the Flevoland (NL) AirSAR dataset. These datasets are comparable in terms of polarimetric radar data, and complementary in terms of temporal coverage. They are suitable for statistical analysis of the frequency, angular, polarimetric and temporal behaviour of crop types prevailing in North Europe, although the lack of detailed ground data preventing rigorous interpretation and modelling.

2.1 The Foulum Dataset

The fully polarimetric Danish airborne SAR system, EMISAR, acquired simultaneous C-band (5.3 GHz) and L-band (1.25 GHz) SAR data at the Foulum agricultural test site in Jutland, Denmark on 21 March, 17 April, 20 May, 16 June, 15 July and 16 August, 1998. The area contains spring crops: beets, peas, potatoes, maize, spring barley and oats, and winter crops: rye, winter barley, winter wheat, winter rape and grass. Hence this dataset is particularly well suited to evaluation of the classification performance of satellite systems giving monthly coverage of the area during the growing season. The nominal one-look spatial resolution is 2 m by 2 m (one-look), the swath-width is approximately 12 km and incidence angles range from 35º to 60º. The processed data are fully calibrated using an advanced internal calibration system.

2.2 The Flevoland Dataset

The Flevoland site was visited by the NASA/JPL AIRSAR system on June 15, July 3, July 12 and July 28, 1991,during the Mac-Europe campaign. P, L and C-band data were acquired at incidence angles from 26° to 65°. Covariance matrix data, calculated on a per field basis, are available through the ERA-ORA Concerted Action European project for the following crop types: potato (406 fields), wheat (394 fields), sugar beet (317 fields), grass (186 fields), barley (101 fields), and for a small numbers of fields of oats, maize, rapeseed, beans peas, alfalfa, oat, onion, flax, lucerne, grass and fruit trees. Classification schemes derived from the field data were also applied at the pixel level, and tested against the crop map provided. The dataset is well suited to assessing classification performance during the peak period of vegetation growth in July.

3 DATA ANALYSIS

The analysis in this paper is based exclusively on C-band data, because of its more reliable performance compared to L-band [1]. This section summarises results from analysis of the polarimetric data from Flevoland and Foulum, and is aimed at selecting optimum parameters for classification.

3.1. Radar Parameters

The following radar measurements were considered:

- The terms in the covariance matrix (ignoring the co-cross covariance terms), including the amplitude and phase of the HH-VV covariance.
- The amplitude of the HH-VV correlation coefficient.
- Ratios of channel powers (in dB).
- Following [2], the circular (RR, LL and LR) powers, the ratios between these powers (RR-LL, RR-RL and LL-RL), and the 45^{o} linear polarisations (copol, crosspol, copol-crosspol).
- Entropy and alpha, as described in [3].

3.2 Data Analysis

3.2.1 Incidence angle variation

The angular variation of the measurements depends on the type of measurement, the frequency, the polarisation, the crop type and the date. For single intensity measurements (HH, VV or HV) at C band:

(a) The variation is of type cos(θ) if volume scattering from the vegetation layer is the prevailing interaction mechanism. This is the case for:
   - HV, at dates when the crops are well developed (e.g. July dates at Flevoland).
   - HH or VV, when crops are well developed and the soil contribution is small, as occurs in July for sugar beet and potato.

(b) When the soil backscatter is dominant (at early and late stages), the attenuation by the crop goes as 1/cos(θ.), but the overall variation depends on the soil backscatter angular variation, which depends on surface roughness.

(c) When the soil-vegetation interaction is important, the angular variation may display quite different behaviour.

(d) When there is large inter-field variability, because of differences in phenological stage or the class taxonomy corresponds to different canopy types, very large dispersions in inter-field backscatter can be observed. This occurs for most crops in June, when the growth rate is high and there is field-to-field variability in scattering mechanisms. The large class variance will then militate against the generality and robustness of any classification procedure.

In summary, $\gamma = \sigma^0 / \cos\theta$ can be used to compensate for incidence angle variation only for HV backscatter at C band in July. For HH and VV, the incidence angle range should be restricted in the analysis (for example, by excluding data at low (<30°) and high (>50°) incidence angles), or by experimentally assessing the angular variations specific to the case where soil backscatter is significant.

As a consequence, the data analysis and classification scheme using airborne data should be applied over small ranges of incidence angle, i.e. 25-35°, 35-45°, 45-55° and >55°. A problem usually encountered with airborne data is that crop types are not evenly distributed across the incidence angle range.

3.2.2 Selection of Parameters

Discrimination between vegetation and bare soils

Early in the growing season, the spring crop fields are characterised by surface scattering, whereas the winter crop fields with vegetation display some degree of volume scattering. Late in the season, most harvested fields can be considered as bare soil surface. Hence, polarimetric parameters are sought which discriminate between surface and volume scattering. Polarimetric parameters that are expected to have potential for discriminating between bare and vegetated fields are those which maximise the difference between surface and volume scattering. These are:

- the cross-polarized backscatter coefficient HV, the entropy and the HV/VV ratio, the latter having higher values for volume scattering than surface scattering,
- the correlation coefficient between HH and VV, which is higher for surface scattering.

Fig. 1 shows HH-VV correlation versus HV in April at Foulum, and indicates that separation of winter and spring crops is possible using these parameters (the separating curve is discussed in Section 4).

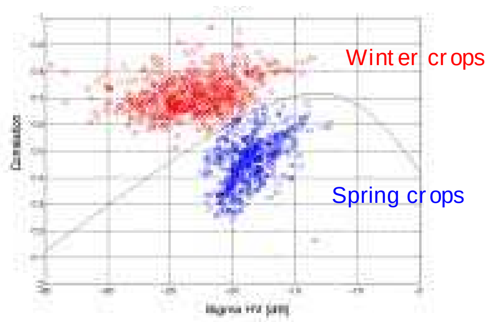

Fig. 1: HH-VV correlation versus HV for winter (red) and spring (blue) crops on April 17 at the Foulum site

Separation between broad leaves and small stems crops

Simulations in [2] show an appreciable difference between RR and RL backscatter when crops with small stems are compared with crops of wide leaves. The difference was interpreted as due to cylinder scattering compared with disc scattering. However, small stem crops, such as wheat and barley, have stems that are predominantly vertical, whereas broad leaf plants like sugar beet and potatoes contain more randomly oriented scatterers, and the difference may be due to the plant structure. Fig. 2 shows RR-RL versus HV-VV ratios (in dB) at the Flevoland site on July 28. Wheat, barley and grass have a limited range of RR-RL, whereas potato and sugar beet have lower values. The separation is also clear on July 12, but less so on July 3 and not at all on June 15. Figure 3 shows similar observations at Foulum, where RR-RL for sugar beet and potato appears to be linearly related to HV-VV, while RR-RL remains in a restricted range for small stem crops.

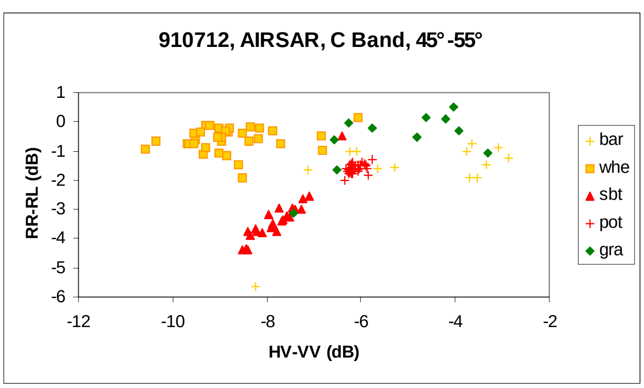

Fig. 2 RR-RL (dB) vs. HV-VV (dB) at Flevoland (July 12)

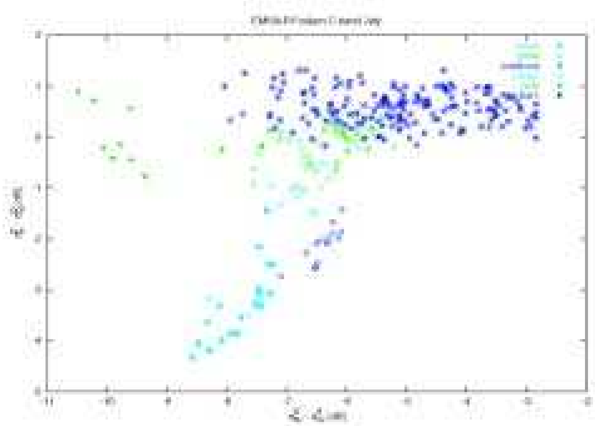

Fig. 3 RR-RL (dB) vs. HV-VV (dB) at Foulum (July 15)

Separation of plants with different biomass levels
HV is a good discriminator of different biomass levels. Figs. 4 and 5 show separation between rape, barley, rye and wheat at Foulum using HV. At Flevoland, separation between rapeseed, barley, wheat and beans is possible. Fig. 5 shows also that sugar beet and potato can be separated using the HH-VV correlation at this mid-July date.

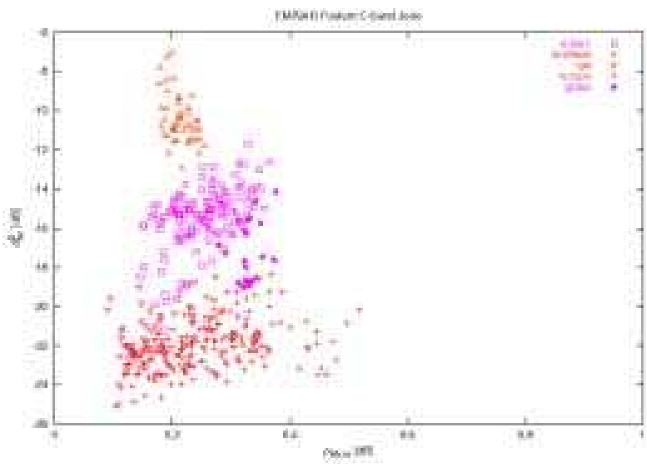

Fig. 4. HV (dB) vs. HH-VV correlation at Foulum (Jun 16)

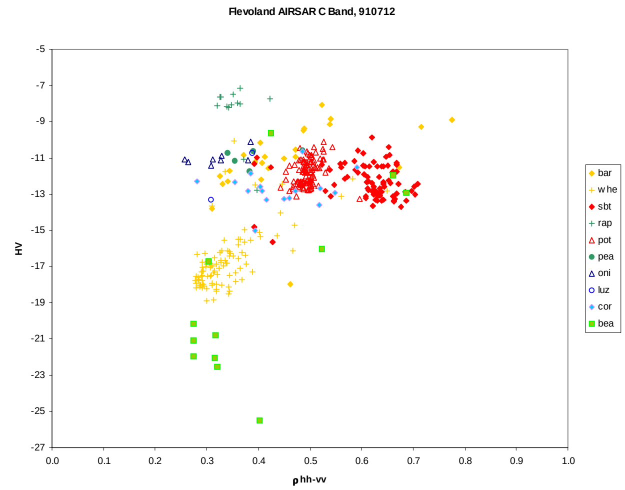

Fig. 5. HV (dB) vs. HH-VV correlation at Flevoland (Jul. 12)

Summary of the data analysis
The analysis carried out on the two datasets indicates the following:

1. The incidence angle variation of the radar parameters is important and needs careful consideration when defining the optimum incidence angle for spaceborne SAR data, and applying classification methods to airborne SAR data.
2. The parameters that can be derived from polarimetric SAR data vary significantly over the April-July growth season, and over intervals of 9-18 days in June-July. These variations could be interpreted in terms of scattering mechanisms if the relevant ground data were available. However, to derive robust classification methods based on scattering mechanisms, the crop calendar at a given test site must be known.
   - Using an acquisition early in the growing season it is possible with a high accuracy to discriminate between winter and spring crops using HV or the HH-VV correlation.
   - It may be possible to discriminate between wide leaf crops and small stem crops using acquisitions later in the growing season (mid to late July) using RR-RL.
   - Small stem crops with different biomass level can be discriminated with HV.

4 FIELD-BASED CLASSIFICATION
Field-based classification using a maximum likelihood ISODATA classifier was applied in three contexts:

1. Separating spring from winter crops
2. Comparing performance at Foulum with that at Flevoland
3. Comparing classification performance at different times for Flevoland

4.1 Separating Spring from Winter Crops
Data analysis shows that individual features cannot accurately separate spring from winter crops, but that several pairs of features can do this very effectively. An example using C band Foulum data from April 1998 is shown in Fig. 1. The curve marked on Fig. 1 is the quadratic decision boundary located by ISODATA; it can be seen that a linear decision boundary would give only slightly worse performance for these data. The performance for a range of feature pairs is shown in Table 1. Most of these pairs give good separation of the two classes, the greatest accuracy (95.1%) arising from the features used in Fig. 1. Addition of extra features did not improve the results.

Table 1: Classification results for selected pairs of parameters

Parameter 1	*Parameter 2*	*Spring OK (No. & %)*	*Spring Bad (No. & %)*	*Winter OK (No. & %)*	*Winter Bad (No. & %)*	*Overall (%)*
VV	*HV*	524 (94.2)	32 (5.8)	395 (88.0)	54 (12.0)	92.6
Correlation	*HV*	524 (94.2)	32 (5.8)	432 (96.2)	17 (3.8)	95.1
Alpha	*Entropy*	535 (96.2)	21 (3.8)	413 (92.0)	36 (8.0)	94.2
Correlation	*Entropy*	539 (96.9)	17 (3.1)	392 (87.3)	57 (12.7)	92.6
HV-HH	*HV-VV*	512 (92.0)	44 (8.0)	421 (93.7)	28 (6.3)	92.8
RR-RL	*HV-VV*	506 (91.0)	50 (9.0)	428 (95.3)	21 (4.7)	92.9
HH	*HV*	452 (81.3)	104 (18.7)	424 (94.4)	25 (5.6)	87.1
Entropy	*RR-RL*	531 (95.5)	25 (4.5)	418 (93.1)	31 (6.9)	94.4

4.2 Comparing Classification Performance at Foulum and Flevoland

Section 3 has shown that a relatively small number of parameters appears to be suitable for classifying the available crop types. Particularly important information-bearing features in early/mid-July are the HH-VV correlation coefficient, the HV backscattering coefficient and the RR-RL ratio. These features were used in the ISODATA algorithm for the Foulum 15/7/98 and Flevoland 12/7/91 datasets. The crops common to both test sites are wheat, barley, potatoes and sugar beet, and for comparability we restricted the dataset to just these classes. Because there are large variations in the number of fields per class, a *maximum a posteriori* (MAP) approach was used. In addition, two forms of the ISODATA algorithm were considered, one carrying out the classification for all four classes in a single step, and a hierarchical form (suggested by the approach described in Fig. 6), in which the fields are first separated into cereals and broad leaf crops, before subdividing each of these classes into their two constituent crop types.

Table 2. Classification accuracies using single-step (S) and hierarchical (H) ISODATA schemes

Site	**Date**	**ISODATA type**	**Accuracy %**
Foulum	15/7	S	89.2
Foulum	15.7	H	93.8
Flevoland	3/7	S	76.7
Flevoland	3/7	H	84.9
Flevoland	12/7	S	92.8
Flevoland	12/7	H	92.1

Table 2 shows the results for early and mid-July at Flevoland and for mid-July at Foulum. The key points are: (1) the algorithm performs well under all these circumstances; (2) the hierarchical form appears to produce better results (the difference between the single-step and hierarchical form for July 12 at Flevoland cannot be considered significant); (3) the approach is transferable between times and locations.

4.3 Comparing Classification Performance at Different Times for Flevoland

In this Section, we consider classification of the six main crops (wheat, barley, potatoes and sugar beet, rapeseed and beans) at Flevoland at all three July dates for which data are available, in order to investigate multi-temporal effects. Three types of ISODATA are used: single-step ML, single-step MAP and hierarchical. We also carry out ML classification based on the Wishart distribution. In this case, the class means and covariances were derived by averaging 10% of the fields of each type, chosen at random. Different random selections did not greatly affect the results. The classification accuracies and kappa coefficients for the three dates are summarised in Table 3(a)-(c).

Table 3(a). Accuracies and kappa coefficients for the four classification methods on July 3.

Algorithm	Accuracy (%)	Kappa coefficient
ML ISODATA	75.9	0.68
MAP ISODATA	80.1	0.73
Hierarchical ISODATA	81.9	0.76
Wishart	84.3	0.79

Table 3(b). Accuracies and kappa coefficients for the four classification methods on July 12

Algorithm	Accuracy (%)	Kappa coefficient
ML ISODATA	80.4	0.75
MAP ISODATA	88.0	0.84
Hierarchical ISODATA	89.5	0.86
Wishart	79.8	0.73

Table 3(c) Accuracies and kappa coefficients for the four classification methods on July 28

Algorithm	Accuracy (%)	Kappa coefficient
ML ISODATA	76.7	0.70
MAP ISODATA	77.3	0.69
Hierarchical ISODATA	75.4	0.67
Wishart	78.5	0.72

There appear to be two general features of the above results. The first is that MAP ISODATA consistently gives better overall accuracy than ML ISODATA; this is almost certainly because of the wide disparity between the numbers of fields of each crop type, and the need for a weighting to counteract this. The second is that the Wishart approach appears to do better under those circumstances where the classes do not seem as well separated (July 3 and 28; see Section 3). On July 12, where the classes separate out very well in feature space, hierarchical and MAP ISODATA perform markedly better than the Wishart classification. This is not easy to interpret. Work in [1] showed that Wishart classification tended to perform badly if there was significant variation within a single class, so that the averaged training statistics were not representative of many of the individual samples. It is not clear if this is the case here.

While MAP ISODATA performs better than ML ISODATA, there is no clear indication about whether it is preferred to hierarchical ISODATA. On the first two dates, the hierarchical form does better, on the third date, MAP does better; in none of these cases is the difference dramatic.

5 PIXEL-BASED CLASSIFICATION

Section 4 was concerned with field-based classification, which requires a field based reference or perhaps a segmented image. When such information is not available, a pixel-based approach is needed. In this Section we compare three methods of pixel-based classification: (1) direct hierarchical classification; (2) ISODATA clustering (both single-step and hierarchical) followed by classification; and (3) maximum likelihood (ML) using the complex Wishart distribution. We also give results for an ISODATA algorithm driven by the Wishart distribution.

The direct hierarchical classification methods are based on analysis of the field-averaged Flevoland data in the ERA-ORA database. An initial algorithm, developed from analysis of the July 12 data, showed a systematic failure associated with ‘rapeseed’ fields when applied to the July 28 image. This occurs because these fields exhibit properties more appropriate to surface than volume scattering; we interpret this as a sign that the fields have been harvested. Catering for this ‘bare soil’ class requires the addition of an extra rule to the initial scheme, as shown in Fig. 6. The algorithm uses the C-band HV-VV, HV-HH and RR-RL ratios, the HH-VV correlation and HV backscatter. After identifying ‘bare soil’ from the cross-pol/co-pol ratios, it separates the broad leaf and small stems crops using the RR-RL difference. These two main classes are then separated into subclasses by using HH-VV correlation coefficient for the broad leaf and HV for the small stem classes. For the broad leaf class, we define two subclasses: potatoes and sugar beets. For the small stem class, we define four subclasses: beans, winter wheat, barley and rapeseed.

Four forms of pixel-based ISODATA classification are considered:

1. Randomly initialised single step ISODATA
2. ML ISODATA initialised using a hierarchical scheme
3. MAP ISODATA initialised using a hierarchical scheme
4. Hierarchical ISODATA initialised using a hierarchical scheme

Each of these four forms of ISODATA is concerned with answering a particular question:

1. Can a purely data driven clustering algorithm identify the main crop classes at the Flevoland site?
2. Does the classification improve if we input prior knowledge into the initialisation?
3. Is ISODATA adversely affected by the large differences in the prior probabilities of different classes (i.e., the large variation in area planted to different crops)?
4. Can ISODATA help to optimise the thresholds used in a hierarchical scheme?

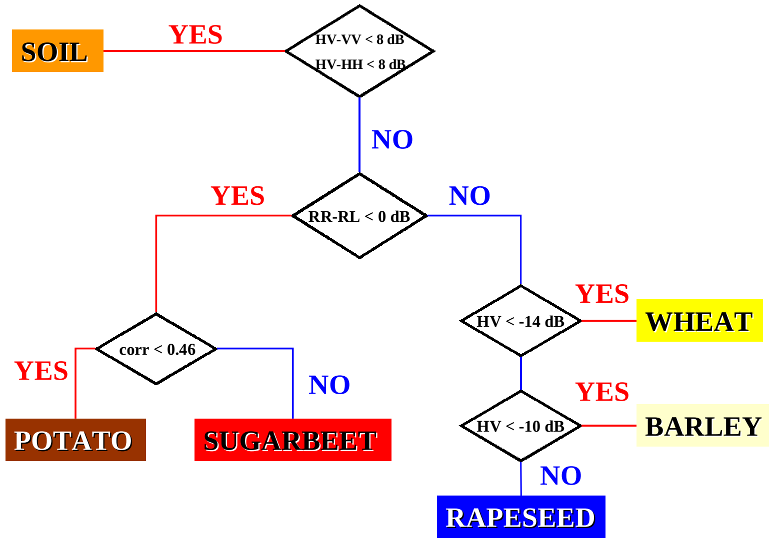

Fig. 6. Direct Hierarchical Classification Scheme

The ISODATA algorithms use the RR-RL ratio, the HH-VV correlation and the HV power, and the number of classes is fixed at six. Note that each iteration of pixel-based ISODATA assigns every pixel in the scene to one of the six classes. Many scene elements, such as roads, ditches and hedges, do not belong to any of the agricultural crop classes. Hence the final clusters formed by ISODATA represent a more general structuring of the image data. This is in contrast to methods trained purely on the crop data, such as direct hierarchical classification or maximum likelihood based on the Wishart distribution.

The Wishart distribution is exploited in two ways:

1. ML classification is carried out based on the Wishart distribution, with prior training on a sample dataset;
2. Each iteration of an ISODATA algorithm uses a ML classification based on the Wishart distribution, initialised using a hierarchical scheme.

The questions being addressed with these two approaches are:

1. Does using all the information in the covariance matrix improve the classification compared to selecting features?
2. Can the Wishart approach be improved by using ISODATA to sharpen up the clusters?

Because we are dealing with pixel data but comparing with a ground cover map, some additional radiometric and geometric processing is necessary. In order to smooth the data, they were first filtered using methods developed at DTU [4]. Geometrical correction was applied after classification. Images were converted from slant to ground range geometry, and all images were superposed by means of ground control points, using the image from July 12 as a reference. The crop map was scanned and superposed on the July 12 ground range image using ground control points. This digital ground map was used for masking borders and all the parts of the images outside the ground truth map.

5.1 Classification Results

July 12

Fig. 7 shows the classification from July 12 using the direct hierarchical method described in Fig. 6, with the crop map below it. Table 4 indicates the accuracy of the decision separating the broad leaf and small stem crops, and shows how effective the RR-RL ratio is for this task. After the subsequent decisions, the overall accuracy is 73%, with a kappa coefficient of 0.66. Detailed examination indicates that there are no large-scale misclassifications of any of the crop types, but a systematic error is that the boundaries of many of the sugar beet fields are misclassified as potatoes. Some barley fields at the top of the image are classified as rapeseed, and some sections of wheat fields together with one whole rapeseed field are assigned to the bare soil class.

Table 4. Accuracy of the broad leaf - small stem separation for the July 12 image.

	No. of fields	Well classified
Small Stems	174	165 (95%)
Broad Leaves	217	212 (98%)

A summary of the performance of the pixel-based classification approaches for July 12 is given in Table 5. The direct hierarchical approach gave the best results. It is not improved by using ISODATA to refine the decision boundaries; on the contrary, hierarchical ISODATA performs marginally worse. In addition, hierarchical ISODATA misclassifies most of the barley fields, while the errors in the direct hierarchical method are less organised, many of them consisting of edges of sugar beet fields being classified as potatoes, rather than wholesale misclassification of a particular crop.

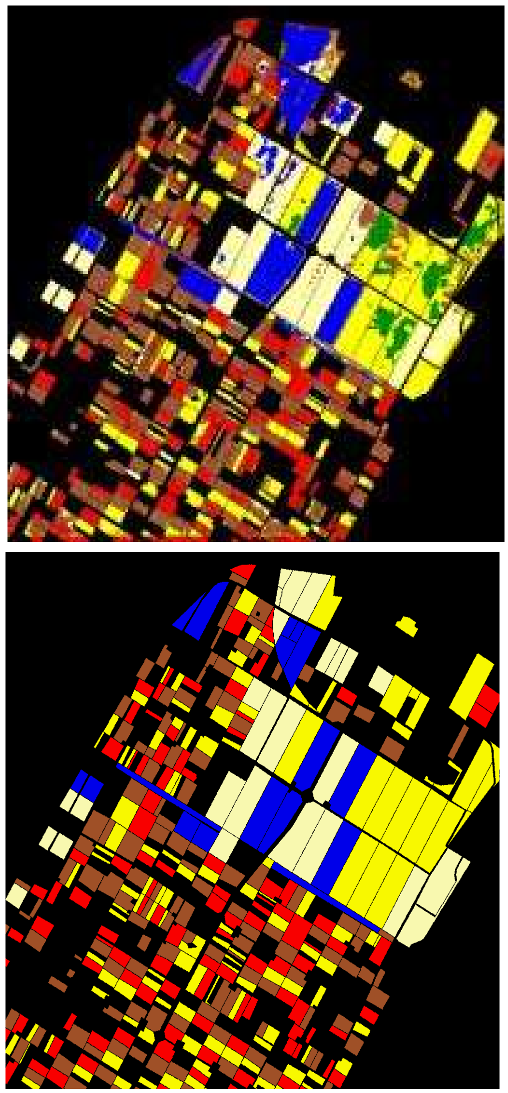

Fig. 7 Top: Classification for July 12 using direct hierarchical algorithm; bottom: ground truth. Classes are: potatoes (sienna), sugar beet (red), rapeseed (blue), wheat (yellow), barley (pale yellow) and bare soil (green). The other classes have been masked.

Wishart ML gave results only slightly better than the completely unsupervised ISODATA with a random initialisation. Both of these approaches were out-performed by ISODATA initialised with the direct scheme, with ML performing better than MAP. Wishart ISODATA performed very badly.

Table 5. Overall accuracies and kappa coefficients for Flevoland data from 12/7/91

Algorithm	Overall accuracy	Kappa coefficient
Direct hierarchical approach	72.9	0.66
ML ISODATA (random init.)	59.1	0.49
ML ISODATA (direct init.)	69.6	0.62
MAP ISODATA (direct init.)	66.4	0.57
Hierarchical ISODATA	72.8	0.65
Wishart ML	59.4	0.49
ML ISODATA (Wishart, direct init.)	50.0	0.33

July 28

The overall summary for July 28 is given in Table 6. Accuracies are much reduced compared to 12 July, as expected from the data analysis of Section 3. Much more separation is seen in feature space on July 12, and simple thresholds on the features are seen to be much more capable of accurately separating classes. From the analysis, it is not clear that a hierarchical decision tree will provide a viable approach on July 28, but it still proves to be the most effective of all the methods considered. Unlike July 12, attempts to improve the decision boundaries by allowing ISODATA to search for thresholds led to a marked decline in performance. The only ISODATA approach that gave reasonable results (in fact, results almost as good as the direct hierarchical method) uses a single step MAP approach. Very marked is the poor performance of both methods that try to exploit the Wishart distribution. The results all suggest that the two root crops are not very well separated from each other in feature space, while the cereals and rapeseed have more integrity.

Table 6. Accuracies and kappa coefficients for Flevoland data from 28/7/91.

Algorithm	Overall accuracy	Kappa coefficient
Direct hierarchical method	65.3	0.55
ISODATA (random init.)	52.7	0.41
ML ISODATA (threshold init.)	57.6	0.46
MAP ISODATA (threshold init.)	65.2	0.54
Hierarchical ISODATA (threshold init.)	55.8	0.43
Wishart ML	48.4	0.34
ISODATA Wishart	50.5	0.36

July 3

The results for July 3 are shown in Table 7. The poor performance of the hierarchical methods is expected, as at this time the different crop types show considerable overlap in feature space. The most remarkable result is the major improvement in the performance of the Wishart distribution methods, particularly when applied within ISODATA.

Table 7. Accuracies and kappa coefficients for Flevoland data from 3/7/91.

Algorithm	Overall accuracy	Kappa coefficient
Direct hierarchical method	40.4	0.29
ISODATA (random init.)	53.2	0.40
ML ISODATA (threshold init.)	53.1	0.39
MAP ISODATA (threshold init.)	57.9	0.45
Hierarchical ISODATA (threshold init.)	20.3	0.06
Wishart ML	72.0	0.65
Wishart ISODATA	78.6	0.73

5.2 Summary of Pixel-Based Classification Results

The essential points arising from the pixel-based analysis are that, in mid to late July, a direct hierarchical method based on specific polarimetric features tuned to plant characteristics (state of development, biomass, structure) provides the best performance, with accuracies of 73% for the main 6 crops in mid-July, dropping to 65% in late July. Similar methods are not applicable in early July, as the different crops do not separate out in feature space. Attempts to refine the decision boundaries using ISODATA do not yield better performance. This may in part be caused by the fact that the iterative learning in ISODATA is hampered by the presence of extraneous classes (field boundaries, ditches, etc) that cannot be excluded in a pixel-based approach. Methods based on the Wishart distribution performed badly in mid to late July but well in early July (exactly opposite to the behaviour of the hierarchical scheme). This is hard to explain, but may result from the classes being better represented by complex Gaussian distributions in early July.

6 CONCLUSIONS

The principal conclusions of this paper are:

(a) A limited set of features carries the information needed to classify the crops present under northern European agricultural conditions. The most effective set of features appear to be the RR-RL ratio, the HH-VV correlation and the HV backscattering coefficient, together with the HV-VV and HV-HH ratios when bare soil (or harvested crops) needs to be catered for. These features indicate relevant biophysical characteristics of the crops.

(b) The behaviour of these features varies markedly through the growing season, as a consequence of variation in the scattering mechanisms. For Flevoland, mid-July was clearly best suited to classification, with well-separated classes in feature space. The situation was not as good in late July, and in early July, feature-based methods were not effective.

(c) For field-based classification, ISODATA algorithms give good performance that is transferable between times and locations. The hierarchical form of ISODATA appears better.

(d) In mid and late July, the most successful pixel-based classification method was direct hierarchical classification, which gave accuracies of around 73% in mid-July and 65% in late July.

(e) The direct hierarchical methods were not improved by using ISODATA (either independently or to set the decision thresholds). This suggests that the thresholds chosen for the direct scheme were close to optimal.

(f) Wishart ML classification performs poorly in both mid and late July, but gives an accuracy of 72% in early July, increasing to around 79% when combined with ISODATA. This may result from the class distributions differing significantly from the complex Gaussian model in mid to late July, but better following this model in early July.

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