The combination of polarimetric SAR with satellite SAR and optical data for classification of agricultural land

Inge Sandholt

Abstract

A multi-spectral SPOT image, polarimetric airborne SAR data as well as satellite based C-band SAR data have been used to perform classification of agricultural fields and areas occupied by forest and lake. Conventional Maximum Likelihood classification has been compared with classification incorporating a Gaussian mixture class model, as well as an algorithm based on multi-resolution structured data and sequential MAP (SMAP). The classification accuracies found were generally high, using combinations of sensors. It is found that multi polarization data gives invaluable information to be used in a classification scheme, a feature that can be exploited in future satellite sen sors, like for instance ASAR on board ENVISAT. The Gaussian mixture class model performed only slightly better than the conventional maximum likelihood algorithm, whereas the SMAP algorithm improved the classification results.

Keywords

Crop classification, Remote Sensing, Synthetic Aparture Radar, combining data, contextual classification

Inge Sandholt, Institute of Geography, University of Copenhagen, Østervoldgade 10, DK-1350 København K, Denmark.
e-mail is@geogr.ku.dk

Geografisk Tidsskrift, Danish Journal of Geography 101: 21-32

Since the first SAR data became available, several attempts to use the data for land use classification have been made. Dobson et al. (1995) compare several SAR classifiers, reporting a wide range of accuracies, spanning from 75% to more than 98%. The studies base primarily the classification on C-band, L-band polarimetric data, or on combinations hereof. Generally, the highest accuracies are found for multi-frequency combinations, and for studies using few classes (three or less). The potential of discriminating crop types using microwave data have been reported by Wegmuller (1993) and Skriver et al. (1999). Wegmuller (1993) concludes that different microwave parameters can be used to distinguish different crops, but maybe more important, the temporal evolution in radar returns for individual crops can be exploited successfully via a multi-temporal data set. This is in agreement with the results found by for instance Bouman and Hoekman (1993), Sandholt et al. (1995), and Skriver et al. (1999). Another study (Anys & He, 1995) reports from a C-band multi-polarization data set, that using supervised classification methods, the accuracy can be improved considerably including textural features (1st, 2nd and 3rd order histograms). Texture measures are difficult to include in multi-temporal data sets though, due to the need to co-register, implying resampling of the images, which may alter the textural information in the images. Textural information should be extracted prior to any resampling of data. Very high classification accuracies have been reported in Chen et al. (1996) using a neural network to classify an agricultural area into 12 classes based on multi-frequency polarimetric SAR data. On the other hand, single polarized C-band SAR data alone have not proved well suited for classification purposes, see for instance Durand et al. (1987). Schotten et al. (1995) base a classification of agricultural land on a multi-temporal data set of ERS-1 images. The area contains a very high number of agricultural fields (980), allowing a field based classification to be done. The overall classification result obtained is 80%.

Several studies have shown that SAR data may provide information on structural features of the surface complementary to the spectral information in optical data, for instance Dobson et al. (1995), Sandholt et al. (1995), Solberg et al. (1994), and Horgan et al. (1992). It has thus been shown, that the discriminating power of SAR images is very much improved when they are used in combination with optical data. Solberg et al. (1996) have compiled a brief but useful review of multi-source classification.

In this paper, classification of agricultural land by means of remote sensing is addressed. The primary goal is to show how multi-source remotely sensed data can be successfully combined to perform classification of agricultural land with respect to crop type, and secondly to test the performance of existing algorithms based on Bayesian classification techniques. Some of the methods belong to the group of contextual classification, and exploit the ideas behind multi-resolution data representation. The data set is quite unique, in the respect that it comprises temporal C-band SAR data with different spatial resolutions, and polarimetric SAR data, together with an optical satellite image. Part of the study will show the effects of using polarimetric SAR data from an airborne SAR in combination with optical data, a very relevant approach to prepare for ENVISAT data, or for ERS data in combination with RADARSAT to obtain multi-polarization data. The paper is organized as follows. First a brief introduction to the applied methods is given. Some remarks are made on contextual classification including Markov Random Fields, on which one of the applied algorithms is based. The test site and data are presented , followed by results and discussion . Finally, the overall results are summarized in the conclusion.

Classification algorithms

Discriminant analysis

In land use classification *discriminant analysis* can be applied when the class identities of some samples (or pixels) are known *a priori*. Two sets of multivariate observations for which the class membership is known are thus chosen, *a training* set, and a *test set*, allowing an independent evaluation of classification results. In discriminant analysis, the class membership of the test set is determined based on the statistics of the training set. We will here consider classical discriminant analysis, a technique described in most textbooks on multivariate analysis, for instance Everitt & Dunn (1991), Krzanowski (1988) or Mardia et al. (1979). A comprehensive exposition of discriminant analysis related to pattern recognition can be found in McLachlan (1992). The classification performed is a conventional per pixel maximum likelihood classification.

The gaussian mixture class

The objective of mixture classes is to improve classification performance by modelling each class as a pro-babilistic mixture of a variety of subclasses. The approach is thus useful when each class contains pixels with a variety of distinct spectral characteristics, like for instance forest with different tree species, or urban areas with streets and buildings. For agricultural crops, where classes are likely to be more homogeneous, the Gaussian mixture class is useful when pixels in each class consist of different sorts of crops. For each class a clustering of subclasses is performed using the method described below. The mixture density for k classes in the multivariate case is given by:

$$f(\vec{x}) = \sum_{i=1}^{k} p_i N_m(\vec{\mu}, \Sigma_i) \quad (1)$$

Typically, the number of subclasses in each group are not known *a priori*. To determine the number of subclasses Rissanen's minimum description length (MDL) has been applied (Rissanen, 1983). Another possibility would have been to use Akaike and Schwarz's information criteria (Schwarz, 1978). Both the number of distinct subclasses in each class and the spectral mean and covariance for each subclass are estimated by the algorithm. More on how this is handled can be found in Bouman and Shapiro (1996).

Contextual classification

In applying classical discriminant analysis, no attention is paid to the spatial dependency between adjacent pixels. This may result in a spotty appearance of the resulting classification image, and also that important information contained in the image is neglected. Therefore attempts have been made to exploit the spatial information. These methods are somewhere in the area between segmentation methods and classification methods, and are denoted *contextual classification*, not to be confused with methods taking the texture of the images into account. Contextual classification deals with the relationship between adjacent pixels, whereas textural classification addresses the composition of the neighbourhood. The latter can be done simply by including texture information in the feature vector. Examples of including texture parameters of SAR data in image classification can be found in for instance Solberg et al. (1994), Horgan et al. (1992), and Anys & He (1995). Context can be considered along three different dimensions: the spectral, the spatial and the temporal dimension (Solberg et al., 1996). *Markov Random Fields* (MRF) provide a methodological framework to exploit spatial information in images, and several studies have been reported. Therrien et al. (1996) utilizes a model for texture based on stochastic linear filtering concepts to segment aerial photographs of a rural area. The texture model is combined with a MRF-model to represent the occurrence of textured regions within an image. He concludes that the MRF-model is superior to a maximum likelihood model for the same image, and that the difficult optimization problems can be overcome by applying a suboptimal procedure in a combination of the texture model and the MRF. Haslett (1985) formulated a widely used classifier based on maximum likelihood discriminant analysis using a Markovian model of spatial context. An early example of a contextual classifier, is ECHO, Extraction and Classification of Homogeneous Objects (Kettig & Landgrebe, 1976). Successful attempts have also been made to apply methods that model spatial context as well as temporal context, see for instance Jeon and Landgrebe (1992) and Solberg et al. (1996).

Multi-scale Markov Random Fields

One of the classification algorithms used in this study, is based on a multi-scale Markov Random Field model developed by Bouman & Shapiro (1994). A *Markov Random Field is* a concept originating from time series analysis. In one dimension, a Markov chain can be defined as a process satisfying (Cressie, 1991):

$$P(z(i)|z(0),...,z(i-1)) = P(z(i)|z(i-1)) \qquad \forall i > 1 \quad (2)$$

where $\{Z(t):t = 0,1,....\}$ is a random process in time where data are observed at the times 0,1,...n. Equation 2 expresses the *lack of memory* property that the conditional probabilities for the present given the past is determined only by the most recent observation. In time series analysis, the definition of the past is straightforward, but when the model is extended to two dimensions several possibilities are available. In the spatial case, the concept of *neighbourhood* is introduced, often as a set of four or eight nearest pixels. The appealing feature of MRF, is that they only require the specification of spatially local interactions using a set of local parameters (Bouman & Shapiro, 1994).

The algorithm developed by Bouman and Shapiro (1994) in short uses a *multi-scale random field* (MSRF), that is a Markov Random Field in scale, and the estimation is done by a *sequential maximum a posteriori* (SMAP) algorithm. The MSRF is composed of a series of random fields progressing from coarse to fine *scale*. The Markov property assumed is that each field depends on the previous coarser field only, and the Markov chain is thus in *scale*. Further it is assumed that points in each field are conditionally independent given their coarser scale neighbours. The SMAP estimation method consists in minimizing the expected size of the largest misclassified region, in a manner such that progressively larger costs are assigned to errors at coarser scales. The algorithm has been described in detail in Bouman and Shapiro (1994) and in Bouman & Shapiro (1996). The actual implementation used here is described in Grass4.1 (1993). The SMAP algorithm has been applied on SAR data from Sweden by Michelson et al. (2000).

Experimental data

The study area is located near Research Centre Foulum in the central part of Denmark, and comprises agricultural land and forest belonging to Tjele Estate – where a 5.12x5.12 km² subset has been selected.

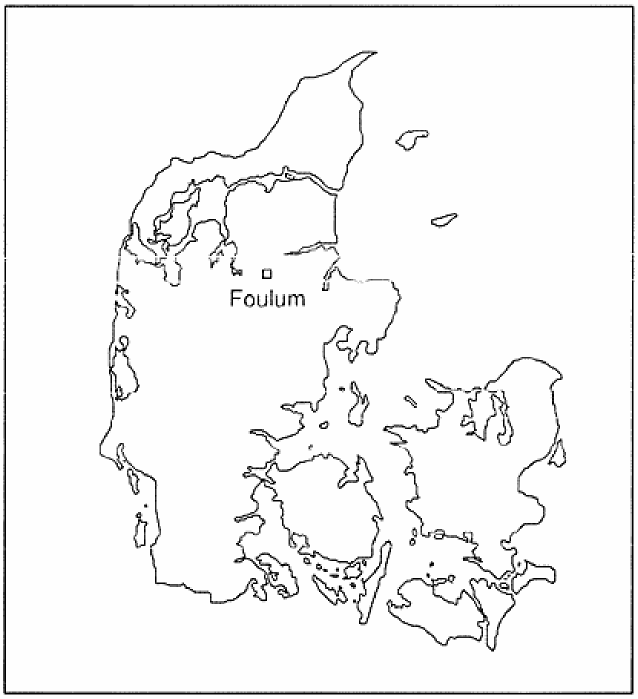

Figure 1: *Test site location near Research Centre Foulum.*

The classifications are based on a subset of the DANMAC 94 data set consisting of ERS-1 SAR data and a SPOT image (Thomsen et al., 1994). In addition, data from the Danish airborne SAR, EMISAR are used. The EMISAR is the result of a research and development project initiated in 1986 at the Department of Electromagnetic Systems (EMI) of the Technical University of Denmark, and it is a fully polarimetric and interferometric L-and C-band SAR (Madsen et al., 1991; Christensen et al., 1998). For this study, only the C-band SAR has been applied. The EMISAR is used for scientific experiments conducted by the Danish Center for

Figure 2: Tjele Gods overview (EMISAR April 1994).

Remote Sensing (DCRS) which was established in 1994 at EMI by the Danish National Research Foundation. The SAR system is flown on a Royal Danish Air Force Gulfstream G-3 aircraft. The SAR system is normally operated from an altitude of approximately 12,500 m, the spatial resolution is 2 m by 2 m, the ground range swath is approximately 12 km and typical incidence angles range from 35 deg. to 60 deg. The processed data from this system are fully calibrated by using an advanced internal calibration system. The multi-temporal image data consist of three ERS-1 SAR images, two polarimetric airborne C-band images from the EMISAR. and the SPOT image.

For the EMISAR data only the VV, HH and HV polarized intensities were used. The most important specifications of the sensors and platforms are summarized in Tables 2, 3 and 4.

The timing of image acquisitions is nearly optimal with respect to crop evolution, only an additional early acquisition from May would have been desirable, see for instance Wegmuller (1993) or Sandholt et al. (1995) for exploitation of the temporal evolution in backscatter measured by SAR during the entire growing season. The classification algorithms require Gaussian distributions, and the SAR intensity data cannot be used directly, as the pdf for intensity data can be approximated by a Gamma distribution. One way of working around this is to logtransform the SAR images (Sandholt et al., 1995) prior to further processing and as such a Gaussian assumption is plausible. This approach has been used here. Another solution would have involved reformulation of the classifier taking the SAR statistics into account, as for instance have been done by Solberg et al. (1996).

All images have been geometrically corrected to UTM, and resampled to 5x5 m^2 pixels in order to be able to superimpose the images. The resampling involved a smoothing of the EMISAR data with a 9x9 weighted mean filter. A number of image and band combinations have been used in the classifications, as listed in Table 5.

A number of fields have been selected for reference and test of results. Six different crops are grown on the selected fields, and together with samples from Tjele Lake and Tjele forest, they comprise the eight cover classes in the study. The set of fields has been divided into a training set and a test set as indicated in Figure 3 and Table 6.

The wheat fields contain four different varieties, and the fields have been divided such that the training set consists of the varieties *hereward, pepital* and *husar* and the test set consists of the varieties *hereward, husar* and *ritmo*. This may result in lower classification performance for wheat than may have been found if pepital and ritmo had been excluded from the data set. However, to keep as many observations in the data set as possible, all four varieties have been used.

Text contiues on page 26

Table 1: Images used in the classifications.

Sensor	Image	Name	Date	Polarization	Pixel Spacing
ERS	15101	pri151	940605	cvv	12.5
	15388	pri153	940625	cvv	12.5
	15632	pri156	940712	cvv	12.5
EMISAR	pm006	pm6	940623	chh,cvv,cxp	5
	pm007	pm7	940729	chh,cvv,cxp	5
SPOT		spot	040703	1,2,3	20

Table 2: Sensor and Scene specific information for the multi-spectral SPOT scene.

Satellite, sensor, spectral mode	SPOT-3, HRV, XS
Scene	46-235
Date	July 3. 1994
Time	10:50:42 UTC
Pixel size	20m x 20m
Production level	1A
Incidence angle	L6.6deg
Solar azimuth	165.4deg
Solar elevation	56.2deg
Spectral bands	0.50-0.59 mm
	0.61-0.68 mm
	0.79-0.89 mm

Table 3: EMISAR parameters.

Frequency/wavelength	C-band, 5.3 GHZ/5.7 cm
Polarization	Fully polarimetric
Incidence angle	20deg- 60deg
Spatial resolution	2m x 2m
Pixel Spacing	1.5m x 1.5m

Table 4: ERS-1 SAR parameters.

Frequency/wavelength	C-band, 5.3 GHZ/5.7 cm
Polarization	VV
Incidence angle	20deg- 26deg
Spatial resolution	30m x 30m
Pixel Spacing (PRI-product)	12.5m x12.5m

Table 5: Image combinations used in the classifications.

Combination name	Images
ERS	pri151, pri153, pri156
EMI	pm6, pm7
SPOT	spot1, spot2, spot3
SAR	pri151, pri153, pri156, pm6, pm7
TOTAL	the total data set
SPOT EMI	spot1, spot2, spot3, pm6, pm7
SPOT EMIcvv	spot1, spot2, spot3, pm6(cvv), pm7(cvv)
SPOT ERS	spot1, spot2, spot3, pri151, pri153, pri156
COMB	pm6(cvv,cxp), pm7(cvv,cxp), pri151, pri153, pri156, spot1, spot3
SPOT PM6	spot1, spot2, spot3, pm6
SPOT PM7	spot1, spot2, spot3, pm7

Table 6: Number of pixels in training and test fields used in the classifications.

Class	Label	pixels in training set	pixels in test set
1	rye	11535	12350
2	oat	21899	11709
3	wheat	31278	27983
4	winter barley	12358	12866
5	grass	10916	8753
6	oil seed rape	27942	27989
7	forest	24014	28336
8	lake	12723	11347

Results and discussion

Classical discriminant analysis

The first task is to perform conventional per pixel maximum likelihood classification. Table 7 shows the classification accuracy for each class in the test set, and the average accuracy for the combinations.

The average accuracy for the ERS image combination (40.0%) is clearly not acceptable. A similar study (Sandholt et al., 1995) with a comparable number of classes and number of ERS-1 images found an average accuracy 51.7% for ERS-1 images. A study using eight ERS-1 images based on per field classification, found accuracies up to 80% (Schotten et al., 1995). The higher accuracies in the latter study may be due to the per field approach, which to some extend also minimizes the effects of speckle, and to the higher number of images available. Average classification accuracy based on the two EMISAR images (80.6%) is comparable to what is found for the multi-spectral SPOT image (83.8%), and only a minor improvement is seen when the two SAR sensors are combined (81.1%). However, the classification based on SPOT has its lowest performance for wheat (23.9%), probably due to the fact that the wheat fields in fact encompass three different varieties of wheat. It should be noted that, although not satisfactory, the SPOT based crop classification accuracy is higher than what could have been expected for a single scene, see for instance Fog et al. (1993) or Sandholt et al. (1995). The most severe problem for the EMI combination, is found for barley with a classification accuracy of 54.0%. 38.0% of the barley pixels in the test set are classified as grass.

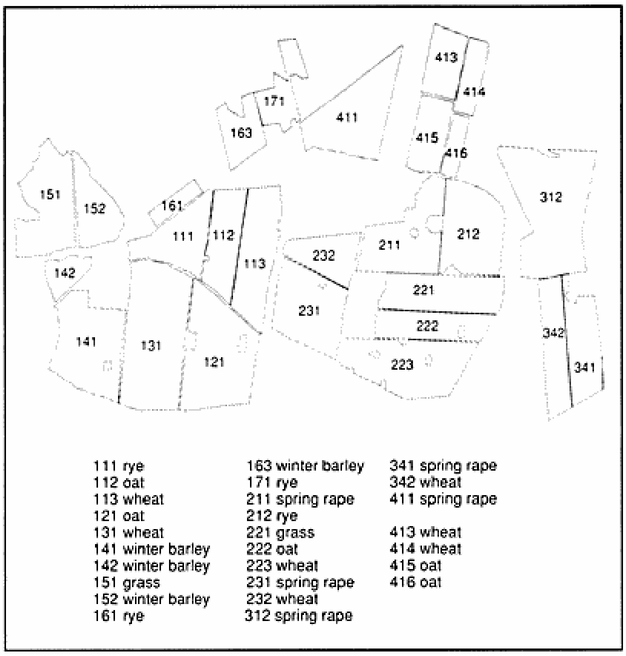

Figure 3: *Map of the 8 classes in the reference set (training and test data) in the Tjele subset.*

Gaussian mixture class classification

The expected improvement of the classification accuracies using Gaussian mixture class classification was not found (Table 8).

The mixture class model allows each class to consist of several subclasses, and for not entirely homogeneous classes like forest an improvement would have been expected. However, the accuracy improvement of the accu-

Table 7: *Maximum likelihood classification accuracy (in %) for the 8 classes and for different image combinations (Table 5). (Calculated as number of correctly classified pixels of that, divided by the total number of pixels in a given class in the test set).*

	rye	oat	wheat	barley	grass	rape	forest	lake	average
ERS	51.1	55.9	27.9	27.5	5.3	46.7	58.9	46.7	40.0
EMI	88.4	78.5	90.6	54.0	72.0	91.0	70.0	100.0	80.6
SPOT	93.0	97.8	23.9	96.3	78.8	98.1	82.7	100.0	83.8
SAR	94.0	88.7	90.7	75.6	21.6	89.5	88.3	100.0	81.1

Table 8: Gaussian mixture class classification accuracy (in %) for the 8 classes and for different image combinations (Table 5). (Calculated as number of correctly classified pixels in a given class, divided by the total number of pixels in a given class in the test set).

	rye	oat	wheat	barley	grass	rape	forest	lake	average
ERS	52.4	57.7	27.7	27.6	5.6	46.4	58.2	49.7	40.7
EMI	87.4	78.4	90.6	53.4	66.1	90.3	70.2	99.8	79.5
SPOT	94.1	98.0	26.7	90.8	7.1	99.6	84.8	100.0	75.1
SAR	93.1	87.3	89.9	74.2	20.5	89.5	88.2	99.8	80.3
TOTAL	98.0	98.5	79.6	91.2	92.7	99.8	95.9	100.0	94.5
SPOT EMI	97.2	98.7	73.0	92.8	98.7	100.0	92.8	100.0	94.2
SPOT ERS	96.4	98.5	45.1	89.8	82.3	99.2	92.4	100.0	88.0
COMB	97.9	99.2	60.8	87.5	90.8	99.9	94.7	100.0	91.4
SPOT PM6	96.3	98.4	33.4	94.4	77.6	99.6	90.8	100.0	73.8
SPOT PM7	96.6	98.5	61.8	92.3	98.5	100.0	88.0	100.0	92.0

racy is small, and for some classes the accuracy is comparable to or even lower than for the conventional maximum likelihood classification (Table 7). The fact that the selected fields are rather large and homogeneous, leaves the only slight improvement to be found for the more complex classes, forest and wheat, the latter comprising four varieties of wheat. The average accuracy for wheat using the SPOT data alone is 4% higher when using the mixture class model, but still the accuracy is generally low for wheat, probably due to the fact, that the training set did not comprise all the wheat varieties.

Turning to a comparison of the chosen sensor combinations, the best average performance is found for the combination comprising the total data set. The average accuracy is 94.5, and except for wheat, the accuracy for each crop type is higher than 90%, and for rye, oat, oil seed rape and lake the accuracies are even equal to or higher than 98.0%. The average classification accuracy for the combination SPOT EMI is comparable to the classification accuracy for the total data set, showing the little effect of including ERS-1 data when EMISAR data is already available. More on the different sensor combinations can be found in the next section.

Multi-scale contextual classification

In Table 9 the multi-scale classification accuracies are shown. The Gaussian mixture class model is included in the multi-scale algorithm. Comparison of Tables 8 and 9 clearly expose how the multi-scale contextual classification algorithm outperforms the previously used algorithms. The improvement in performance is largest for the most noisy images with the highest resolution. For the SPOT image with 20 m pixel spacing, the relatively coarse resolution (at least in comparison to EMISAR data) has the effect that the hierarchical data structure is not fully exploited. Classification based on the speckly SAR images in contrast, takes advantage of the simple segmentation inherent in the algorithm.

The confusion matrices for classification based on the SPOT image and EMISAR images are shown in Tables 10 and 11 and the confusion matrix for classification based on the total data set is shown in Table 12.

Table 10 clearly shows how the SPOT-based classification is not able to discriminate the wheat pixels, 63.5% are classified as rye. It also fails to classify the grass pixels, only 6.44 % are correctly classified as grass. Instead the grass pixels are classified as rape. In contrast the EMISAR based classification confuses barley and grass, the two crops having a similar structure in the early growing stages. When the two data types are combined, the confusion between the mentioned groups are considerably lower, as can be seen in Table 12, and the discrimination between the other classes is improved as well. The highest average classification accuracies are found for the total data set and for the SPOT EMI combination (95.9% and 95.5% respectively), as was the case in per pixel Gaussian mixture class classification, only the accuracies here are improved considerably. The

Table 9: multi-scale classification accuracy (in %) for the 8 classes and for different image combinations (Table 5). (Calculated as number of correctly classified pixels in a given class, divided by the total number of pixels in a given class in the test set).

	rye	oat	wheat	barley	grass	rape	forest	lake	average
ERS	61.5	65.7	26.8	29.3	2.8	50.0	66.1	59.3	45.2
EMI	97.3	92.1	99.1	57.8	90.3	97.4	91.8	99.8	90.8
SPOT	96.0	98.2	27.2	92.6	6.4	99.7	86.3	100.0	75.8
SAR	97.9	95.4	96.6	85.1	11.8	95.8	96.9	99.2	84.8
TOTAL	98.8	98.5	83.6	93.4	95.2	99.8	97.6	100.0	95.9
SPOT EMI	98.5	98.7	76.8	94.5	99.2	99.9	96.2	100.0	95.5
SPOT sim ERS	98.1	98.3	36.2	93.2	93.8	99.9	92.7	100.0	89.0
SPOT ERS	97.3	98.5	45.7	91.1	82.9	99.2	93.9	100.0	88.6
COMB	98.9	99.1	62.0	91.2	92.7	99.9	97.3	100.0	92.6
SPOT PM6	97.4	98.5	32.8	95.6	86.9	99.7	93.8	100.0	88.1
SPOT PM7	98.0	98.6	62.2	94.2	99.2	100.0	91.4	100.0	93.0

classified image with the best average accuracy can be seen in Figure 4.

The results are in agreement with what has been found earlier in a comparison between SMAP and Maximum Likelihood classification of McCauley and Engel (1995), who based on airborne scanner data for eight classes, found SMAP to perform better than conventional maximum likelihood classification. Solberg et al. (1996) report overall classification accuracies for a Landsat TM image and a multi-polarization C-band SAR image from the MAESTRO experiment acquired seven days apart. They achieved 71.3% classification accuracy for their simple fusion model, and 73.0% for their Markov random field model based classification in a 7 classes classification problem. The accuracies found in the present study are significantly higher, if we compare with the SPOT PM6 combination in Table 9. For comparison of the two studies, we should be aware, that the overall accuracy (number of correctly classi-

Table 10: Confusion Matrix for classification based on the SPOT image using the multi-scale classifier. Units are classified pixels as percent of test pixels (percent of rows).

		rye	oat	wheat	barley	grass	rape	forest	lake
t	rye	95.96	0.00	1.02	0.53	0.00	0.00	2.49	0.00
e	oat	0.00	98.25	1.35	0.00	0.40	0.00	0.00	0.00
s	wheat	63.53	0.00	27.15	2.04	0.01	0.01	7.26	0.00
t	barley	1.15	0.00	1.34	92.56	2.84	0.56	1.54	0.00
	grass	0.00	0.00	0.02	0.19	6.44	93.34	0.00	0.00
s	rape	0.00	0.00	0.00	0.00	0.32	99.68	0.00	0.00
e	forest	6.25	0.00	5.47	0.74	1.25	0.00	86.28	0.00
t	lake	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00

Table 11: Confusion matrix for classification based on the EMISAR images using the multi-scale classifier. Units are classified pixels as percent of test pixels (percent of rows).

		rye	oat	wheat	barley	grass	rape	forest	lake
t	rye	97.25	0.00	2.39	0.00	0.00	0.23	0.14	0.00
e	oat	0.22	92.08	6.93	0.65	0.00	0.00	0.12	0.00
s	wheat	0.43	0.39	99.07	0.00	0.00	0.00	0.11	0.00
t	barley	0.06	0.37	1.00	57.79	39.15	0.04	1.59	0.00
	grass	0.00	0.00	0.00	8.77	90.29	0.00	0.94	0.00
s	rape	1.36	0.00	0.00	0.00	0.00	97.74	0.90	0.00
e	forest	0.73	0.11	1.02	3.94	0.47	1.94	91.79	0.00
t	lake	0.00	0.00	0.00	0.00	0.00	0.00	0.17	99.83

fied pixels in relation to the total test set) typically is less than the average accuracy (average of number of correctly classified pixels in relation to total number of pixels within each class). In the same study, by Solberg et al. (1996) accuracies of combining Landsat TM with ERS-1 SAR (5 classes) for a different test site were found to be improved when the Markov random field model was applied. The improvements found by applying the multi-scale classification model in the present study are considerably higher, but again the two studies are not directly comparable; for instance, the reference models used here (ML-classification and Gaussian mixture class classification) are simpler than the one applied in the study reported by Solberg et al. (1996), and the timing of the image acquisitions is not comparable. In addition, it is well known, that Landsat TM due to its wavelengths further up in near infra red band is better suited for vegetation classification than SPOT. Typically users will not have the airborne SAR data available, often only satellite data can be included in the feature vectors. Currently satellite SAR sensors are limited to output single polarized data. The multi-polarized data are expected to provide valuable information easily exploited in classification algorithms, and the above results makes that argument even stronger. Therefore two vertically polarized EMISAR images have been combined with the SPOT image. It should be noted that the vertically polarized EMISAR data is not a simulation of ERS-1 data with a higher spatial resolution due to the fact that the incidence angles for ERS-1 and

Table 12: Confusion matrix for classification based on the total data set using the multi-scale classifier. Units are classified pixels as percent of test pixels (percent of rows).

		rye	oat	wheat	barley	grass	rape	forest	lake
t	rye	98.75	0.00	0.19	0.00	0.00	0.00	1.05	0.00
e	oat	0.00	98.53	1.18	0.00	0.00	0.00	0.29	0.00
s	wheat	16.22	0.00	83.62	0.11	0.00	0.00	0.04	0.00
t	barley	0.35	0.00	1.24	93.39	2.14	0.00	2.88	0.00
	grass	0.00	0.00	0.77	3.84	95.16	0.00	0.24	0.00
s	rape	0.00	0.00	0.06	0.00	0.11	99.79	0.04	0.00
e	forest	1.25	0.00	0.53	0.51	0.11	0.00	97.61	0.00
t	lake	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00

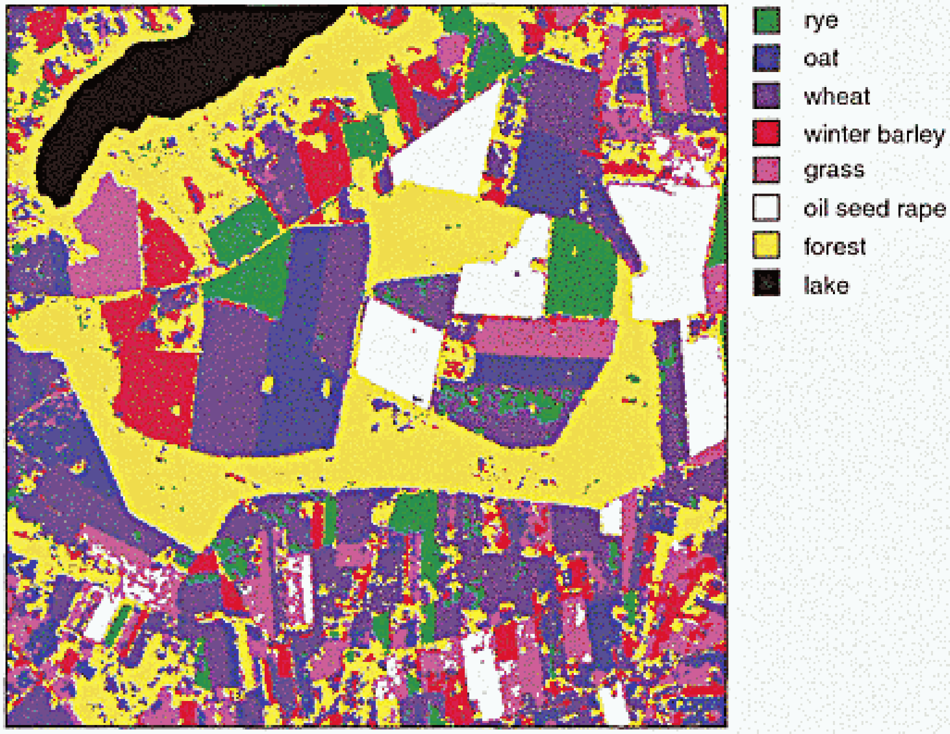

Figure 4: Classified image based on the total data set. Average accuracy is 95.9%.

EMISAR are very different, and thus the backscatter coefficients are different. However, the combination enables us to analyse how inclusion of multi-polarized data improves the classification accuracy by comparison with the single polarized data. The results are found in Table 9, and it is interesting to note, that the accuracies for the SPOT EMIcvv combination in general match the accuracies for SPOT ERS apart from wheat and grass. The average accuracy is considerably higher for the SPOT EMI combination (95.5% versus 89.0%), leading to the conclusion that multi-polarized SAR data is a valuable data source in classification of crop types. The study done by Dobson et al. (1996) based on ERS-1 (C-band, vv-polarization) and JERS-1 data (L-band, hh-polarization), reports similar improvements in classification accuracies when multi-polarization data are used. However, the composite images used in that study, are multi-frequency as well, and a major part of the improvement could be found here.

Conclusions

A unique data set was used to perform classification of agricultural land with respect to six different crop types and areas occupied by forest and lake. The performance of a classification algorithm based on Gaussian mixture class, and of a multi-scale classification algorithm were tested. Also different image combinations were tested. The best combination of images was the one comprising all of the available data, but only little difference in overall classification accuracies was found between the combination consisting of the SPOT image and the airborne multi-polarized SAR data (EMISAR). In addition to that, it was found, that multi-polarized data gives invaluable information to be used in a classification scheme, a feature that can be used in future satellite based sensors like ASAR on board ENVISAT. In fact, classification accuracies based on multi-temporal, polarimetric SAR data, were higher than for a single SPOT scene. That may have important implications for classification set ups in operational applications, when ENVISAT is launched, due the all weather capabilities" of SAR sensors, which ensures a multi-temporal data set. However, one has to be cautious when comparing the results from satellite sensors and airborne sensors due to the differences in incidence angles and spatial resolution. However, the increase in classification performance of polarimetric data is significant.

The Gaussian mixture class model was found to improve the scores for forest and wheat, the latter which comprised four varieties, but generally, the mixture class model does

not improve classification accuracies for agricultural fields, due to the relatively homogeneous classes, and in some instances the accuracies are even decreased. The multi-scale classification algorithm (SMAP) clearly outperformed the per pixel classification. The largest improvement was found for the relatively noisy high resolution SAR data (EMISAR), whereas the improvement for the coarser scale, less noisy SPOT data was much less.

Using the SMAP algorithm on the total data set, an average classification accuracy of 95.9% was achieved, which is considered to be satisfactory, specifically taking into account, that neither multi-spectral SPOT data nor C-band SAR data are measured at optimal wavelengths with respect to vegetation monitoring. The result is expected to be improved if Landsat data is included, taking advantage of the near infrared band in Landsat data.

Acknowledgements

The work was done while the author was with the Department of Mathematics and Physics at the Agricultural University of Denmark. It has been funded by Dina, the Danish Informatics Network in the Agricultural Sciences, and by the Danish Space Board via DANMAC, the Danish Multisensor Airborne Campaign. The EMISAR data were acquired and processed by the Danish Center for Remote Sensing. Development of the EMISAR has been co-sponsored by the Thomas B. Thriges Foundation, the Danish Technical Research Council (STVF), the Royal Danish Air Force, the Technical University of Denmark, and the Joint Research Centre. The data acquisitions and the data processing have been sponsored by the Danish National Research Foundation. The author wishes to thank Henning Skriver, DCRS, for usefull comments to the manuscript and help and advice.

References

Anys, H. & He, D.-C. (1995): Evaluation of textural and multipolarization radar features for crop classification. IEEE Transactions on Geoscience and Remote Sensing, 33(5).

Bouman, B. & Hoekman, D. (1993): Multi-temporal, multi-frequency radar measurements of agricultural crops during the Agriscatt-88 campaign in The Netherlands. International Journal of Remote Sensing, 14(8): 1595-1614.

Bouman, C. A. & Shapiro, M. (1994): A multiscale random field model for bayesian image segmentation. IEEE Transactions on Image Processing, 3(2):162-177.

Bouman, C. A. & Shapiro, M. (1996): SMAP image segmentation software package. Users manual. http://dynamo.ecn.purdue.edu/ bouman/software/segmentation_and_clustering/.

Chen, K. S., Huand, W. P., Tsay, D. H. & Amar, F. (1996): Classification of multifrequency polarimetric sar imagery using a dynamic learning neural network. IEEE Transactions on Geoscience and Remote Sensing, 34(3): 814-820.

Christensen, E., Skou, N., Dall, J., Woelders, K., Jorgensen, J., Granholm, J. & Madsen, S. (1998): EMISAR: An absolutely calibrated polarimetric L- and C-band SAR. IEEE Transaction Geoscience and Remote Sensing, 36(6):1852-1865.

Cressie, N. (1991): Statistics for spatial data. John Wiley and Sons, New York.

Dobson, M., Pierce, L. E. & Ulaby, F. T. (1996): Knowledge-based land cover classification using ERS-1/JERS-1 SAR composites. IEEE Transactions on Geoscience and Remote Sensing, 34(1):83-99.

Dobson, M. C., Ulaby, F. T. & Pierce, L. E. (1995): Land-cover classification and estimation of terrain attributes using synthetic aperture radar. Remote Sensing of Environment, 51:199-214.

Durand, J. M., Gimonet, B. J. & Perbos, J. R. (1987): SAR data filtering for classification. IEEE Transactions on Geoscience and Remote Sensing, 25(5):629-637.

Everitt, B. S. & Dunn, G. (1991): Applied Multivariate Data Analysis. Edward Arnold, London.

Fog, B., Poulsen, J. N., Sandholt, I., Stjernholm, M. & Skriver, H. (1993): Monitoring land cover and crop types in Denmark using ERS-1 SAR and optical satellite images. Pp. 71-80 in Proc. Int. Symp. From Optics to Radar, SPOT and ERS applications, Paris May 5-9 1993, number 312 in CNES.

Grass4.1 (1993): Grass 4.1 User's Reference Manual. USACERL, Champaign, Illinois.

Haslett, J. (1985): Maximum likelihood discriminant analysis on the plane using a Markovian model of spatial context. Pattern Recognition, 18(3):287-296.

Horgan, G. W., Glasbey, C., J.N., Cuevas Gozalo, S. L. S. & Alonso, F. G. (1992): Land-use classification in central Spain using SIR-A and MSS imagery. International Journal of Remote Sensing, 13(15):2839-2848.

Jeon, B. & Landgrebe, D. A. (1992): Classification with spatio-temporal interpixel class dependency contexts. IEEE Transactions on Geoscience and Remote Sensing,

not improve classification accuracies for agricultural fields, due to the relatively homogeneous classes, and in some instances the accuracies are even decreased. The multi-scale classification algorithm (SMAP) clearly outperformed the per pixel classification. The largest improvement was found for the relatively noisy high resolution SAR data (EMISAR), whereas the improvement for the coarser scale, less noisy SPOT data was much less.

Using the SMAP algorithm on the total data set, an average classification accuracy of 95.9% was achieved, which is considered to be satisfactory, specifically taking into account, that neither multi-spectral SPOT data nor C-band SAR data are measured at optimal wavelengths with respect to vegetation monitoring. The result is expected to be improved if Landsat data is included, taking advantage of the near infrared band in Landsat data.

Acknowledgements

The work was done while the author was with the Department of Mathematics and Physics at the Agricultural University of Denmark. It has been funded by Dina, the Danish Informatics Network in the Agricultural Sciences, and by the Danish Space Board via DANMAC, the Danish Multisensor Airborne Campaign. The EMISAR data were acquired and processed by the Danish Center for Remote Sensing. Development of the EMISAR has been co-sponsored by the Thomas B. Thriges Foundation, the Danish Technical Research Council (STVF), the Royal Danish Air Force, the Technical University of Denmark, and the Joint Research Centre. The data acquisitions and the data processing have been sponsored by the Danish National Research Foundation. The author wishes to thank Henning Skriver, DCRS, for usefull comments to the manuscript and help and advice.

References

Anys, H. & He, D.-C. (1995): Evaluation of textural and multipolarization radar features for crop classification. IEEE Transactions on Geoscience and Remote Sensing, 33(5).

Bouman, B. & Hoekman, D. (1993): Multi-temporal, multi-frequency radar measurements of agricultural crops during the Agriscatt-88 campaign in The Netherlands. International Journal of Remote Sensing, 14(8): 1595-1614.

Bouman, C. A. & Shapiro, M. (1994): A multiscale random field model for bayesian image segmentation. IEEE Transactions on Image Processing, 3(2):162-177.

Bouman, C. A. & Shapiro, M. (1996): SMAP image segmentation software package. Users manual. http://dynamo.ecn.purdue.edu/ bouman/software/segmentation_and_clustering/.

Chen, K. S., Huand, W. P., Tsay, D. H. & Amar, F. (1996): Classification of multifrequency polarimetric sar imagery using a dynamic learning neural network. IEEE Transactions on Geoscience and Remote Sensing, 34(3): 814-820.

Christensen, E., Skou, N., Dall, J., Woelders, K., Jorgensen, J., Granholm, J. & Madsen, S. (1998): EMISAR: An absolutely calibrated polarimetric L- and C-band SAR. IEEE Transaction Geoscience and Remote Sensing, 36(6):1852-1865.

Cressie, N. (1991): Statistics for spatial data. John Wiley and Sons, New York.

Dobson, M., Pierce, L. E. & Ulaby, F. T. (1996): Knowledge-based land cover classification using ERS-1/JERS-1 SAR composites. IEEE Transactions on Geoscience and Remote Sensing, 34(1):83-99.

Dobson, M. C., Ulaby, F. T. & Pierce, L. E. (1995): Land-cover classification and estimation of terrain attributes using synthetic aperture radar. Remote Sensing of Environment, 51:199-214.

Durand, J. M., Gimonet, B. J. & Perbos, J. R. (1987): SAR data filtering for classification. IEEE Transactions on Geoscience and Remote Sensing, 25(5):629-637.

Everitt, B. S. & Dunn, G. (1991): Applied Multivariate Data Analysis. Edward Arnold, London.

Fog, B., Poulsen, J. N., Sandholt, I., Stjernholm, M. & Skriver, H. (1993): Monitoring land cover and crop types in Denmark using ERS-1 SAR and optical satellite images. Pp. 71-80 in Proc. Int. Symp. From Optics to Radar, SPOT and ERS applications, Paris May 5-9 1993, number 312 in CNES.

Grass4.1 (1993): Grass 4.1 User's Reference Manual. USACERL, Champaign, Illinois.

Haslett, J. (1985): Maximum likelihood discriminant analysis on the plane using a Markovian model of spatial context. Pattern Recognition, 18(3):287-296.

Horgan, G. W., Glasbey, C., J.N., Cuevas Gozalo, S. L. S. & Alonso, F. G. (1992): Land-use classification in central Spain using SIR-A and MSS imagery. International Journal of Remote Sensing, 13(15):2839-2848.

Jeon, B. & Landgrebe, D. A. (1992): Classification with spatio-temporal interpixel class dependency contexts. IEEE Transactions on Geoscience and Remote Sensing,

30(4):663-672.

Kettig, R. & Landgrebe, D. A. (1976): Classification of multispectral image data by extraction and classification of homogeneous objects. IEEE Transactions on Geoscience Electronics, 14(1):19-26.

Krzanowski, W. J. (1988): Principles of multivariate analysis: a users perspective. Oxford Statistical Science Series. Clarendon Press.

Madsen, S., Christensen, E., Skou, N. & Dall, J. (1991): The danish sar system - design and initial tests. IEEE Transactions on Geoscience and Remote Sensing, 29:417-426.

Mardia, K. V., Kent, J. T. & Bibby, J. M. (1979): Multivariate analysis. Academic Press.

McCauley, J. D. & Engel, B. A. (1995): Comparison of scene segmentations: SMAP, ECHO and maximum likelihood. IEEE Transactions on Geoscience and Remote Sensing, 33(6):1313-1316.

McLachlan, G. J. (1992): Discriminant analysis and statistical pattern recognition. Wileys series in Probability and Mathematical Statistics. John Wiley and Sons, New York.

Michelson, D., Liljeberg, B. & Pilesjo, P. (2000): Comparison of algorithms for classifying swedish landcover using landsat tm and ers-1 sar data. Remote Sens. Environ. 71(1):1-15.

Rissanen, J. (1983): A universal prior for integers and estimation by minimin description length. Annals of Statistics, 11(2):417-431.

Sandholt, I., Fog, B., Poulsen, J. N., Stjernholm, M. & Skriver, H. (1995): Classification of agricultural crops in Denmark using ERS-1 SAR and SPOT imagery. Askne, J., editor, Sensors and Environmental Applications of Remote Sensing, Proccedings of the 14th EARSeL Symposium, Goteborg, Sweden 6-8 June 1994, pages 37-44. Rotterdam. A.A. Balkema Publishers.

Schotten, C. G., Rooy, W. W. L. V. & Janssen, L. L. F. (1995): Assessment of the capabilities of multi-temporal ERS-1 SAR data to discriminate between agricultural crops. International Journal of Remote Sensing, 16(14): 2619-2637.

Schwarz, G. (1978): Estimating the dimension of a model. The Annals of Statistics, 6(2):461-464.

Skriver, H., Svendsen, M. T. & Thomsen, A. G. (1999): Multitemporal C- and L-band polarimetric signatures of crops. IEEE Transactions on Geoscience and Remote Sensing, 37(5):2413-2429.

Solberg, A. H. S., Jain, A. K. & Taxt, T. (1994): Multisource classification of remotely sensed data: Fusion of Landsat TM and SAR images. IEEE Transactions on Geoscience and Remote Sensing, 32(4):768-785.

Solberg, A. H. S., Taxt, T. & Jain, A. K. (1996): A Markov random field model for classification of multisource satellite imagery. IEEE Transactions on Geoscience and Remote Sensing, 34(1):100-113.

Therrien, C. W., Quatieri, T. F. & Dudgeon, D. E. (1986): Statistical model-based algorithms for image analysis. Proceedings of the IEEE, 74(4).

Thomsen, A., Fog, B., Skriver, H. & Stjernholm, M. (1994): The DANMAC data report 1994. Danish Institute of Plant and Soil Science.

Wegmuller, U. (1993): Signature research for crop classification by active and passive microwaves. International Journal of Remote Sensing, 14(5):871-883.

not improve classification accuracies for agricultural fields, due to the relatively homogeneous classes, and in some instances the accuracies are even decreased. The multi-scale classification algorithm (SMAP) clearly outperformed the per pixel classification. The largest improvement was found for the relatively noisy high resolution SAR data (EMISAR), whereas the improvement for the coarser scale, less noisy SPOT data was much less.

Using the SMAP algorithm on the total data set, an average classification accuracy of 95.9% was achieved, which is considered to be satisfactory, specifically taking into account, that neither multi-spectral SPOT data nor C-band SAR data are measured at optimal wavelengths with respect to vegetation monitoring. The result is expected to be improved if Landsat data is included, taking advantage of the near infrared band in Landsat data.

Acknowledgements

The work was done while the author was with the Department of Mathematics and Physics at the Agricultural University of Denmark. It has been funded by Dina, the Danish Informatics Network in the Agricultural Sciences, and by the Danish Space Board via DANMAC, the Danish Multisensor Airborne Campaign. The EMISAR data were acquired and processed by the Danish Center for Remote Sensing. Development of the EMISAR has been co-sponsored by the Thomas B. Thriges Foundation, the Danish Technical Research Council (STVF), the Royal Danish Air Force, the Technical University of Denmark, and the Joint Research Centre. The data acquisitions and the data processing have been sponsored by the Danish National Research Foundation. The author wishes to thank Henning Skriver, DCRS, for usefull comments to the manuscript and help and advice.

References

Anys, H. & He, D.-C. (1995): Evaluation of textural and multipolarization radar features for crop classification. IEEE Transactions on Geoscience and Remote Sensing, 33(5).

Bouman, B. & Hoekman, D. (1993): Multi-temporal, multi-frequency radar measurements of agricultural crops during the Agriscatt-88 campaign in The Netherlands. International Journal of Remote Sensing, 14(8): 1595-1614.

Bouman, C. A. & Shapiro, M. (1994): A multiscale random field model for bayesian image segmentation. IEEE Transactions on Image Processing, 3(2):162-177.

Bouman, C. A. & Shapiro, M. (1996): SMAP image segmentation software package. Users manual. http:// dynamo.ecn.purdue.edu/ bouman/software/segmentation_and_clustering/.

Chen, K. S., Huand, W. P., Tsay, D. H. & Amar, F. (1996): Classification of multifrequency polarimetric sar imagery using a dynamic learning neural network. IEEE Transactions on Geoscience and Remote Sensing, 34(3): 814-820.

Christensen, E., Skou, N., Dall, J., Woelders, K., Jorgensen, J., Granholm, J. & Madsen, S. (1998): EMISAR: An absolutely calibrated polarimetric L- and C-band SAR. IEEE Transaction Geoscience and Remote Sensing, 36(6):1852-1865.

Cressie, N. (1991): Statistics for spatial data. John Wiley and Sons, New York.

Dobson, M., Pierce, L. E. & Ulaby, F. T. (1996): Knowledge-based land cover classification using ERS-1/JERS-1 SAR composites. IEEE Transactions on Geoscience and Remote Sensing, 34(1):83-99.

Dobson, M. C., Ulaby, F. T. & Pierce, L. E. (1995): Land-cover classification and estimation of terrain attributes using synthetic aperture radar. Remote Sensing of Environment, 51:199-214.

Durand, J. M., Gimonet, B. J. & Perbos, J. R. (1987): SAR data filtering for classification. IEEE Transactions on Geoscience and Remote Sensing, 25(5):629-637.

Everitt, B. S. & Dunn, G. (1991): Applied Multivariate Data Analysis. Edward Arnold, London.

Fog, B., Poulsen, J. N., Sandholt, I., Stjernholm, M. & Skriver, H. (1993): Monitoring land cover and crop types in Denmark using ERS-1 SAR and optical satellite images. Pp. 71-80 in Proc. Int. Symp. From Optics to Radar, SPOT and ERS applications, Paris May 5-9 1993, number 312 in CNES.

Grass4.1 (1993): Grass 4.1 User's Reference Manual. USACERL, Champaign, Illinois.

Haslett, J. (1985): Maximum likelihood discriminant analysis on the plane using a Markovian model of spatial context. Pattern Recognition, 18(3):287-296.

Horgan, G. W., Glasbey, C., J.N., Cuevas Gozalo, S. L. S. & Alonso, F. G. (1992): Land-use classification in central Spain using SIR-A and MSS imagery. International Journal of Remote Sensing, 13(15):2839-2848.

Jeon, B. & Landgrebe, D. A. (1992): Classification with spatio-temporal interpixel class dependency contexts. IEEE Transactions on Geoscience and Remote Sensing,