

Environmental monitoring using ENVISAT ASAR data in agricultural areas

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ABSTRACT: The drinking water catchment of “Fuhrberger Feld” in the north of Hannover in Lower Saxony is being studied aiming at a reliable and continued evaluation of chemical emissions from agricultural activities. This research work is carried out together with the Institute for Landscape Planning and Nature Conservation, University of Hannover.

Within this research and development project, ENVISAT polarimetric SAR data (provided free of charge by ESA-Pilot-Project “AO335”) are used together with GIS information and ground surveys.

Available data are amplitude images from VV/VH polarisations of swaths 5, 6 or 7.

Due to little number of polarisations of ASAR data together with the coherence of different polarisations, the coherent response of different vegetation types to radar emissions and the high variance of pixel values in ASAR images, a classification using single images proved to be too inaccurate.

Some methods have been investigated to increase the classification accuracies, namely: Using different (time series) sets of despeckled images and signatures, which are merged based on the main crop covering the fields together with a combination rule, based on distance files resulting from classification. The accuracy of classification for crops with fixed and known phenological period increased up to 55% to 98% for different crops and with an average of 83% in the study area.

Using an object based approach, the influence of local parameters on the statistics of pixel values from images over the extent of agricultural fields is evaluated in the study area and a multi temporal-object based classification algorithm based on statistics of fields is tested and evaluated.

1 INTRODUCTION

The “Fuhrberger Feld” (Figure 2) is situated north of Hannover, the capital from Lower Saxony in Germany. The water protection area of the same name supplying about 90% of the drinking water consumption of the region of Hannover covers a size of approx. 300 sq. km. According to the water quality reports of the past years of the lower Saxony office for water and refuse, in numerous surface near fair places are groundwater nitrate values above the drinking water-threshold of 5 to more than 50 mg nitrates per liter. These values reflect a strong threat to the sustainability of the drinking water extraction.

The raw water quality depends next to the chemically-microbiological conversion in the water body itself (STREBEL et al. 1985) especially on the distribution of land use in that area and the related land use specific quality and groundwater regeneration rate (quantity). While the habitat specific causes (climate, ground and others) must be accepted as given, utilization contingent effects on the quality and the quantity of the groundwater are controllable. Since pastures and agricultural fields are important sources of chemical emissions and the area is intensively cultivated or utilised as pasture, it is required to monitor the area continuously. Considering the very high costs of classical surveying methods and aerial photography besides the demand of continuous monitoring, in this project, utilising space based data is offerable. Because of the frequently cloud cover in the study area ASAR data from ENVISAT Satellite are selected to monitor the agricultural activities.

2 DATA

2.1 Images

The image data consists of SAR acquisitions (intensity data) of both VV and VH polarisation modes of Envisat ASAR with about 30 meters spatial resolution and 12.5 Meters pixel size. All of the images originate from descending acquisitions taken from swath 5 to 7. Eleven data sets are available for the year 2004, which are listed in Table 1.

2.2 Ground surveys

About 50 fields have been selected to be used as references which cover all main types of agricultural crops present in the area. Each field selected had to be relatively homogenous in its extent and large enough in any direction.

The study area has been inspected close to each acquisition date. Information, which has been gathered for each field under observation, consists of:

- Land use
- Treatment direction (e.g. rows of asparagus)
- Distance between plant rows

Table 1: Data takes of ENVISAT ASAR APG images, polarisation VV/VH, IS 5-7.

Nr.	Image Date	Inspecting Date	Orientation	Swath IS
1	17.11.2003	26.11.2003	Descending	6
2	17.03.2004	19.03.2004	Descending	7
3	05.04.2004	05.04.2004	Descending	6
4	21.04.2004	21.04.2004	Descending	7
5	10.05.2004	10.05.2004	Descending	6
6	26.05.2004	10.05.2004	Descending	7
7	30.06.2004	14.06.2004	Descending	7
8	07.08.2004	07.08.2004	Descending	5
9	11.09.2004	08.09.2004	Descending	5
10	13.10.2004	13.10.2004	Descending	7
11	01.11.2004	01.11.2004	Descending	6

- Weather condition
- Situation of land and farming activities
- Vegetation coverage %
- Vegetation height
- Soil and vegetation moisture
- Condition of vegetation
- One or two handheld photographs
- Position and geometry of the field (geometry can vary over time)

2.3 *Field maps*

It is necessary to create a separate ground truth map for each inspection, because the field borders are not always fixed and can change frequently. Therefore, some fields may become too small to be used with respect to the resolution of the images and must be eliminated, and some fields are added in order to keep record of most important farming activities.

With respect to the 30 meters spatial resolution, a 30- meter wide buffer has been eliminated from the boundary of each field to keep each training field as homogenous as possible and to eliminate mixed or unreliable pixels in the statistics. These maps will be used for all further processing.

3 PRE-PROCESSING

Speckle in radar images reflect physical properties of microwaves as well as the target. It means that speckle has a meaningful variable behaviour on different surfaces. On the other hand, it influences strongly the statistics of digital numbers (DN) in the image. Therefore the question is yet open, if the images should be filtered (despeckled) or not in order to maximize the classification accuracy.

A lee filter with 7×7 kernels has been used to despeckle images. The kernel size (7×7) has been chosen with regard to data resolution (30 meters) and pixel size (12.5 meters). 12.5×7 is equal to 87.5. Therefore a 7×7 filter on an image with 12.5 meters pixel size covers 87.5×87.5 m², which is almost equal to a 3×3 kernel for the 30 meters resolution, and is the smallest meaningful kernel size for this resolution.

Radiometric analyses:

To eliminate speckle and local effects present in the image, PCA and normalised difference (ND) of the images are being computed in addition to the filtered and original images.

4 EFFECTS OF THE SURFACE PROPERTIES ON ASAR IMAGES

4.1 *Farming direction*

A study [2] has shown that the farming direction does not strongly affect digital numbers (DN) in ASAR images of the above mentioned resolution within the study area. The

Figures 1 and 2 show the mean value of DNs of some potato and asparagus fields in different directions.

Figure 1 represents the changes in mean of pixel values of VV (11) and VH (12) polarisations over the extent of two asparagus fields (“field 47” and “field 28”). Farming direction of Field 47 is SW-NE and of field 28 is W-E.

Figure 2 represents the changes in mean of pixel values of VV (11) and VH (12) polarisations over the extent of four potato fields (“field 39”, “field 41”, “field 44” and “field 45”). Farming direction of Field 39, 41 and 44 is W-E, but field 45 is NW-SE.

As can be seen, there is not any significant change due to the farming direction. It can be considered as a function of grain resolution (30 meters) relative to row distances. Effects from other elements of the surface may prevent the effect of farming rows as well.

4.2 Moisture of the soil and vegetation:

The moisture condition of soil and vegetation of fields have been ascertained by visual inspection for specific dates. The fields are classified of being either dry or wet. Therefore it is not possible to evaluate the effect of moisture on reflectance of the surface for a single image. A comparison between different acquisition dates may be done only after considering other important factors, such as look angle of the sensor, aiming to get a normalized set of images, because the look angle seems to have more impact than moisture. (Figure 3) The small influence of moisture may originate by the high incidence angle of the images [19]. (Swaths 5, 6 and 7: $35.8^\circ - 45.2^\circ$)

Though land cover types, shown in Figure 3, are stable in time, their pixel values may change in different images. It can be seen clearly that images of IS6 tend to have higher pixel values than images from IS7 and the changes seems to be independent of moisture.

In this situation, it is impossible to evaluate the effect of moisture without considering also the effect of look angle.

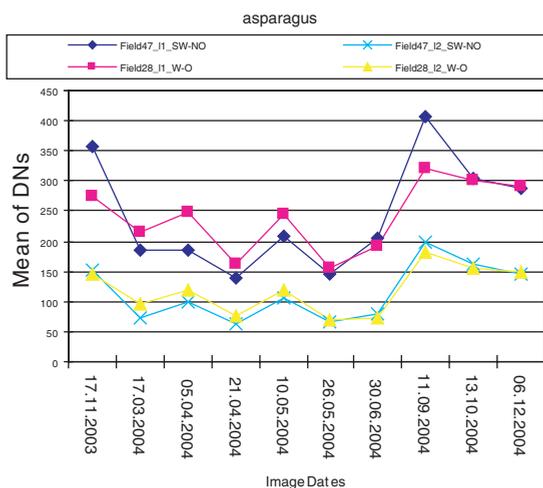


Figure 1. changes in the average of DN from rows of asparagus.

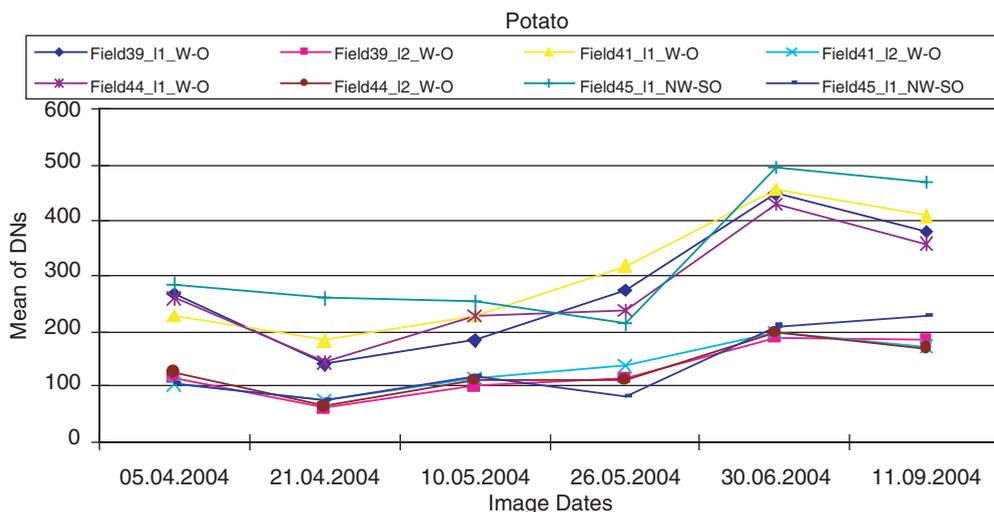


Figure 2. changes in the average of DN from four fields of potatoes.

4.3 Vegetation Height and coverage (Biomass)

Height (cm) and coverage (%) of vegetation are registered for each field, which can be used to have an approximation of Biomass content.

Figure 4 shows the average brightness of fields compared with the evaluated Biomass on the VV band of the image of 12.06.04. Biomass is evaluated as multiplication of height of vegetation by class of canopy coverage (0 = <12.5%, 1 = 12.5–25%, 2 = 25–50%, 3 = 50–75%, 4 = 75–100%). As can be seen in the Figure 4, the average DN from fields with higher biomass values tend to be close to each other and stay in the range of

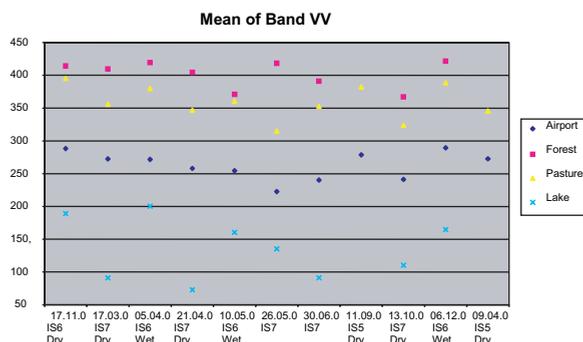


Figure 3. Changes in average of DN in the study area on four land use types (Grassland of airport, forest, pasture and lake).

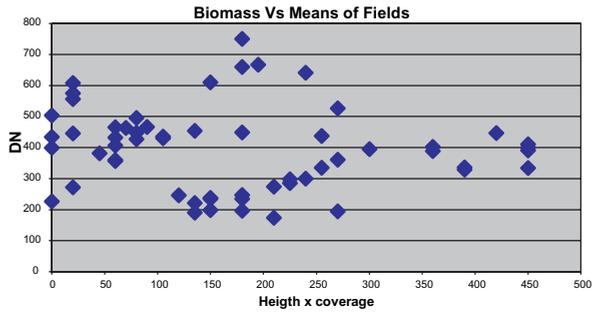


Figure 4. comparison of brightness values with biomass (Height * class of canopy coverage).

320–420. The brightness of fields with a very low or no biomass is more variable than fields having a high value of biomass, which represents the effect of different soil conditions. The medial fields show the highest variability which can be considered as result of the complex reflection of vegetation and soil.

4.4 Look angle

As shown in Figure 3 the influence of look angle (Swath) on the brightness of the images is so high that any comparison between brightness values from images with different look angles is meaningless as long as the effect of the look angle is not eliminated. It can be clearly seen that images from IS6 tend to have higher pixel values than IS7. But images from IS5 can not be easily interpreted, because of the few images from IS5 (only 2) and the missing coverage of the test areas from lake and forest.

The data presented in Figure 3 are from four low-changeable land cover classes, i.e. grassland coverage of the airport of Hannover, pastures from the study area, a lake in North West of Hannover (Steinhuder Meer), and a homogenous area of forest. It can be seen that the variability of images on different surfaces is not similar. The highest variation is in the lake area and the lowest in the grass area of the airport.

4.5 Soil

Table 2 shows a list of sample fields in the study area. The list is ordered based on the mean of pixel values of 47 fields on the VV band of images 17.03.04. The red records had no or very low (<12.5%) coverage of vegetation on the acquisition date.

It can be seen that bare soils tend to be darker in the images. But there are some bright bare fields which show the importance of the soil, too. The field “ID 11” is a pasture and has been the darkest pasture field on all acquisitions. This field was used as a racecourse previously and has probably a hard base under the surface. This fact explains the importance of the subsurface condition of soil as well.

4.6 Vegetation Types

The Land use types in Table 3 are sorted according to the mean of pixel values on the VV band of acquisition on 10.05.04. It can be seen that crops of the same species tend to be

Table 2. List of sample fields sorted by mean of pixel values on VV band of the acquisition on 17.03.04.

Order	ID	Mean VV 17.03.04
1	29	183.357
2	41	190.816
3	37	202.867
4	39	202.967
5	36	203.704
6	47	204.333
7	33	206.351
8	34	206.917
9	7	211.302
10	30	211.951
11	8	217.596
12	17	220.132
13	43	220.793
14	42	221.767
15	45	221.954
16	11	222.533
17	38	225.191
18	18	227.585
19	28	228.782
20	32b	229.039
21	44	235.306
22	1	235.898
23	5	236.151
24	9	241.415
25	21	243.906
26	46a	248.385
27	14	250.264
28	6	250.958
29	31	254.021
30	3	255.300
31	16	257.244
32	32a	259.244
33	2	261.459
34	4	264.062
35	46b	264.571
36	12	268.027
37	23	272.950
38	20	275.830
39	26	276.602
40	40	293.860
41	24	303.078
42	13	305.762
43	22	307.466
44	15	333.448
45	25	339.006
46	19	358.819
47	50	451.309

Table 3. Land cover of sample fields in study area sorted based on mean of pixel values from VV band of image 10.05.2004.

Order	Field ID	Vegetation Type	Mean
1	5	Winter barley	164.593
2	23	Winter barley	169.184
3	7	Winter barley	171.356
4	6	Winter barley	179.503
5	39	Potato	182.707
6	42	sugar beet	201.785
7	43c	sugar beet	217.984
8	47	Asparagus	218.358
9	15	sugar beet	219.059
10	38	Potato	219.251
11	36	sugar beet	223.027
12	43b	None	224.758
13	16	Winter rye	225.777
14	21	Winter barley	226.113
15	11	pasture	226.597
16	31	Willow	227.835
17	3	Winter rye	229.078
18	32b	Willow	229.226
19	44	Potato	231.409
20	32a	Winter rye	233.392
21	2	Winter rye	235.483
22	50	Winter rye	238.006
23	20	pasture	238.142
24	41	Potato	241.128
25	8	sugar beet	242.700
26	12	pasture	246.659
27	45	Potato	251.101
28	33	sugar beet	251.346
29	17	Winter rye	255.090
30	14	pasture	255.837
31	4	pasture	256.147
32	28	Asparagus	262.912
33	29	Summer barley	265.587
34	13	Winter rye	269.960
35	43a	Summer rye	277.917
36	30	Summer barley	278.856
37	34	Summer barley	280.637
38	46b	Lea	281.268
39	1	pasture	282.463
40	18	Winter wheat	285.713
41	37	Summer barley	316.312
42	40	sugar beet	317.324
43	9	Fallow	317.855
44	24	Summer barley	322.645
45	46a	Peas	364.135
46	22+25	sugar beet	372.768
47	19	Rape	381.894
48	26	Strawberry	524.000

closer but they don't often make any grouping because of other effective parameters (Such as soil and look angle) on pixel values.

As can be seen some crops such as grains show a better arrangements compared to some others such as asparagus and potato. This can be explained as a function of the season. Because of the date of the image (May) used for the Table 3, grains made a high volume of biomass over the fields but at this time sugar beets and potatoes are only small plants and the reflection from agricultural fields of sugar beets and potatoes depends highly on the soil and not vegetation.

5 CLASSIFICATION

The extraction of agricultural activities from radar images is demanding and there are some special difficulties, like:

- The number of polarisations, which can be compared with bands of images from optical systems, is very small, which reduces the multi dimensional feature space of radar images.
- Different bands (polarisations) are sometimes more correlated compared to spectral channels of optical images.
- The speckle, especially in SAR images, results in a large variance within the training samples yielding an unsatisfactory classification.
- Spatial resolution of radar images is often not as good as in optical imagery under similar conditions.
- Radar images are strongly affected by look angle, soil moisture and other physical properties of the soil. These parameters often affect signatures more than vegetation.

The most important advantage of radar systems is their (almost) independence to weather conditions and therefore data can be acquired irrespective of cloud cover. Because of this fact, more frequent usable images and therefore a better temporal resolution is available. In addition SAR images can sometimes prove to be better suited than optical images [6, 31].

A variety of papers demonstrate how to overcome the limitations and use the benefits of SAR images.

Numerous filters are offered [20] and evaluated [7, 16] to reduce speckle of radar images, while keeping details, edges and statistical parameters unchanged.

To classify crops using ASAR data, it is tested to use all available polarisations [14, 20], multi-temporal data [12, 25], object based classification techniques [12], combination of passive data [12], knowledge driven classification [10] and to evaluate the effects of local characteristics on radar images [19]. Using these methods an exterior accuracy of 70% to 90% is achievable. However the results of different crops don't have the same reliability. Some crops can not be classified as satisfactorily as some others [10].

5.1 *Classification of single images*

To test the ability of standard classification methods on single ASAR images, we have derived different classification methods on two-band single images. As a result, only 20-30% of the sample fields using unfiltered images have been correctly classified

(interior accuracy). The interior accuracy of classification on filtered images rose to 25–45% of the sample fields, depending on filtering method and date of acquisition. We did not find any important effect from the used classification method on the results. [17]

It is noticeable that the accuracy of classification is strongly dependent on the type of land use and the acquisition date. It means each crop can be extracted from some images better than other images and on the other hand from each image some crops can be extracted better than other crops. As can be seen on Figure 5, some crops such as pea, strawberry and winter grains are classified relatively well but others not at all.

5.2 Pixel based Multi temporal classification

Multi temporal classification of SAR data is a well known method for overcoming the limitations of SAR data and improving the accuracy of classification.

The multi-temporal approach becomes possible because of the independency of weather conditions and can be applied more frequently and reliable in comparison to optical images.

It is assumed to be useful due to the changeable nature of agricultural fields. Each crop has its specific growth period and therefore it can be separated from other crops. This means the changes of fields of one crop can be used as a signature of the crop.

This method has been vastly used and tested over different areas and for different crops e.g. K. Tröltzsch [28] in Mali, V. Hochschild [12] in Germany, S. Baronti [1] in Italy, G.M. Foody [8] in England, B. Schieche [24] in Germany, G. Davidson [3] in Japan . . .

Exterior accuracy of multi temporal classification in the study area is evaluated between 55% and 98% for different crops with an average of 83% if a proper set of despeckled images are classified using adequate signatures [27].

Despite the acceptable accuracy, there are yet two important limitations:

- This method needs a good knowledge of the phenological period of crops and therefore crops without a fixed and known growth cycle can not be reliably classified with this method.

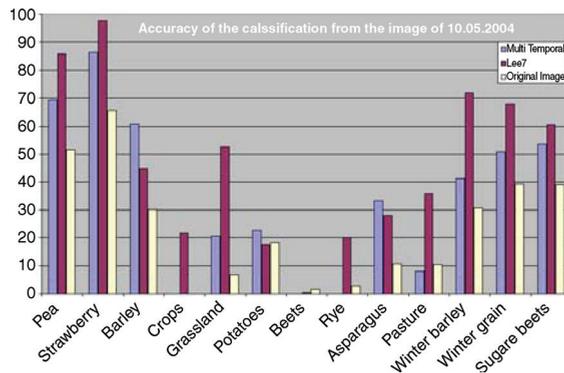


Figure 5. Accuracy of classification using filtered (multi temporal and Lee) and unfiltered images from 10.05.04.

- images from different dates with different characteristics are globally diverse due to the effect of look angle, soil/vegetation moisture and other possible elements (weather condition, changes in sensor and pre-processes). Therefore signatures from one year can not be used for the classification of another year so new sets of signatures are needed.

5.3 *Object based Multi temporal classification*

Each field can be considered as an object but vegetation patterns on agricultural fields are very fine compared to the resolution of ASAR images (30 meters). Distances between rows of cultivation are ranging from 12 cm (grains) up to about 200 cm (asparagus) and even sometimes rows can not be recognised for some types such as pastures, grass and rapes.

Especially, when crops grow up a pattern is rarely visible.

Besides the invisibility of patterns on ASAR images, no significant remarkable effect from cultivation pattern and their direction can be recognised in the statistics of fields in this area. As shown in [2], the direction of rows does not significantly affect the statistics of fields even for asparagus and potatoes.

In addition, speckle in radar data prohibits the appearance of fine patterns and contexts. Applying despeckle filters may decrease these patterns together with speckle. Therefore, object oriented classification based on patterns and texture of agricultural fields in images with 30 meters resolution is not very successful.

There are only few samples for attempts of object oriented classification of SAR data. R. Hermans et al [11] detected flooded areas on ENVISAT/ASAR images using object oriented method of eCognition software. Sun Xiaoxia et al. [30] classified airborne SAR data enhanced with optical data of SPOT5 using an object oriented method offered by eCognition software and reported better results in comparison to pixel based classification on the same data set.

We tried to evaluate the accuracy and possibility of object (field)-based classification using statistics of agricultural fields. But the problem of segmentation still persists.

5.3.1 *Methodology*

Tables of means (M) and standard deviation (SD) of pixel values within sample fields on sets of multi temporal ASAR images have been computed to be used as signatures. Table 4 represents a small part of one signature table. There is at least one record for each crop. Each column represents statistics (M or SD) of sample fields on each band (VV or VH) of multi temporal set of images. L1 indicates the VV polarisation and L2 VH. Dates in the header of the columns are the date of images.

Values of each record represent the average of statistics (M or SD) obtained from pixel values over the area of fields, which are covered by the desired crop at the time of imaging. Therefore any record can be considered as a multi temporal statistical signature of one crop. The value – 1 means that the desired crop was not cultivated at the time of imaging in the study area.

Next, the multi temporal statistical signature must be compared with multi temporal statistics of each sample field and the field assigned to the most likely crop. For this

Table 4. A part of one signature table used for multi-temporal object-oriented classification.

Crop	M_L1 17.11	SD_L1 17.11	M_L2 17.11	SD_L2 17.11	M_L1 17.03	SD_L1 17.03
Lea	292	80	170	47	293	32
Fallow	358	97	154	37	351	36
Peas	-1	-1	-1	-1	-1	-1
Strawberry	456	122	188	43	460	38
Willow	272	82	144	32	292	32
Potato	-1	-1	-1	-1	-1	-1
None	387	97	166	43	389	33
Summer grains	-1	-1	-1	-1	-1	-1
Asparagus	321	105	149	33	331	47
Pasture	284	86	138	36	281	31
Winter grains	314	90	131	32	317	28
Sugar beets	-1	-1	-1	-1	-1	-1

comparison, we have to calculate the distances between statistics of one field to each record of signature table separately.

Since absolute distance (d_c) between statistics of a field and statistical signature of a crop (a record of signature table) is the summation of differences from a multi temporal set of images and not a single value, the distances from different images must be merged to get an absolute distance between the statistics of a field and the statistical signature of a crop.

There are some methods to calculate d_c :

1- We tried a simple distance method, which simply adds distances to each other.

$$d_c = \sum_n^{i=1} d_i$$

2- Another distance method is Euclidian distance which calculates the root of summation of square of distances.

$$d_c = \sqrt{\sum_n^{i=1} d_i^2}$$

It must be noticed that the growth periods of different crops are not identical and some of them are planted for only two or three months and some others for a whole year (We do not exactly use one image from each month. Table 1). Therefore to make the distances to crops for one field comparable to each other, they must be normalized by means of division by number of values (dates) of each desired crop.

It can be formulated as below:

$$d_{cn} = \frac{d_c}{n_c}$$

Where:

d_{cn} : is the normalized distance between statistics of one field and statistics of one crop

d_c : is the absolute distance (simple or Euclidian) between statistics of the field and statistics of the crop

n_c : is the number of valid values (growth period) in the signature record of the crop

Figure 6 represents cultivation period of different crops in the study area.

5.3.2 Pre-processing

To test if pre-processing of the original images can improve the accuracy of classification some approaches have been compared. The pre-processing approaches are listed in Table 5 and a reference number is assigned to each one to be used for referencing. PCA in Table 5 is the first principle component between two bands (VV and VH) of each image. ND is the normalized difference between two bands (VV and VH) of each image, which is calculated as:

$$\frac{VV - VH}{VV + VH}$$

Images	17.	17.	05.	21.	10.	26.	30.	11.	13.
Crops	11	03	04	04	05	05	06	09	10
Winter grains									
Sugar beets									
Lea									
Fallow									
Strawberry									
Willow									
None									
Potato									
Summer grains									
Peas									
Asparagus									
Pasture									

Figure 6. Growth period of different crops in the study area between Nov. 2003 and Oct. 2004.

Table 5. Pre-processings tested in this study.

Ref. number	Pre-process
1	Original (no pre-process)
2	Filtered Image (Lee filter)
3	PCA from Original
4	PCA from Filtered
5	ND from Original
6	ND from Filtered

5.3.3 Classification and results

Different combinations of input data (1 to 6), statistics (M and SD) and distance methods (simple or Euclidian) were used to find out which combination of data, statistics and classification method is optimal. To do this, statistics from each field were compared with statistics of each crop in the growth period of that crop. The crop, whose statistics are closest to the statistics of the desired field, is assigned to the field in the growth period of the crop.

This classification method is tested on sample fields to evaluate the accuracy of the method in this area. The accuracy is evaluated based on results for crops with a fixed and known growth period, for which more than one training sample were available.

We can not use multi temporal classification for crops without a known phenological period. On the other hand, we are comparing statistics of signatures with statistics of fields by applying an object-oriented classification method. Therefore we can not evaluate the accuracy of classification for one crop if only one sample is available for it. In this case the accuracy for the crop would be calculated as 100%, which is not reliable. Results of classification and information from field visits are presented in tables (one for each combination) to evaluate the accuracy of classification. Table 6 is an example of these tables. Each row represents one field and each column represents one imaging date between 17.11.2003 and 13.10.2004. Coloured cells explain the existence of one type of crops, which are used for evaluation. A legend on the left column indicates meaning of each colour. The numbers in the cells explain if the field of that date is classified correct (1) or false (0).

Because of the fact that winter grains are more similar to bare lands in winter and they look like summer grains in summer, there is a high value of mixture in the results of winter and summer grains. The accuracy of winter and summer grains classified as one crop in the classification process is evaluated, too. Classification accuracies in different combinations of data and distance methods are presented in Table 7. M in Table 7 means “mean” and S means standard deviation and the numbers in the first column refer to Table 5.

From Table 7 it can be seen, that the best accuracy is achieved when the mean of all pre-processings is classified using simple distance method (Simple Distance, 1-2-3-4-5-6, M). The accuracy gain of filtered data is noticeable when they are classified using the Euclidian distance method, especially when all grains are assumed as one crop.

Generally the classification results for original data (not pre-processed) are better when they are classified using simple difference method, but pre-processed data (filtered, PCA, ND) are often better classified using the Euclidian distance.

PCA and ND do not improve the classification of primary bands (VV and VH) but when combined with primary bands they raise the accuracy slightly.

As expected, considering all grains as one crop improves the total accuracy of classification, because the mixture between grains is not considered as error any longer.

Using mean and SD of fields instead of only mean does not improve the accuracy of classification in most cases.

6 CONCLUSION

The influence of some environmental elements on ASAR images from the study area of “Fuhrberger feld” is discussed in this paper and an object oriented classification method

Table 7. Accuracies evaluated from results for crops with fixed and known phenological period.

Input Data	Accuracy (Grains separated)		Accuracy (Grains merged)	
	Simple Distance	Euclidian Distance	Simple Distance	Euclidian Distance
Pre-processes (Tab.5), Statistics				
1,M	0.84	0.83	0.85	0.88
1,M-S	0.82	0.82	0.85	0.88
2,M	0.84	0.84	0.88	0.89
2,M-S	0.83	0.86	0.86	0.91
3,M	0.65	0.64	0.68	0.69
3,M-S	0.62	0.72	0.68	0.77
4,M	0.59	0.63	0.65	0.69
4,M-S	0.55	0.63	0.62	0.69
1-5,M	0.86	0.83	0.88	0.88
1-5,M-S	0.86	0.82	0.88	0.88
2-6,M	0.85	0.86	0.88	0.91
2-6,M-S	0.83	0.86	0.86	0.91
1-2-3-4-5-6,M	0.89	0.83	0.91	0.88
1-2-3-4-5-6,M-S	0.85	0.82	0.88	0.88

based on statistics of agricultural fields is evaluated over the study area. A good a priori segmentation of images or a map of agricultural fields in the study area is necessary to apply this method for classification, because it is based on the statistics of fields and requires field boundaries. A poor map or segmentation of images can strongly decrease the accuracy of classification.

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