# 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 a reliable and continues 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
- Weather condition
- Land and farming activities situation
- 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)

| 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 |

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

**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 7x7 kernels has been used to despeckle images. The kernel size (7x7) has been chosen with regard to data resolution (30 meters) and pixel size (12.5 meters). 12.5x7 is equal to 87.5. Therefore a 7x7 filter on an image with 12.5 meters pixel size covers 87.5x87.5 m^2, which is almost equal to a 3x3 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.

The figure 1 represents the changes in mean of pixel values of VV (l1) and VH (l2) 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.

The figure 2 represents the changes in mean of pixel values of VV (l1) and VH (l2) 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.

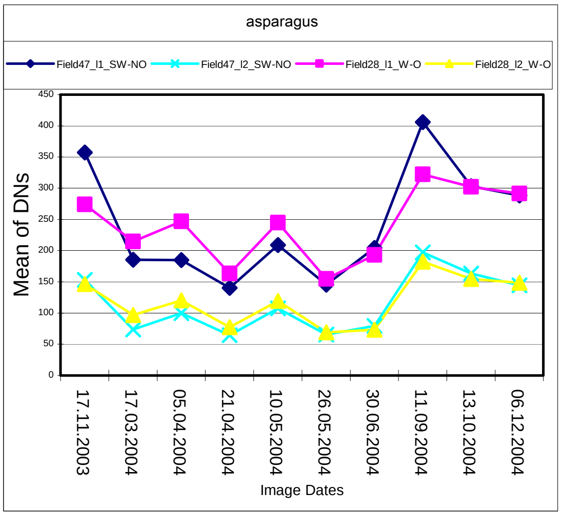


Figure 1: changes in the average of DN from rows of asparagus.

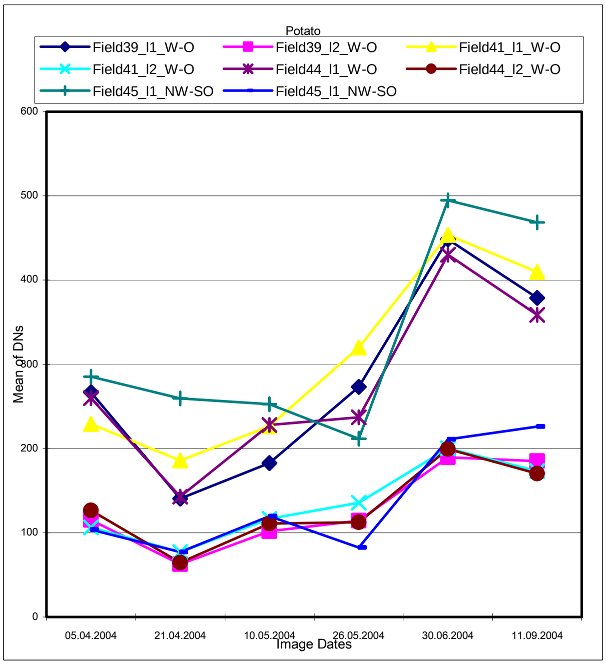


Figure 2: changes in the average of DN from four fields of potatoes.

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˚ - 45.2˚)

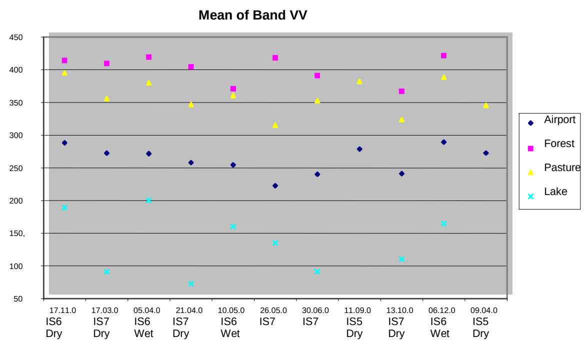


Figure 3: Changes in average of DNs in the study area on four land use types (Grassland of airport, forest, pasture and lake).

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 to moisture.

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

### 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.

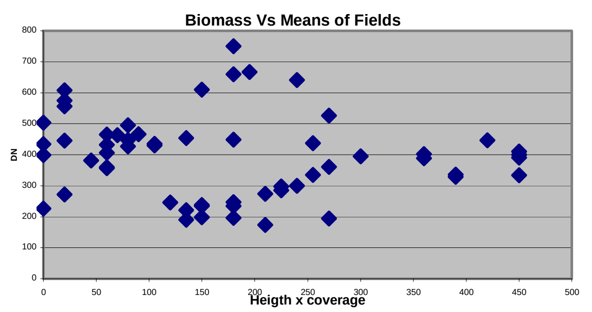


Figure 4: comparison of brightness values with biomass (Height * class of canopy coverage)

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 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 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 are 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 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 on the date of the image (May) used for the table 3, grains made a high volume of biomass over the fields but on 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.

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

| Order | Field ID | Vegetation Type | Mean VV 10.05.04 |
|---|---|---|---|
| 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 |

Table3: Land cover of sample fields in study area sorted based on mean of pixel values from VV band of image 10.05.2004.

## 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 the 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]

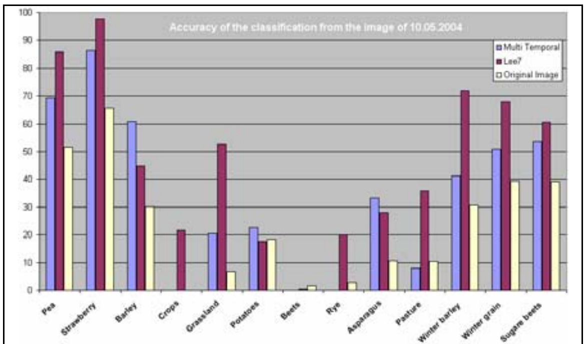


Figure 5: Accuracy of classification using filtered (multi temporal and Lee) and unfiltered images from 10.05.04

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 relative 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 phenological period of crops and therefore crops without a fixed and known growth cycle can not be reliably classified with this method.

-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 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 12cm (grains) up to about 200cm (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], 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. Appling 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. all [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 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.

**5.3.4. 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 columns are 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.

| 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 |

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

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

Since absolute distance (dc) 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 dc:

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 bellow:

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

Where:

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

$d_c$: is 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.

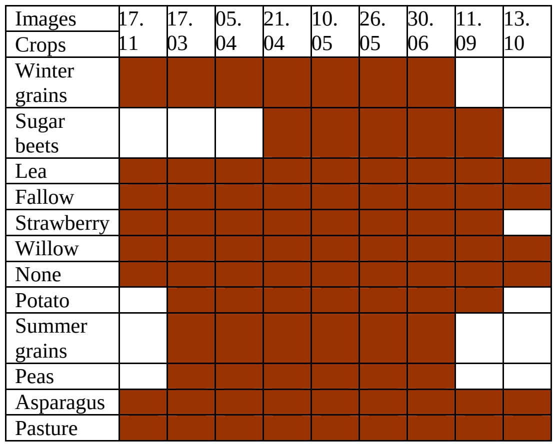


Figure 6: Growth period of different crops in the study area between Nov. 2003 and Oct. 2004

**5.3.5. 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 normalized difference between two bands (VV and VH) of each image, which is calculated as:

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

| 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 |

Table 5: Pre-processings tested in this study

### 5.3.6. 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 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.

| | 17. 11 | 17. 03 | 05. 04 | 21. 04 | 10. 05 | 26. 05 | 30. 06 | 11. 09 | 13. 10 |
|---|---|---|---|---|---|---|---|---|---|
| Winter Grains | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Sugar Beets | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Potato | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Summer Grains | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Asparagus | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Pasture | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | | | | 1 | 1 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | | | 1 | 1 | 1 | 1 | 1 | | |
| | | | 1 | 1 | 1 | 1 | 1 | | |
| | | | | | 0 | 0 | 0 | 0 | |
| | | | 1 | 1 | 1 | 1 | 1 | 1 | |
| | | | | 1 | 1 | 1 | 1 | 1 | 1 |
| | | | | | 1 | 1 | 1 | 1 | 1 |
| | | | | 1 | 1 | 1 | 1 | | |
| | | | | 1 | 1 | 1 | 1 | | |
| | | | | | 1 | 1 | 1 | 1 | 1 |
| | | | | 0 | 0 | 0 | 0 | 0 | |
| | | 0 | 0 | 0 | 0 | 0 | 0 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | | | 1 | 1 | 1 | 1 | 1 | 1 | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | |
| | | | | | 1 | 1 | 1 | 1 | 1 |
| | | | | | 1 | 1 | 1 | 1 | 1 |
| | | | | | 1 | 1 | 1 | 1 | 1 |
| | | | 1 | 1 | 1 | 1 | 1 | | 1 |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | 1 | 1 | | | 1 | 1 | | | |
| | | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | | | | | 1 | 1 | 1 | 1 | 1 |
| | | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| | | | | | 0 | 0 | 0 | 0 | |
| | | | | | | | 0 | 0 | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | | | 1 | 1 | 1 | 1 | 1 | 1 | |
| | | | 1 | 1 | 1 | 1 | 1 | 1 | |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | |
| | | | | | 1 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | |
| | | | | | 1 | 1 | 1 | 1 | |
| | | | | | | | 0 | 0 | |
| Correct | 0,88 | 0,85 | 0,88 | 0,87 | 0,86 | 0,86 | 0,82 | 0,83 | 0,91 |
| Accuracy | 0,86 | | | | | | | | |

Table 6: comparison between results of multi temporal object oriented classification and information from field visits

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 existence of one of crops, which are used for evaluation. A legend on the left column indicates meaning of each colour. 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 numbers in the first column refer to the 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.

| Input Data | Accuracy (Grains separated) | | Accuracy (Grains merged) | |
|---|---|---|---|---|
| Pre-processes (Tab.5) ,Statistics | Simple Distance | Euclidian Distance | Simple Distance | Euclidian Distance |
| 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 |

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

PCA and ND do not improve 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 anymore considered as error.
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 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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