

Classification of Agricultural Sites using Time-series of High-resolution dual-polarisation TerraSAR – X Spotlight images

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ABSTRACT:

Increasing demands for lasting and environmentally conscious use of natural resources together with a cost effective and restrictive use of fertilizers and pesticides require the employment of new technologies in agriculture. The preliminary results presented here consist in the automatic land use classification of agricultural fields based on multi-temporal TerraSAR-X images in dual polarization obtained in the high resolution Spotlight mode of the satellite. The classified data in turn can be used to enhance and validate existing models on ground water quality as a function of agricultural usage and soil treatment.

Within the past years investigations have been carried out on the usefulness of ENVISAT ASAR dual polarimetric data for environmental mapping in the same area, which show some deficiencies mainly because of the spatial resolution of the data, which was too coarse for many cultivations and could not reflect agricultural treatments (irrigation, fertilization, soil and plant treatment) sufficiently. However, the ENVISAT investigations showed that a proper selection of images out of a time series according to the crop-calendar of that region is beneficial and gives in general more accurate results than using all of the images.

This is due to the fact that some fields are covered by different types of crops during the year and such sequence is often hard to model because it is usually governed by phenologic, ecologic, and economic reasons. The latter might be influenced either from sudden change of global or national economic constraints (e.g., oil prize, taxes, and subsidies), by strategies of individual farmers, or both. In this paper, results obtained from multi-temporal classifications of TerraSAR-X image pairs (HH and VV) covering a whole season (11 images from March to November) are presented. Even though the temporal grid was irregular (revisit time was nine times 22 days and once 44 days) in every month at least one pair was available.

The investigations and results are based on standard pixel based Maximum Likelihood classification techniques, which however are amended by the use of regional crop calendar conditions and rules to account for seasonal variations of specific cultivations with respect to permanent crops. Results obtained have been compared to ground truth, which has been carried out in-situ to the satellite measurements.

It can be shown that even when not using all images of the year, but only those which are indicated by the crop-calendar or those which show high loadings using Factor Analysis a considerable classification accuracy of more than 90% can be achieved. Besides, the crop-calendar,

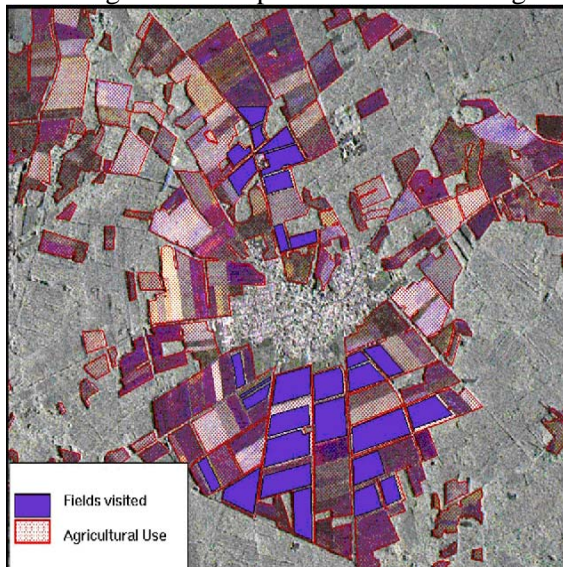
which has been set-up using ground observations can be verified or sometimes improved by this method.

The accuracy obtained, can be improved by different types of pre-processing (i.e., filtering) as is demonstrated. Some remaining discrepancies for some species can be explained by investigating the structural behaviour of the plants on ground as compared to close range photos being taken during ground truth.

As could be demonstrated the use of time-series of images from TerraSAR-X despite of frequent cloud cover offers an excellent tool for monitoring crops and serve as indicator for the estimation of the amount of fertilizers used within that area. Using this information, farmers could improve their efforts in establishing good agricultural practice, as being claimed by recent legal and environmental jurisdiction. In future work the validity of this work, which is limited by the small amount of training and control fields will be extended and also other modern classification techniques applied, such as support vector machine.

1 INTRODUCTION

Increasing demands for lasting and environmentally conscious consumption of natural resources together with a cost effective and restrictive use of fertilizers and pesticides require the employment of new technologies in agriculture. The preliminary results presented here consist in the automatic land cover classification of agricultural fields based on multi-temporal TerraSAR-X images in dual polarization obtained in the high resolution Spotlight mode of the satellite. The classified data in turn can be used to enhance and validate existing models on ground water quality as a function of agricultural crop cover and soil treatment. Within the past years investigations have been carried out on the usefulness of ENVISAT ASAR dual polarimetric data for environmental mapping in the same area, which show some deficiencies mainly because of the spatial resolution of the data, which was too coarse for many cultivations and could not reflect agricultural treatments (irrigation, fertilization, soil and plant treatment) sufficiently. However, the ENVISAT investigations [Tavakkoli et al., 2008] showed that a proper selection of images out of a time series according to the crop-calendar of that region is beneficial and gives in general more accurate



results than using all of the images. This is due to the fact that some fields are covered by different types of crops during the year and such sequence is often hard to model because it is usually governed by phenological, ecologic, and economic reasons. The latter might be influenced either from sudden change of global or national economic constraints (e.g., oil prize, taxes, and subsidies), by strategies of individual farmers, or both.

It could be shown, that for some crop-types the dual-polarized SAR imagery was highly correlated. In addition, as with the ENVISAT ASAR Data, the speckle phenomenon resulted in high interclass variances leading to unsatisfactory classification results.

Figure 1: Test area

Finally, it is known, that SAR is sensitive to incidence angle, soil moisture, and physical properties of soil, such as roughness. These parameters may affect signatures and deteriorate the vegetation signal. Despite these limitations the all-weather capability, enabling high temporal resolution and data acquisition on a regular basis, is an important advantage in the application of SAR images for agricultural monitoring purposes [De Matthaes et al., 1995 and Yakam-Simen et al., 1998].

The test site (see Figure 1) called “Fuhrberger Feld” is situated north of Hannover, the capital of state Lower Saxony in Germany. Ground truth data was collected on 14 % of the total agricultural land cover. The analysis of the field data led in a first attempt to 8 major crops from March till October. One of the major crops (Strawberry), however, showed a very strong correlation to pea-beans. Because there was only one single Strawberry field within the image data used, it was abandoned from further investigations.

For all fields, topographic as well as base maps and digital orthophotos in color are available. Furthermore, ground surveys were conducted at or close to the image acquisition time. Initially a monthly coverage by TerraSAR satellite images was planned to get a time-series covering the whole growing season, but practically a TerraSAR-X dual-pol. (HH and VV) irregular temporal grid with 10 images from March to October (see Table 1) was acquired.

Acquisition No.	Acquisition Date	Ground Truth Date
1	13-03-2008	14-03-2008
2	04-04-2008	04-04-2008
3	18-05-2008	21-05-2008
4	09-06-2008	10-06-2008
5	01-07-2008	02-07-2008
6	23-07-2008	22-07-2008
7	14-08-2008	14-08-2008
8	05-09-2008	04-09-2008
9	27-09-2008	25-09-2008
10	19-10-2008	20-10-2008

Table 1: Acquisition & Ground-Truth Dates

During ground surveys, relevant features such as coverage and treatment pattern were observed. Additionally, information on the kind of mechanical soil treatment, vegetation coverage in percent of the area, colour, observable fertilizers, irrigation etc. have been collected. Digital terrestrial photographs have been taken, which later on proved very helpful during interpretation. It is important to note that for some crop types, the coverage periods on the one hand coincide significantly, but on the other hand, even for the same crop on neighbouring fields the dates of start and end of cultivation can vary. The reason for this behaviour is not known for sure, but probably economic considerations of individual farmers cause this effect, resulting in different choices of subsequent use of the field after harvest.

2. MULTI-TEMPORAL ANALYSIS OF SAR DATA

Different plants have different surface properties and their growth process (phenology) influences the backscatter signal. This is the basis of distinction of the types of crops in a multi-temporal classification [Del Frate et al. 2003, Hochschild V. et al. 2005, Karjalainen M. et al. 2008, and Tavakkoli et al. 2008].

[Lohmann et al. 2005] indicated in a test, that only about 45% of the training samples could be correctly classified with only one images of two polarizations (VV and VH). Instead, almost 100% of the same training samples were correctly classified by a time series covering 12 dates.

In another work [Bruzzone et al., 2004] extracted two features, namely “temporal variability of backscattering” and “long-term coherence” from multi-temporal SAR images and showed that classification of these two features was more accurate than classifying raw data to map four classes (forest, urban, water and agricultural fields). These among others explains the importance and benefit of using temporal plant behaviours in crop classification, especially those, that reflect growth and cultivation activities, influencing SAR backscatter.

For the classification of crops, successful attempts have been demonstrated with all available polarizations [Kreisen A. et al. 2002, Nezry E. et al. 1995] especially in case of full polarimetric data. The same holds for multi-temporal data [Hochschild V. et al., 2005, Troeltzsch K. at al., 2002], yielding a large feature space and enables the mapping of temporal change due to plant growing. Besides specific farming activities can be used for recognizing crop types. Hence multi-temporal radar data are used vastly for monitoring of agricultural activities.

There are quite a variety of methods which are applied to improve information extraction from SAR data. Object based classification techniques, combination of SAR and passive data [Hochschild et al., 2005], knowledge driven classification [Habermeier M. et al., 1997], and investigating the effects of local characteristics on radar images [McNarin H. et al., 2002] are used by different research groups. Using these methods, an overall accuracy (i.e., accuracy as compared to reference field maps) of 70% to 90% is achievable. However, the accuracy differs significantly for different crop types. Some crops can not be classified satisfactory others do [Habermeier M. et al., 1997].

A variety of methods for multi-temporal classifications of ERS and ENVISAT SAR data has been tested by different authors [Tavakkoli et al., 2007]. Some of these approaches include information from the site specific crop conditions (crop calendar) reflecting the phenological differences in plant development during the growing cycle within a year.

Within this project a time series of data is available, which reflects not only the growing cycle of one crop but also the intermediate planting of fertilizer plants, sometimes even the subdividing of a field into different cultures and other related treatments such as irrigation can be observed. Because, in general, monthly images are not available, the question arises on the actual number of images necessary for a classification of a specific crop, the acquisition time and the importance of the polarization (HH or VV for the case of TerraSAR-X). Therefore an analysis will be carried out to verify the importance and significance of an existing crop calendar.

3. DATA PROCESSING AND ANALYSIS

3.1 PRE-PROCESSING

The images have been precisely matched to each other as required for speckle reduction by time-series filters [Aspert et al., 2007] and processed into geocoded products using a pixel spacing of 1 m in range and azimuth direction. However, the spatial resolution of the data is about 5 m.

It could be shown in previous work, that speckle suppression improves classification results. Therefore the filter as proposed by [De Grandi et al. 1997] a multi-temporal optimum weighting filter to balance differences in reflectivity between images taken at different times was used.

This multi-temporal filtering is based on the assumption that the same resolution element on the ground is illuminated by the radar beam in the same way, and corresponds to the same co-ordinates in the image plane (sampled signal) in all images of the time series. In other words the SAR geometry is the same for all acquisitions. Fig. 2 shows as an example the result of this filter on a subset of the data.

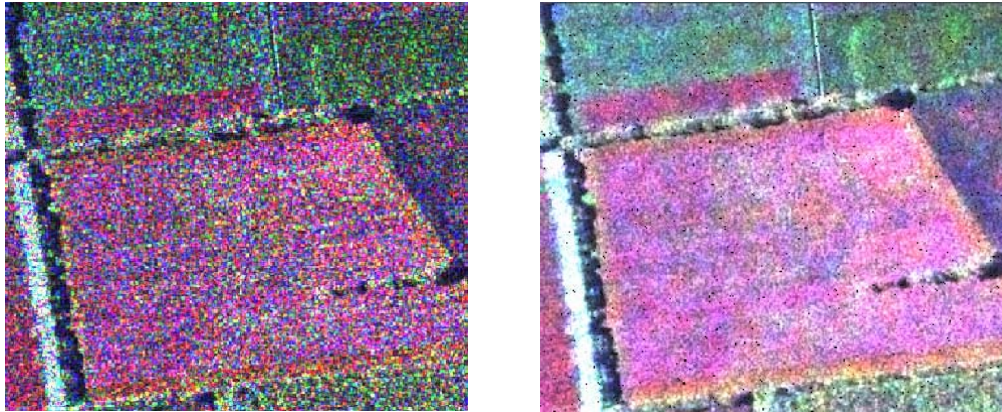


Figure 2: De Grandi speckle reduction

Next a mask covering all the unwanted objects like forest, settlement and other non-agricultural areas is generated, to exclude other classes from classification. This was accomplished using a time-varying segmentation approach as reported from [Aspert et al., 2007] which is part of the SARscape software within the ENVI image processing software.

3.2 ANALYZING THE IMPORTANCE OF ACQUISITION DATES BY FACTOR ANALYSIS

As can be seen by Table 1 altogether 10 acquisition times with 2 polarizations each were available. Ground truth was performed close to each data take and this data served as input to derive an empirical crop calendar stating the “in the field” visible beginning of cultivation of a crop by the farmer. The results of the classification process depends on the selection of appropriate bands (acquisition times) as sometimes the use of all bands together may give misleading results especially when a multi-temporal classification method is applied. This is because very often the farmers cultivate fertilizer-plants inbetween economic plants to strengthen the soil capacity. Therefore, a tool for choosing the effective bands is required in order to achieve accurate classification results. In addition it is almost impossible in practical applications and due to costs to have one acquisition each month. Therefore it is desirable to get an indication of those acquisition dates, which are essential for proper crop classification.

Factor analysis is a statistical method used to describe the variability among observed variables in terms of fewer unobserved variables, called “factors”. The observed variables are modelled as linear combinations of the factors, plus “error” terms. The information gained about the interdependencies can be used later to reduce the set of variables in a dataset. There are two main reasons for this analysis. The first is for data reduction, i.e. to find those few factors, that describe correlations of the variables (multi-temporal backscatter of the training areas used for classification) and thus is a procedure for modelling or generating hypothesis, while another application of factor analysis is to confirm existing models and samples and tries to find the so called “free” parameters

of a model i.e. to explain multivariate relationships (correlations) between observations (indicators) by a smaller number of not directly observable variables ("factors"), while it is often assumed that these factors are responsible for the correlations between the observable variables. This method [Überla, K., 1971] is a standard procedure of the well known statistical software package SPSS which was used in this investigation.

The first example (Figure 3) shows the factor loading diagram of the ten TSX acquisition dates in the case of *potatoes*. It can be seen, that in the beginning (March) due to the farming treatment and the well developed leaves in July/August the significance of these acquisition times is high and therefore these dates are important.

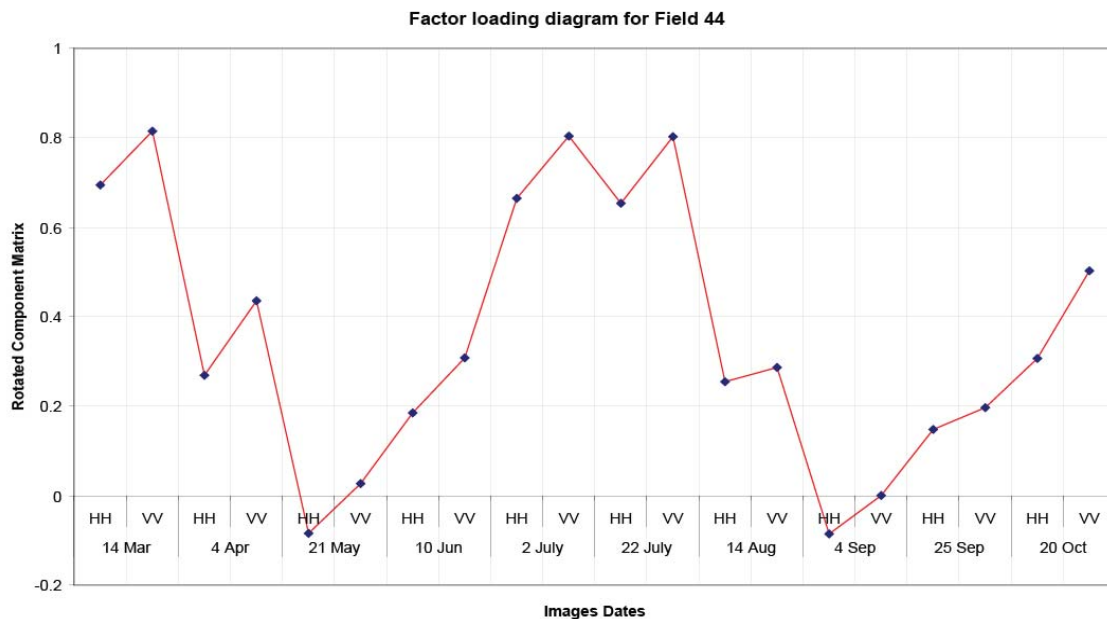


Figure 3: Factor loading diagram of *Potatoes* (Component 1)

Within this analysis we applied a “Scree test” of the Eigenvalues to estimate the number of components to analyze and extract the sums of the squared loadings of the components to explain the total variance [see Überla, K., 1971].



Potatoes March, 14.

Potatoes July, 02.

Potatoes July, 22.

Figure 4: Ground Truth photos of Field 44 *Potatoes*

Using the 3 images of Fig. 3 with a factor loading > 0.5 will explain 57% of the total variance of all images for this crop. Figure 4 shows the associated ground truth photos, which show one date

without and two dates with fully developed foliage. In addition the row direction of the plants, which is pronounced with *potatoes*, in this case is nearly normal to the look direction of the TSX sensor. We will see for the case of *asparagus* that this is important for plants with distinct geometric planting alignment.

Figure 5 shows the factor loading diagram for the case of *asparagus* with an orientation normal (left) and parallel (right) to the look direction of the sensor.

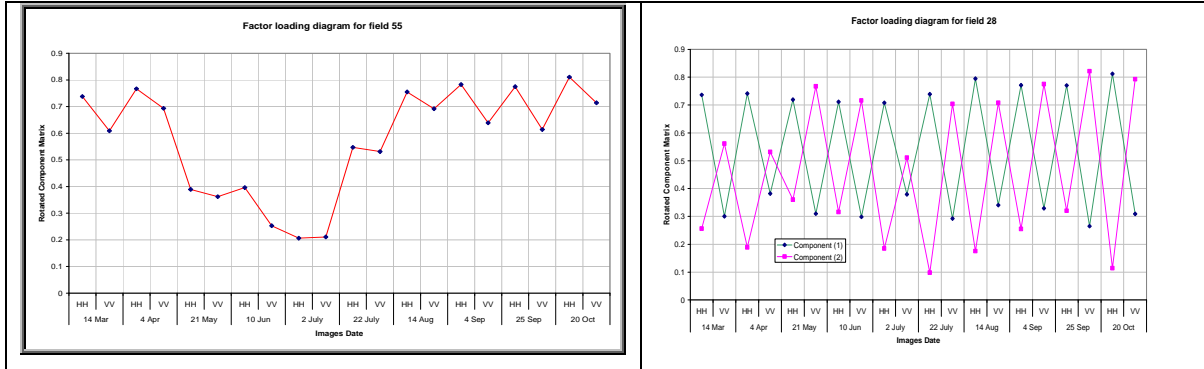


Figure 5: *Asparagus* with two different orientations of plant direction with respect to look direction Component 1 (left image), Component 1 and 2 (right image)

Especially for *asparagus* another difficulty arises, due to the partly covering of the fields with protection foils, as can be seen in Figure 6.

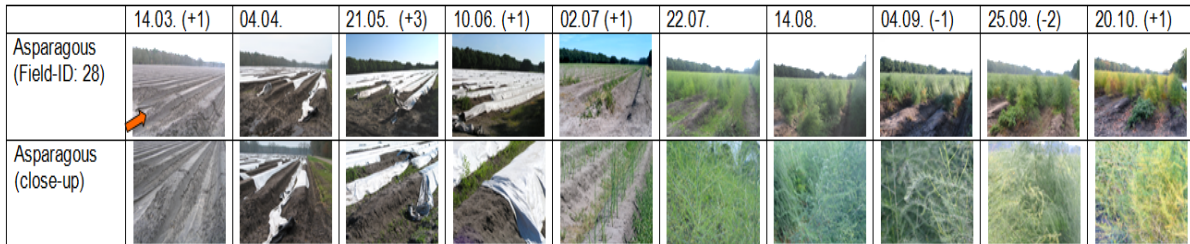


Figure 6: *Asparagus* partly covered with protection foils

Altogether, the rotated component matrix shows high factor loadings for *asparagus* when using the first 4 and last 3 acquisition dates instead of all. It will be shown later, that this results in only a minor reduction of accuracy in the classification process.

Date	Polarization	Bands	Component		
			1	2	3
14 Mar	HH	B1	0.881	-0.145	0.35
	VV	B2	0.827	-0.236	0.4
4 Apr	HH	B3	0.883	5.11E-02	0.295
	VV	B4	0.863	0.112	0.362
21 May	HH	B5	0.828	0.12	-2.08E-02
	VV	B6	0.619	0.326	3.06E-02
10 Jun	HH	B7	0.901	-1.79E-02	0.105
	VV	B8	0.977	-1.84E-02	5.89E-02
2 July	HH	B9	-0.165	0.903	-0.128
	VV	B10	-0.194	0.868	-0.185
22 July	HH	B11	0.315	-5.64E-02	0.87
	VV	B12	0.398	3.48E-02	0.832
14 Aug	HH	B13	5.11E-02	0.891	0.188
	VV	B14	9.88E-02	0.928	-0.108
4 Sep	HH	B15	0.851	-0.192	-0.194
	VV	B16	0.82	-5.70E-02	-0.436
25 Sep	HH	B17	0.461	-0.731	-0.246
	VV	B18	0.468	-0.639	-0.499
20 Oct	HH	B19	0.807	-0.41	9.07E-03
	VV	B20	0.807	-0.251	-0.358

Table 2: Rotated component matrices for *asparagus* showing the factor loadings

The Factor Analysis was carried out for the major crops of this investigation, namely: *Winter Grains* (as a combined group of different cereals), *Asparagus*, *Pea Beans*, *Maize*, *Sugar Beet*, *Pasture* and a single field of *Strawberry*, which because of its singularity is neglected in the further investigation.

Factor Analysis allows determining not only the necessary acquisition dates, but also the contribution of the polarization (band) for further classification as sometimes the use of only one of the

Culture	March	April	May	June	July	August	September	October	Polarization	
Winter Grains	[Solid Yellow]					[Hashed Yellow]				HH + VV
Sugar Beet			[Solid Brown]	[Hashed Brown]	[Solid Brown]	[Hashed Brown]	[Solid Brown]	[Hashed Brown]		VV or HH
Pasture (Grass)	[Solid Green]					[Hashed Green]				HH + VV
Potatoes			[Solid Red]	[Hashed Red]	[Solid Red]	[Hashed Red]	[Solid Red]			HH + VV
Peas & Beans		[Solid Green]	[Hashed Green]	[Solid Green]	[Hashed Green]	[Solid Green]				HH or VV
Asparagus	[Solid Green]	[Hashed Green]	[Solid Green]	[Hashed Green]	[Solid Green]	[Hashed Green]	[Solid Green]	[Hashed Green]		HH + VV
Maize				[Solid Green]	[Hashed Green]	[Solid Green]	[Hashed Green]	[Solid Green]		HH + VV
Strawberry	[Solid Red]	[Hashed Red]	[Solid Red]	[Hashed Red]	[Solid Red]	[Hashed Red]	[Solid Red]	[Hashed Red]		HH + VV

Figure 7: Crop calendar as observed in field and computed by factor analysis

two polarizations proved advantageous. Fig. 7 shows both, the crop calendar as determined by ground-truth (solid - top - bars) and the result of factor analysis (hashed - bottom - bars).

4. CLASSIFICATION

A total of three different strategies for supervised classification (pixel-based Maximum Likelihood) have been applied:

- Based on entire set of dual-pol images (“all”)
- Using images according to crop calendar (“Cal”)
- Using images as indicated by factor analysis (“SPSS”)

The total area of the surveyed fields within the pilot area covers about 176 Hectares.

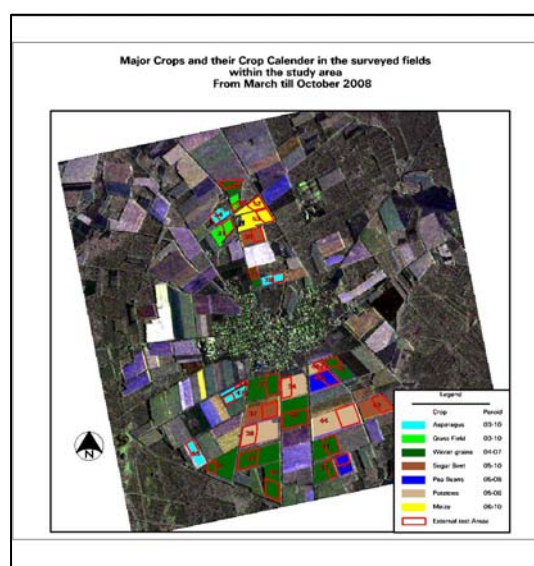


Figure 8: Training and Control fields

Because of the small number of training and control fields, most of them have been subdivided, so that one part of the field serves as training the other as control area. In total 98 ha (56%) could be used as training fields while 78 ha (44%) served as control fields (Fig. 8).

We are well aware of the limited significance of the absolute results due to the rather small data set. However, we focus here on the relative performance of the compared approaches.

For pea beans the combination of “SPSS”- strategy with the “Cal”- strategy for the other crops lifted the pea beans producer accuracy from about 54% to 99 %.

Table 2 lists the classification results obtained and Figure 9 shows the class-map for the “all”-strategy.

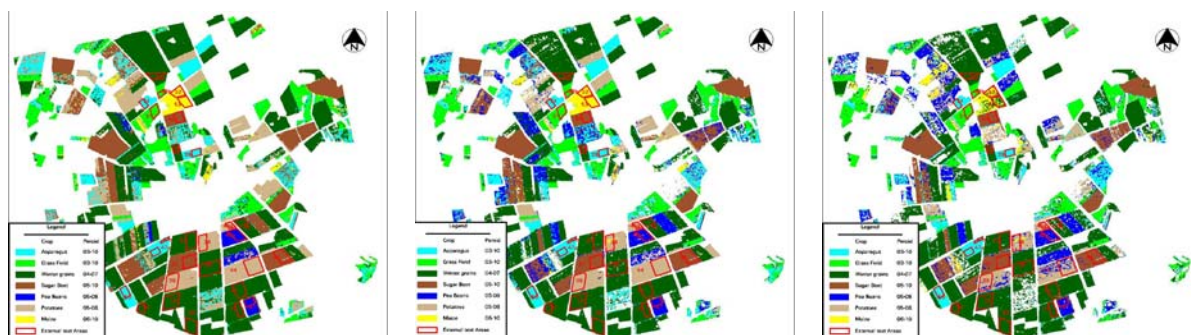


Figure 9: Class-maps using the „all“-strategy (left), “Cal” (middle) and “SPSS” (right)

5. CONCLUSIONS

As shown in Table 2, the results obtained by the “all”-strategy appears to be very accurate (approx. 100 %); however one should keep in mind the small number of independent control fields because of the subdividing.

Crop	Accuracy of Strategy [%]		
	all	Cal	SPSS
Asparagus	100	100	99
Pasture	99	99	100
Winter Grains	100	98	79
Sugar Beet	100	100	100
Pea Beans	99	97	86
Potatoes	100	96	78
Maize	98	97	92
Total Accuracy	100	98	87

Table 2: Classification Results (Producer Accuracy)

In addition the “all” strategy ignores knowledge given by the crop calendar. Furthermore, in general satellite images are not available on a monthly base and if they were, such extreme acquisition scheme would be too costly for routine applications. The total accuracy resulting from the “Cal”- strategy is also very high (98%), while the SPSS strategy yields only 87 % on average. Here the producer accuracy ranges from 79% in case of *winter grains* to 100% for *sugar beet*. As with the “SPSS”-strategy only images having a factor loading > than 0.5 are considered, they tend to

underestimate the information available as only fractions of the total variance are explained by these few images. But nevertheless they indicate the important images.

From the obtained results, the following conclusions can be drawn:

- The “*Cal*”-strategy (classification according to crop calendar) led in most cases to high producer and total accuracy results
- The combination of “*SPSS*”- strategy for *pea beans* with the “*Cal*”- strategy for the other crops improved the *pea beans* producer accuracy of about 54% and hence the total accuracy by more than 6%.
- The separate classification of HH and VV polarized images alone in case of *pea beans* led to two different results since none of them yield optimal results for all fields; however the combination of the results could classify nearly the whole field area covered by this crop.

Due to the above obtained results it is recommended to:

- Apply the “*Cal*”-strategy in order to achieve better producer and total accuracy, moreover apply “*SPSS*”-strategy on crops having small producer accuracy and re-combine the results to improve the total accuracy.
- Factor analysis proved to be a successful tool to select the subset of *necessary* images (i.e. determine the most significant acquisition dates) helping to solve the problems of limited producer accuracy for some crops.
- Survey more fields in order to increase the validity of the obtained preliminary results. This is being started at the moment in a PhD study.

6. ACKNOWLEDGEMENTS

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