MAPPING OF AGRICULTURAL ACTIVITIES USING MULTI-TEMPORAL ASAR ENVISAT DATA

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ABSTRACT:

Space borne radar data facilitates continuous monitoring of almost any location on the earth (limitations in polar zones) at quite low costs. Almost weather-independent operation of radar systems enables a reliable and continuous record of data from earth's surface.
In the framework of an ESA pilot project (AO335), ENVISAT polarimetric SAR data of year 2004 are examined for their usefulness in environmental monitoring within a drinking water protection area, north east of the city Hanover in Germany. This is done by using ENVISAT ASAR images together with GIS information like topographic maps, orthophotos and also ground surveys.
Because of only 2 polarisations of ASAR, with a coherent response of different vegetation types and the high variance of pixel values, the results from classification approaches using monotemporal images are unsatisfactory.
Our experiments and the experience of other authors as well as the knowledge about crop phenology led to a multi-temporal classification approach improving the classical methods. In multi-temporal classification, images from different dates, which cover the phenological period of desired crops, are treated as bands of a multi-temporal image. The feasibility and accuracy of this multi-temporal approach is evaluated using a pixel based approach. The benefit of some pixel based classification rules, the influence of some speckle filters on overall accuracy and the importance of adaptation to phenological period of crops are tested for this approach.

1. INTRODUCTION

Motivation of this study is monitoring of pollution of a ground water body by nitrate emissions from agricultural activities. The quantity of nitrate emissions strongly depends on crop types, cultivated on the fields. Hence threat potential can be evaluated based on information about agricultural activities in the area [22]. Estimating the threat potential of catchments by area wide land use mapping requires an enormous effort using traditional survey methods, but it is indispensable in order to assess the complex interrelationships in time and space of the effective emissions into the soil and hence into the drinking water.
A possible solution to this bottleneck is remote sensing. Due to frequent cloud cover only microwave techniques of SAR systems on satellites like ENVISAT can be used for an effective regular monitoring. Airborne remote sensing techniques offer a good alternative but can not be used because of the associated high data acquisition costs [18] in comparison to satellite data. This project therefore makes use of ENVISAT dual polarized ASAR data, which are provided free of charge by ESA within a pilot project.
However information extraction of agricultural activities from radar images is demanding because of some difficulties, like:
- The number of polarisations, comparable to bands of VIR images (Visible/Infrared), is very limited, which makes the multi-dimensional feature space of radar images very small.
- 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 of the same class yielding an unsatisfactory classification.
- Radar images are strongly affected by look angle, soil moisture and the physical properties of soil. These parameters often affect signatures more than vegetation.

The most important advantage of radar systems is their (almost) independency to weather conditions and therefore, data can be acquired irrespective of cloud cover. Hence, SAR images can be gathered on a regular basis and with high temporal resolution. In addition SAR images have proven to be better suited for certain classification tasks than optical images [3], [24].
A variety of papers demonstrate how to overcome the limitations in using SAR images. Numerous filters are offered [16] and evaluated [4], [12] to reduce speckle of radar images, while keeping details, edges and statistical parameters unchanged. Conventional, multi-look and multi-temporal filters try to eliminate noise and speckle in images using statistical processes. For the classification of crops, attempts are made to use all available polarisations [10], [16], multi-temporal data [9], [21], object based classification techniques [9], combination of passive data [9], knowledge driven classification [7] and investigating the effects of local characteristics on radar images [14]. Using these methods an exterior accuracy of 70% to 90% is achievable. But comparing the results of different crops don't give the same reliability. Some crops can not be classified satisfactory others do [7]. As reported in [13] the tests using single radar images (VV/VH amplitude images) show an unsatisfactory interior accuracy of only 25% to 35% using raw data and about 30% to 45% for filtered data. The accuracy of the results is highly time-dependent for different crops. On the other hand, tests using multi-temporal data resulted in an interior accuracy of up to 100% for some crops.

2. TEST AREA, GROUND TRUTH MEASUREMENTS AND SATELLITE DATA

The Fuhrberg area (Figure 1) is situated north of Hannover, the capital from Lower Saxony. The water protection area of the same name, in which about 90% of the drinking water is produced for the region of Hanover, extends over a size of approx. 300 sq. km. Within this area a total of about 50 fields around the villages Brelingen and Mellendorf and the city of Fuhrberg have been selected as ground truth samples. The location of these fields is shown in Figure 2.
For these field plots, topographic maps, base maps and digital orthophotos in colour are available. In general ground truth were collected at or close to the time of satellite overpass.

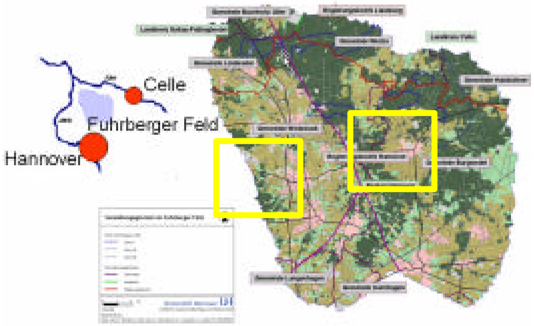

Figure 1: Test site "Fuhrberger Feld"


Figure 2: 50 sample field plots for ground truth data collection

A monthly coverage of satellite images was planned to get a whole growing season of the different vegetation types. However many data takes could not be performed as planned due to priority programming of the satellite for other projects.
Table 1 lists the data, which have been acquired.

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

Table 1: Data takes of ENVISAT ASAR APG images, polarisation VV/VH, IS 5-7 of agricultural season 2004

Imaged	17.11	17.03	05.04	21.04	26.05 10.05	30.06	07.08	11.09	13.10	01.11
Visited	26.11	19.03	05.04	21.04	10.05	14.06	07.08	08.09	13.10	01.11
11	Pasture	Pasture	Pasture	Pasture	Pasture	Pasture	Pasture	Pasture	Pasture	Pasture
21	W. Bar	W. Bar.	W. Bar.	W. Bar.	W. Bar.	W. Bar.	Rest	Wd. Gr.	Fallow	Rape
3	W. Rye	W. Rye	W. Rye	W. Rye	W. Rye	W. Rye	Rest	Wd. Gr.	W. Rye	W. Gr.
5	W. Bar	W. Bar.	W. Bar.	W. Bar.	W. Bar.	W. Bar.	W. Bar.	Rape	None	W. Gr.
8	None	None	None	S.B.	S.B.	S.B.	S.B.	S.B.	S.B.	S.B.
9	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow
18	W. W.	W. W.	W. W.	W. W.	W. W.	W. W.	W. W.	Wd. Gr.	None	W. Gr.
19	Rape	Rape	Rape	Rape	Rape	Rape	Rest	Rape	W. Rye	W. Gr.
16	W. Rye	W. Rye	W. Rye	W. Rye	W. Rye	W. Rye	Rest	None	Rest	W. Gr.
28	Asp.	Asp.	Asp.	Asp.	Asp.	Asp.	Asp.	Asp.	Asp.	Asp.
29	Fallow	None	S. Bar.	S. Bar.	S. Bar.	S. Bar.	S. Bar.	Phc.	Phc.	Phc.
30	Rape	None	S. Bar.	S. Bar.	S. Bar.	S. Bar.	None	Rape	Rape	Rape
42	Rape	Rape	Rest	None	S.B.	S.B.	S.B.	S.B.	Rest	Rest

Table 2: Crops planted on some fields on different dates and related images

The images have been processed by the different PAFs into geocoded products using a pixel spacing of 12.5 m in range and azimuth direction. This corresponds to a resolution of 30 m using two looks in azimuth and 3 looks in range. Only look angles between 35.8 – 45.2 deg. (corresponding to Image Swath IS5 to IS7) and VV / VH polarisation have been used.

Ground truth consisted of sampling general information such as usage and treatment pattern. Additionally, information on the kind of mechanical treatment of the soil and the plants, vegetation coverage, colour, observable fertilizers, irrigation etc. have been stored into a GIS, based on the Arc View software. In addition, digital ground photographs have been taken. A list of some example fields with information about dates of visits, crops and imaging is presented in Table 2.

3. MULTI-TEMPORAL CLASSIFICATION

Because of the independency from weather conditions SAR multi-temporal data sets can be applied more frequently and reliable in comparison to optical images. Multi-temporal classification 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 that crop. Such methods have been vastly used and tested over different areas and for different crops e.g. Tröltzsch, K. 2002 in Mali[21], Hochschild, V. 2005 in Germany[9], Baronti, S. 1995 in Italy[1], Foody, G.M. 1988 in England[5], Schieche, B. 1999 in Germany[19], Davidson, G. 2002 in Japan[2] . In this paper, the advantages of applying multi-temporal classification are presented and some questions are answered, like

- The separation of forest and residential from agricultural areas
- Can we use a fixed set of images (dates) to classify all crops or do we have to use separate sets of images for each single or group of crops?
- If separate sets of images for each crop or group of crops are used, how can the results be combined?
- Can the classification results be improved using despeckled images? Which filter yields best accuracy?
- How does the number and date of acquisitions influence the results of classification?

3.1. Rules for masking forests and residential areas

Forests in radar images are characterized as continuous bright areas and residential areas as non-continuous very bright areas close to dark areas (shadows). In addition, forests and residential areas do not change very much on time series of SAR images with 30 meters resolution. On the other hand farmland and pasture is usually darker and very variable in its time appearance. Therefore, a reliable separation of forest-residential areas can be set up using multi-temporal images.

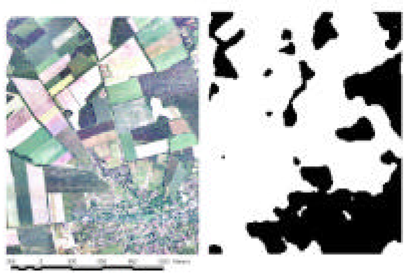
Figure 3: Forest-residential mask with 30m resolution (Right) compared to an orthophoto 0.4m resolution (Left)

A time series of images was used. Signatures of farmlands and some signatures of forests and residential areas are applied to support a supervised classification in the study area. Post processing using majority filter eliminated almost all disadvantages of the classification. The results show a little mixture between forest and residential areas. But farmlands are well separated from forest-residential areas. From the results of this classification a reliable mask of forest-residential areas in the study area could be derived. Part of the mask and an orthophoto is shown in Figure 3. Small features were eliminated by majority filter.

3.2. Data and parameters of pixel based multi-temporal classification

The types of vegetation in the study area are:
Lea, Fallow, Peas, Strawberry, Willow, Potato, None (bare), Rape, Phacelia, Summer barley, Summer rye, Asparagus, Pasture, Wild grain, Winter barley, Winter rye, Winter wheat, Sugar beet. Results for lea, fallow and willow are not evaluated and presented here, because these types do not have a fixed planting cycle. In addition, farmers' activities on fields of these types are not periodical. Therefore results from multi-temporal classification for these types are only valid for the applied training samples in the time of sampling and they are not reliable for other fields with same plantation type. This problem persists for asparagus fields as well, because after scythe of asparagus (usually in June), farming activities don't have any fixed schedule. It means that asparagus fields appear very different between June and April of the following year.
Rape and phacelia are sometimes planted as fertilizer between two cultivation seasons and therefore have no fixed cultivation calendar in this case. These fields are considered having only the main crop and not the fertilizer crop. However signatures of all types even from fields without any plantation are used in the classification process.
Different options influencing the accuracy of classification are tested
-Raw versus filtered images
-Filter Selection
-Common set of images (dates) for all crops versus separate set of images for each crop or group of crops with the same cycle.
-Single or Merged signatures per crop type

3.2.1. Results of multi-temporal classification using filtered and raw images

Tables 3 and 4 show the accuracies of multi-temporal classifications using one set of images in percent (%). All available images of year 2004 have been used and all signatures were applied in this test. In addition, signatures are merged based on the planted crops per field. If more than one crop type is planted on a field in the same year, the crop, with the longest period, is considered.

Set of Images	Class	Interior Accu.	Ext.A	Ext.B	Ext.C	Ext.D	Ext.E	Mean
1-11	Peas	100						
1-11	Strawberry	100						
1-11	Potato	92	92	85	97	53	39	73,2
1-11	Summer barley	85	41	71	42	75	70	59,8
1-11	Summer rye	97						
1-11	Asparagus	95	54	99	67	60		70
1-11	pasture	79	68	61	68	61	64	64,4
1-11	Winter barley	97	96	73	70	75	83	79,4
1-11	Winter rye	85	17	71	73	28	59	49,6
1-11	Winter wheat	98						
1-11	sugar beet	74	42	100	90	68	51	70,2

Table 3: Accuracy of classification (%) using 11 images of the year 2004 and signatures, which are merged based on crops. Exterior accuracy at sum: 67%

Set of Image	Class	Interior Accu.	Ext.A	Ext.B	Ext.C	Ext.D	Ext.E	Mean
1-11	Peas	100						
1-11	Strawberry	100						
1-11	Potato	100	96	93	100	86	19	78,8
1-11	Summer barley	100	84	86	82	76	100	85,6
1-11	Summer rye	100						
1-11	Asparagus	100	25	97	70	27		54,75
1-11	pasture	100	98	94	81	98	92	92,6
1-11	Winter barley	100	100	18	2	74	100	58,8
1-11	Winter rye	99	20	99	100	0	42	52,2
1-11	Winter wheat	100						
1-11	sugar beet	99	88	100	100	100	100	97,6

Table 4: Accuracy of classification (%) using 11 images of the year 2004 filtered by Lee 7x7 and signatures, which are merged based on crops. Exterior accuracy at sum: 75%

The results in Table 3 are from raw images while Table 4 reflects the results from images despeckled with a Lee filter of size 7×7 pixel. The column "Set of Images" determines which images are used for classification. (Referred to Table 1).The column "interior Accu." represents interior accuracy of each class in percent. Columns "Ext.A" to "Ext.E" show exterior (overall) accuracy of each class on different control fields. There is only one or less than 5 samples for some crops, therefore some cells are empty. The field "Mean" presents average of exterior accuracy for each class. It can be seen that using filtered images, results are significantly improved for most crops, except asparagus and winter barley, with 16% and 20% lower accuracy. The fields covered by these crops are misclassified as sugar beets using filtered images.
Asparagus is usually harvested in June. There is almost no vegetation on the field before harvesting the asparagus, but plants grow rapidly after harvesting, parallel to sugar beets rising at the same time. According to the general crop cycle, winter barley will be harvested in June or July and can be well separated from sugar beets. But if deviations from this crop cycle exist, difficulties in separation may arise as can be seen from Table 4. Nevertheless some fields of winter barley are planted with rapes in September and therefore look like sugar beets. The control fields B, C and D of winter barley are examples of such fields.
Using this set of images for classification, the results for asparagus and winter barley from raw images is more accurate than from filtered images. On the other hand the results for other crops are more accurate when filtered images are classified.

3.2.2 Multi-temporal classification using a common set of images versus sub sets of images

Table 5 shows accuracy of results using filtered images and signatures which were merged based on the crops on the fields. Separate sets of images (dates) are used in this classification. The period of each set is selected based on cropping calendar. Comparing Table 5 and Table 4 shows that at sum, results from a classification using different sets of images (dates) is better than using a common set of images for all classes. Results from separate sets of images for classes "summer barley" and "sugar beet" are a little less accurate than with a common set of images for all classes. Results for asparagus are more accurate in Table 5 than in Table 4 but not as accurate as from raw images (Table 3). Besides the results for winter barley are much better in Table 5 than using a common set of filtered or raw images (Tables 3 and 4).

Set of Images	Class	Interior Accu.	Ext.A	Ext.B	Ext.C	Ext.D	Ext.E	Mean
2-8	Peas	100						
1-11	Strawberry	100						
3-9	Potato	98	98	90	99	97	98	96,4
2-7	Summer barley	99	87	86	69	87	91	84
2-7	Summer rye	100						
2-8	Asparagus	99	50	100	78	24		63
1-11	pasture	100	98	94	100	100	98	98
1-7	Winter barley	99	100	79	89	77	100	89
1-7	Winter rye	97	54	77	91	0	54	55,2
1-7	Winter wheat	100						
3-9	sugar beet	88	76	100	93	100	94	92,6

Table 5: Accuracy of classification (%) using separate sets of despeckled images from the year 2004 and signatures which are merged based on crops. Exterior accuracy at sum:83%

3.2.3. Comparing results of multi-temporal classification using merged signatures versus non-merged signatures

It is very important to decide whether to merge signatures before classification or not. If signatures from each class are used separately, there will be the risk that each signature is too specialized for itself and the feature space of signatures from one class is not large enough to encapsulate conditions of the class and parts of the class may be excluded. On the other hand, if signatures from one class differ from each other, so that a part of feature space from the other class is inserted between them, a merging of these signatures causes an unwanted mixture between two classes. In general, classification using signatures separately results in a high interior but a less exterior accuracy. Table 6 shows the accuracy of results from multi-temporal classification using separated sets of filtered images (such as Table 5) but applying non-merged signatures. As expected applying separated signatures results in a high interior accuracy of almost 100% but the exterior accuracy (wanted) is strongly decreased. The exception is winter barley, which is classified significantly better with separated signatures.

Set of Images	Class	Interior Accu.	Ext.A	Ext.B	Ext.C	Ext.D	Ext.E	Mean
2-9	Peas	100						
1-12	Strawberry	100						
2-10	Potato	100	83	22	96	92	97	78
2-8	Summer barley	100	93	38	94	57	43	65
2-8	Summer rye	100						
2-8	Asparagus	100	32	92	42	18		46
1-12	pasture	100	89	62	45	36	38	54
1-8	Winter barley	100	100	100	100	83	100	96,6
1-8	Winter rye	100	93	57	23	1	33	41,4
1-8	Winter wheat	100						
4-10	sugar beet	99	19	97	56	44	23	47,8

Table 6: Accuracy of classification (%) using separate sets of images from the year 2004 filtered by Lee 7x7 and signatures which are not merged. Exterior accuracy at sum: 62%

Altogether, it is advisable to use a separated set of despeckled images for each crop or group of crops with a similar phenological period and to merge signatures based on the crops on fields before classification.

3.2.4. Results of different classification rules

For the previous classifications, the Maximum Likelihood classifier was used. Classification rules in pixel based approaches evaluate the similarity of each pixel with respect to the desired class and assigns the pixel to the most similar class. Classification rules vary in the method of evaluation and therefore give diverse results. Three classification rules (Minimum Distance, Mahalanobis Distance and Maximum Likelihood) are tested in order to investigate, which rule classifies multi-temporal SAR data best. The test is performed using the same options of classification as presented in Table 5 but using different classification rules. Table 7 shows the interior and exterior accuracy of the three classification rules. Evaluation of exterior accuracy of Mahalanobis Distance and Maximum Likelihood is done using two control fields (A and B) per class. The Minimum Distance rule is evaluated by only one control field (A) per class. The Maximum Likelihood rule performs best in the classification of these multi-temporal SAR data sets.

Class. Rule	Interior	EXT. A	EXT. B
Max. Likelihood	98	80	89
Min. Distance	77	48	-
Mahalanobis Distance	95	75	88

Table 7: Accuracy of three classification rules (%)

3.2.5. Influence of different filters

The comparison between values of tables 3 and 4 shows the benefit of speckle filters for improving the accuracy of classification. Some other filters are tested in order to investigate, if type of filter influences the classification.

Filter	Interior Acc.	EXT. A	EXT. B	EXT. C	Overall Acc
Lee	98	80	89	88	86.1
Frost	96	76	87	82	81.7
Gamma Map	97	78	90	84	84.3
Local Region	91	68	86	71	75.1
Lee-Sigma	98	80	91	84	85
Median	98	80	93	86	86.5

Table 8 Accuracy of classification (%) using separate sets of images from the year 2004 filtered by different filters.

Classifications have been tested using separate sets of images filtered by different filters and adapted to the phenological period of crops with signatures merged based on crop types. Exterior (overall) accuracies of classification are evaluated over three control fields (A, B and C) and presented in Table 8, showing the influence of despeckle filters on the accuracy of multi-temporal classification. The overall classification accuracy using images filtered by Gamma Map, Lee-Sigma, Lee and Median filters varies between 84.3% and 86.5%, resulting in a good accuracy and showing only small variations of these filters. Images filtered by median filter gave the best accuracy level (86.5%), although is not being significantly higher than Lee (86.1%) filter.

3.2.6 Combining the results

When different sets of images are used, several classifications are carried out independently. Results for one or more crops are accepted from a classification if the set of processed images fits to the phenological period of that crop. For example, peas can be extracted from classification of images obtained between March and September and sugar beets from classification of images between April and October.

It is necessary to combine the different independent classification results to derive a land use map for the study area. As can be seen in Figure 4, one or more crops are classified separately and the rest is labelled as other unknown plants. In a perfect condition, one might expect completely separated areas to be classified with each set of images. But this is not the case in the reality. Results from one set of images can be accepted as final result when no contradicting other classification exists for the same area. If one area is classified into two classes, the area remains undefined. Therefore three types of fields remain after combination:

Classified: areas classified as known crops with fixed phenological period.

Unclassified: areas are not identified as crops having a fixed phenological period.

Undefined: areas of competing classification results as known crops with fixed phenological period for more than one crop.

About 12% of the agricultural areas have been labelled as undefined after combination.

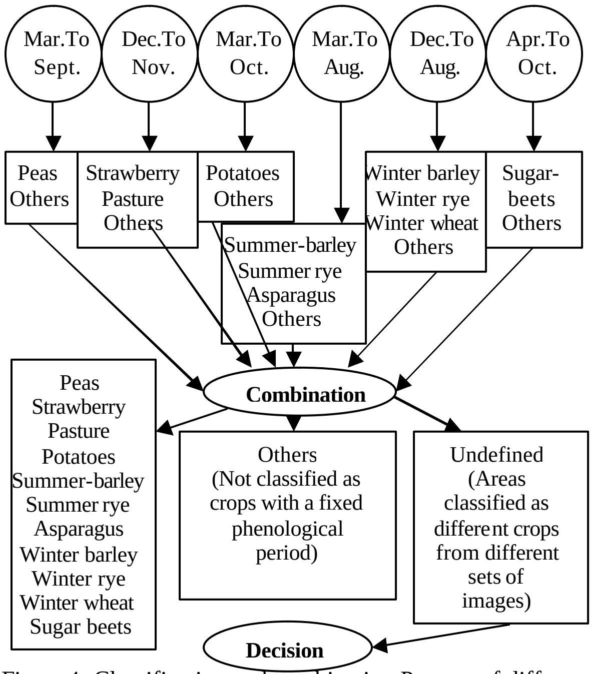

Figure 4: Classification and combination Process of different sets of images.

Undefined areas are most probably covered by one of the competing result classes (12% of agricultural extent). Distance images obtained as by-products of classification, representing the likelihood of each classified pixel to its class and/or other classes, can be used for decision. Since distances are strongly dependent on the number of bands used in a classification process and fewer number of bands results in smaller distances, each distance image must be divided by the number of images, which are used for the related classification, to make it comparable with other distance images (normalizing).

After normalizing, undefined areas which are classified by more than one known class are concentrated. In this phase, the normalized distances of each undefined pixel are compared with different conflicting classes and the pixel is labelled by the class of smallest normalized distance. The accuracy of results after combination is shown in Table 9. It can be seen, that the values do not significantly alter from Table 5 and the combination process keeps the exterior accuracy acceptable. In detail it can be seen, that only about 0.5 percent of the agricultural area is misclassified by the combination process, and most of the 12 percent undefined areas is well classified.

A small number of fields exist, which can be considered as classes without a fixed phenological period. It is noticeable that no pixel from these fields is classified as crops with fixed phenological period.

Set of Images	Class	Interior Accu.	Ext.A	Ext.B	Ext.C	Ext.D	Ext.E	Mean
2-9	Peas	100						
1-12	Strawberry	100						
2-10	Potato	98	98	90	99	97	98	96,4
2-8	Summer barley	99	87	86	69	86	91	83,8
2-8	Summer rye	100						
2-8	Asparagus	99	49	100	77	24		62,5
1-12	pasture	100	98	94	99	100	98	97,8
1-8	Winter barley	99	100	79	89	77	100	89
1-8	Winter rye	97	54	77	91	0	52	54,8
1-8	Winter wheat	100						
4-10	sugar beet	88	72	100	91	100	94	91,4

Table 9: Accuracy of classification (2004) in percent after combination of classifications. Exterior accuracy at sum: 83%

3.2.8. Post processing

The resulting classification is filtered by a majority filter to eliminate the appearance of mixed pixels. The accuracy of the 2004 classification after post-processing is presented in Table 10. The majority filter assigns the most frequent value in a kernel to the central pixel of the kernel and therefore eliminates single pixels and small areas expanding large homogenous areas. If results of a classification are filtered by majority filter, the accuracy of classification for well-classified classes will increase but for miss-classified classes will decrease.

Set of Images	Class	Interior	Ext.A	Ext.B
2-8	Peas	100		
1-11	Strawberry	100		
3-9	Potato	98	99	94
2-7	Summer barley	100	94	99
2-7	Summer rye	99		
2-8	Asparagus	100	23	99
1-11	pasture	100	100	100
1-7	Winter barley	93	100	80
1-7	Winter rye	97	62	83
1-7	Winter wheat	100		
3-9	sugar beet	94	94	100

Table 10: Accuracy of classification after majority filter Exterior accuracy at sum: 88%

Comparison between Table 9 and 10 shows that the overall accuracy calculated from two control fields is increased from 85% to 88% after filtration by majority filter. As previously mentioned, the results of this method are only valid for crops with fixed and known phenological period and the results are not reliable for other crops or plants. The final map provided by the described process is presented on Figures 5 and 6.

4. CONCLUSION

The practicality of a multi-temporal approach for classifying SAR images in agricultural areas is proved and some possible options are evaluated to find the optimal method for multi-temporal classification in the study area. It is acknowledged that classifying separated sets of despeckled images (dates) for each crop or group of crops with the same phenological period and applying merged signatures gives the best accuracy for most of the crops with a fixed phenological period. A combination method is applied at the end as decision tool to solve uncertainties. A segment-based classification of agricultural fields based on the statistics of fields improves the accuracy and can be done if a map of crop borders is available.

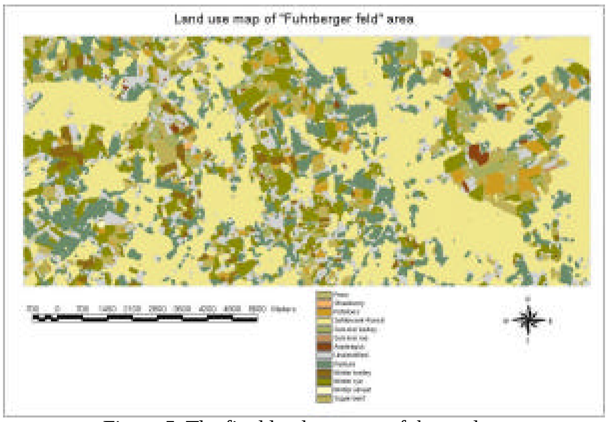

Figure 5: The final land use map of the study area

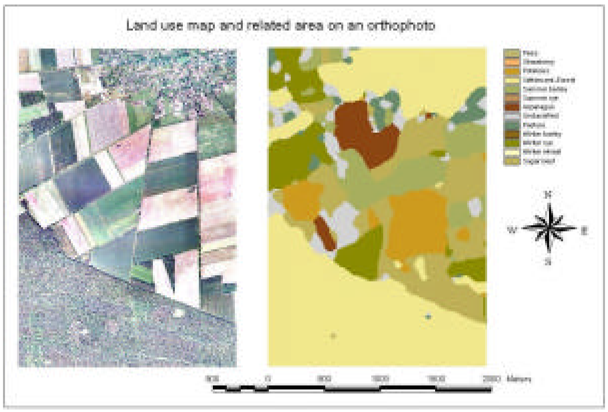

Figure 6: A close up from South of Fuhrberg town on an orthophoto and land use map

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