MULTI-TEMPORAL CLASSIFICATION OF ASAR IMAGES IN AGRICULTURAL AREAS

M. Tavakkoli, P. Lohmann
Institute of Photogrammetry and GeoInformation
University of Hanover
(Tavakkoli, Lohmann)@ipi.uni-hanover.de

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ABSTRACT:

Human activities strongly affect the environment and impact natural resources. To reduce the disadvantages, we have to monitor the human activities as well as the environment. Therefore demand on continuous and inexpensive methods for environmental monitoring is strongly increasing.
In this research and development project, ENVISAT polarimetric SAR data are examined for their usefulness to environmental monitoring within a drinking water protection area named "Fuhrberger Feld", north east of the city of Hanover in Germany. This is done by using ENVISAT ASAR images together with GIS information like topographic maps, orthophotos, also ground surveys.
Because of only 2 polarisations of ASAR, yielding 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, we assume images from different dates, which cover the phenologic period of desired crops, as bands of a multi-temporal image. The feasibility and accuracy of this multi-temporal approach is evaluated within a study area and answers some questions about multi-temporal classification in this paper, namely the necessary images (dates) to be used, the pre-processing (filters) to improve the accuracy of classification together with the accuracy of multi-temporal classification for crops with fixed phenological period. The classification of crops with different phenological periods and the combination of results from classifying different sets of images is shown and the limitations of multi-temporal classification is demonstrated.

1. INTRODUCTION

The water quality reports of the past years of the lower Saxony state office for water and refuse state in numerous surface near fair places 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. Herewith 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 other.) must be accepted as given, utilization contingent effects on the quality and the quantity of the groundwater are controllable. With respect to the edaphic conditions, the danger of eluviation of nitrate raises with the existence of clay to loamy and sandy soils. Drinking water catchments with sand soils like that of the »Fuhrberger Feld«, in the north Hannover, are influenced accordingly especially through nitrate emissions. Under same climatic and edaphic conditions a decline within the threat potential exists [26] following the present land use (see figure 1).
Forest stands do have a relatively small threat potential. In addition the extent and spatial distribution of forest stands does not change very much, while in agricultural habitats of drinking water catchments a great variability of usages exist, which also changes very much over time. This makes it difficult or even impossible to map with established procedures.
Estimating the threat potential of catchments by area wide land use mapping requires an enormous effort using traditional survey methods, but they are 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.

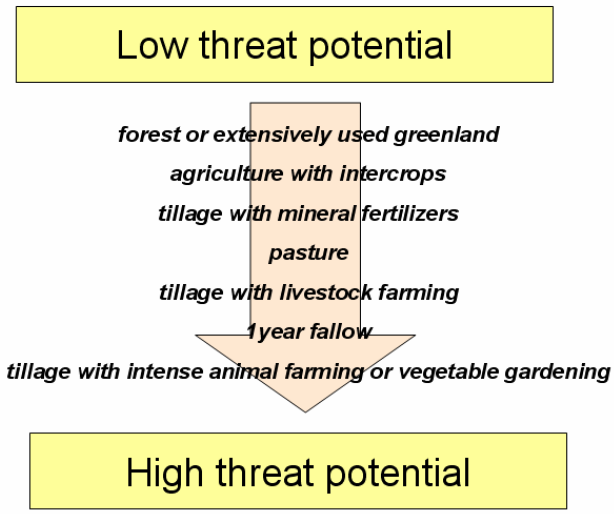

Figure 1: Influence of land use to the threat potential of drinking water catchments

A possible solution to this bottleneck could be the use of remote sensing techniques, but 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 cannot be used because of the associated high data acquisition costs [21] in comparison to satellite data. This project therefore makes use of ENVISAT dual polarized

ASAR data, which is provided free of charge by ESA within a pilot project.

2. TEST AREA, GROUND TRUTH MEASUREMENTS AND SATELLITE DATA

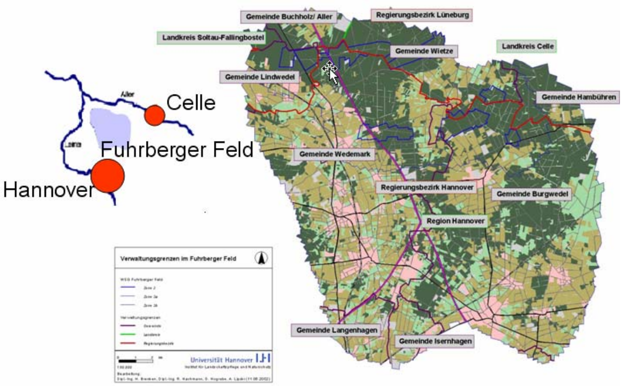

Figure 2: Test site Fuhrberger Feld

The Fuhrberger Feld (figure 2) 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 Hannover 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 3.

Figure 3: 50 sample field plots for ground truth data collection

For these field plots, topographic maps, base maps and digital orthophotos in colour are available. In general the ground truth was collected at or close to the time of satellite overpass. Although a monthly coverage of satellite images was planned to get a whole growing season of the different vegetation types. 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 for the year 2004.

Nr.	Image Date	Inspecting Date	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 2: Data takes of ENVISAT ASAR APG images, polarisation VV/VH, IS 5-7

The images have been processed by the different PAF's 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 2 looks in azimuth and 3 looks in range. Only looking 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 like 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 sampled and introduced 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 date of visit, crops and imaging date is presented in table 3.

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	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Rest	Wild Grain	Fallow	Rape
3	Winter Rye	Winter Rye	Winter Rye	Winter Rye	Winter Rye	Winter Rye	Rest	Wild Grain	Winter Rye	Winter Grain
5	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Rape	None	Winter Grain
6	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Winter Barley	Rest	Rape	Rape	Rape
8	None	None	None	Sugar Beet	Sugar Beet	Sugar Beet	Sugar Beet	Sugar Beet	Sugar Beet	Sugar Beet
9	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow	Fallow
18	Winter Wheat	Winter Wheat	Winter Wheat	Winter Wheat	Winter Wheat	Winter Wheat	Winter Wheat	Wild Grain	None	Winter Grain
19	Rape	Rape	Rape	Rape	Rape	Rape	Rest	Rape	Winter Rye	Winter Grain
16	Winter Rye	Winter Rye	Winter Rye	Winter Rye	Winter Rye	Winter Rye	Rest	None	Rest	Winter Grain
28	Aspara gus	Aspara gus	Asparag us	Asparag us	Aspara gus	Asparagu s	Asparagus	Aspara gus	Aspara gus	Aspara gus
29	Fallow	None	Summer Barley	Summer Barley	Summe r Barley	Summer Barley	Summer Barley	Phaceli a	Phaceli a	Phaceli a
30	Rape	None	Summer Barley	Summer Barley	Summe r Barley	Summer Barley	None	Rape	Rape	Rape
42	Rape	Rape	Rest	None	Sugar Beet	Sugar Beet	Sugar Beet	Sugar Beet	Rest	Rest

Table3: Crops planted on some fields on different dates and related images

In addition to the SAR images, 2 acquisitions of ASTER data have been acquired. The images have been taken in March 2003 and October 2004 respectively and a vast amount of change can be observed by visual inspection..

3. BACKGROUND

Agricultural land use studies using radar images is an interesting field of study for researchers, because of the economic importance of crops and frequently cloud cover of many agricultural areas in northern regions of Germany.
However information extraction of agricultural activities from radar images is demanding because of some difficulties, like:
- The number of polarisations, which can be compared with bands of images from passive systems, 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 yielding an unsatisfactory classification.
- Spatial resolution of radar images are often not as good as images from passive systems under similar conditions.
- Radar images are strongly affected by look angle, soil moisture and physical properties of 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 [5, 27].
A variety of papers demonstrate how to overcome the limitations and use the benefits of SAR images.
Numerous filters are offered [18] and evaluated [6, 14] to reduce speckle of radar images, while keeping details, edges and statistical parameters unchanged. Conventional, multi-look and multi-temporal filters try to find unexpected anomalies on the images like speckle and its elimination using statistical processes.
To classify crops, it is tried to use all available polarisations [12, 18], multi-temporal data [10, 25], object based classification techniques [10], combination of passive data [10], knowledge driven classification [9] and evaluate the effects of local characteristics on radar images [17]. Using these methods an exterior accuracy of 70% to 90% is achievable. But results of different crops don't have the same reliability. Some crops can not be classified satisfactory others do [9].
As reported in [15] 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 and image dates
On the other hand, tests using multi-temporal data resulted in an interior accuracy of up to 100% for some crops.

4. MULTI-TEMPORAL 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.
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. It 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 [25] in Mali, V.Hochschild [10] in Germany, S. Baronti [1] in Italy, G.M.Foody [7] in England, B.Schieche [22] in Germany, G.Davidson [2] in Japan …
In this paper, we are presenting the advantages of applying multi-temporal classification and answer some questions:
- How to separate forest and residential areas 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 one or groupings of crops?
- If separate sets of images for each crop or group of crops are used, how can the results be combined?
- How far can the classification results be improved using despeckled images?

4.1. 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 appearance over time.
Therefore a reliable separation of forest-residential areas can be set up using multi-temporal images.
In practice, the existence of speckle and temporal similarity of some farmlands to forests does not enable a reliable mask using raw single image data. To overcome this problem, a temporal set of images (more dates) instead of a single one was used. Signatures of farmlands and some signatures of forests and residential areas are used to support a supervised classification in the study area. A post processing using majority filter with a kernel size of 7x7 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 Fuhrberg could be derived. Part of the mask and an orthophoto is shown in figure 4. Small features are eliminated because of filtering.

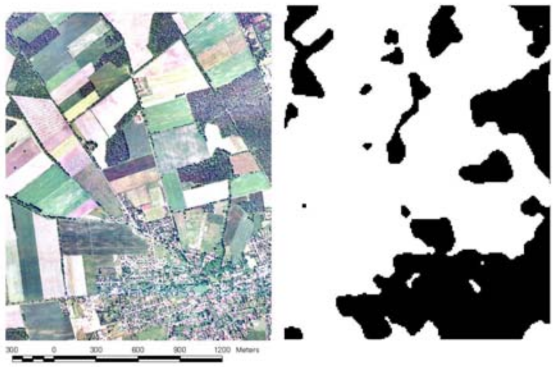

Figure 4: Forest-residential mask with 30m resolution (Right) and appropriate area on an orthophoto 0.4m resolution (Left)

4.2. Data and parameters of multi-temporal classification

The types of vegetation in the study area are:
Lea, Fallow, Peas, Strawberry, Willow, Potato, None, N.I., Rape, Phacelia, Rest, Summer barley, Summer rye, Asparagus, pasture, Wild grain, Winter barley, Winter rye, Winter wheat, sugar beet

The results for lea, fallow, willow, phacelia and rape 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 any asparagus field can look different from others between June and April of the next year.
However signatures of all types even from fields without any plantation are used in the classification process.
The advantage of using different options on the result of classification is tested. The possible options are:
-Using raw or filtered images?
-Using a common set of images (dates) for all crops or a separate set of images for each crop or group of crops with the same cycle.
-Merging of signatures from one crop or not?

4.3. 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 are used and all signatures are applied in this phase of test. In addition, signatures are merged based on the crops planted on fields (signatures). If more than one crop type is planted on a field in this year, the crop, which was longest on the field, is considered.
The results in table 3 are from raw images while table 4 reflects the results from images filtered by Lee 7x7. Table 5 shows the accuracy of classification using mean 7x7 filtered images.
The field "Set of Images" determines which images are used for classification. (Referred to table 2).
The field "interior Accu." represents interior accuracy of each class in percent.
Fields "Ext.A" to "Ext.E" show exterior 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.

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 multi-temporal classification in percent using 11 images of the year 2004 and signatures, which are merged based on crops. Exterior accuracy at sum: 67%

It can be seen that using filtered images, results for most crops are significantly improved. Excepted are asparagus and winter barley, whose results are about 16% and 20% respectively less accurate from filtered images. The fields covering with these crops are strongly classified as sugar beets when filtered images are used for classification.

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 multi-temporal classification in percent using 11 images of the year 2004 filtered by Lee 7x7 and signatures, which are merged based on crops. Exterior accuracy at sum: 75%

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.
The usefulness of some despeckle filters has been tested in classifying single images and it could be shown that accuracy of classification improved. However the results of different filters did not differ significantly from each other [15]. Therefore in the following only results of applying lee filter 7x7 will be presented.

4.4. Results of multi-temporal classification using a common set of images versus separated 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 phase of classification. The period of each set is selected based on cropping calendar.

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 multi-temporal classification in percent using separate set of images from the year 2004 filtered by Lee 7x7 and signatures, which are merged based on crops. Exterior accuracy at sum: 83%

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 6 than using a common set of filtered or raw images (tables 3 and 4).

4.5. 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 all 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.
Figure 5 simulates the condition in a 2-dimensional space.

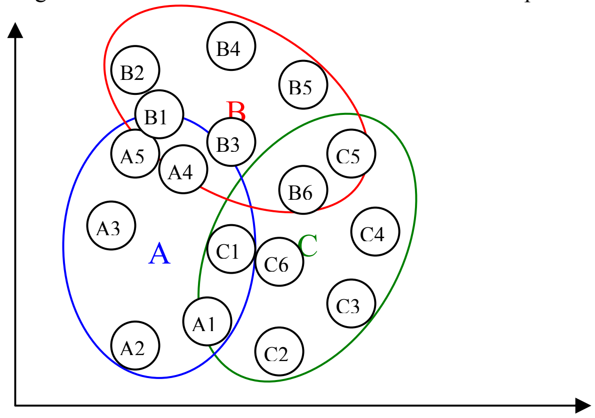

Figure 5: Merging signatures can change the results. Small black circles are signatures and large coloured circles are feature spaces after merging similar signatures.

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 set of filtered images (such as table 5) but applying non-merged 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 multi-temporal classification in percent using separate set of images from the year 2004 filtered by Lee 7x7 and signatures, which are not merged.
Exterior accuracy at sum: 62%

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. This leads to group signatures of winter barley in two or more sets.
Altogether, it is advisable to use 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.
The exterior accuracy with these parameters is strongly dependent on the crops and varies between 55% up to 98% for different crops and an average of 83% for all crops with fixed and known phenological periods.

5. Combining the results

When different sets of images are used, more parallel classifications are being derived. Results for one or more crops are accepted from a classification if the set of processed images is identical to phenological period of crops. 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 results of different crops to derive a land use map for the study area. As can be seen in Figure 6, one or more classified crops are derived from each classification and the rest is labelled as other unknown plants. In a perfect condition, one expects completely separated areas to be classified with each set of images. But this is not the case in the reality. Results from a set of images can be accepted as final result when no other opposer from other classifications exists for the same area. If one area is classified in two classes, the area remains undefined. Therefore there are three types of fields after combination:
Classified: areas classified as known crops with fixed phenological period
Unclassified: areas are not identified as crops with fixed phenological period
Undefined: areas classified as known crops with fixed phenological period for more than one crop. About 12% of agricultural areas are labelled as undefined after combination.

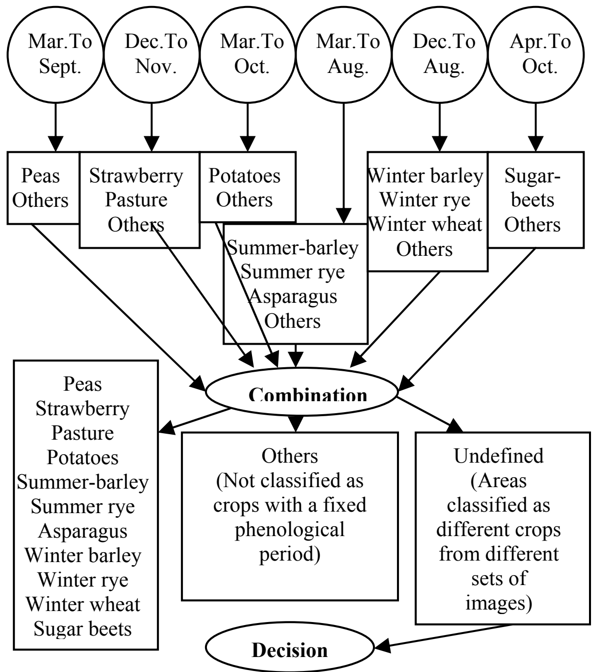

Figure 6: Classification and combination Process of different sets of images.

Undefined areas are reasonably one of the crops with a fixed and known phenological period and the area labelled as undefined is noticeable (12% of agricultural extent), hence it is necessary to develop rolls to this situation.
Distance images obtained as by-products of classification, representing the likelihood of each classified pixel to the centre of 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 a 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 labelled by the

class, to which is the pixel closest. The accuracy of results after combination is shown in table 7. It can be seen, that the values do not significantly alter from table 6 and the combination process kept the exterior accuracy acceptable.

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 7: Accuracy of classification in percent after combination of classifications. Exterior accuracy at sum: 83%

There are a small number of fields, 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.
The resulted image is filtered with a majority filter 7x7 in the last step to eliminate the disadvantages of noise and mixed pixels.
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 7 and 8.

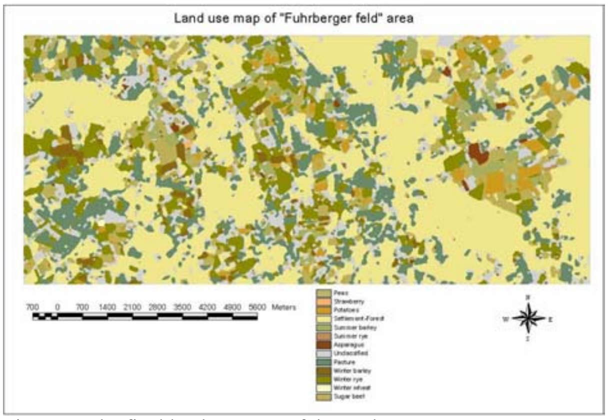

Figure 7: The final land use map of the study area

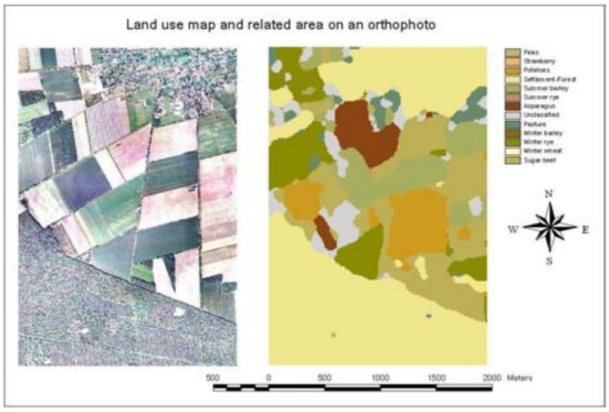

Figure 8: A close up from South of Fuhrberg town on an orthophoto and land use map

6. 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 fuzzy combination method is applied at the end as decision tool to solve uncertainties.

7. Acknowledgment

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Field observations have been carried out by Ulla Wissmann, a colleague of Institute of Photogrammetry and GeoInformation.

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