MONITORING AGRICULTURAL ACTIVITIES USING 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) with 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 years 2004 and 2005 are examined for their usefulness to 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, also ground surveys.

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 improve information extraction from 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 on the images using statistical processes. To classify crops, it is tried 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 evaluate the effects of local characteristics on radar images [14]. Using these methods an overall 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.

2. TEST AREA, GROUND TRUTH MEASUREMENTS AND SATELLITE DATA

The Fuhrberg area (Fig. 1) is situated north of Hanover the capital from Lower Saxony. 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 Fig. 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. A monthly coverage of satellite images was planned to get a whole growing season of the

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different vegetation types. However many data takes could not be performed as planned due to priority programming of the satellite for other projects.

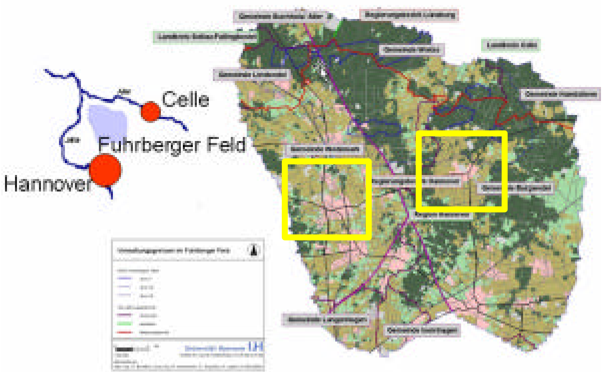

Figure 1. Test site Fuhrberger Feld

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

Table 1. Data takes of ENVISAT ASAR APG images, polarisation VV/VH, IS 5 -7 of agricultural season 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 of agricultural season 2005

Nr.	Image Date	Inspecting Date	Orientation
1	06.12.2004	06.12.2004	Descending
2	02.03.2005	02.03.2005	Descending
3	09.04.2005	08.04.2005	Descending
4	18.06.2005	15.06.2005	Descending
5	12.09.2005	12.09.2005	Descending
6	21.11.2005	21.11.2005	Descending

Tab.s 1 and 2 list the data, which have been acquired. The images have a pixel spacing of 12.5 m and nominal resolution of 30 meters. 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 samp ling 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.

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 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 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?
- Does a segment based method improve the 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 appearance over time. Therefore, a reliable separation of forest-residential areas can be set up using multi-temporal images. A temporal set 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. 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 Fig. 3.

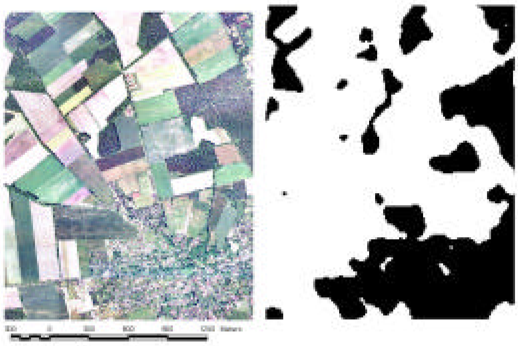

Figure 3. Forest-residential mask with 30m resolution (Right) compared to an orthophoto 0.4m resolution (Left)

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

Images from different dates can be used as bands of an image in a multi-temporal process. Some options are considerable related to this method. Different options influencing the accuracy of multi-temporal classification are tested.

-Raw versus filtered images?

- Filter selection.

-Common set of images (dates) for all crops versus a separate set of images for each crop or group of crops with the same cycle.

-Single or merged signatures per crop type

-Selection of classification type and rule to give best results.

Tests combining the above options have been carried out and are summarized with respect to the overall accuracy in Tab. 3. The columns of Tab. 3 (T1, T2,…) show in which option has been applied. "Sig. Merged" means, that samples (signatures) are merged based on crop type for this test. "Images adapted" indicates, that images are adapted to the phenological period of crops, which means classification of different sets of images for each crop or group of crops with the same phenological period has been performed. The next two rows show, if raw or filtered images are classified. The rows "Min. Distance", "Mahalanobis D." and "Max. Likelihood" explain which classification rule was applied for each test. The next record indicates, how many control fields per crop are used for evaluation of the overall accuracy. As can be seen in Tab. 3, the selected options for multi-temporal classification strongly affect the classification results. The high variation between accuracies of T5 and T3 which is caused only by the classification rule is an example that explains the importance of the selected option for classification. Best accuracy is achieved using phenological adopted sets of filtered images, samples which are merged based on crop type and the maximum likelihood classifier.

Table 3. Influence of some options on overall accuracy of multi-temporal classification.

Options	T1	T2	T3	T4	T5	T6
Sig. Merged	×	×	×		×	×
Images adopted			×	×	×	×
Raw Data	×					
Filtered (Lee 7 × 7)		×	×	×	×	×
Min. Distance					×	
Mahalanobis D.						×
Max. Likelihood	×	×	×	×		
Overall Accuracy	67	75	85	62	48	82

Different filter settings of the lee filter and other despeckling filters have been tested to investigate, if the type of filter affects the classification accuracy. The exterior (overall) accuracy of classification is computed from three control fields (A, B and C) per crop and presented in Tab. 4, which shows the influence of despeckle filters on the accuracy of multi-temporal classification. The overall accuracy of classification using images filtered by Gamma Map, Lee-Sigma, Lee and Median filters varies between 84.3% and 86.5%, which shows beside a good accuracy also a small variation between these four filters. Images filtered by median filter gave the best value of accuracy (86.5%), although it is not significantly higher than Lee (86.1%) filter. It should be mentioned, that the control fields used for Tab. 3 are not the same as for Tab. 4.

Table 4. Influence of despeckle filters on accuracy of multi-temporal classification.

Filter	Interior Acc.	A	B	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

3.3. Combining the results

When different sets of images are used, each set of images is being classified separately. Results for one or more crops are accepted from a classification if the set of processed images matches to the phenological period of that crops. For example, peas can be extracted from classification of images obtained between March and September. Combining the different independent classification results gives a land use map for the study area. As can be seen in Fig. 4, crops have been classified separately from each set of images 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 a set of images can be accepted as final classes when no contradicting other classification exists for the same area. If one segment is classified into 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 of competing classification results as known crops with fixed phenological period for more than one crop on same place. About 12% of agricultural areas are labelled as undefined after combination.

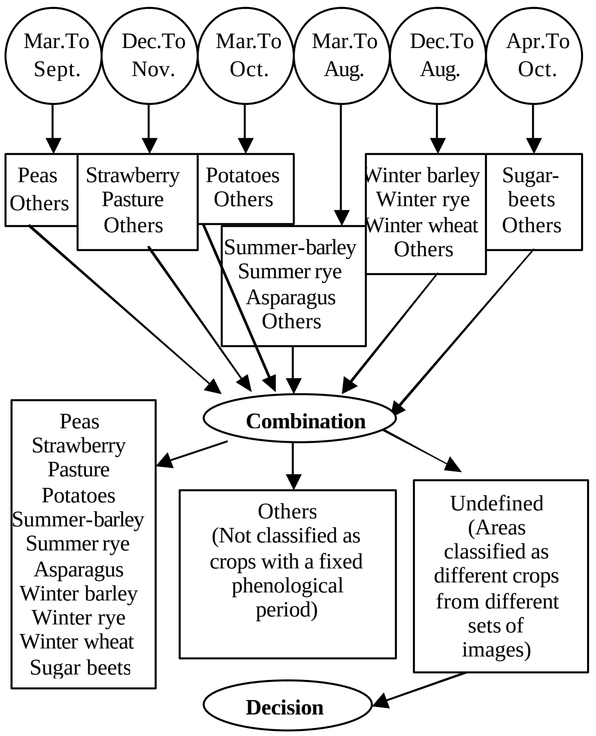

Figure 4. Classification and combination Process of different sets of images.

Undefined areas are most probably covered by one of the competing result classes. Distance images obtained as by-products of classification, representing the likelihood of each classified pixel to belong to this class, can be used for decision. Since distances are strongly dependent on the number of bands, they must be normalized first. The normalized distances (to different classes) of each undefined pixel are compared with each other and the pixel is labelled by the class of smallest normalized distance. The values of accuracy after combination does not significantly change from that before combination so that the exterior accuracy remains acceptable.

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.

3.4. Post processing

The classified result is filtered by a majority filter 7×7 to eliminate the appearance of scattered classified pixels. Classification accuracy of 2004 after post processing is presented in Tab. 5. 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 within large homogenous areas. If the result of a classification is filtered by majority filter, the classification accuracy of well-classified classes will increase but accuracy of miss-classified classes will decrease.

Table 5. Accuracy of classification after majority filter
Exterior accuracy at sum: 88%

Set of Images	Class	Interior	A	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

A comparison between results shows that the overall accuracy calculated from two control fields raises 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 Fig. 5.

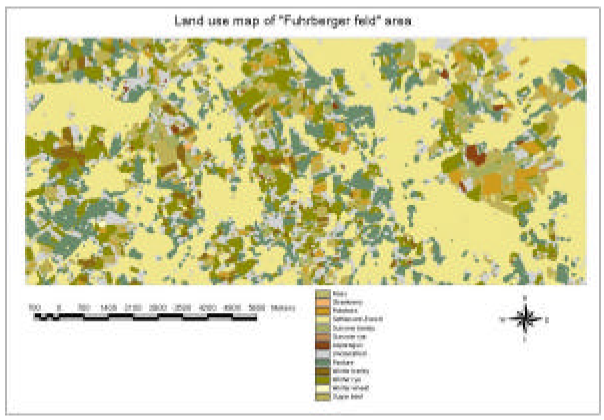

Figure 5. The final land use map of the study area

3.5. Segment based classification

Each field can be considered as a homogenous segment. Patterns of vegetation on agricultural fields are very fine compared to the resolution of space borne ASAR images

(30 meters). Distances between rows of cultivation are between 12cm (grains) and up to about 200cm (asparagus) and row patterns for some crops such as pastures, grass and rapes can not be observed. Especially, when crops grow up and the canopy covers all the area a pattern is rarely visible. Besides the absence of patterns on ASAR images, hardly any significant effect from rows of cultivation and their direction can be recognised on the field's statistics of that area. Our study showed that the direction of rows does not significantly affect the field's statistics (intensity of backscattering). In addition, speckle in SAR data may mask the appearance of fine patterns and contexts. Appling despeckle filters suppresses such patterns together with the speckle. Therefore, an object oriented classification based on patterns and texture of agricultural fields using images of 30 meters resolution is not very successful.

There are only a few examples for attempts of object oriented classification of SAR data. Heremans R. et al. (2005) [8] detected flooded areas on ENVISAT/ASAR images using object oriented method of eCognition software. Xiaoxia S. et al. (2006) [25] classified airborne SAR data enhanced by 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.

3.5.1. Methodology

In our investigation we consider the map of agricultural fields (parcels) representing crop borders as given. Classification of these given fields then was based on using mean (M) and standard deviation (SD) of the intensities over the extent of the fields. Therefore two values (M and SD) are available for each field per band of multi-temporal image (two polarisations × number of dates). The multi-temporal statistics of each field has to be compared to the multi-temporal statistics of each sample field and the field has to be assigned to the most likely crop. Eleven images of 2004 and six images of 2005 within the cultivation period of crops are used for classification. Based on an existing cultivation calendar of crops, it is possible to have rape and another crop e.g. sugar beets even on one field in one agricultural season, because they have different phenological periods. Therefore the classification process must be able to account for more than one class per field, if crops with separate phenological periods are cultivated on the same place.

3.5.2. Test of Method and data combination

Statistics from each field were compared with statistics of each crop during the growth period of that crop in the year 2004 and 2005. The crop type having statistics closest to the desired field is assigned to the field within the growth period of the crop. This classification method is tested using 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 was available. Winter grains in winter are more similar to bare lands and they appear like summer grains in summer. Also different grains have similar phenological periods and characteristics. Hence, there is a high degree of mixture analyzing the results of grains. The best accuracy is achieved by classifying the fields using mean and standard deviation of filtered images (86%). The accuracy is better if all grains are combined as one class and therefore their mixture is not counted as error (91%). This evaluation has been done using sample data of crops for which more than one sample field was available.

3.5.3. Influence of number and date of images on results of classification

The major difference between the classification of images of 2004 and 2005 is the number of available images. Only 6 images for the year 2005 are used which results in a poor average accuracy of 64%. Another difference is that there are 3 fields of maize and 6 fields of rape which are well classified in the year 2005 but there were no Maize field and only one rape field in the year 2004. If all grains are assumed as one class, 75% of sample fields are correctly classified for the year 2005. This shows 11% difference in comparison to the accuracy of different grains as separate classes, while there is only less than 5% difference between accuracy of the two representations of classification in the year 2004. This indicates a high value of mixture between different grains, which is caused by the small number of images for the year 2005.

4. CONCLUSION

The practicality of a multi-temporal approach for classifying SAR images in agricultural areas has been shown and some possible options were evaluated to find the optimal method for multi-temporal classification in the study area. It could be demonstrated that classifying separate 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 was tested and showed a comparable accuracy related to the pixel based method. The method can be applied if a parcel map of crop borders is available.

5. ACKNOWLEDGMENT

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