MONITORING AGRICULTURAL ACTIVITIES
USING MULTI-TEMPORAL ASAR ENVISAT DATA

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ABSTRACT:

Agricultural activities affect strongly their environment. Therefore and because of their other economic, industrial and political effects, monitoring agricultural areas is increasingly demanded. Space borne remote sensing is a very cost effective and beneficial means for monitoring and mapping of earth's surface. Due to independence from weather conditions, radar data are regularly available and facilitate a continuous monitoring of almost any area on the earth. In the framework of an ESA pilot project (AO335), methods are investigated aiming at reliable, cost efficient, and continuous monitoring of cultivation activities. A time series of doal polarization (VV/VH) of ENVISAT is used for the analysis. In addition, ground truth data are gathered by field acquisitions. The methodological approach for the monitoring task consists of supervised classification based on field data. For classification, some conventional methods and support vector machine (SVM) are applied and evaluated. In addition, the influence of some conventional despeckle filters on the classification accuracy is investigated. Results show that despeckling images by some filters before classification improves accuracy of multi temporal classification.. Matching of time series data to phenological period of crops is evaluated and compared with results of classification based on the entire data set. The results show that applying proper sets of data results in an exterior accuracy of over 80% on control fields. Overall accuracy of Maximum Likelihood and SVM are close to each other but their accuracy over control fields changes diversely. On the other hand, Maximum Likelihood is efficiently more accurate if data are matched to crop calendar. This is not the case for SVM.

1. INTRODUCTION

Monitoring agricultural activities is strongly demanded because of close relations between agriculture and other fields such as economy, environment, industry, and politics. Classical surveying methods are very expensive and time consuming. A possible solution to this bottleneck is remote sensing. In contrast to optical sensors in regions of frequent cloud cover, space borne SAR systems like ENVISAT ASAR are capable to provide data for monitoring on a regular basis. Airborne remote sensing techniques are in general not suitable for monitoring of large areas because of the associated high data acquisition costs [20] in comparison to satellite data. Therefore, ENVISAT dual polarized ASAR data are used for this project, which are provided free of charge by ESA within a pilot project. However, information extraction of agricultural activities from radar images is a challenging field because of a variety of reasons. Active SAR sensors may provide either elements of or the entire polarimetric scattering matrix, even in the case of fully polarimetric SAR data the dimensionality of the feature space is in general smaller than for electro optical (EO) data because SAR is a narrow band technique, whereas EO sensors cover wide spectral rang. Furthermore, for some crop-types the polarimetric SAR imagery is highly correlated. In addition, the speckle phenomenon may result in high intra-class variance leading to unsatisfactory classification results. Finally, SAR is sensitive to incidence angle, soil moisture, and the physical properties of soil, such as roughness. These parameters often affect signatures more than vegetation. Despite these limitations the mentioned all-weather capability enabling high temporal resolution and data acquisition on a

regular basis, SAR is an important means for monitoring purposes. In addition, SAR images have proven to be better suited for certain classification tasks than optical images [5], [27]. A vast body of literature deals with image processing of SAR data and land cover classification. Numerous filters are offered [18] and evaluated [6], [14] to reduce speckle of radar images in homogeneous areas, while preserving point targets and edges. In general, multi-look, and multi-temporal filters try to eliminate noise and speckle in images using statistical models. Filters affect SAR image in different manner, some of theme preserve statistical characteristics of data and are suitable for classification purposes, and some others keep borders and small objects. For the classification of crops, attempts are made to use all available polarizations [12], [18]. Fully polarimetric data (i.e., HH, VV, and one of the cross polarization channels in mono static radar) provide larger feature space with more dimensions. Unfortunately, only fully polarimetric airborne data are available, while this data from space platforms is not yet available. Dual polarization space borne data provide only a subset of the full feature space and two polarizations are often correlated with each other. Using multi-temporal data [11], [23], a larger feature space is available and temporal change of agricultural fields due to plants growing and farming activities can be considered to recognize crop types. In addition, radar data can be acquired more frequently than optical data. Hence multi-temporal radar data are used vastly for monitoring of agricultural activities.

Some methods are applied to improve information extraction from SAR data. Object based classification techniques[11], combination of SAR and passive data [11], knowledge driven classification [9], and investigating the effects of local

characteristics on radar images [16] are used by different researchers. 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 [9]. As reported in [15] the tests using single radar images (VV/VH amplitude images) show an unsatisfactory interior accuracy (as to classification based on training areas) of only 25% to 35% using raw data and about 30% to 45% for filtered data.

Because of seasonal changes, the appearance of certain crop types may vary considerably in SAR images at different growing phases. Using images from specific periods crop separation can be enhanced, e.g., winter grains are easier classified by images from winter while for Sugar beets images from end of summer should be preferred. Therefore, this progress can be considered as a special character of a crop and it improves accuracy of classification if multi-temporal data are processed. This paper is organized as follows. In Section 2, the test site and the data are briefly described. The different investigated approaches for multi-temporal classification are presented in Section 3 together with individual classification results for each method. Finally, in the last Section the conclusions are drawn.

2. TEST AREA, GROUND TRUTH MEASUREMENTS AND SATELLITE DATA

The test site called "Fuhrberger Feld" is situated north of Hanover, the capital of state Lower Saxony in Germany. 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. For these fields, topographic maps, base maps and digital orthophotos in color are available. Furthermore, ground surveys were conducted at or close to the time of satellite overpass. Initially a monthly coverage by ENVISAT satellite images was planned to get a time-series as dense as possible over the whole growing season of the different vegetation types for a period of three subsequent years. Despite some data takes could not be performed as scheduled, due to priority programming of the satellite for other projects, during a period of one year 11 pairs of dual polarization SAR data have been acquired from November 2003 until November 2004 (Table 1.).

The images have been processed into geocoded products using a pixel spacing of 12.5 m in range and azimuth direction. However, the spatial resolution of the data is about 30 m. Only look angles between 35.8 – 45.2 degree (corresponding to Image Swath IS5 to IS7) and VV/VH polarization have been used. During ground surveys, relevant features of the status of the fields were observed and collected such as usage and treatment pattern. Additionally, information on the kind of mechanical treatment of the soil and the plants, vegetation coverage, color, observable fertilizers, irrigation etc. have been stored into a GIS. In addition, digital ground photographs have been taken. It is important to note that for some different crop types, the coverage periods on the one hand coincide significantly, but on the other hand, even for the same crop on neighboring fields the dates of start and end can vary. The reason for this behavior is not known for sure, but probably economic considerations of individual farmers cause this effect, which for example result in different choice of subsequent use of the field after harvest.

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

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

3. MULTI-TEMPORAL CLASSIFICATION

Because of the independency from weather conditions, multi-temporal SAR data sets can be applied more frequently and reliable in comparison to optical images. Multi-temporal classification is assumed to be beneficial 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 that changes of fields due to the phenology of one crop can be used to discriminate this crop from others. Such methods have been vastly used and tested over different areas and for different crops e.g. Tröltzsch, K. 2002 in Mali [23], Hochschild, V. 2005 in Germany [11], Baronti, S. 1995 in Italy [1], Foody, G.M. 1988 in England [7], Schieche, B. 1999 in Germany[21], Davidson, G. 2002 in Japan [4] . In this paper, the advantages of applying multi-temporal classification are presented.

3.1. Data and parameters of multi-temporal classification

Images from different dates can be used as bands of an image in a multi-dimensional classification approach The crops in the study area are Lea, Fallow, Peas, Strawberry, Willow, Asparagus, Pasture, Potato, Sugar beet, Rape, Phacelia, Winter barley, Winter rye, Winter wheat, Summer barley, Summer rye, Wild grain and None (bare soil). This paper focuses on crop types with regular planting cycle. Therefore, the results for lea, fallow, and willow are not evaluated and presented here, because these types are usually not cultivated according to predictable schemes, but follow instead often considerations and constraints of individual farmers. Hence results from multi-temporal classification for these types would be only valid for the applied training samples and could hardly be transferred to other fields of same type. Rape and phacelia are sometimes planted as fertilizer between two cultivation seasons and therefore have no fixed cultivation calendar in this case. Such fields are considered to have only the main crop neglecting the intermediate fertilizer coverage.

However, training samples of all types even from fields without any plantation are used in the classification process. There is only one field for some crops in the study area. The field can be used as signature and it is not possible to have a control field for them. These crops are used in classification, but because of lack in control field, an evaluation of classification accuracy is not possible. Influence of despeckling and some filters on classification is investigated in this research project. In addition, data are matched to phenological calendar of crops and accuracy of Maximum Likelihood and SVM methods are evaluated and compared. Tests showed that despeckling, the set of time series data, and classification rule affect the results of classification [22]. Therefore, decisions must be made about pre-processing and time series data.

3.2.1 Despeckling

Speckle of SAR images increases interior variety between pixel values in each class (crop type) and decrease separability between different classes resulting in low accuracy. However, speckle is highly dependent on surface properties and can not be easily counted as noise. Therefore, the speckle in SAR data carries information which may be useful for separation between classes. Different filter settings of some speckle filters have been tested to investigate, how despeckling and the type of filter affect the classification accuracy. Interior accuracy (i.e., auto classification of the set of training fields) and the average of producer accuracy (correctly classified area of control fields) computed from three control fields per crop are presented in Table 2, which shows the influence of despeckle filters on the accuracy of multi-temporal classification. The average of producer 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.

Filter	Interior Acc. %	Producer Acc. %
None	91	70
Lee	98	86.1
Frost	96	81.7
Gamma Map	97	84.3
Local Region	91	75.1
Lee-Sigma	98	85
Median	98	86.5

Table 2. Influence of despeckle filters on accuracy of multi-temporal classification.

3.1.2. Time series data

The phenological periods of different crops are not equal. For example, Winter grains are planted in autumn and harvested in summer, Potatoes and Sugar beets are planted in spring and harvested in autumn. Therefore, as reported in [15], each crop can be classified by some images (of different dates) better than others. This is because of temporal separation between crops in different seasons. A good separation between grains

and Sugar beets can be achieved using images of June, when Sugar beets are small but grains are close to the harvesting. On the other hand, Winter and Summer grains may be separated better from winter images, when Winter grains are planted and even grew up to some centimeters but Summer grains are not yet planted. Hence it is very important to use proper images for classification of crops.

Based on information from field visits, following series are used for classification of crops:

- All images for Lea, Fallows, Strawberry, Willow, Pasture and Bare land
- Images from November till June for Winter grains
- Images from March till June for Summer grains
- Images from March till August for Peas and Asparagus
- Images from May till September for Potatoes and Sugar beets

Besides the considerations, tests showed that classification of images in the mentioned order was about 10% more accurate than the case if all images were used for classification of all crops [22].

3.1.3. Classification rule

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 classes and assign the pixel to the most similar class. Classification rules vary in the method of evaluation and therefore give diverse results. Three classical classification rules (Minimum Distance, Mahalanobis distance and Maximum Likelihood) and a support vector machine classifier are tested in order to investigate, which rule classifies multi-temporal SAR data best. Minimum distance and Mahalanobis distance classifiers assign each pixel to the closest class in multi dimensional feature space. Maximum Likelihood considers covariance matrix of classes besides distance to classes and therefore includes the probabilities.

Support vector machines (SVMs) are a set of related supervised learning methods used for classification. A special property of SVMs is that they simultaneously minimize classification error and maximize the margin between classes. Although, proposed already in the late seventies [24], it only now receives increasing attention in the remote sensing community [3], [25]. SVMs are especially beneficial if many dimensions (e.g. bands of hyperspectral scanners or images of multi-temporal data) are available [2]. In this study, we used the program ImageSVM provided by S. Van der Linden et.al (2006) for classification. ImageSVM performs a grid search to optimize parameters of SVM for each class in the training phase.

Classification. Rule	Interior	Control A	Control B
Max. Likelihood	98	80	89
SVM	100	79	90
Euclidean distance	77	48	52
Mahalanobis Distance	95	75	88

Table 3. Accuracy of four classification rules (%)

A series of tests are performed using one data set but different classifiers. Table 3 shows the accuracy of the classification rules. The evaluation is done using 2 control fields per crop. The

Maximum Likelihood and SVM perform best in the classification of these multi-temporal SAR data sets.

Although the values of accuracy for SVM and Maximum Likelihood(ML) are close to each other, obvious differences between SVM and ML can be seen in calculated accuracy of control fields. Table 4 (see appendix) is the error matrix of classification by ML using three control fields for each crop. Table 5 (see appendix) is the error matrix of classification by SVM using three control fields for each crop. Following, table 6 presents detailed accuracy of classification for ML and SVM over control fields in percent. Time series data used in these tests are matched to crop calendar. On tables 4 and 5 can be seen that overall accuracy of ML is higher than SVM but it is not the case for all crops. Some crops are classified by SVM better than by ML. Considering table 6 a high variation between calculated accuracies for different control fields classified by SVM can be observed. Even control fields of one crop are diversely classified. E.g. control field A of Summer barley is 87% correct classified by Maximum Likelihood but only 11% by SVM. On the other hand, field C of the same crop is much better classified by SVM than by Maximum Likelihood.

It is known that SVM is more accurate than other classifiers if large number of variables is available[2]. In the case of this study, we can not refer the variations to the number of variables. E.g. Pasture with the greatest number of images(as variables) is classified less accurate by SVM than by ML and Summer barley with the least number of images is better classified by SVM than by ML on two of three control fields.

Images	Class	Field A		Field B		Field C	
		ML	SVM	ML	SVM	ML	SVM
3-9	Potato	98	90	90	86	99	92
2-7	Summer barley	87	11	86	100	69	91
2-8	Asparagus	50	100	100	100	78	67
1-11	pasture	98	94	94	73	100	100
1-7	Winter barley	100	100	79	88	89	94
1-7	Winter rye	54	70	77	83	91	83
3-9	Sugar beet	76	87	100	100	93	61
	Mean	80	79	89	90	88	84

Table 6. Accuracy of classification(%) for control fields in detail. Data is the same as table 4 and 5.

Diverse noticeable results are driven from the classification of crops without considering the phenological periods. In this case, all images are used for classification of all crops (common set of images). Tables 7, 8 (see appendix) and 9 show result of same classifications as tables 4, 5 and 6 respectively without considering the crop calendar e.g. all images are used in only one classification process for all crops. As can be seen, overall accuracy of SVM (83%)(not matched to crop calendar) is higher than ML (79%)(not matched to crop calendar) by 4%, but overall accuracy of SVM (84%)(matched to crop calendar) presented in table 5 (see appendix) is five percent less than ML(89%)(matched to crop calendar). It means, classification by ML is significantly more accurate if time series data is matched to crop calendar. On the other hand, matching to crop calendar does not seem to be beneficial for classification by

SVM. Considering the details presented in tables 6 and 9, calculated accuracy of classification by SVM for many control fields in table 9(not matched to crop calendar) is better than table 6(matched to crop calendar) and the high variations in accuracy of classification by SVM can be observed in the table 9 too.

Images	Class	Field A		Field B		Field C	
		ML	SVM	ML	SVM	ML	SVM
1-11	Potato	96	93	93	99	100	100
1-11	Summer barley	84	74	86	100	82	53
1-11	Asparagus	25	82	97	100	70	55
1-11	pasture	98	94	94	73	81	100
1-11	Winter barley	100	100	18	92	2	0
1-11	Winter rye	20	76	99	97	100	100
1-11	Sugar beet	88	98	100	100	100	22
	Mean	73	88	84	94	76	61

Table 9. Accuracy of classification(%) for control fields in detail. Data is the same as table 7 and 8.

The insignificant improvement in accuracy of SVM by matching data to crop calendar may be explained as a result of reducing the number of used images. While overall accuracy of maximum likelihood is about 10% better if time series data are matched to crop calendar the one percent increment in accuracy of SVM is not significant. These results show, that if crop calendar is not known or a fast classification using all available data is aimed, SVM is more accurate than ML. On the other hand, ML performs the best classification if crop calendar is available and classification of different crops is done by individual classification processes.

3.1.4. Combining the results

If different sets of images are classified, 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(s). 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 September.

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 1, one or several other crops are classified separately and the rest is labeled as "Others" (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 the same area is classified twice, the area remains undefined. Therefore three types of fields remain during combination:

- Classified: areas classified as crops with known phenological period.
- Unclassified: areas are not identified as crops having a fixed phenological period.
- Undefined: areas of competing classification (known crops with fixed phenological period for more than one crop).

About 12% of the agricultural areas have been labeled as undefined during combination.

Undefined areas are most probably covered by one of the competing classes (12% of agricultural extent). Distance images obtained as by-products of classification, representing the likelihood of each classified pixel to belong to its class and/or other classes, can be used for decision. Since distances are strongly dependent on the number of images used in a classification process and fewer number of images results in smaller distances, each distance image must be divided by the number of images, which are used for the related classification, in order 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 distance of each undefined pixel is compared with different conflicting classes and the pixel is labeled by the class of smallest normalized distance. The accuracy after this combination is not significantly altered from values of table 4 and the combination process keeps the overall accuracy acceptable. Only about 0.5 percent of the agricultural area is misclassified by the combination process, and most of the 12 percent of the undefined area is well classified.
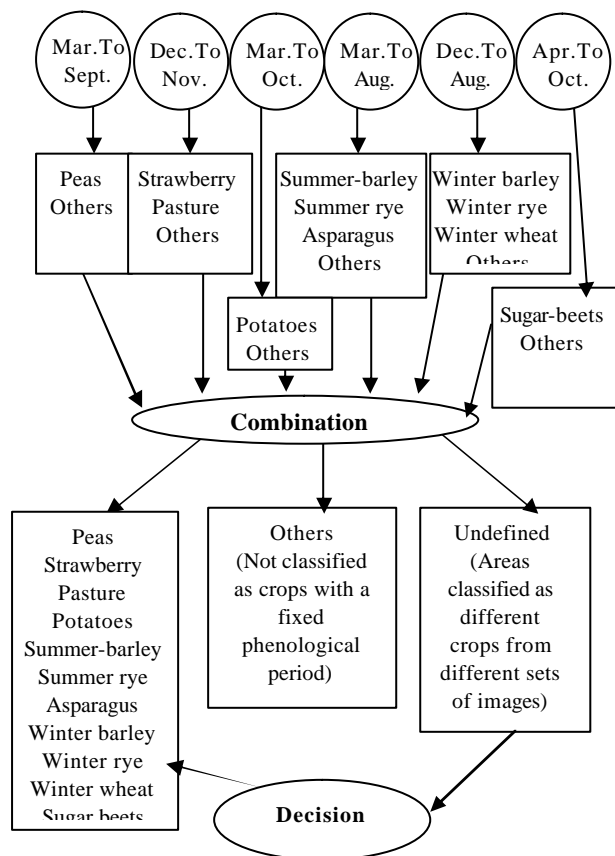

Figure 1. Classification and combination Process of different sets of images.

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 approach an optimal method for multi-temporal classification in the study area. It could be demonstrated that classifying separated sets of despeckled images (dates) by Maximum likelihood classifier and with consideration of crop calendar results in highest accuracy under investigated methods. On the other hand SVM classifier is more accurate than Maximum Likelihood if time series data is not matched to crop calendar. Classification by SVM is not significantly improved using time series matched to crop calendar. A combination method is applied at the end as a decision tool to solve overlapping.

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Appendix

	Class names	Reference Data (Pixel)								
		Potato	Summer Barley	Asparagus	Pasture	Winter Barley	Winter Rye	Sugar beets	Sum	User accuracy
Classified Data (Pixel)	Potato	1967	0	0	0	0	0	0	1967	1.00
	Summer Barley	0	896	3	22	0	78	0	999	0.90
	Asparagus	0	0	516	0	0	0	0	516	1.00
	Pasture	0	0	0	440	0	29	0	469	0.94
	Winter Barley	0	0	0	0	881	32	51	964	0.91
	Winter Rye	0	118	0	2	69	533	0	723	0.74
	Sugar beets	97	0	207	0	47	2	628	981	0.64
	Sum	2064	1015	726	464	998	674	679	6620	
Producer accuracy		0.95	0.88	0.71	0.95	0.88	0.79	0.93	Overall accuracy= 0.89	

Table 4. Error Matrix for classification by Maximum likelihood. input data is matched to crop calendar.

	Class names	Reference Data (Pixel)								
		Potato	Summer Barley	Asparagus	Pasture	Winter Barley	Winter Rye	Sugar beets	Sum	User accuracy
Classified Data (Pixel)	Potato	1848	0	29	0	0	0	203	2080	0.89
	Summer Barley	40	664	9	40	0	82	0	835	0.80
	Asparagus	0	247	688	0	0	0	0	936	0.74
	Pasture	0	38	0	409	0	8	0	455	0.90
	Winter Barley	0	28	0	0	927	52	6	1013	0.92
	Winter Rye	5	34	0	15	56	530	0	639	0.83
	Sugar beets	172	5	0	0	14	2	470	663	0.71
	Sum	2064	1015	726	464	998	674	679	6620	
Producer accuracy		0.90	0.65	0.95	0.88	0.93	0.79	0.69	Overall accuracy= 0.84	

Table 5. Error Matrix for classification by SVM. input data is matched to crop calendar.

	Class names	Reference Data (Pixel)								
		Potato	Summer Barley	Asparagus	Pasture	Winter Barley	Winter Rye	Sugar beets	Sum	User accuracy
Classified Data (Pixel)	Potato	1984	0	44	0	0	0	0	2027	0.98
	Summer Barley	0	852	10	24	0	0	0	887	0.96
	Asparagus	0	0	412	0	0	0	0	412	1.00
	Pasture	0	0	0	440	0	11	0	450	0.98
	Winter Barley	0	0	0	0	354	10	15	379	0.93
	Winter Rye	0	0	0	0	5	537	0	541	0.99
	Sugar beets	80	163	260	0	639	117	664	1923	0.35
	Sum	2064	1015	726	464	998	674	679	6620	
Producer accuracy		0.96	0.84	0.57	0.95	0.36	0.80	0.98	Overall accuracy= 0.79	

Table 7. Error Matrix for classification by Maximum likelihood. input data is not matched to crop calendar.

	Class names	Reference Data (Pixel)								
		Potato	Summer Barley	Asparagus	Pasture	Winter Barley	Winter Rye	Sugar beets	Sum	User accuracy
Classified Data (Pixel)	Potato	2021	0	31	0	0	0	398	2450	0.82
	Summer Barley	0	795	36	13	10	0	0	854	0.93
	Asparagus	0	0	611	0	0	0	0	611	1.00
	Pasture	0	19	0	409	0	0	0	428	0.96
	Winter Barley	0	28	23	23	706	15	3	797	0.89
	Winter Rye	1	173	24	20	9	660	0	885	0.75
	Sugar beets	42	0	0	0	273	0	281	596	0.47
	Sum	2064	1015	725	464	998	674	682	6622	
Producer accuracy		0.98	0.78	0.84	0.88	0.71	0.98	0.41	Overall accuracy= 0.83	

Table 8. Error Matrix for classification by SVM. input data is not matched to crop calendar.