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Agricultural Monitoring Using Envisat Alternating Polarization SAR Images

Mika Karjalainen, Harri Kaartinen, and Juha Hyyppä

Abstract

In agricultural remote sensing, applied images should be acquired frequently enough in order to monitor important crop growth stages. Thanks to the cloud penetrating and flexible swath-positioning capabilities of space-borne SAR at present, images can be acquired even at the interval of few days during a growing season. In this study, dual-polarization (VV/VH) Envisat SAR images with high a temporal resolution were used in association with limited ancillary data to monitor crop growth and to classify crop species. It was noticed that the high temporal resolution enabled nearly continuous monitoring, but it also caused problems because of the varying incidence angles. Moreover, to carry out field surveys rapidly enough for research purposes was observed as a problem. An R^2 of 0.55 was obtained for estimating the crop growth, when average crop height in parcels was used to describe the amount of biomass. An overall accuracy of 74.7 percent was achieved for crop species classification. Envisat VH polarization appeared to be useful in the estimation, even though, the noise equivalent σ^0 was too high to detect early crop growth. Field-based averaging was required, thus, for example for precision farming purposes a better spatial resolution would be needed to detect biomass variations within parcels.

Introduction

In general, the utilization of agricultural remote sensing can be categorized into the following application areas: (a) mapping of yield losses caused by lodging, flooding, pests, etc., (b) estimation or prediction of crop yield, (c) assessment of the area under cultivation, (d) crop species interpretation, (e) precision farming, where maximum yield is sought with minimum fertilization, and (f) control of agricultural subsidies (Henderson and Lewis, 1998; Lillesand and Kiefer, 1994; Cramp, 2003). A characteristic feature of all these application areas is that the time window for an appropriate image acquisition is very narrow compared with, for example, topographical mapping applications.

In Finland, the Ministry of Agriculture and Forestry (MAF) publishes crop yield predictions three times a year, i.e., in June, July, and August. Nowadays, these predictions are based on the reports acquired from experts working in the Finnish Rural Development Centers (Yield estimation seminar of the MAF, unpublished, 2004). On a small scale, the yield estimates are relatively reliable since these experts are specialists in crop husbandry, and they know the weather and growing conditions of the previous few months of the growing season

The most common instruments used in agricultural remote sensing are optical cameras and synthetic aperture radars (SAR) if ground based close-range remote sensing methods are excluded. For optical images, there are wellestablished methods to obtain vegetation-related information from the intensity of the image, because films and digital sensors are sensitive to wavelengths that overlap the region of the photosynthetically active radiation of the vegetation (Lillesand and Kiefer, 1994). Nonetheless, the major problem in the use of optical images in agriculture is cloudiness. For example, in Finland, there are roughly only up to four possible cloud-free periods in a growing season. Thus, a crop yield estimation based only on optical images would be rather unreliable.

SAR overcomes the problem of cloudiness by using microwaves that have wavelengths from a few centimeters to one meter. Basically, the SAR sensor sends a pulse of electromagnetic radiation, and then records the amplitude and phase of the radiation coming back from the target. The backscattering coefficient, σ^0 , is a measure describing the strength of the recorded radar signals from the target per unit area (Henderson and Lewis, 1998). Despite the advantages of SAR over optical images, the exploitation of SAR in real-time agricultural applications has been almost non-existent. There are two reasons for this. First, the cost of SAR image data is high, and second, crop information retrieval from the SAR images has proved to be a complicated inverse problem (Ulaby, 1998).

With respect to agricultural fields the inverse problem means that the recorded SAR backscattering is a function of several physical properties, such as soil surface moisture and roughness, vegetation biomass and moisture, crop type, land slope and the orientation of seed rows with respect to the SAR look direction. In crop yield estimation, one would like to estimate the biomass of the vegetation, but its inversion from the recorded SAR backscattering is very

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in question. However, at present the predictions and estimations lack geographical details, and furthermore, there is great variability between municipalities in the estimates due to the subjective nature of the yield estimation. The objective is to ensure that in the future equally good predictions will be available for each municipality in Finland; this means that to improve the present estimation system more objective and frequent data about the crop growth during a growing season is needed. In principle, these requirements could be satisfied using satellite images.

Finnish Geodetic Institute, Department of Remote Sensing and Photogrammetry, Geodeetinrinne 2, 02430 Masala, Finland (Mika.Karjalainen@fgi.fi).

difficult since other parameters are usually unknown. In particular, soil surface roughness and moisture have a very significant effect on the recorded SAR backscattering. There are *in situ* systems for measuring surface roughness, such as that described by Davidson *et al.* (2000). However, in practical yield estimation, it would not be possible to carry out such massive field surveys covering large agricultural areas. Methods using SAR polarimetry have been recently developed also for the inversion of the soil surface roughness and moisture. However, the SAR polarimetric method described by Hajnsek *et al.* (2003), for example, works restrictedly only for non-vegetated soil surfaces. By using longer wavelengths than C-band, it is possible determine soil surface moisture even in sparsely vegetated areas as was demonstrated by Dubois *et al.* (1995).

Theoretical modeling where the recorded SAR backscattering is simulated from the actual physical parameters, also called solving a direct problem, is needed not only to develop algorithms and methods for crop yield estimation, but also to determine the optimal wavelength, polarization and look angle for the SAR system to be used in agricultural applications (Ulaby, 1998). In general, an ideal SAR system for any agricultural application would have multi-frequency, multi-temporal, and multi-polarization capabilities, and, in addition, very high spatial resolution compared to the parcel size (McNairn and Brisco, 2004). When taking into account single-frequency SAR systems, C-band microwaves are usually considered the most suitable for agricultural purposes. C-band has a wavelength of about 5 cm, which is comparable to the size of the leaves and stems of cereal crops (Wooding et al., 1995). As the wavelength gets longer, the microwave radiation tends to penetrate the vegetation more easily (Henderson and Lewis, 1998). In the past few years, a considerable amount of research has been carried out on SAR in agriculture, especially, in the field of fully polarimetric images. Skriver et al. (1999) used airborne L- and C-band fully polarimetric SAR and found that C-band was better for crop classification and that at the end of the growing season C-band backscattering was dominated by volume scattering from crop vegetation. Brown et al. (2003) proposed that the HH and VV amplitude difference in C-band could be a good measure for estimating the biomass of the crops. Mattea et al. (2003) used a C-band ground-based scatterometer for studying backscattering from wheat fields and observed that the ratio of HH and VV polarizations at an incidence angle of 40° was strongly related to the aboveground biomass. Some very promising results have been obtained on the use of one-day SAR interferometric coherence for vegetation biomass estimation (Blaes and Defourny, 2003). Unfortunately, at the moment, there are no operative satellite SAR systems with which to acquire fully polarimetric or oneday SAR interferometric images.

In the last decade, the development of satellite-borne SAR in agricultural remote sensing has been closely connected to the success of the ERS-1 and ERS-2 satellites, which were launched in 1991 and 1995, respectively. The SAR of both ERS satellites uses C-band in VV polarization. Wooding et al. (1995) effectively summarize the agricultural SAR research carried out using the ERS-1 satellite. Satellite SAR provides images frequently, thus the temporal variation in the backscattering can be used, for example, for the crop species interpretation (Schotten et al., 1995; Saich and Borgeaud, 2000). Le Toan et al. (1997) used ERS-1 SAR images successfully in the monitoring of rice growing areas and crop growth. Another satellite-borne SAR system being used is the Canadian Radarsat-1 satellite, which has slightly better spatial resolution than ERS, but studies show that its HH polarization is not very suitable for the extraction of crop related information (Karjalainen et al., 2003).

Now, owing to the dual-polarization and flexible swath positioning capabilities of the European Space Agency Envisat SAR, an improvement in agricultural monitoring is anticipated. We believe that the cross-polarization image channel would increase the retrievable crop related information, as can be seen in forestry, where cross-polarization has been found to be the best choice for estimating stem volume (Le Toan *et al.*, 1992). Therefore, this study made use of an alternating polarization mode, where VV and VH polarization images are acquired simultaneously.

The objective of this study was to evaluate the feasibility of using Envisat alternating polarization (VV/VH) SAR images along with limited ancillary information to provide supportive information for current agricultural information systems, such as subsidy controlling or crop yield forecasting. The monitoring of crop growth was aimed to be carried out in a practical situation, where applied SAR images should be acquired as frequently as possible, and detailed information about soil surface and vegetation parameters is usually limited. Accordingly, fresh and dry biomass parameters of crop vegetation were excluded from the study since their measurement with a non-destructive way was considered as impractical even though they are known to be relevant parameters that describe SAR response from cereal crops. Only those soil surface and vegetation parameters were field surveyed that can be determined relatively effortlessly or alternatively could be determined by using other methods and data sources. Therefore, the hypothesis of the study was that the variation in the crop height represents the variation in the crop biomass to most extent similarly as in forestry, where canopy height has shown to be the most important parameter for obtaining volume or biomass (Hyyppä et al., 2005).

Test Area, Data and Methods

Test Area

The test area is located in western Finland near the city of Seinäjoki, and it covers an area of approximately 40 by 40 kilometers. This area is one of the northernmost agricultural areas in the world, located at 63° North latitude (see Plate 1). The overall topography of the area is extremely flat, especially in the agricultural regions, which is favorable for SAR studies. Approximately 18 percent of the total area in this region is under cultivation. The shares of the species cultivated are: oats 25 percent, barley 25 percent, grass silage 18 percent, fallow 10 percent, turnip rape 5 percent, wheat 3 percent, rye 1 percent, potato 3 percent, and the remaining 10 percent consists mostly of sugar beet, grassland, pasture, and garden (TIKE, 2003). The average $% \left({{\left[{{{\rm{TIKE}}} \right]}_{\rm{TIKE}}} \right)$ parcel size is about two hectares, which is quite small when compared to the pixel size of the Envisat SAR images. Cereal crops are mostly spring-sown varieties, with the exception of a small amount of rye and autumn wheat. In 2003, the average crop yields in the Seinäjoki region were: oats 3.6 t/ha, barley 3.8 t/ha, wheat 3.5 t/ha, and rve 2.8 t/ha (TIKE, 2003). Crop yields are low compared with those obtained in the southern regions of Europe. The river Kyröjoki, which has been embanked in the last centuries, divides the test area. Nowadays, there is no regular flooding in the springtime, but in some places floodwater from the melting snow may stay on the low-lying fields for a few weeks. The growing season in the test area lasts from 150 to 160 days per year. The sowing date is usually at the end of May or at the latest in the beginning of June. The cereal crops are harvested late August or early September.



Field Surveys

The foundation of this study is an accurate parcel boundary map, which was obtained from the Information Centre of the Ministry of Agriculture and Forestry in Finland. The Finnish Land Parcel Identification System (LPIS) contains geographical boundaries of the base parcels and it is linked to the Integrated Administration and Control System (LACS), which includes information about farmers, crop species, etc. There are about 40,000 base parcels in the test area, but since there was a limited time window to carry out field surveys, 24 parcels were selected as a test set, for which following attributes were retrieved: soil surface roughness, orientation of seed rows with respect to SAR look direction, soil surface moisture, and crop height.

The soil surface roughness values (the symbol R denotes the soil surface roughness value) were measured using a Leica laser distometer which was attached to a two meters long steel rod. When the distometer was moved along the rod, a soil surface profile was obtained. All profiles were acquired perpendicularly with respect to the seed rows. Two sample profiles were recorded for each test parcel. After field measurements, a mean surface was calculated for each profile. The *R* value used in this study is the standard deviation of the distance samples of the profiles from the mean surface, therefore, it corresponds to the root mean square (RMS) surface height (Henderson and Lewis, 1998). Since the measured profiles were only two meters long, correlation lengths associated with the *R* values were not calculated. The surface roughness values were measured once at the beginning of the growing season, and they were assumed to be constant during the rest of the growing season.

The orientation of seed rows with respect to SAR look direction (symbol D) of test parcels were also determined. The range of D value is from 0 to 1, where parcels seeded perpendicularly with respect to the SAR look direction have highest values.

The soil surface moisture values (M) were measured using a ThetaKit TK2-BASIC soil moisture measuring device, which measures the volumetric moisture using steel spikes that penetrate the soil surface to a depth of 6 cm. For each test parcel at each image acquisition there were altogether 15 moisture measurements (five measurements on three locations within the parcel). Since the moisture value (M)used in this study is the average of these 15 measurements, it is only a rough estimate of the average soil surface moisture of the whole parcel, and it cannot be used to estimate the moisture variations within the parcel.

The average crop height (\hat{H}) was used describe the crop biomass growth, and it was determined by using a measuring tape. The *H* value is an average of three measurements that were located on different parts of parcels. Therefore, crop height variations within parcels cannot be estimated. In order to estimate the biomass more accurately and to produce a biomass map, a handheld biomass mapping device of Kemira GrowHow[®] was attached to the personal digital assistant (PDA) and GPS to obtain biomass information in 2004. Unfortunately, the most of our Envisat image requests in 2004 were cancelled due to the acquisition conflicts.

Satellite Images

Our objective was to achieve as high a temporal resolution as possible, thus 16 Envisat SAR image acquisitions were requested in the summer of 2003. A similar image set was also requested in 2004, but unfortunately, the most of the acquisitions were cancelled because of the conflicts with commercial requests. The SAR incidence angle in the test parcels varied from 23° to 41°. The average time interval between the image acquisitions was one week, but in midsummer, when the crop growth is usually the most intensive, the time interval was the shortest. In the end, 12 Envisat SAR alternating polarization images in VV and VH polarizations were actually received (images are listed in Table 1). All SAR images were orthorectified using the PCI Geomatica® v.9.03 software. Ground control points were acquired from the Finnish base maps and additionally, a 25-meter digital terrain model was used to obtain height information. Altogether, there were 138 control points and 10 image-to-image tie points. Residual errors for the control points were 0.53 pixels in the east-west direction and 0.81 pixels in the north-south direction, which should be relatively good when compared to the 12.5-meter pixel size of the Envisat SAR precision images. All images were rectified into the Finnish uniform coordinate system (YKJ), which uses a Transverse Mercator projection, where the longitude

Table 1. Envisat sar Images Used in the Agricultural Monitoring Project. All Images were Acquired in $_{\rm VV/VH}$ Alternating Polarization Mode

Image #	Date	Processing and Archiving Facility	Swath
1	15 June 2003	D-PAF	4
2	18 June 2003	I-PAF	3
3	21 June 2003	D-PAF	2
4	28 June 2003	I-PAF	6
5	04 July 2003	I-PAF	4
6	07 July 2003	UK-PAF	3
7	14 July 2003	I-PAF	6
8	23 July 2003	I-PAF	3
9	02 August 2003	UK-PAF	6
10	11 August 2003	D-PAF	3
11	24 August 2003	I-PAF	4
12	15 September 2003	UK-PAF	3

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of the central meridian is 27°. Visually, the rectification accuracy was also excellent, which enabled the parcel-specific information to be derived from the time series of SAR images.

Preparation of Test Data

The base parcels of the Finnish LPIS may contain more than one crop species, so first, those parcels that had only one crop species and were relatively large compared to the pixel size of Envisat SAR were selected. When a threshold value of 1 hectare was used, there were 5,571 test parcels left. This test parcel set also included the 24 parcels for which reference measurements were made in the field surveys. The test parcels were then buffered using a 10-meter-wide zone in order to avoid pixels near the boundaries, since these may contain information about adjacent parcels, ditches, etc.

Next, an average SAR backscattering intensity (squared amplitude) for the test parcels was calculated, thus, a field based approach that overcomes the problem of SAR speckle was used in this study. Because the areas of the test parcels were relatively small, the sigma nought backscattering values can be calculated using the following formula (ESA, 2002):

$$L^{0} = (\langle DN \rangle / K)^{*} \sin(\alpha_{d}) \tag{1}$$

where σ^0 is the sigma nought backscattering value in linear scale, <DN> is digital number describing the average backscattering intensity (squared amplitude) of pixels within a given parcel, K is an absolute calibration constant, and α_d is the average incidence angle at parcels. K determines the SAR system calibration and it is given in the header information of each SAR image file. Finally, the sigma nought backscattering values were converted to the logarithmic scale. However, there still remain variations in the σ^0 values of a given test parcel due to the variation in the incidence angles in different images. In order to obtain high temporal resolution Envisat SAR imaging swaths from 2 through 6 were used, thus incident angle interval in the test parcels was from 23° to 41°. Figure 1 shows the average backscattering time series for major crop species based on the 5,571 selected parcels in the test area in summer 2003.

A field-based approach was used throughout the analysis. Crop species interpretation was carried out using the backscattering time series of 5,571 parcels. The reference classes for crop species were acquired from the Finnish LPIS, which contains the farmers' declarations of the sown crop species in the growing season of 2003. Having carried out various studies in the test area over five years, we can safely say that the crop species of LPIS are extremely reliable. Only those classes that had over 20 test parcels were selected, thus the final classes used in the classification were: grassland, potato, turnip rape, autumn rye, spring wheat, barley, and oats. The grassland class consists of perennial grass, grass silage, pasture grass, Common Agricultural Policies (CAP) fallow, etc., which had apparently very similar temporal backscattering signatures during the growing season. The classification was carried out using three-nearest neighbor classification, and the error was estimated using the leaveone-out method. SAR images were added cumulatively into the classification process.

In order to evaluate the feasibility of the crop related information extraction, various multiple linear regression analyses were carried out using the 24 test parcels, for which there were field surveyed reference data. The test data was normalized, so that each predictor had a mean of zero and a standard deviation of one. First, the SAR backscattering was estimated from the reference measurements

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(direct problem). Although, the reference data is incomplete, the solution of the direct problem should, however, explain to what extent our rapid field surveys are able to predict variations in the SAR backscattering. Second, and more importantly, a linear regression model was used to predict the crop height from SAR backscattering in a situation that is comparable to the current yield prediction system, where only limited information about soil surface and vegetation is available.

Results

The sar Backscattering Time Series

The time series of VV and VH backscattering for selected crop species classes are represented in Figure 1. Since Envisat imaging swaths from 2 through 6 were used, some of the variation of the backscattering signatures can be explained by the differences in the incidence angles. Variation was great, especially in the beginning of growing season, when vegetation was sparse for which surface scattering is usually the dominant scattering mechanism.

In the beginning of the growing season, from crop emerging in early June to crop heading in early July, the average VH backscattering of the cereal crops was from -16 dB to -18 dB, which is very close to the noise equivalent σ^0 of -20 dB of the Envisat alternating polarization images (ESA, 2002). The dynamic range of the VH backscattering signatures is narrow, thus it appears that the early crop growth cannot be detected using Envisat cross-polarization. At the same time, VV backscattering decreased from about -9 dB to its minimum of around -14 dB. According to 24 test parcels, the soil surface moisture decreased in that time period from 35 percent to 25 percent of volumetric moisture on the average.

In the middle of the growing season, from early July to early August, both VV and VH backscattering values of cereal crops started gradually to increase. The increase started when the crop height was around 50 cm based on the average of the 24 test parcels. In the middle of growing season, the volumetric soil moisture according to the field measurements was relatively constant (on the average 25 percent for all test parcels) thus, the increase in SAR backscattering was most likely caused by the increase of the vegetation biomass. The increase of SAR backscattering was 3 dB and 5 dB for VH and VV polarizations, respectively.

In the end of the growing season, from late August to September, one can detect a slight decrease of both VV and VH backscattering. The decrease is probably caused by ripening of cereals, which lowers the water content of vegetation. However, the decrease could be partly related to the soil surface moisture, which according to our measurement decreased from 25 percent to 20 percent based on the average of the 24 test parcels. It should be noticed, that the backscattering signatures concerning the last two images (24 August and 15 September) are unreliable, because the harvesting in the test area started in the last week of August, and it was not possible to eliminate the harvested parcels from the calculation of the average backscattering signatures.

Crop Species Interpretation

The confusion matrix of the classification, when all 12 dual polarization images were used, is represented in Table 2. The final overall classification accuracy was 74.7 percent, when both polarizations were used. On the other hand, when single polarization was used, the overall classification accuracy was 69.2 percent for VV images and 69.9 percent for VH images. The best individual classification accuracy was achieved for turnip rape at 87.4 percent. The grassland samples were classified with an accuracy of 74.5 percent and they were mostly misclassified (23.2 percent) as barley and oats. The potato class had 73.3 percent accuracy, and there was misclassification of grassland, turnip rape, barley, and oats classes evenly. Barley and oats classes had accuracies of 86.0 percent and 66.7 percent respectively, but autumn rye and spring wheat had significantly lower accuracies (13.3 percent and 20.3 percent). However, cereal crops were mostly misclassified with each other. Figure 2 shows the improvement of the classification accuracies when SAR images were added cumulatively into the classification

TABLE 2. CONFUSION MATRIX OF THE CROP SPECIES CLASSIFICATION USING THREE-NEAREST NEIGHBOR CLASSIFICATION AND LEAVE-ONE-OUT ERROR ESTIMATION. VALUES IN THE TABLE SHOW THE PERCENTAGE OF PARCELS CLASSIFIED INTO THE CLASS IN QUESTION. ALL 12 IMAGES AND BOTH VV AND VH POLARIZATION WERE USED IN THE CLASSIFICATION

		Classification Result					
					Cereal	Crops	
Correct Class (# of parcels)	Grassland	Potato	Turnip Rape	Autumn Rye	Spring Wheat	Barley	Oats
Grassland (993)	74.5%	0.2%	0.6%	0.0%	0.7%	12.8%	10.4%
Potato (31)	3.3%	73.3%	6.7%	0.0%	0.0%	13.3%	3.3%
Turnip rape(486)	2.2%	0.4%	87.4%	0.0%	0.0%	8.3%	1.7%
Autumn rve (46)	8.9%	0.0%	0.0%	13.3%	0.0%	66.7%	11.1%
Spring wheat (291)	6.8%	0.0%	0.0%	0.0%	20.3%	32.0%	40.9%
Barley (2090)	2.7%	0.1%	0.8%	0.1%	0.8%	86.0%	9.6%
Oats (1499)	4.4%	0.1%	0.4%	0.0%	2.3%	26.0%	66.7%
Overall classification	1 accuracy =	74.7 %					



Figure 2. The improvement of the overall classification accuracy when SAR images were added cumulatively into the classification process. The highest accuracy was achieved when VV and VH polarization were used simultaneously. VV polarization was slightly better than VH polarization.

process. Naturally, accuracy was very low in the beginning of the growing season, but by August, when ripening of the crops started, classification accuracy had already reached its maximum.

saR Backscattering Simulation from Field Surveyed Reference Measurements

In this case, the objective was to analyze the importance of the field surveyed soil surface and crop-related parameters with respect to the SAR backscattering recorded by Envisat. In the field surveys, the following parameters were retrieved: soil surface roughness, orientation of seed rows with respect to the SAR look direction, soil surface moisture, and crop height. It should be taken into account that detailed information about vegetation was omitted. The following regression model was used to estimate SAR backscattering (σ^0) from the field survey measurements: $\sigma^{0}(VV \text{ or } VH) = a_{0} + a_{1}R + a_{2}D + a_{3}M + a_{4}H$ (2)

where a_0 to a_4 are coefficients of the regression modeling, *R* is the RMS soil surface roughness of parcels, *D* is a value describing the orientation of seed rows of parcels with respect to SAR look direction, *M* is the average soil surface moisture of parcels, and *H* is the average crop height of parcels. Results for both VV and VH polarizations are given in Table 3. The significance values of independent predictors were calculated using a 95 percent confidence interval. A lower significance value means that the predictor in question has more impact on the model than the higher significance values. R^2 value is the coefficient of determination, which describes how much of the backscattering variation was explained by the model in each case.

R² values for backscattering estimation were the highest in the beginning of the growing season varying from 0.5 to 0.65. In early June, when crops were just emerging, the most significant terms were roughness (R) and crop height (H). The most rapid stem extension from 30 to 60 centimeters occurred between images on 28 June and 07 July. The worst R² values were achieved on 04 July, implying that none of the field measurements was able to explain the variation of the recorded SAR backscattering. At the turn of June and July, crops usually have the highest moisture content, which was not measured in the field surveys. In general, after cereal crops reached their full height, the R² values were quite low from 0.1 to 0.4. At the end of the growing season, the R² values increased slightly, and soil surface roughness became again the most significant predictor. Most likely, the reason is that cereal crops start to ripen, which dries up the plants, making the soil again more visible to SAR. The orientation of seed rows with respect to SAR look direction had a low impact on the models. According to the results, the volumetric soil surface moisture also had considerably low significance values during the growing season, and the explanation is that the most intensive dehydration of the soil surface happened before the end of June.

These results indicate that the field surveys of soil surface roughness, orientation of seed rows with respect to SAR look direction, soil surface moisture, and crop height insufficiently predicted the SAR backscattering recorded by Envisat, especially in the middle of growing season. More detailed measurements of vegetation and more appropriate modeling would have been required to acquire better results. However, the results of the time series in Figure 1 clearly showed that there was an increase in average SAR backscattering in the middle of growing period, which was most

	Significance of the Predictor (95% Significance Level)				
Date	RMS Soil Surface Roughness (R)	Orientation of Seed Rows with Respect to SAR Look Direction (D)	Soil Surface Moisture (M)	Crop Height (H)	\mathbb{R}^2
15 June					
VV	0.001	0.916	0.473	0.010	0.523
VH	0.144	0.193	0.049	0.003	0.635
18 June					
vv	0.007	0.319	0.658	0.006	0.606
VH	0.132	0.090	0.641	< 0.001	0.629
21 June					
VV	< 0.001	0.449	0.696	0.021	0.652
VH	0.115	0.098	0.573	< 0.001	0.581
28 June					
VV	0.717	0.306	0.187	0.355	0.219
VH	0.966	0.264	0.063	0.203	0.279
04 July					
VV	0.977	0.364	0.635	0.804	0.081
VH	0.633	0.745	0.545	0.534	0.108
07 July					
vv	0.181	0.732	0.199	0.896	0.145
VH	0.412	0.818	0.988	0.329	0.115
14 July					
vv	0.832	0.814	0.703	0.044	0.266
VH	0.889	0.330	0.405	0.023	0.393
23 July					
vv	0.736	0.543	0.875	0.530	0.084
VH	0.673	0.508	0.907	0.553	0.092
02 August					
vv	0.054	0.616	0.163	0.753	0.250
VH	0.029	0.476	0.234	0.970	0.257
11 August					
vv	0.014	0.229	0.568	0.578	0.303
VH	< 0.001	0.010	0.541	0.044	0.574
24 August					
VV	0.066	0.902	0.622	0.954	0.207
VH	0.005	0.714	0.892	0.194	0.476
15 September					
VV	0.015	0.556	0.507	0.878	0.378
VH	0.133	0.011	0.840	0.361	0.455

TABLE 3. RESULTS OF THE MULTIPLE REGRESSION ANALYSIS WHEN SAR BACKSCATTERING WAS PREDICTED FROM THE FIELD SURVEY MEASUREMENTS (THE NUMBER OF PARCELS WAS 24, EXCEPT IN THE CASE OF 04 JULY AND 23 JULY, WHEN THE NUMBER OF PARCELS WAS 19)

likely related to the growth of the cereal crops, thus, extraction of crop related information from Envisat VV/VH backscattering seems plausible.

$\label{eq:constraint} \mbox{Crop Height Estimation Using sAR Backscattering and Limited Ancillary Data }$

The objective was to evaluate if crop-related information could be extracted from the SAR backscattering. The average crop height measured in the field surveys was used to express the crop growth. In 2004, detailed biomass maps were also produced, but they were not used in this study because of the lack of Envisat SAR images in growing 2004 period. Firstly, we used the following model, where crop height was estimated directly from the SAR backscattering values:

$$H = a_0 + a_1 V V + a_2 V H + a_3 V V / V H$$
(3)

where a_0 to a_3 are coefficients of the regression modeling, *H* is the average crop height of parcels, and *VV*, *VH*, and *VV/VH* are field averaged SAR backscattering values of parcels on a given date. Results are summarized in Table 4 and on the left in Figure 3. The coefficient of determination of the model was quite low (0.33), and it was clear that the linear regression model was not suitable, because the model started to saturate after the crop height exceeded about 70 cm. VH polarization

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seemed to be somewhat more significant than VV and the ratio of VV to VH. In order to enhance the model in Equation 3, the crop height values were changed to the logarithmic scale ln(H). Subsequently, the coefficient of determination improved to 0.47 (see Figure 3b). The physical basis that supports the use of the logarithmic scale is that in unlimited conditions, the crop growth is an exponential process. However, in reality, crop growth is a sigmoid function of biomass. Again, VH polarization was slightly better for crop height estimation than VV and VV/VH predictors.

TABLE 4. RESULTS OF THE MULTIPLE REGRESSION ANALYSIS WHEN CROP
HEIGHT WAS PREDICTED FROM THE SAR BACKSCATTERING. THE REGRESSION
MODEL IS DESCRIBED IN EQUATION 3. ALL 12 IMAGES WERE USED FOR OATS
and Barley Parcels, thus the Number of Samples was 214

	Crop Height (linear scale)	Crop Height (logarithmic scale)
R ² VV significance VH significance VV/VH significance	0.331 0.077 0.016 0.352	0.469 0.001 <0.001 0.027
Constant significance	< 0.001	< 0.001



Finally, it was assumed that in addition to SAR backscattering values, rapidly field surveyed soil surface roughness (R), the orientation of seed rows with respect to SAR look direction (D), and soil surface moisture (M) were also known. Using again logarithm scale of crop height, the model became:

$$ln(H) = a_0 + a_1VV + a_2VH + a_3VV/VH + a_sR + a_5D + a_6M$$
(4)

where a_0 to a_6 are coefficients of the regression modeling. VV, VH, and VV/VH are field averaged Envisat SAR backscattering values of parcels. Results are summarized in Table 5 and in Figure 4. When compared to model used in Figure 3b, the coefficient of determination improved from 0.47 to 0.55, therefore, the use of ancillary field measurements (soil surface

TABLE 5. RESULTS OF THE MULTIPLE REGRESSION
ANALYSIS DESCRIBED IN EQUATION 4.
Results are Represented for Oats and
BARLEY FIELDS. THE NUMBER OF SAMPLES WAS 214

	Crop Height (logarithmic scale)
R ²	0.547
VV significance	< 0.001
VH significance	< 0.001
VV/VH significance	0.007
R significance	0.523
D significance	0.896
M significance	< 0.001
Constant significance	< 0.001



crop heights using the multiple regression model described in Equation 4. The number of samples was 214.

roughness, the orientation of seed rows, and soil surface moisture) slightly improved the accuracy of the crop height estimation. As mentioned earlier, it is expected that these simple soil parameters can be determined in practice. For example, the soil surface moisture and roughness can be estimated from other SAR systems or even from soil type maps and weather statistics. Accordingly, it seems that Envisat SAR images can be used to estimate crop height to some extent, even though, the regression analysis results in the case of this direct problem were poor in the middle of the growing season.

Summary and Conclusions

The objective of the study was to evaluate the feasibility of satellite-borne SAR in agricultural remote sensing when images were acquired as frequently as possible. In this study, altogether 12 Envisat alternating polarization SAR images (VV and VH polarizations) were collected roughly at one-week intervals in the growing season 2003. The results of the extraction of crop-related information were based on SAR backscattering time series and reference measurements that were non-destructively and rapidly surveyed simultaneous with all image acquisitions. Destructive biomass and water content determination (fresh and dry biomass) was excluded, since their use as auxiliary information in the estimation was considered as impractical.

In general, the results of the VV polarization backscattering signatures of Envisat were similar to the results obtained with the ERS-1 satellite (Saich and Borgeaud, 2000; Wooding *et al.*, 1995). On the other hand, VH backscattering signatures showed that there was an increase of 3 dB from bare soil to full crop, which was most likely related to the stem extension of the cereal crops. However, the problem in using VH polarization was that the backscattering in the beginning of the growing season was very close to the noise equivalent σ^0 of Envisat alternating polarization images, which is around -20 dB depending on the antenna look angle (ESA, 2002). According to the results, the VH backscattering started to increase in the middle of July, when crop height exceeded

about 50 cm on the average in our test parcels. Thus, a more sensitive SAR system would probably enhance the crop monitoring capability, especially in the cross-polarization. A current topic in agricultural remote sensing is crop

species interpretation, which could be used to control the subsidies of farmers. For example, the European Union spends annually about 63 Billion USD (45 Billion Euros) on the Common Agricultural Policy (Cramp, 2003). According to our crop species interpretation results, the final overall classification accuracy was 74.7 percent, when crop species classes of grassland, potato, turnip rape, autumn rye, spring wheat, barley, and oats were used. High temporal resolution improved the classification accuracy rapidly in the beginning of the growing season (Figure 2), but the accuracy did not improve after the ripening of the crops had started in early August. It is evident that the achieved accuracy is not good enough to be used in controlling farmers' subsidies in Finland, thus additional information such as optical satellite images other SAR images, and information about crop rotation would be required to improve the classification accuracy. Nevertheless classification with this accuracy might be usable in such areas where accurate parcel information system is not available.

In order to carry out yield estimation or vegetation biomass mapping, one must be able to extract crop related information from the SAR backscattering. To evaluate the feasibility of Envisat alternating polarization (VV/VH) images in crop biomass mapping a set of 24 parcels was selected to more detailed analysis. For the test parcels soil surface roughness, the orientation of seed rows with respect to SAR look direction, soil surface moisture, and crop height were determined in the field surveys. In this study, the measurements of the average crop height of the test parcels were used to describe the crop growth. Massive field surveys, including vegetation biomass and water content, were considered to be impractical to carry out. Nevertheless, when crop height was predicted from Envisat SAR backscattering, an \mathbb{R}^2 of 0.55 was obtained in the best case, and the model was able to predict crop heights even up to about 110 cm ($e^{4.7} \approx 110$). Despite the problem of high noise equivalent $\sigma^{\scriptscriptstyle 0}$ compared to the dynamic range of the VH backscattering signatures, VH polarization appeared to be more suitable for biomass detection for cereal crops than vv polarization. However, the best estimation result was achieved when both VH and VV backscattering were used concurrently with soil surface roughness and moisture values. Since, in practice, the soil parameters are unknown, another system, such as a satellite SAR system fine-tuned for soil properties extraction, would be needed. The results of extracting crop related information from Envisat VV/VH

polarization images appear promising despite the lack of detailed information about vegetation biomass. As men-tioned a lower noise equivalent σ^{0} , however, would be needed to improve the prediction accuracy especially in the early stages of the crop growth. Additionally, it was observed that the 30-meter spatial resolution of the Envisat SAR was too low for detecting crop height variations within a parcel. Consequently, a better spatial resolution is necessary, for instance, for precision agriculture purposes. Nevertheless, it seem evident that a high temporal resolution is an essential feature in agricultural remote sensing, and due to the cloudiness in some areas, this can only be obtained by using SAR. Further research is still required before SAR images can be considered to be used in agriculture for current agricultural information and yield forecasting systems. Moreover, more efficient reference measurement systems should be developed for research purposes that are capable to produce detailed information about vegetation. In this light, laser scanning appears to be very promising method in the future.

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