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Sensitivity of ENVISAT ASAR image classification accuracy to spatial variability of selected environmental parameters in rural areas

K. Stankiewicz
Institute of Geodesy and Cartography, Warsaw, Poland; krystyna.stankiewicz@igik.edu.pl

E. Wisniewska
Institute of Geodesy and Cartography, Warsaw, Poland; emilia.wisniewska@igik.edu.pl

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ABSTRACT: ENVISAT images acquired in the alternating polarization mode are an important step forward in land use classification based on microwave satellite data. The application of ASAR images for crop recognition confirmed their applicability in vegetation mapping although a significant spatial variability of vegetation signatures is observed. The variability of signatures derived from ASAR image for a particular land use class is related to the inner variability of moisture and roughness. In order to specify more accurately the sources of such variability and to estimate the influence of variable parameters on the classification accuracy one needs detailed information concerning the investigated area.
Valuable information concerning spatial distribution of moisture and roughness can be deduced from very high resolution (VHR) optical images acquired from IKONOS satellite. In order to investigate the influence of parameters deduced from optical images with the backscattering of the microwave signal the following images were examined: IKONOS image acquired on 12th of July, 2005 and two ASAR images acquired over the same area on 11th and 14th of July 2005. The analysis was conducted for a test site which is located in the western part of Poland in the traditional agriculture area. Arable land covers most of this area and at least 10 different types of crops can be found there. Other land use forms are: grasslands, forest, lakes and built-up area. The signatures of these classes were related to some spatial characteristics derived from IKONOS as for example: normalized vegetation index (NDVI), row direction in crop fields and spatial distribution of soil moisture.

1 INTRODUCTION

The objective of this paper is to assess the influence of internal variability of selected land use / land cover classes on the classification accuracy of ENVISAT ASAR images. It is a part of a larger project aiming at the specification of ASAR images usefulness in the creation of thematic maps. A rural area located in the central lowlands in Poland was chosen as a test site for the presented case. Urban areas, arable land, grasslands, forest and water bodies are all represented in rural areas in Poland, although the main focus of this work is on vegetation classes: arable land, grasslands and forest. The considered subdivision of the selected classes is driven by the potential of the source data. For example arable land is represented by more detailed classes corresponding to particular crops. The variability of signatures derived from ASAR image for definite land use class is related to the variability of moisture and roughness (Oliver & Quegan 1998). On the other hand, the spatial variability of moisture and roughness can be partially attributed to certain constant patterns which can be observed in the investigated area. Soil type, relief of terrain and climate create together a local habitat for vegetation. This habitat influences natural as well as cultivated vegetation and leads to the variability of such features as fractional vegetation cover or biomass density. Microwave backscattering is sensitive to such variations and there are many projects which concentrate on modeling these dependences using detailed description of canopy as well as underlying ground (Notarnicola *et al.* 2006). Empirical models of electromagnetic interaction within the complex soil-vegetation medium usually need the extensive sampling of ground data required for model justification. Until now, the proposed inversion models are not as robust as expected (Vecchia *et al.* 2006) and their results are not generally useful in the estimation of vegetation classification accuracy. The approach which was applied here is based on an assumption that the spatial diversity of habitats characterized by soil type, terrain model and location related to the watershed is the main factor which influences the internal variability of vegetation classes. The habitats can be distinguished on optical images acquired at various phenological stages of plant development because they create constant patterns observed over a longer period of time. Vegetation itself creates an evidence of the quality of a habitat and one can infer on the quality of habitat by observing the distribution of some vegetation indices derived from optical satellite images. The question is whether this variability of habitat within a specific vegetation class influences the microwave signature so strongly that it disturbs the classification. VHR optical images from IKONOS satellite as well as topographic maps and soil maps were used in order to identify spatial patterns observed in a selected rural area. The correlation of ASAR signatures to several spatial descriptors derived from these sources were examined. Vegetation type, relative density of vegetation, structure of crop canopy resulting from farming practices (row direction) and spatial distribution of soil moisture were considered.

The information contained in IKONOS image is partially valid only for a short period of time. NDVI calculated from infrared and red IKONOS bands is a good indicator of biomass and biomass water content as well. Its value depends on a current phenological phase of the selected vegetation class and on growth conditions. Spatial distribution of NDVI derived from IKONOS can be compared to the microwave signal registered in ASAR images acquired on 11th and 14th of July. However, the spatial distribution of NDVI can also be extrapolated to a more distant period of time because it follows certain constant patterns present in the environment, such as soil type or the location in the watershed. IKONOS image was also used for the determination of row direction at each considered agriculture plot. The azimuth of rows which is valid for a specified crop from its sowing to harvest was introduced to the database.

2 TEST SITE

The test site is located in the western part of Poland in Wielkopolska and is centered around the longitude of 16°50'E and the latitude of 52°05' N. It spreads over the area which is 18 kilometers wide in EW direction and 16.5 kilometers wide in NS direction. This area belongs to the European central lowlands and is mostly flat. It is a traditional agriculture region with highly productive soils suitable for growing sugar beets and wheat as well as moderate productive soils which are the most suitable for growing rye. However, soils with low water storage capacities prevail. One of the most pronounced features of the climate of Wielkopolska is low precipitation. Most of the region has a long-term average yearly precipitation value of about 500 mm which is much less than the average calculated for the whole country.

Main land use/ land cover classes are: arable land, forest, grasslands, built-up area and water bodies. According to the CORINE data base 77,3% of the area belongs to non-irrigated arable land, 12.6% is covered by forest, 5.1% is covered by pastures and grasslands and 2.6% belongs to discontinuous urban fabric. Contribution of each other class is below 1% At least 10 different types of crops can be found in the test site, although wheat, sugar beets, maize and rape are the most common. The vegetation season starts usually in March when the average daily air temperature exceeds 5°C and lasts more or less 220 days. Winter crops like winter wheat, rye, oilseed rape which are sown in autumn are first to emerge in early spring while sugar beets and maize are usually sown in the second half of April. In July cereals are yellowing and ripening, oilseed rape is harvested and sugar beets and maize are growing intensively. The test area was visited during the satellite overpasses. The field observations supplied ground truth data which were used in the classification task. Crops on selected plots were identified and several plant parameters were measured or estimated.

3 MATERIALS AND PRE-PROCESSING

Microwave ENVISAT ASAR images acquired in C-band with spatial resolution of 30 m as listed in Table 1 were used in the classification tasks.

Table 1. Set of ENVISAT ASAR images.

Date	Polarization	Swath	Inc. angle degrees
02 May 2005	VV, VH	IS4	31.0 – 36.3
08 May 2005	HH, HV	IS2	19.2 – 26.7
15 May 2005	VV, VH	IS6	39.1 – 42.3
12 June 2005	HH, HV	IS2	19.2 – 26.7
19 June 2005	VV, VH	IS6	39.1 – 42.3
11 July 2005	VV, VH	IS4	31.0 – 36.3
14 July 2005	HH, HV	IS3	26.0 – 31.4
24 July 2005	VV, VH	IS6	39.1 – 42.3
28 August 2005	VV, VH	IS6	39.1 – 42.3

Table 2. Spectral characteristics of IKONOS images.

Band	Lower 50% nm	Upper 50% nm	Bandwidth nm	Centre nm
Pan	525.8	928.5	403	727.1
MS-1 (Blue)	444.7	516.0	71.3	480.3
MS-2 (Green)	506.4	595.0	88.6	550.7
MS-3 (Red)	631.9	697.7	65.8	664.8
MS-4 (VNIR)	757.3	852.7	95.4	805.0

Primary processing of ASAR images included speckle filtering, image coregistration and georeferencing as well as calibration to gamma coefficient:

$$\gamma = \frac{\sigma}{\cos \alpha} \tag{1}$$

where:

σ - microwave backscattering coefficient; α - beam incidence angle.

The applied microwave image processing was accomplished using ESA software BEST and is described in more detail in (Stankiewicz 2006).

The optical VHR image from IKONOS satellite acquired on 12th of July, 2005 supplied detailed information on the test site area. Spectral characteristics of IKONOS panchromatic image (1 meter spatial resolution) and multispectral image (4 meter resolution) are given in Table 2. Panchromatic image and RGB colour composite created using near infrared, red and green bands were visually interpreted in order to identify the row direction in crop fields and to delineate the current network of drainage ditches. The normalized vegetation index NDVI was calculated using near infrared and red bands. This index is highly correlated to biomass and shows the inner spatial variability of vegetation classes which are expected to influence the spatial variability of dielectric constant and consequently the within-class variability of microwave backscattering. The analysis of spatial characteristics of selected features was performed within GIS project using topographic and soil maps of the area at the scale of 1:50000, digital surface model and other existing land use layers. LANDSAT ETM image acquired on the 5th of May, 2000 was examined in order to confirm the existence of certain long-term patterns within vegetation classes.

4 CLASSIFICATION METHOD

Urban areas, arable land, grasslands, forest and water bodies can be recognized on ENVISAT microwave images acquired in alternating polarization mode with satisfying accuracy. Some of these classes can be further subdivided into more detailed units. Arable land, for example, can be partitioned into fields covered by particular crops. For each class there is a certain limit of subdivision beyond which one cannot expect repetitive and stable results of image classification. This threshold depends on spatial resolution and spectral characteristics of the image.

Per pixel classification of microwave images is complicated because speckle phenomena induce large variations of the backscattered signal within each land use / land cover class. Better classification accuracy can be achieved when the image is segmented prior to classification and after that classified using backscattering intensity averaged over segments. Segments should represent homogeneous regions corresponding to distinct classes. In the presented analysis mean values of the gamma coefficient calculated for each segment provided class signatures. These signatures were classified using neural network classifier while image segmentation has been performed with eCognition software (eCognition *User Guide* 2002). eCognition uses a patented multiresolution segmentation procedure which was developed especially for textured or low contrast data such as radar or VHR images.

In order to obtain comparable segments of optical and microwave images the process of segmentation was divided into separate steps. At first three channels of IKONOS image: green, red and near infrared were segmented jointly. A thematic layer containing boundaries of agricultural plots was also taken into account in order to guarantee that segments do not cross these boundaries and represent distinct crops. The basic strategy of segmentation in eCognition software is to build up a hierarchical network of image objects, which allows the representation of the image information content at different scales simultaneously. Here, the required scale was the one at which segments were representing variations within land use / land cover classes which could be attributed to variations of moisture or biomass density observed at the test site. However, the final choice of scale was somewhat arbitrary and based on the visual inspection of the segmented image. At the selected level of segmentation the objects identified on IKONOS composite represented either individual forest patches, fields covered by homogeneous crops, uniform grasslands etc. or large subsets of such items which differed spectrally in a significant way from the rest of an item.

The subsequent segmentation of two-band ENVISAT ASAR image was performed using IKONOS segments as super-objects. This procedure led to ASAR segments which were fully embedded in IKONOS segments. Thus, each ASAR segment belonged to a specific object which was recognized on the IKONOS image. ASAR segments were created at various scaling levels. Alternatively segments were created using simultaneously four bands originated from two ASAR images registered on 11^{th} and 14^{th} of July. In the case of ENVISAT images the choice of scaling was governed by the requirement that an object representing vegetation should contain on average several dozens of pixels.

The class signatures were calculated by averaging γ coefficient over segments. Averaging helps to reduce the effect of speckle induced by the coherent imaging technique. Several sets of signatures referring to different scaling factors were compared. Finally two sets of segments were selected for further analysis: set 1 which represented the selected IKONOS super-objects and set 2 of sub-objects derived using two ENVISAT images acquired in July.

In order to investigate the influence of signatures variability on classification accuracy the signatures representing segments at various scales were classified separately. The supervised classification was performed using multi-layer perceptron (MLP) as a classifier (Tso & Mather 2001). The neural network was trained and validated using data collected at the test site. Two classifiers differing by the neuron weights obtained during training phase were generated. These classifiers were generated using two different sets of signatures: set 1 and set 2. The performance of both classifiers was rather low with the overall accuracy equal to 50% The differences in the classification accuracy obtained from these classifiers for each class were not larger then 1%.

5 SIGNATURES VARIABILITY

Poor classification results obtained using two ENVISAT images can be easily explained by examining mean signatures of land use classes which are shown in Fig. 1 together with the corresponding standard errors. Low separability of signatures was observed for each of the considered bands. On the one hand it could be attributed to the inappropriate time of image acquisition. In mid July cereals are yellowing and they are very much alike, deciduous and coniferous forest response is close to each other as well as similar to that of oilseed rape and so on. On the other hand it is known that a single-date C-band polarimetric image usually does not contain enough information to guarantee high classification accuracy. In order to improve classification results based on one – frequency microwave images it is necessary to exploit multi-temporal acquisitions. Images acquired at different phases of vegetation development supply signatures leading

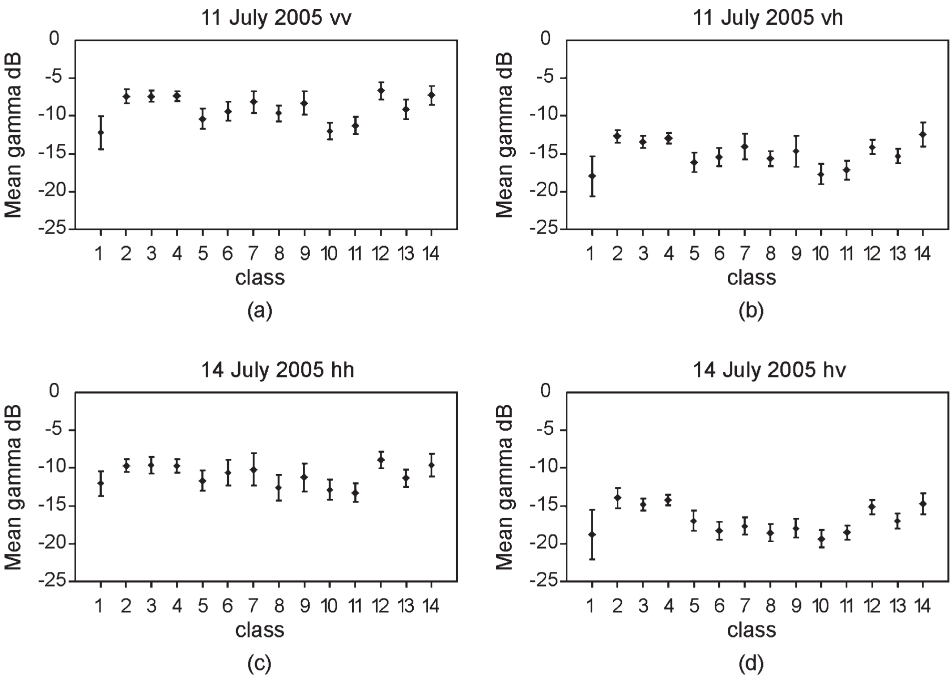


Figure 1. Signatures of the following classes: 1 - water bodies; 2 - coniferous forest; 3 - deciduous forest; 4 - mixed forest; 5 - grassland; 6 - winter wheat; 7 - triticale; 8 - rye; 9 - spring barley; 10 - oat; 11 - alfalfa; 12 - sugar beets; 13 - maize; 14 - rape.

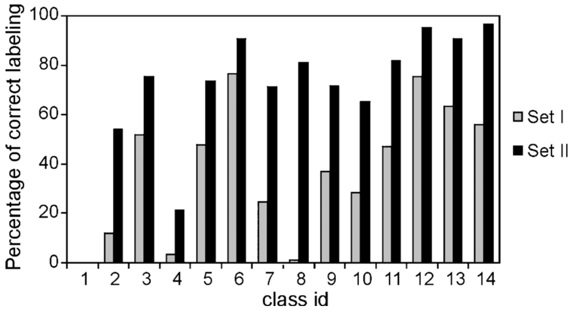


Figure 2. Comparison of classification accuracy of two sets ASAR images. Set I: 2 images acquired on July 11 and July 14. Set II: 7 images acquired on May 2, May 8, May 15, June 12, June 19, July 11 and July 14. Class id as in Fig. 1.

to better class recognition. The simultaneous usage of signatures derived from the series of 7 ASAR images acquired between 2nd of May and 14th of July, as listed in Table I, led to the overall classification accuracy equal to 81%. The classification accuracy obtained using 2 and 7 ASAR images is shown for each class in Fig. 2. Unsatisfactory results were obtained for water which had highly variable signatures in all cases. Microwave response of water depends usually on the strength of wind and it often mixes with the response from other classes. For all other considered classes the improvement of accuracy was observed with the increase of the number of images taken into account.

However, signature variations of more than 2 dB can decrease classification accuracy considerably for any class. In order to understand the influence of such variations on classification accuracy various examples of wrongly classified image objects were analyzed. Object properties evaluated from IKONOS image like NDVI or row direction for crops were considered in the analysis.

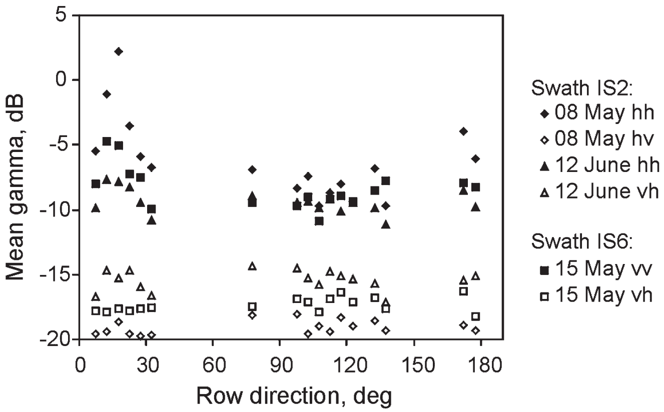
The dependence of γ coefficient on NDVI was examined separately for each vegetation class and for each ASAR image listed in Table I. Generally, in each analyzed case NDVI variability explains less than 50% of γ variability (Table 3). The scatterplots of mean γ values versus NDVI show weak correlation between these two quantities for all presented classes. On the other hand when the analysis is limited to the wrongly

Table 3. Coefficient of determination between γ coefficient and NDVI for winter wheat and sugar beets.

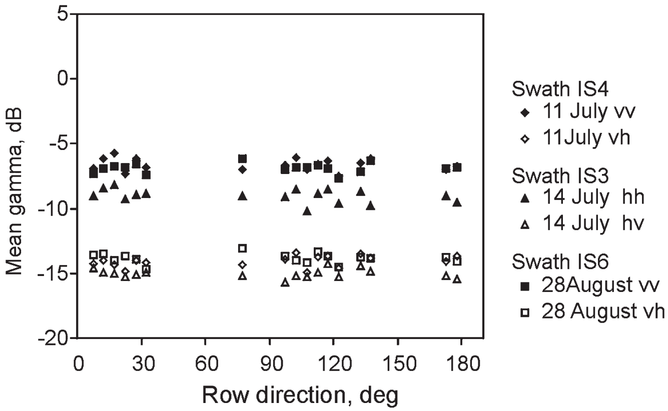
Date	Polarization	Swath	coefficient of determination r^2	
			Winter wheat	Sugar beets
19 June	VV	IS6	− 0.49	− 0.13
19 June	VH	IS6	− 0.37	− 0.64
11 July	VV	IS4	− 0.55	+ 0.40
11 July	VH	IS4	− 0.48	− 0.40
14 July	HH	IS3	− 0.22	+ 0.30
14July	HV	IS3	0.22	− 0.03
24 July	VV	IS6	− 0.60	+ 0.33
24 July	VH	IS6	+ 0.41	+ 0.39

classified image objects the influence of NDVI on classification accuracy can be noticed for certain classes. For example maize with extremely low NDVI is usually classified as sugar beets while maize with extremely high NDVI is usually classified as grass. Similarly, alfalfa with high NDVI is recognized as grass.

The dependence of γ signatures on row direction was examined for various crops. It was found that for sugar beets and maize the influence of row direction on mean γ is pronounced at VV and HH polarizations on images acquired just after sowing and before canopy closure. Backscattering from fields with rows perpendicular to the microwave beam was much more intensive than in all other cases as it was shown for sugar beets in Fig. 3a. The dependence on row direction was not observed neither on images acquired in July or August (Fig. 3b) nor at HV polarization for any acquisition time. Since the dependence of VV and HH signatures on row direction is rather strong - the observed



(a)



(b)

Figure 3. Dependence of mean gamma coefficient for fields with sugar beets on row direction (a) – ASAR images acquired on May and June; (b) – ASAR images acquired on July and August.

changes of γ coefficient were of the order of 5 dB – it may considerably spoil the classification results. In order to avoid such sources of classification errors it is recommended to use only HV bands from images acquired in May. It was difficult to draw conclusions concerning the influence of spatial distribution of soil moisture on classification accuracy. Due to the low level of precipitation in July soil moisture within the test area was rather low and stable within vegetation classes.

6 CONCLUSIONS

Using the multi-temporal set of ASAR images it is possible to achieve the acceptable accuracy of classification (> 86%) for the following vegetation classes:

forest (as one class)
grasslands
oilseed rape
sugar beets
maize
winter wheat
other cereals as one group

Differentiation among individual types of cereals is worse and its accuracy is lower than 80%. The neural network classifier which was used in the presented analysis is to a large extent insensitive to the variability of class signatures. The disadvantageous influence of within-class variability of NDVI or an unfavorable canopy structure can be diminished by a special strategy of classification. The separate classification of arable land and permanent vegetation is highly recommended. During vegetation classification water should be masked because it mixes with other classes depending on the wind intensity. It is better to use cross-polarization images than co-polarization ones for the classification at the beginning of the growing season because co-polarization images are much less sensitive to the row structure of crops. Maize and sugar beets can be differentiated from other crops by the usage of images acquired in April and May. The analysis of the sensitivity of ASAR classification accuracy to the spatial variability of selected environmental parameters is not yet completed and will be continued.

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