SNNS CLASSIFICATION OF HYPERSPECTRAL DATA OF EXTENSIVELY USED AGRICULTURAL AREAS

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ABSTRACT

The goal of this paper is a presentation of artificial neural networks for land cover classifications of the DAIS 7915 hyperspectral data. The research area covers seminatural ecosystems of pastures and meadows and extensively used agricultural areas of the Low Beskid Mountains (the northern Carpathian Mts.) in southern Poland. Algorithms based on the SNNS classification (multilayer one-way perceptron with backpropagation learning method) of 3 key polygons (Biesnik S, Biesnik N and Wiatrowki) using training sets of 60 and 40 original bands (after geometric and atmospheric correction) and first 13 MNF channels in different textural windows (1×1, 3×3, 5×5 and 7×7 pixels) were used. The results were compared with the reference sets acquired from ground validation. The best accuracy (92.1%) for the test set was achieved using 60 original bands with the 3x3 pixel subpattern size, and for the training set – 93.9% for this architecture.

INTRODUCTION

The new kind of available remote sensing data are hyperspectral images that are characterised by a large number of closely spaced spectral channels. They make it possible to distinguish the physico-chemical properties of the objects that are located on the earth area, e.g. the land cover reflectance registered is an average of the reflectance of photosynthetic, non-photosynthetic active parts (i.e. branches, dry leaves), shadow and ground. Artificial nets are very useful for classifying heterogeneous objects, because they are based on whole object characteristics (spectral and neighbourhood pattern recognition), so-called non-parametric classification, where the relationship between pixels are analysed. This kind of classification can be supported by textural windows (they are sets of neighbours of a classified pixel). Typical window sets consist of 1×1, 3×3, 5×5 and 7×7 pixels (matrix of neurons). These relationships between image objects frequently appear over seminatural and agriculturally used areas, and traditional classification that uses parametrical approaches does not show satisfying results. The implemented neural network is a multilayer one-way perceptron, the learning method is backpropagation. For training the neural network, particular layers of the cover classes were used which were identified during land research using the aircraft. Land research turned out to be the reference material for estimating the precision of the classification. Whether the hyperspectral data compression procedure was suitable was evaluated by using the Miniumum Noise Fraction transformation (MNF), including the classification of the texture and information in the object's neighbourhood. This method may be especially useful to separate and classify vegetation communities (1) or land cover units; preliminary results on land cover were presented during the 28th EARSeL Symposium (2) and the 6th EARSeL Workshop on Imaging Spectroscopy (3).

STUDY AREA AND DATA SOURCES

The study was conducted in the Low Beskid Mountains, which constitute one of the most natural ranges in the Carpathian Mts. in Poland. The research area covers the Wiatrowki key polygon of the Bystrzanka catchment (Figure 1), which extend from 49º34' - 49º41'N to 21°01' - 21°09'E. The area constitutes a mountain zone located at the altitude range of 400-750 m. The region is agricultural, but extensively used; with a domination of seminatural forests, meadows, cereal and potato crops.

DAIS 7915 hyperspectral data used in this study was acquired on 29 July 2002 in cooperation with the German Space Agency (DLR) (HySens PL02_05 project). This instrument is a 79-channel imaging spectrometer operating in the wavelength range 0.4-12.5 µm with 15 bit radiometric resolution. After preprocessing the resulting pixel size was 3 metres. During the overflight three lines of DAIS images were acquired.

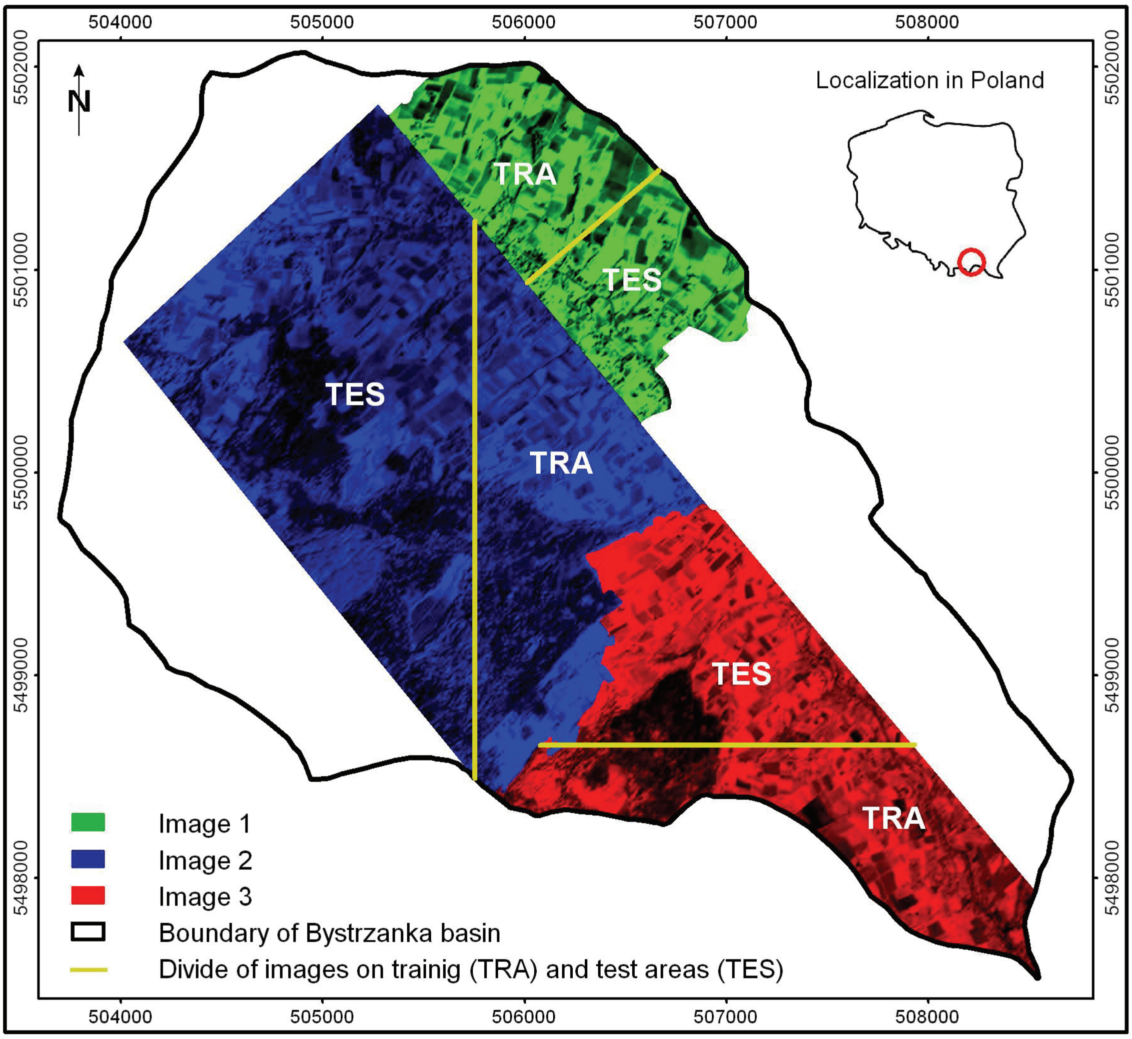

Figure 1: DAIS 7915 images covering the study area. Image 1 covers Biesnik N key polygon, Image 2 Biesnik S, and Image 3 Wiatrowki.

METHODS

The classification procedures began with a preparation of reference layers of dominant land cover units (grasslands, wastelands, coniferous, deciduous and mixed forest, tree clumps, orchards, beet crops, potato crops, oat crops, stubbles, arable areas, asphalt roads, side roads, built-up areas, buildings). This stage, based on terrain and Spectral Angle Mapping (SAM) (Figure 2). SAM classification, was used to verify land cover maps performed in 2002 during the terrain mapping. Endmembers were obtained from DAIS imagery (corresponding to the key polygons from the ground measurements). All the polygons represented in each class on the training area were used to train nets.

Parallel to this procedure, an extraction from all 79 bands covering the VIS-TIR regions of the spectrum was made. The first step was a visual histogram analysis (inspection of bands with severe striping problems) and the reselection of 60 spectral bands. The second step was the reduction to 40 original and 13 MNF bands (Figure 2).

For classifying land cover types, a multilayer, one-directional network and a supervised back-propagation method were applied. In the experiments four variable pattern sizes were used: 1×1, 3×3, 5×5 and 7×7 (Figure 3.). In the per-pixel process, the number of input nodes was dependent on the number of bands, but in the 3×3 subpattern size window it must be increased by 9 neurons (matrix of 3×3) or 25 neurons (5×5), or 49 (7×7). To define the number of hidden nodes the formula 3Ni+1 was used. Each class was classified separately (the value of training land cover polygons takes 1, and rest 0). The learning parameters were obtained from Kavzoglu and Mather (4) papers: the initial weight range [-0.25, 0.25], learning rate 0.2, number of training samples 2500. Trained neural nets were tested on the area shown in Figure 4 as Test.

The accuracy was measured using ENVI software's algorithms based on test and training sets (prepared from ground mapping).

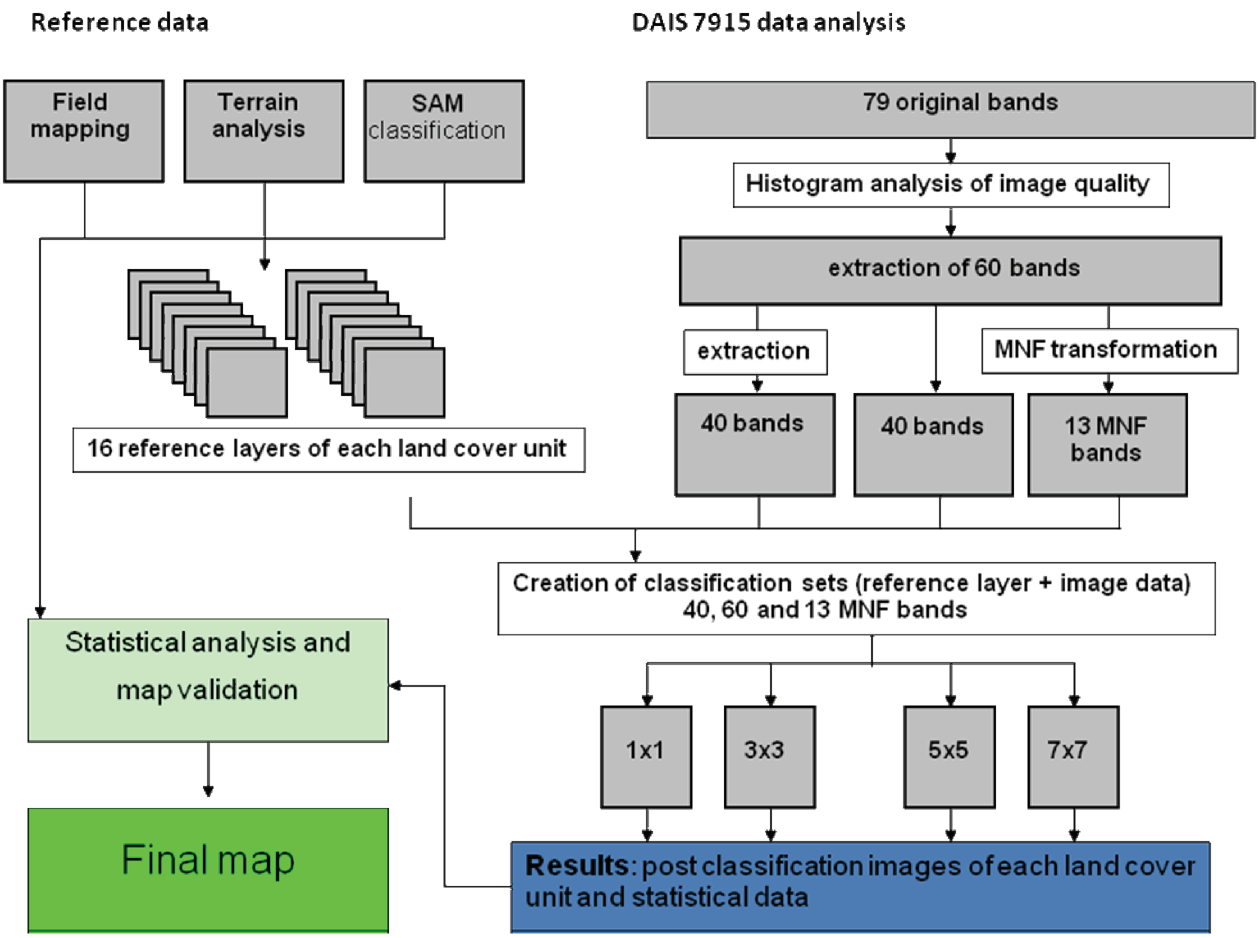

Figure 2: Workflow of the classification.

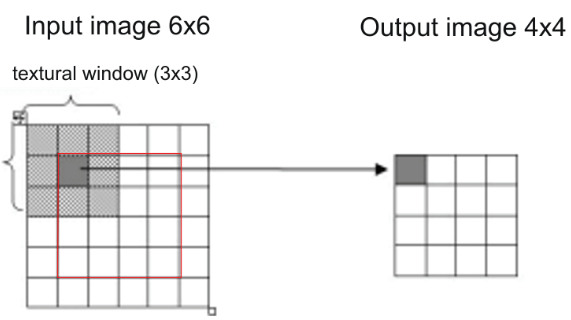

Figure 3: Variable size pattern (source: SNNS user manual; modified).

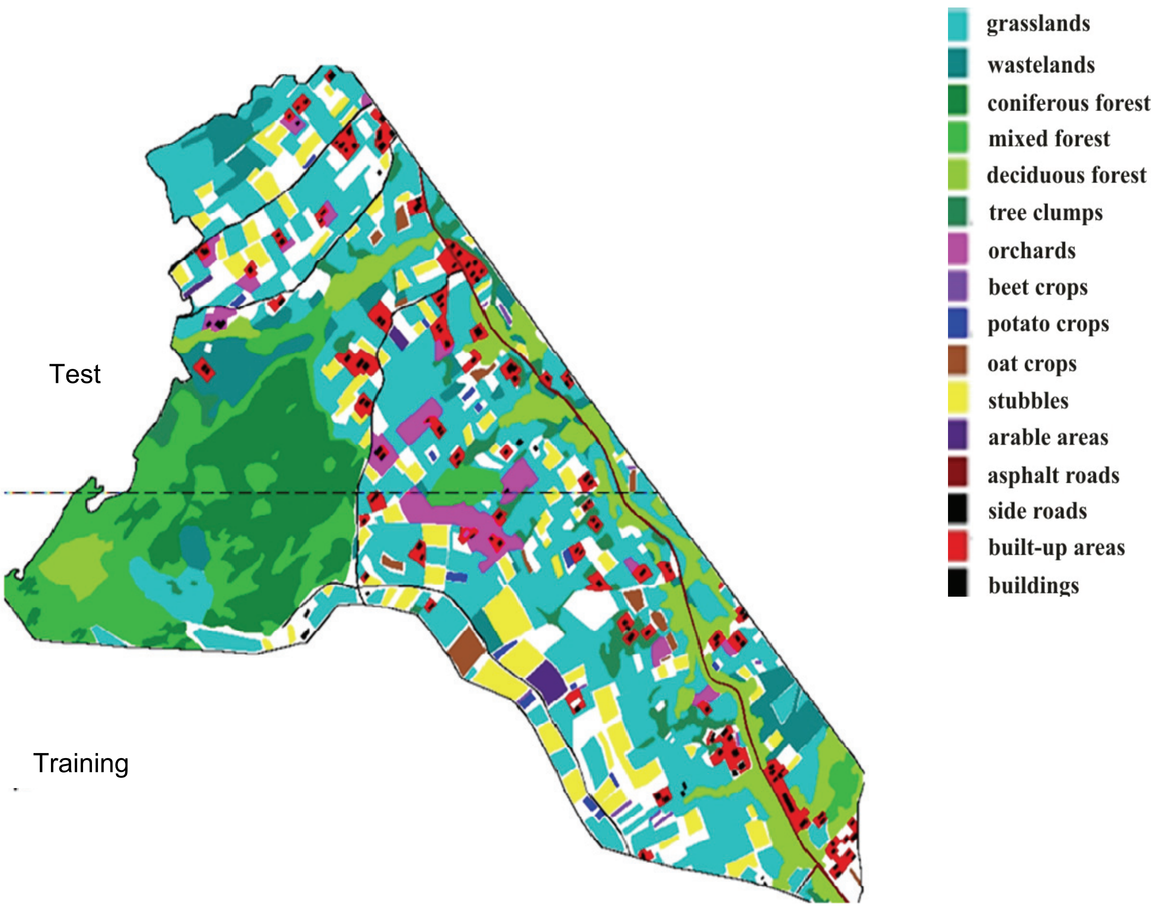

Figure 4: Teaching (Training) and validation (test) sets of the Wiatrowki key polygon.

RESULTS

All single land cover layers were merged to a map based on a higher probability of overlaying polygons (Figures 5, 6 and 7). The overall accuracy was measured pixel by pixel using the test and training reference layer as a basis (Figure 4). The final results of the Wiatrowki key polygon are shown in Table 1. Generally, the sixty-band set of input data offered higher accuracy (by more than 2%), and the 3×3 and 5×5 window size (including textural information) process gives better results than per-pixel (1×1) and 7×7 windows. In the case of 7×7 pixel's window, the smallest polygons were too much generalised. The textural window is better for heterogeneous land cover units. The increasing number of classified bands does not offer a significantly better total accuracy, but eliminates the worst results. In the case of 13 MNF bands sets the worst classification results were achieved in the range of 63-84%, and the best results 89.1%.

The percentage of classified pixels is relatively high: 88.4% for the Wiatrowki key polygon, (Biesnik N – 86.3%, and Biesnik S – 86.0%), because not all land cover patterns were created (e.g. small parcels, gardens or ecotones zones between forests, tree clumps and pastures or very heterogeneous polygons). Similar accuracy could be found by other workers, e.g. P. Mahesh and P. M. Mather (5) noted 87,1% basing on 13 MNF DAIS 7915 bands, and 92% for 65 original bands. The classification of 67 original and PCA transformed HyMap bands gave 92% (original bands) and 84,6 - 84,3% (PCA compressed) (6).

The best results are observed for oat crops (99.7 %), stubbles (96.7 %), grasslands (93.9 %), coniferous (92.8%) and deciduous forest (91.9 %); and the worst for tree clumps (58.4 %), orchards (65.3 %) and side roads (73.2 %). The use of a textural window (3x3 and 5x5) increases the classification accuracy.

Table 1: Overall accuracy of the Biesnik S, Biesnik N and Wiatrowki key polygons

Polygon		13 MNF bands				40 bands				60 bands			
		1×1 [%]	3×3 [%]	5×5 [%]	7×7 [%]	1×1 [%]	3×3 [%]	5×5 [%]	7×7 [%]	1×1 [%]	3×3 [%]	5×5 [%]	7×7 [%]
Biesnik N	Training	80,1	88,1	88,6	87,4	85,3	92,1	90,2	89,6	90,3	91,8	92,3	89,2
	Test	74,9	75,9	81,3	81,2	74,5	83,7	85,1	89,1	88,8	90,4	90,1	88,7
Biesnik S	Training	79,6	80,7	86,3	90,3	88,2	86,6	91,3	88,9	90,2	91,8	93,2	90,9
	Test	75,1	63,7	75,5	88,2	84,4	79,6	85,6	87,0	88,0	89,3	91,7	89,2
Wiatrowki	Training	80,6	90,8	90, 9	88,8	89,4	91,8	92,4	88,4	91,1	93,9	93,2	89,2
	Test	75,4	89,1	88,2	85,1	86,9	89,1	89,3	86,5	89,7	92,1	92,0	88,6

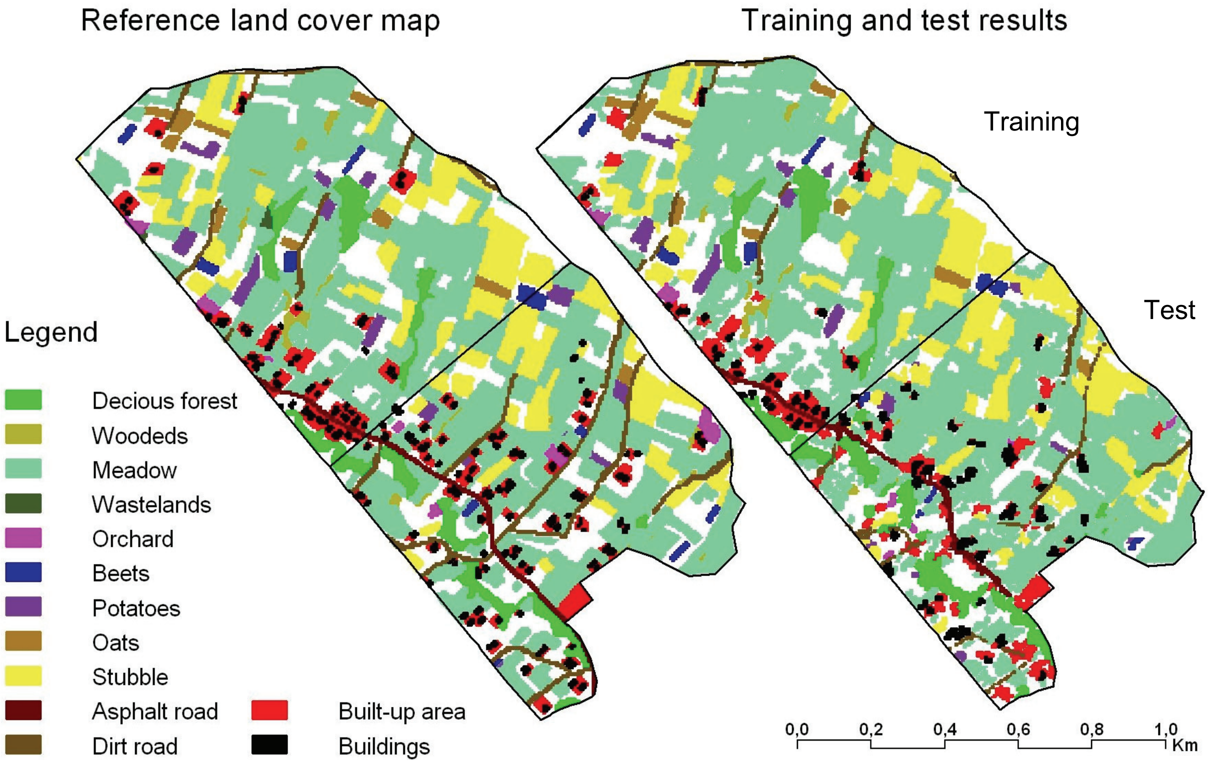

Figure 5: Classification results of the 13 MNF bands (3×3 textural window) of the Biesnik N key polygon.

CONCLUSIONS

The use of an artificial neural network is a proper method for land cover classification, and hyperspectral data showed significant potential for discriminating land cover types.

The achieved results oscillate around 89-92% (total accuracy). The worst results (64-75%) were observed for MNF transformed data. The classification of original bands offers 5-8% better accuracy.

A long training time is the most inconvenient aspect of this kind of classification, but the trained nets could be applied for other areas, and it is very easy to apply.

Textural windows are useful for heterogeneous land cover units and eliminate single pixels in post classification maps. In most cases, the 3×3 set gave the best results.

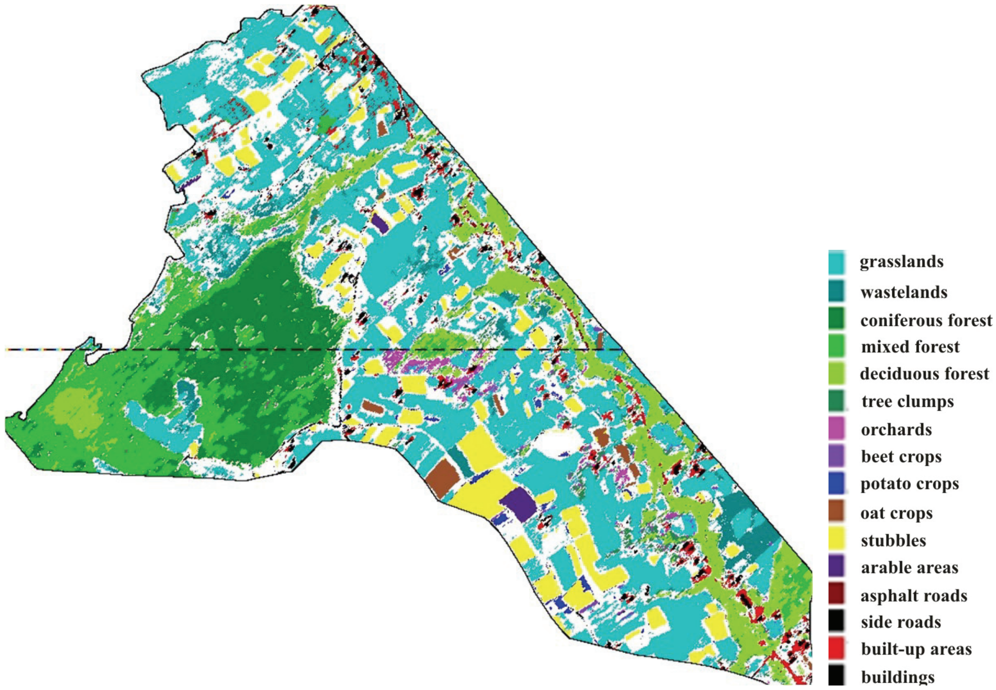

Figure 6: Classification results of the 40 bands (1×1 textural window) of the Wiatrowki key polygon.

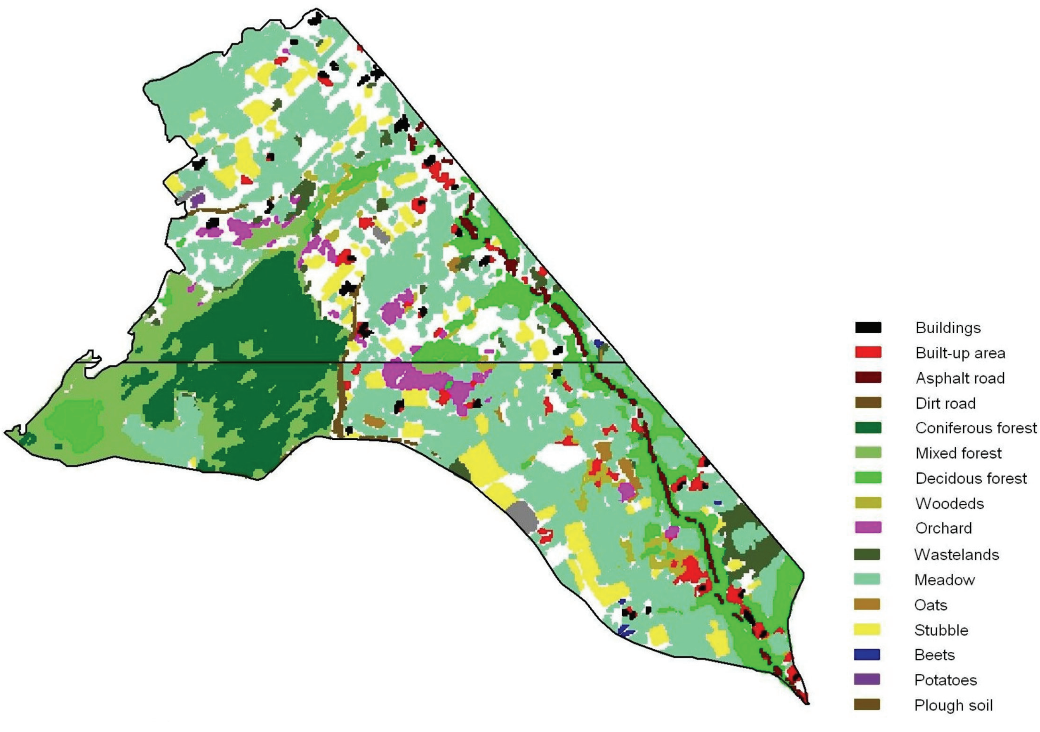

Figure 7: Classification results of the 60 bands (5×5 textural window) of the Wiatrowki key polygon.

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REFERENCES

1 Zagajewski B, A Kozlowska, M Krowczynska, M Sobczak & M Wrzesien, 2005. Mapping high mountain vegetation using hyperspectral data. EARSeL eProceedings, 4(1): 70-78

2 Zagajewski B & D Olesiuk, 2009. SAM and ANN classification of hyperspectral data of seminatural agriculture used areas. In: Remote Sensing for a Changing Europe. Proceedings of the 28th EARSeL Symposium, Istanbul, Turkey, June 2-5 2008, edited by D Maktav (IOS Press, Amsterdam, The Netherlands) 505-510

3 Zagajewski B & D Olesiuk, 2009 (in print). Classification of hyperspectral data of seminatural ecosystems. In: Proceedings of the 6th EARSeL Imaging Spectroscopy Workshop on *Imaging Spectroscopy: Innovative Tool for Scientific and Commercial Environmental Applications*, edited by E Ben-Dor, EARSeL and ISPRS Technical Commission VII (Tel Aviv, Israel) March 16-18, 2009

4 Kavzoglu T & P M Mather, 2003. The use of backpropagating artificial neural networks in land cover classification. International Journal of Remote Sensing, 24(23): 4907-4938

5 Mahesh P & P M Mather, 2006. Some issues in the classification of DAIS hyperspectral data. International Journal of Remote Sensing, 27: 2895-2916

6 Mader S, M Vohland, T Jarmer & M Casper, 2006. Crop classification with hyperspectral data of the HyMap sensor using different feature extraction techniques. In: 2nd Workshop of the EARSel SIG on Remote Sensing of Land Use & Land Cover, edited by M Braun (Bonn, Germany) 96-101 (last date accessed: 30.09.2009)