ACCURACY ASSESSMENT AND CLASSIFICATION EFFICIENCY OF OBJECT-BASED IMAGE ANALYSIS OF AERIAL IMAGERY

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ABSTRACT

Following text is focused on finding a proper balance between classification accuracy and classification efficiency of object based image analysis of aerial imagery. For image classification were used tools of Feature Analyst, an ArcGIS extension, which are based on image filtering and searching for homogeneous segments corresponding to the threshold values defined by the training areas and corrected with tools of object recognition.

The classification accuracy was assessed using the error matrices and calculating user's and producer's accuracy. To evaluate the time and work consumption, index of classification efficiency was introduced, which is a weighted value of accuracy and number of objects. To evaluate the tools of object recognition, the principle of fuzzy logic was used, which calculates accuracy with inclusion of alternative category.

For the study was used a cut of aerial imagery of protected area of Křivoklátsko as a typical example of the character of available image data in the territory of Czech Republic – large area of fields, forests and meadows with a very heterogeneous character, water body with sun reflection, net of narrow roads and small villages.

From the final values of accuracy is obvious, that Feature analyst provides comparable results with other authors. From the point of view of classification efficiency, application of tools of object recognition and its effect on the time and work consumption, it is a question of the extent of study area and the heterogeneity of the features of the physical world on the image data.

Key words: OBIA, accuracy assessment, feature analyst, classification efficiency, object recognition

1. Introduction

In the territory of the Czech Republic is aerial imagery currently the most accessible image data that can be used for mapping the land cover structure and its time-changes. The imagery covers the whole state territory in several time horizons (the oldest ones date back to the mid-20th century) in a detailed spatial resolution. Until recently, the evaluation process was based above all on a visual interpretation and manual vectorization. The development of image analysis methods has enabled particular automation and application of procedures.

The basic unit for an object based image analysis (OBIA) is a group of spatially related pixels with similar characteristics, which are joined by the process of segmentation until the classification criteria (shape, size, homogeneity) are met (Dobrovolný 1998). Through these methods, the image is divided into segments (objects) that relate to features in the physical world and correspond with features in the input image (Železný 2005).

The basic principle of object-based image analysis is the search for homogeneous areas within the image data. In this study were used the tools of Feature Analyst, an ArcGIS extension, to classify the aerial imagery. The tools are based on image filtering, during which the filter window searches through the image for homogeneous segments corresponding to the threshold values defined by the training areas. Classification runs together with the segmentation, and during one set of iterations all image areas which correspond to the given conditions (one class of land cover) are found.

Since the spatial delimitation of naturally homogeneous areas in the landscape, and therefore also in the image data, often do not match the individual areas of land cover, the classified vector features also do not correspond with features in the physical world.

Accuracy assessment is currently perceived as a fundamental component of the thematic classification of the image data, although a standard evaluation method has not yet been accepted (Foody 2002). The general potential of the accuracy evaluation was discussed, for instance, by Foody (2002 and 2006), and an evaluation of the result accuracy by means of segmentation and object-based image analyses by Bruzzone (2008) and Chmiel (2010).

Accuracy assessment is also often specified by the principle of fuzzy logic. Benz (2004) defined fuzzy logic as multi-valued logic quantifying uncertain statements. The basic idea consists in replacement of the two Boolean logical statements "true" and "false" with a continuous range of values in the interval <0,1>, where "0" means "false" and "1" means "true". All values between "0" and "1" represent a transition between the statements "false" and "true" (Benz et al. 2004).

This principle is used when interpreting analysis results, where a numerical value of affiliation degree to various categories of the analysis is assigned to the individual

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features. However, the principle is only used by analysis methods which first segment the image into homogeneous features, and in the second step classify all categories on the basis of training areas represented by segmented homogeneous features. The affiliation values are calculated by means of affiliation equations.

The classification accuracy depends mostly on the character of the imagery, on the definition of the training areas and on the number of the classification iterations. The specific value of accuracy (both producers and users) is calculated using the error matrices, where the area of correctly- and wrongly-classified objects is compared. In general – the better specified training areas and the higher number of iterations, the higher is the final accuracy but also the higher number of objects that correspond to one feature in the physical world and bigger time consumption. Because of that a proper balance between classification accuracy and classification efficiency must be found.

2. Study area

For the needs of this project, emphasis was put during the selection of the study area on the data representativeness with respect to the character of commonly available data sources. The selection of classification categories was aimed to the needs of a hydromorphological evaluation of the watercourses, which needs to evaluate, in addition to the basic categories of land cover, the presence of single trees and green belts on the banks and along the rivers.

As the study area was used a mosaic of two orthorectified aerial photographs taken above a protected landscape area in the Křivoklát region (near the village of Kalinova Ves) in the Berounka river basin. It represents a settled, rural landscape with a road network, a significant proportion of forest and green belts, and a watercourse with an alluvial plain.

The photographs were scanned in the spring 2003, with a spatial resolution of 1 m; the size of the processed area was 10 km^2 (2.5 × 4 km). There are only few overshadowed features and the image data is representative in term of the homogeneity of individual features. The aim was to determine the classification accuracy and efficiency of commonly available data, which is usually complicated by cast shadows, reflecting water bodies and heterogeneity within vegetation objects of the physical world and its change during the year seasons. The features are heterogeneous within one category of land cover as well as within the individual objects. Furthermore, the various categories are represented by a similar interval of the DN pixel values. Therefore, these categories coincided during the analysis.

On figure 1 is shows a cut-out of an aerial photograph, where the internal heterogeneity of the individual objects (fields are partly bare and partly covered with crops) and their mutual diversity (some fields have differently-grown crops, others are ploughed) is obvious. The similarity between various land cover categories is also obvious (e.g. roads x parts of ploughed field, or meadow x fields with crops, etc.).

Fig. 1 A cut-out of the aerial photograph of the study area

3. Methods

3.1 Image Analysis

The Feature Analyst extension works on the basis of defining the training sets delimited in the image. The image is classified and segmented in the same time while the filter window searches through the image for homogeneous segments corresponding to the threshold values defined by the training areas. During one set of iterations all image areas which correspond to the given conditions (one class of land cover) are found. It is possible to use a predefined settings for single land cover classes which takes into account the size, shape and homogeneity of searched features (e.g. long and narrow objects for the class “roads”). A user settings is also possible.

The objects classified according the training sets (spectral class) are however not identical with a class of the land cover (information classes). For example the spectral class “permanent herbage” can be further divided, e.g. into the information classes “meadows”, “gardens”, “parks”, etc. Or, on the contrary, the classes “red roofs” and “brown roofs” can be merged into the “built-up area” category.

In the second step objects can be automatically removed on the basis of the DN pixel values or by means of the characteristics of the object's shape and size. According to (Opitz 2008), the combination of methods that works with both spectral (radiometric) pixel values and spatial parameters is called "object recognition".

The individual categories were classified in several steps. In the first step, all image features which met the given conditions were selected on the basis of the definition of the training areas. In the following steps, the wrongly-detected features were removed, and the missing ones were added.

Except the "*water*" category, the analysis began with large and very heterogeneous objects and continued to tiny homogeneous objects. First was detected the Berounka watercourse and two small water bodies. The training areas for this class were defined so widely, that there were as few as possible final vector objects for the watercourse (the individual features displaying free water body, overshadowed water surfaces, rapids sections under the weir and reflecting surfaces were merged into one whole). It was also essential that the definition of water body features remained in contrast to the bank zone. The classification resulted in a layer of 936 objects, in which field and forest features were also delimited, in addition to the successful classification of the water bodies. Since only six features corresponded to the water bodies, the water bodies were exported into a single layer and the layer was removed from the vector mask for the next analysis. So it does not represent a real result of the classification, and therefore the user's accuracy was expected to be 100%.

Next, the forest features were analysed. In the addition to the forests were also delimited the features of green belts along the watercourses and the fields covered with crops. These wrongly-classified areas were removed by means of the shape and size characteristics of the object recognition (large homogenous forest features *vs.* small non-compact wrong features). The minimum area of the features was set as large as the built-up area could not be includeded into the layer (the DN pixel value of some roofs corresponds to the DN pixel value of forests).

As third was analysed the built-up area and the roads. The clutter was removed using characteristics of the size of the object recognition. By removing the roads layer from the vector mask were definitively separated the areas, which could otherwise be joined over a narrow road in one object (e.g. field – road – field, field – road – meadow, etc).

Then, the "field" land cover class was analysed. The fields in the study area had a very heterogeneous character at the moment of aerial scanning (Figure 1) and six different training sets had to be defined to detect all objects in the study area. Collision with the "meadow" land cover class occurred very often. Clutter was removed using characteristics of compactness and size by means of object recognition.

The "meadow" class was then analysed. Since other "green" areas had already been removed from the vector mask, the user's accuracy should have been 100%. The minimum classification area was set as large as the gardens were not included in this class.

The "green belts" class was analysed in order to detect the vegetation zones in the alluvium along the watercourses. This class was distinguished from the "single trees" on the basis of the size criterion.

Finally, the "garden" class was analysed. In this layer were included all remaining unclassified image areas. A total of 2,338 features were classified in this category, but the clutter could not be simply removed from the layer. Therefore alow value of user's accuracy can be expected in this category.

3.2 Accuracy assessment

The accuracy was assessed by comparing the areas of correctly- and wrongly-classified features from both points of view – the producer's and the user's. The producer's accuracy gives the probability with which the physical world feature (captured in the image data) is correctly classified. The user's accuracy gives the probability with which the vector feature corresponds to the physical world feature.

The classification accuracy was determined on the basis of two different approaches – one using the error matrix, and another error matrix based on a fuzzy evaluation according to Sarmento (Sarmento 2008). The fuzzy evaluation was based on the creation of a reference file of features, where to each feature was assigned two possible categories of land cover – the primary reference class and the alternative reference class.

The feature reference file was selected from the features set created by means of an unsupervised segmentation. The unsupervised segmentation works with the image data without setting the training areas, i.e. only according to the definition of the number of final classes, number of the iterations, and size of the minimum area. The unsupervised segmentation thus results in homogeneous image objects, whose degree of homogeneity is not defined by the user but results from the natural process of segmentation. On figure 2 are shown two examples of classification results and unsupervised segmentation of aerial imagery.

3.3 Classification efficiency

Internally heterogeneous features of physical world are mostly divided into several large correctly-classified objects and a high number of wrongly-classified, small-area objects. The final number of vector objects within one heterogeneous physical world feature depends on the precision of definition of the training sets. The more precise definition, the higher is the accuracy, but also higher number of the vector objects and bigger time consumption. To evaluate the time and work consumption, a classification efficiency index was defined (formula 1).

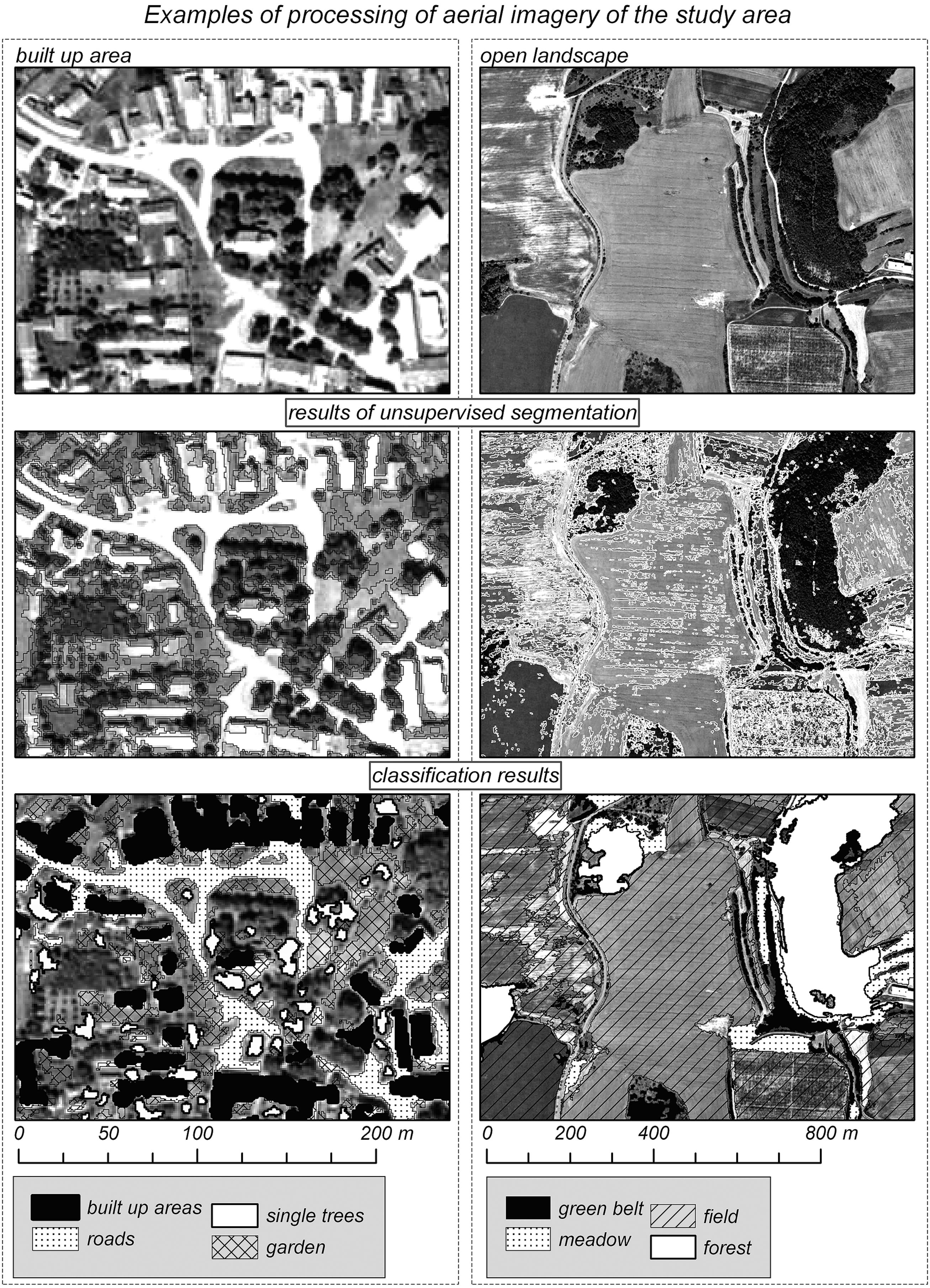

Fig. 2 Examples of processing of the aerial imagery

The index normalizes the frequency of the features by their area and is based on the principle of weighted values, which assigns different importance to the individual elements of the file. The assignment of importance can be viewed from two different points. The application of the index according to theof object frequency suppresses the importance of a large number of small-area objects and emphasises the importance of a small number of large objects. According to the object area, the small suma of areas of small objects is balanced by their high frequency, and the importance of large objects is decreased by their low frequency.

The formula (1) for the index calculation is as follows:

$$Obj(a) = \frac{n(a)\,\Sigma\, p(a)}{N\,\Sigma\, p} \cdot 100 \qquad (1),$$

where $Obj(a)$ is weight index of features in interval a,
$n(a)$ is number of features in interval a,
$p(a)$ are areas of features in interval a,
N is number of features in analysed file,
p are areas of features in analysed file.

The indices were calculated for single intervals (Table 1), inserted into error matrices (the frequency in the "a" interval was multiplied by the index of the "a" interval), and the producer's efficiency and user's efficiency were determined. For the calculation was used a data file created by removing the reference file features from the final file to provide the independence of the reference file The final file contains 6,135 features.

Tab. 1 Values of the index *Obj*(*a*) for individual intervals

Area interval	***Obj*(*a*)**
≤30 m²	0.1878
(30–50> m²	0.0839
(50–100> m²	0.177
(100–1,000> m²	0.7267
≥1,000 m²	5.8465

It must be stressed that this is not the classification accuracy. The final value includes the internal heterogeneity of features in individual categories (represented by the feature frequency) in addition to the accuracy, and therefore it also includes the efficiency and time consumption. The "efficiency and time consumption" term means multiple definitions of the training areas and the whole classification procedure, until the physical world features are represented in the given category by the vector features as much as possible. The index is not exactly numerically expressed, but if the training areas and the analysis are correctly set, it can generally be said that the lower the user's accuracy, the higher the heterogeneity of the physical world features and the lower the classification efficiency, as well as the need for a higher number of training sets.

3.4 Accuracy assessment using the principle of fuzzy logic

In the case of processing with the Feature Analyst, where classification runs together with segmentation, the fuzzy logic principle has not been used for classification but rather for determination of the classification accuracy. The reason for using fuzzy logic consisted in the fact that the areas (which actually represent various categories of land cover) are represented in the image data by pixels in the same DN value interval, and in terms of processing and the search for image homogeneous areas, they are assigned to the same category. A typical example is the grown green parts of fields versus herbage areas in meadows and gardens. These areas can be distinguished by feature recognition on the basis of shape and size characteristics, but only to a limited extent.

These objects were thus detected correctly according to the definition of the training set; however, they did not belong to the classified category and it was not possible to remove them from this category using the tools of object recognition. For that reason was defined the alternative category, as the second possible classification category into which the object could be assigned, according to the training set. The use of the alternative category should help to evaluate the potential of the Feature Analyst for detecting the image homogeneous areas more precisely.

When determining the classification accuracy, the following values was assigned to the reference object:

- 1 if the feature was classified correctly,
- 0.5 if the alternative category corresponded to the character of the physical feature,
- 0 if the feature was classified wrongly.

By means of the contingency tables, error matrices were formed, and the producer's and user's accuracy were determined for all classification categories. The accuracy was calculated according to the frequency and the area of individual features. If the classification results did not correspond to the reference category but complied with the alternative category, only the half-value (both of frequency and area) was taken into account.

4. Results

4.1 Accuracy assessed by error matrices

Classification of aerial images of the study area resulted in a file of 6,459 vector objects, classified into 9 categories of land cover (hereinafter the "*final file*").

In the first part of classification, the image was searched for large features (forest, field, meadow, water bodies, green belts) and uniquely detectable features (roads, built-up area). The final layers for these catego-

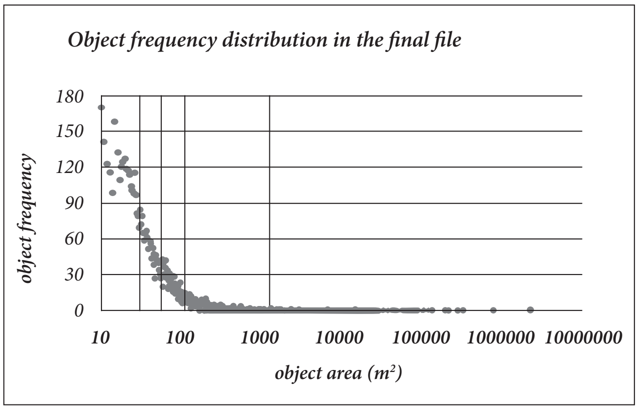

Fig. 3 Object frequency distribution in the final file, semi-logarithmic diagram with delimitation of limits of the size categories, the logarithmic scale was used for the category axis x

ries contain (in comparison with other categories) a small number of objects whose area is relatively large or close to the physical world features. For these categories, we can expect both the producer's and user's accuracy to be high.

In the second part of classification, the image was searched for small-area features (gardens, single trees), which are not typical in terms of their spectral reflectance, but are different due to their size and shape. Besides the searched features, so-called remaining areas (smaller areas in the middle of large heterogeneous features) were also assigned to these categories during the classification. The vector layers of these categories contain a large number of small-area features. The high number of "remaining areas" caused a low value of the producer's accuracy, while the user's accuracy was relatively high. This means that a high percentage of, e.g. gardens in the study area were identified correctly in the image, but a low percentage of vector objects classified as gardens, really are gardens.

The reference file intended for a comparison of results has traditionally been created by manual vectorization. In the case of this study area, the individual physical-world objects are internally heterogeneous, and therefore one physical object is represented by several vector objects. For the reasons of a better accuracy determination as well as time savings, the reference file was selected from the final file.

The selection of the reference file features was first limited by the object area (according to frequency distribution in both the final file and categories of land cover), and then were objects chosen randomly. The frequency distribution in the final file is displayed in the following semi-logarithmic diagram (Figure 3).

The frequency distribution was studied in five intervals with the limits of 30 m², 50 m², 100 m², 1,000 m², and over 1,000 m², which covered the whole interval of obtained values. The interval limits are marked (vertical lines) in figure 3, and were selected so that the number of features in eachinterval was equal, and corresponds to the specificity of the final categories. A percentage representation of the number of category features for the individual size intervals is provided in the following table 2.

A limit of minimum 5% was set for the selection of features from the final file for the reference file. A total of 324 features were selected for the reference file and the percentage representation varied within the individual categories (5–50%). For example, 50% of the features from the water body category were selected; however, this represented only three features. On the contrary, 108 features from the garden category were selected, representing, however, only 5% of all features classified as a garden.

The selection of the reference objects itself was run in the database table outside the ArcGIS workspace to avoid a preferential selection of wrongly- or correctly-classified features and the reference file was independent. Then was each object assigned to a correct classification category (according to aerial imagery), and by means of contingency tables were created error matrices (using the area

Tab. 2 A percentage representation (%) of the analysis categories, by size intervals, for the final file (*Ff*) and the reference file (*Rf*), with the number of features (*No.*) given for a random selection in the individual intervals

Size interval (m²)	≤30			(30–50>			(50–100>			(100–1,000>			≥1,000			Total		
Final file (*F*) / Reference file (*Rf*)	*Ff*	*Rf*		*Ff*	*Rf*		*Ff*	*Rf*		*Ff*	*Rf*		*Ff*	*Rf*		*Ff*	*Rf*	
Percentage share (%) / number of features (*No.*)	%	%	*No.*	%	%	*No.*	%	%	*No.*	%	%	*No.*	%	%	*No.*	*No.*	*No.*	%
Roads	2	3	3	5	4	2	5	5	3	11	9	6	10	5	2	344	16	5
Forest	0	0	0	0	0	0	0	0	0	1	3	2	16	27	11	73	13	18
Meadow	0	0	0	0	0	0	0	0	0	0.2	2	1	17	29	12	73	13	18
Field	0	0	0	0	0	0	0	0	0	2	6	4	38	24	10	192	14	7
Single trees	24	24	27	29	30	15	25	25	14	14	12	8	0	0	0	1,392	64	5
Green belts	14	13	15	29	30	15	26	25	14	30	26	17	13	7	3	1,416	64	5
Water body	0	0	0	0	0	0	0	0	0	0.2	3	2	1	2	1	6	3	50
Garden	59	59	66	30	30	15	22	23	13	22	20	13	4	2	1	2,337	108	5
Built up area	1	1	1	7	6	3	21	21	12	20	18	12	2	2	1	626	29	5

Tab. 3 User's and producer's accuracy and classification efficiency (all values in %)

	Roads	Forest	Meadow	Field	Single trees	Green belts	Water body	Garden	Built-up area
producer's accuracy	95	99	96	97	78	95	99	76	96
user's accuracy	93	96	100	99	44	92	100	52	98
efficiency – producer's view	87	93	72	84	70	79	95	73	93
efficiency – user's view	86	72	100	89	47	81	100	40	98

Tab. 4 Accuracy assessment using the alternative categories, values in %

	Roads	Forest	Meadow	Field	Single trees	Green belts	Water body	Garden	Built-up area
producer's accuracy	100	93	98	95	97	95	100	78	100
user's accuracy	94	66	95	100	87	100	100	79	84

of objects) and calculated producer's (hereinafter PA) and user's accuracy (hereinafter UA).

In the categories classified in the first part (forest, field, meadow, water bodies, green belts, roads and built-up area) were reached values of more than 90%, while the categories that included a high number of remaining areas reached relatively lower values. All values are written in table 3.

Classification efficiency was calculated also using contingency tables and error matrices, but the area of the objects was weighted by the quantity of objects according to formula 1. Values of efficiency from the producer's and user's point of view are written in table 3.

4.2 Accuracy assessment using the principle of fuzzy logic

For accuracy assessment was used the result of unsupervised segmentation. This divides the image into homogeneous features on the basis of definition of the minimum area size, number of classification categories, size and shape of the input representation, and number of iterations. The result of the unsupervised analysis is represented by objects that should be internally homogeneous and should represent (or should be a part of) only one physical world feature.

A total of 60,156 objects were created, from which was selected a reference file consisting of 263 objects with identical frequency distribution in the size intervals (analogously to the selection of the reference file described above). To all objects in the reference file were then assigned the results of classification by Feature Analyst, the reference category according to image data, and the alternative category. Accuracy values are given in the following table 4.

5. Discussion

The number of reference features is always limited within the study, and is mostly a compromise between the most accurate evaluation possible and time efficiency (Grenier 2008). The particular numbers are from within tens and hundreds of reference samples. For example, Huang (2008) used 257 reference features, and Xiaoxia (2005) determined the accuracy on the basis of 65 checkpoints. The potential for the exact determination and calculation of the minimum number of reference points was discussed in detail by Grenier (2008).

The accuracy of object-based analyses of aerial imagery by the Feature Analyst extension mainly depends on the character of the analysed data. The homogeneity of individual areas is affected by vegetation season, overshadowed of the objects, and the sun reflection in the water bodies. The second important factor is the selection of the classification categories and correct definition of the training areas.

The above mentioned conditions influenced especially the number of final objects within one feature of physical world and within a category, and time and work consumption. Therefore the number of objects was included in the calculation of classification efficiency as a weighted index.

As for the accuracy assessment, in the main analysis categories were achieved values of 90% for both producer's and user's accuracy. As to the "single trees" and "gardens" categories, the producer's accuracies were 78% and 76%, and the user's accuracies 44% and 52%, respectively. Both categories were classified at the end of the analysis. Since they represent small-area features of various shapes and radiometric characteristics, it was not possible to easily remove the wrongly-classified objects from these categories using tools of object recognition. The values and number of reference objects are comparable with other authors (Table 5).

The highest differences of accuracy and efficiency values were noticed in the land cover categories with very heterogeneous character in the image data – forests, fields and meadows (Figure 2). These categories are in the image represented with a few large objects. From the point of view of time and work consumption it would be easier in a small-extent study area, to vectorise these land cover categories manually and run the classification for the categories with small heterogeneous objects in a masked-out extent.

In the comparison of accuracy assessment with and without alternative category were noticed the highest differences in the categories "forest", "garden" and "single trees", whereas trees in the forests were often classified as

Tab. 5 Comparison of the analysis results with other authors, *the author analysed the data by means of Feature Analyst extension

	Study area		Honková (2006)		Huang (2008)		Xiaoxia (2005)		Rahman (2007)		Walker (2005)		Arroyo (2010)	Weih (2009)*	
	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	PA	UA
Roads	95	93	76	56	80	58	75	60						87	94
Forest	99	96	89	97							88	99	98	67–91	56–87
Meadow	96	100	75	53									49	91	84
Field	97	99	87	79									87		
Green belts	95	92	84	73											
Water body	99	100			90	100	100	91	100	100			83	90	100
Built-up area	96	98	54	79	76–100	82–100	80–100	67–80	97	80			99	86	86
Data source	Aerial RGB		Aerial BW		QuickBird		QuickBird		IRS P6 LISS III		Aerial RGB		Ultra Cam-D	various data	
Spatial resolution	1 m				MS, 2.44 m		0.7 m, pansharp		23.5 m		0.61 m		0.25 m		
Reference file	minimum 5% of class				257 ref. features		65 points (pixels)				500 points		50 points in class		

single trees, or garden. So the errors were caused rather by wrong object recognition than a wrong classification This also shows, that manual vectorisation of large heterogeneous objects would put more precise in the classification accuracy.

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REFERENCES

ARROYO, L. A., JOHANSEN, K., PHINN, S. (2010): Mapping land cover types from very high spatial resolution imagery: Automatic application of an object based classification scheme, GEOBIA 2010, Geographic Object Based Image Analysis, 29 June–2 July 2010, Ghent, Belgium

BENZ, U. C., HOFMANN, P., WILLHAUCK, G., LINGENFELDER, I., HEYNEN, M. (2004): Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing, 58 (3–4), 239–258.

BRUZZONE, L, PERSELLO, C. (2008): A novel protocol for accuracy assessment in classification of very high resolution multispectral and SAR images, In IGARSS, International Geoscience and Remote Sensing Symposium, 6–11 July 2008, Boston, Massachusets.

CHMIEL, J., FIJALKOWSKA, A. (2010): Thematic accuracy assessment for object based classification in agriculture areas: comparative analysis of selected approaches, GEOBIA 2010, Geographic Object Based Image Analysis, 29 June–2 July 2010, Ghent, Belgium.

DOBROVOLNÝ, P. (Ed.) (1998): Dálkový průzkum Země. Digitální zpracování obrazu. Masarykova univerzita, Brno, 208 pp.

FOODY, G. M. (2002): Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80, 185–201.

FOODY, G. M. (2008): Harshness in image classification accuracy assessment. International Journal of Remote Sensing, Vol. 29, No. 11, 3137–3158.

GRENIER, M. LABRACQUE, S., BENOIT, M., ALLARD, M. (2008): Accuracy assessment method for wetland object-based classification. In Proceedings GEOBIA, 2008 – Pixels, Objects, Intelligence: Geographic Object Based Image Analysis for the 21st Century, pp. 285–289.

HONKOVA, M. (2006): Extrakce informací o druzích povrchu z leteckých snímků, MSc thesis, Masaryk University, Czech Republic.

HUANG, L., NI, L. (2008): Object-oriented classification of high resolution satellite image for better accuracy. Proceedings of the 8th International Symposium on Spatial Accuracy Assessmen in Natural Resources and Environmental Sciences, Shanghai, China, pp. 211–218.

OPITZ, D., BLUNDELL, S. (2008): Object recognition and image segmentation: the Feature Analyst approach. In Object-based image analyses, spatial concepts for knowledge-driven remote sensing application, T. Blaschke, S. Lang, G. J. Hay (Eds.), pp. 153–167. Springer, Berlin.

RAHMAN, Md. R., SAHA, S. K. (2008): Multi-resolution segmentation for object-based classification and accuracy assessment of landuse/land cover classification using remotely sensed data. Journal of the Indian Society of Remote Sensing, Vol. 36, No. 2, 189–201.

SARMENTO, P., CARRAO, H., CAETANO, M. (2008): A fuzzy synthetic evaluation approach for land cover cartography accuracy assessment. The 8th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, 25–27 June 2008, Shanghai, China, pp. 348–355.

XIAOXIA, S., JIXIAN, Z., ZHENGJUN, L. (2005): A comparison of object-oriented and ixel-based classification approaches using QUICBIRD Imagery. Proceeding of XXXVI ISPRS meeting, 14–16 October 2005, Hangzhou, China, pp. 309–312.

WALKER, J. S., BRIGGS, J. M. (2005): An object-oriented classification of an arid urban forest with true-color aerial photography. Proceeding of XXXVI ISPRS meeting, 14–16 October 2005, Hangzhou, China, p. 6.

WEIH, R. C., RIGGAN, N. D. (2009): A comparison of pixel-based versus object-based land use/land cover classification methodologies. Available online at http://www.featureanalyst.com/feature_analyst/publications/Access/comparosin.pdf (accessed October 5, 2010).

ŽELEZNÝ, M. (2005): Dálkový průzkum Země. Available online at http://artin.zcu.cz/dpz (accessed December 12, 2009).

RÉSUMÉ

Přesnost a efektivita objektové klasifikace leteckých snímků

Článek se zabývá objektovou klasifikací výřezu leteckých snímků z území CHKO Křivoklátsko v okolí obce Kalinova Ves. Sledována je především přesnost objektové klasifikace v porovnání s její efektivitou, pracností a časovou náročností zpracování. Pro zpracování leteckých snímků byly použity nástroje extenze Feature Analyst pro ArcGIS, pracující na základě vyhledávání homogenních ploch v rámci obrazu, které odpovídají kriteriím nastaveným pomocí trénovacích ploch a pomocí tzv. rozpoznávání objektů.

Přesnost klasifikace byla stanovena pro jednotlivé sledované kategorie krajinného krytu pomocí kontingenčních tabulek a chybových matic na základě referenčního souboru objektů, který z hlediska počtu a velikosti objektů odpovídal rozložení objektů v jednotlivých kategoriích. Byla sledována přesnost jak z hlediska uživatele (zda všechny vektorové objekty, které reprezentují objekty reálného světa v rámci jedné kategorie, byly klasifikovány správně), tak z hlediska zpracovatele (zda objekty v rámci jedné kategorie byly klasifikovány správně). Zároveň byl definován index efektivity, který přesnost klasifikace váží počtem objektů v rámci kategorie, čímž je do výpočtu zahrnuta i pracnost a časová náročnost zpracování.

Přesnost klasifikace byla rozšířena i o tzv. alternativní kategorii využívanou v rámci fuzzy principu, tedy druhou možnou kategorii, do které mohl být objekt zařazen s ohledem na radiometrické hodnoty definované pomocí trénovacích ploch. Porovnáním výsledků přesnosti klasifikace se započtením alternativní kategorie a bez jejího započtení je možné posoudit úspěšnost rozpoznávání objektů v jednotlivých kategoriích.

Z hlediska zpracování je možné rozdělit výsledné kategorie krajinného krytu na kategorie, které jsou tvořeny několika velkými plochami s heterogenním charakterem na obrazových datech (pole, les, louky), kategorie, které jsou tvořeny velkým počtem plošně malých objektů s radiometricky homogenním obrazem (komunikace, zastavěná plocha), a kategorie, které mají podobnou radiometrickou definici jako jiné kategorie a je možné je identifikovat pouze pomocí funkce rozpoznávání objektů (zahrada vs. louka, telené pásy podél toků vs. les).

Obrazově heterogenní kategorie byly klasifikovány v první fázi a pro následné zpracování byly z klasifikační masky odstraněny. Z porovnání přesnosti se započítáním alternativní kategorie, přesnosti bez jejího započítání a s efektivitou klasifikace vychází, že z hlediska pracnosti a časové náročnosti (s ohledem na rozsah zpracovávaných dat) je vhodnější vytvořit vektorový obraz těchto kategorií pomocí manuální vektorizace. Oproti tomu plošně malé a radiometricky homogenní objekty jsou poté v obrazových datech identifikovány bez pracného několikanásobného definování trénovacích ploch, časově náročné vícenásobné iterace a rozpoznávání objektů. Z hlediska přesnosti zpracování jsou výsledky dosažené pomocí extenze Feature Analyst porovnatelné s výsledky, které byly dosaženy v pracích jiných autorů.

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