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IMPLEMENTATION OF SEMI-AUTOMATED OBJECT-BASED IMAGE LAND COVER CLASSIFICATION METHODS: A CASE STUDY OF THE MALÉ KARPATY MTS. (SLOVAKIA)

Marián Gábor*, Lukáš Karlík, Vladimír Falťan*, František Petrovič*****

* Comenius University in Bratislava, Faculty of Natural Sciences, Department of Physical Geography and Geoecology, Mlynská dolina, Ilkovičova 6, 842 15 Bratislava, Slovakia, gabor9@uniba.sk, vladimir.faltan@uniba.sk

** Comenius University in Bratislava, Faculty of Natural Sciences, Department of Regional Geography, Planning and Environment, Mlynská dolina, Ilkovičova 6, 842 15 Bratislava, Slovakia, karlik@fns.uniba.sk

*** Constantine the Philosopher University in Nitra, Faculty of Natural Sciences, Department of Ecology and Environmental Sciences, Tr. A. Hlinku 1, 949 74, Nitra, Slovakia, fpetrovic@ukf.sk

Implementation of semi-automated object-based image land cover classification methods: a case study of the Male Karpaty Mts. (Slovakia)

The semi-automated object-based image classification (OBIA) has recently become a key method in land cover mapping. Our study demonstrates this robust procedure using OBIA analysis obtained by LANDSAT 8. The advantages of this classification system include time-efficiency and images of greater detail with the same quality as a manual interpretation. A delineation algorithm was created in the Malé Karpaty Mts. with 93.6% overall accuracy and 0.81 Kappa coefficient. Our process was based on multiresolution segmentation that was created on 4 hierarchical levels, with emphasis placed on the expected segmentation result and classification with the following applied spectral indices: the normalized differenced vegetation index, simple ratio index and built-up area extraction index. We delineated 11 dominant land cover classes of the Malé Karpaty Mts. on the 4^{th} hierarchical level of our classification, with emphasis on forest and semi-natural areas. This procedure was concurrently applied to other Western Carpathian ranges with the best overall accuracy determined at 78.4% in the Slanské vrchy Mts., 74.16% in the Tríbeč Mts., and 73.1% in the Považský Inovec Mts.

Key words: Landsat 8, spectral index, multiresolution segmentation, hierarchical classification, Western Carpathians, Slovakia

INTRODUCTION

The results of land cover and land use mapping are useful both in landscape planning practice and in various fields of research. For example, Hussain et al. (2013), Grekousis et al. (2015) and Jovanović et al. (2015) presented actual analysis of land cover and landscape changes. Land cover maps are important also in forestry research (Asner et al. 2006), e.g. in the evaluation of vegetation damage caused by the bark beetle (Havašová et al. 2015), in the investigation of agricultural landscape changes (Alcantara et al. 2012 and Blasch et al. 2015), and in climate change evaluations (Keegan et al. 2014).

In terms of land cover mapping, land remote sensing (LRS) has more advantages and is financially more efficient than a field survey. The results can repeatedly cover very large areas. Over the last few decades, the satellite and aerial photos have also been used more frequently for land cover mapping because of their availability and quality. This usage has also contributed to an increased availability and quality of Landsat and SPOT data, or MODIS and ASTER tools that are

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being used globally. Subsequently, the higher resolution 1999 IKONOS satellite images and the 2001 QuickBird and 2003 OrbView implementations began to be used. Thus, satellite images have replaced those from airplanes.

LANDSAT images are one of the most important sources for land cover mapping on a global scale (Bodart et al. 2011, Raši et al. 2011 and Chen et al. 2015), national (Castilla et al. 2014, Meng 2015 and Gounaridis et al. 2016) and regional levels (Lucas et al. 2007, Vieira et al. 2012, Ceccarelli et al. 2013, Zulkarnian et al. 2013 and Tengyun et al. 2016). Ikonos imagery is frequently utilized for mapping city areas on a small scale area (Bhaskaran et al. 2010), small shrub areas (Laliberte et al. 2004), mapping of habitats (Bock et al. 2005) and biotopes (Ehlers et al. 2003).

The two main approaches to the LRS data classification are the usual manual interpretation of images (Skokanová et al. 2012, Havlíček and Chrudina 2013 and Pazúr et al. 2015) and the novel semi-automated and automated classification (Blaschke 2005 and 2010, Dragut and Blaschke 2006, Blaschke et al. 2014, Gounaridis et al. 2016, Heremans et al. 2016, Khatami et al. 2016 and Yu et al. 2016). The second group of classification methods is divided into the supervised and unsupervised pixel classification (Heremans et al. 2016, Khatami et al. 2016 and Yu et al. 2016) and the object-oriented classification (Blaschke 2005 and 2010, Dragut and Blaschke 2010 and Blaschke et al. 2014). The basic assumption in spectrometric land cover analysis is that land types absorb solar energy uniquely and their spectral radiation is therefore different. Pixel classification based on automated categorization of all image pixels in land cover classes (Lillesand and Kiefer 1994), gave unsatisfactory results because of reduced classification accuracy, especially in urbanized areas with spectrally heterogeneous areas. Despite many efforts to innovate a pixel based classification, the existing problems of spectral uncertainties and mixed pixels (Forster 1983) have caused remote land sensing to change its classification paradigm from the spectral classification of pixels to object based image classification (OBIA). OBIA is the classification of objects – grouped pixels based on spectral, spatial, textured, relation and contextual methods. It is based on homogenous regional segments which arose from merged imaging pixels gained from LRS. OBIA is formed of processes bound to obtaining these object segments and their attributes, on analysis of these segments and their classification, and eventually on proven classification accuracy and removal of post classification errors. The development of semi-automated OBIA classification techniques offers the potential to significantly improve the existing manual land cover mapping techniques, especially when combined with a degree of visual interpretation to create a "hybrid" approach to land cover identification.

Besides a land cover classification, OBIA is also used in others fields of research, e.g. geomorphology (Dragut and Blaschke 2006 and Bertani et al. 2013), landslide mapping (Blaschke et al. 2014) and biogeography (Bock et al. 2005, Lucas et al. 2007, Asner et al. 2009 and Skidmore et al. 2015).

Land cover is defined as the material demonstration of natural and socio-economic processes affecting land use on the earth´s surface. It is spatially differentiated on the basis of physiognomic and morphostructural elements; and it documents the processes in land change intensity. Identification of land cover is the foremost condition required in land use analysis, its causes and consequences, the evaluation of human impact on land, as well as for the consequent solution to ecological stability (Bossard et al. 2000).

Since 1991, Slovakia has been party to the CORINE Land Cover project (CLC). This became the first comprehensive, harmonized and the most important classification of land cover in Europe (European Environmental Agency – EEA 1999). According to the first mentioned classification, maps of land cover for European countries were made by manual image interpretation (Bossard et al. 2000).

OBIA methodology has been used for more than 20 years, but in Slovakia, manual image interpretation methodology within land cover classification still prevails. The aim of this study is to design the algorithm of OBIA land cover model and modify the parameters of the classification model on four levels of the classification tree for a case study of the Malé Karpaty Mts. Consequently, we will present the transition of the model to other similar mountain areas (Považský Inovec, Slanské vrchy and Tríbeč) in the Western Carpathian mountain range.

DATA AND METHODS

Study area

The study area comprises the Malé Karpaty Mts., geomorphological unit of the Western Carpathians, with prevailing natural and semi-natural landscape. It represents its two subunits, the Devínske Karpaty Mts. and the Pezinské Karpaty Mts. (Fig. 1).

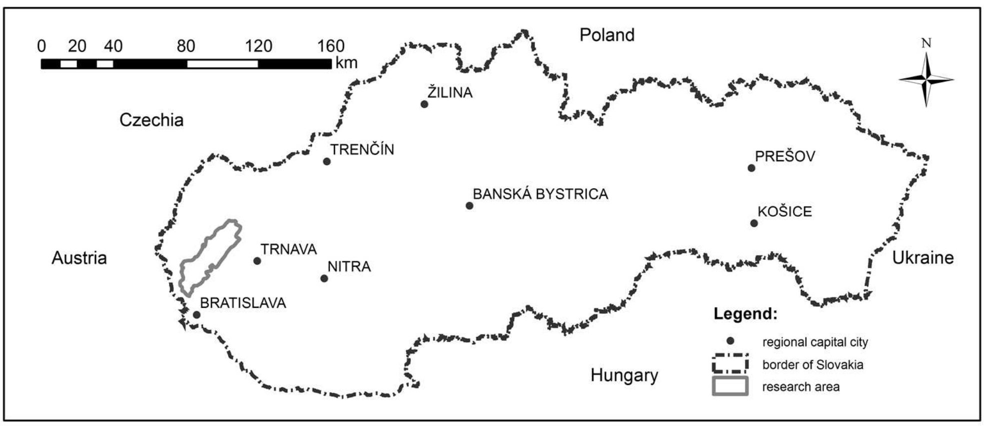

Fig. 1. Localization of the study area in Slovakia

Data

The input data came from the Landsat 8 satellite image taken on 19th July 2015. Data set was obtained from the United States Geological Survey's (USGS) National Center for Earth Resources Observation and Science at full (30 m) spatial resolution (USGS 2015).

Methods

Land cover delineation based on OBIA is divided into the following steps: data preprocessing, legend creation, spectral indexes calculation and delineation of formerly created land cover classes. Multiresolution-segmentation is realized on each level, always with another value scale parameter. Objects in the formerly created hierarchical structures are then classified according to spectral and spatial provisions (Burnett and Blaschke 2003).

Data preprocessing

Data preprocessing was conducted by the conversion to top-of-atmosphere reflectance (TOA_λ – Bodart et al. 2011). While these authors recommended using cloud and cloud shadow masking to remove clouds and avoid their influence, this provision was unnecessary because we focused on cloudless images. Radiometric calibration by Chander et al. (2009) reduced differences in the altered illumination conditions and also instrument errors, with the first calibration step requiring the conversion of raw digital number (DN) into at-sensor-spectral-radiance ($Lsat_\lambda$) for each band, as in the following formula:

$$Lsat_\lambda = g_\lambda * DN_\lambda + o_\lambda,$$

where g_λ and o_λ are the band specific gain and offset factors.

The available metadata file provided gain and offset factors, and at-sensor radiance was converted into top-of-atmosphere reflectance according to:

$$TOA_\lambda = \frac{\pi * Lsat_\lambda}{ESUN_\lambda * \cos\sigma_s},$$

where $ESUN_\lambda$ is the mean solar exoatmospheric irradiance obtained from (USGS 2015) and the solar zenith angle (σ_s) was derived from the sun elevation angle provided in the satellite scene's metadata.

Hierarchical legend creation

We used modified CLC legend on four hierarchical levels (Feranec and Oťaheľ 1999). Modification was important both for the character of the study area and the resolution of input data. The hierarchical classification was chosen because of the previous authors' successful results (Burnett and Blaschke 2003, Laliberte et al. 2004, Wehrmann et al. 2004, Bock et al. 2005, Lucas et al. 2007, Stanková 2010, Malinverni et al. 2011, Bertani et al. 2013, Machado et al. 2014 and Beltrame et al. 2014). Figure 2 highlights the hierarchy of classes and describes basic identification factors. Image quality (negating small area patterns) limited land cover class identification. The first hierarchical level of the legend was based on morphostructural and physiognomic features. In following levels of interpretation, the land cover unit of the study area were classified into 11 types (Tab. 1).

Tab. 1. Description of modified land cover legend on 4th hierarchical level

Broad-leaved forests with discontinuous canopy	Areas of broad-leaved forest forming a discontinuous canopy (less than 80%), locally with coniferous forest smaller than the minimal mapping area
Natural young stands	Areas of young stands after cutting, stage of natural forest regeneration, or areas formed by shrubs with dispersed trees
Grassland	Areas of meadows and pasture without trees and shrubs (less than 30%)
Forest tree line	Areas of forest tree line or small fragment of trees in cultural landscape
Urban and industrial areas	Built-up areas with apartment blocks or family houses, urban centers, industrial, commercial and transport units
Arable land	Areas of arable land with mixed types of agricultural plants
Permanent crops and grassland	Areas of permanent irrigated land (e. g. vineyards, orchards), meadows, pastures and complex cultivation patterns with scattered houses
Clear cuts	Areas of glades before planting trees, cutting area
Water bodies	Water areas of natural origin or created by man with prevailing regular shape
Open cast mines	Areas of open gravel mine

Spectral indexes calculation

Spectral indexes are more effective tool for delineating land cover classes, compared to satellite image bands. Texture indexes were tested by the tool sample editor in eCognition software, however the resulting values have not reached satisfactory results. Following spectral indexes were computed and applied here in the land cover class identification:

$NDVI = (NIR–Red)/(NIR+Red)$

NDVI (Normalized differentiation vegetation index) is a widely used vegetation index mainly for the green vegetation detection from other areas (Rouse et al. 1974). However it is also used for ravine mapping (Blaschke et al. 2014) and for land cover change mapping (Jovanović et al. 2015).

$SRI = (NIR/Red)$

SRI (Simple ratio index) is used to differentiate vegetation in a worse condition than healthy vegetation (Tucker 1979). *SRI* is used to differentiate forests with thicker treetop canopy from forests with thinner canopy (Stenberg et al. 2004).

$BAEI = (Red+0,3)/(Green+SWIR1)$

BAEI (Build-area extraction index) is used for differing the built-up areas from other land types (Bouzekri et al. 2015).

Classifying of land cover classes

Multiresolution-segmentation is a bottom-up technique which merges the most similar adjacent regions, and this approach was used for each algorithmic level of object creation (Baatz and Schäpe 2000). This commences with pixels, provided that the internal heterogeneity of the resulting object does not exceed the user defined scale factor threshold (Benz et al. 2004). The multiresolution-segmentation was achieved with eCognition software (Definiens 2007). We tested the scale parameter rating from 1 to 25 in every segmentation, although the best object primitives were achieved in ratings less than 5 which satisfied the minimal mapping area.

Segmentation with the highest NDVI significance was performed at the first level to differentiate forest and semi-natural vegetation from other areas (Figure 2). Different scale parameter levels were then tested until the created borders corresponded with the real borders between required first level classes.

First level outputs were subsequently used as inputs for second-level segmentation and classification, and the following two parallel segmentations were obtained: 1) Segmentation of forest and semi-natural patterns, and 2) artificial, agricultural and water-bodies patterns. These were later determined by both NDVI and PAN (panchromatic satellite image band), where NDVI provided patterns with and without vegetation, as in water-bodies and quarries, and the PAN is an auxiliary factor clearly delineating quarries from surrounding segments. After visual testing, the second level objects were classified.

Second level classes were parallel segmented for third level classification as follows: 1) second level forests objects were added to deciduous forests; 2) classes of semi-natural patterns were again segmented with higher NDVI values (Fig. 2); 3) parallel segmentation of artificial and agricultural patterns was then obtained. The creation of segments securing precise delineation of built-up areas, agricultural land and clear cut objects was defined in higher NDVI and BAEI index values.

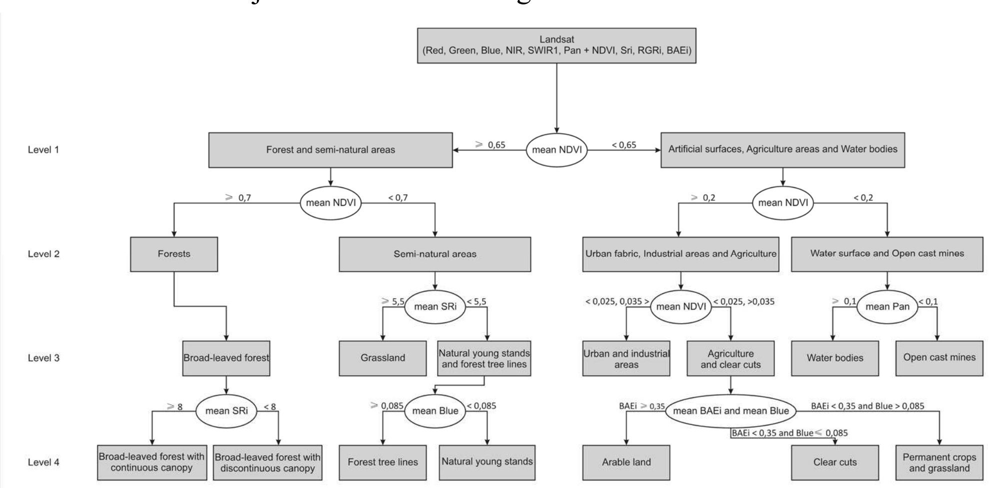

Fig. 2. Flowchart picturing hierarchical work layout

The fourth classification level contains objects further divisible by satellite image input. Segmentation of deciduous forests was defined by the highest SRI value with object demarcating borders between forest with continuous and discontinuous canopy. These objects were then classified. Initial segmentation divided permanent crops, meadows and clear cuts, so that clearing objects could be classified separately. The remaining urbanized and technical pattern were then segmented, with special emphasis on the green band with the clearly delineated border between urbanized and technical patterns and arable land. Figure 2 clearly highlights this classification scheme.

Accuracy assessment

The overall accuracy and the Kappa coefficient quantified individual land cover class accuracy. This is based on the supposition that land cover manual interpretation provides optimal classification. The Kappa coefficient indicates the classification accuracy of each individual class and compares individual class differences in distinct classifications (Alcantara et al. 2012, Vieira et al. 2012, Bertani et al. 2013, Hussain et al. 2013, Machado et al. 2014 and Meng 2015). Error maps are then generated to explore differences in spatial distribution between classifications. Accuracy assessment values resulted from creating a test area and training mask (TTA), this latter mask emanated from the official 2012 European Union CORINE land cover database which covers the entire study area.

RESULTS AND DISCUSSION

We present land cover maps on 4 hierarchical levels, where each map depicts one classification level (Fig. 3). Results highlight how a satellite image can be used to create an environmental data set without the need of field survey data. These data sets form the basis for delimitation of forest, agricultural and artificial areas and provide a baseline understanding of the environment, which will ultimately influence management decisions. A total of 11 land cover classes were depicted. Although input data quality did not enable us to delineate classes close to one pixel in size, the images form a very important source for land cover mapping on all levels: global (Bodart et al. 2011, Raši et al. 2011 and Chen et al. 2015), national (Castilla et al. 2014, Meng 2015 and Gounaridis et al. 2016) and regional (Lucas et al. 2007, Vieira et al. 2012 and Tengyun et al. 2016). In addition, the 30m middle resolution level prevented mapping of very small land cover classes and their changes; for example green mosaics in urbanized and technical areas (Qian et al. 2015). However, this problem is not restricted to semi-automated land cover definition, it also occurs in the manual interpretation of satellite and aerial images prevailing in the land cover mapping of our region (Pazúr et al. 2015).

Analysis accuracy evaluation based on data gained from manual image interpretation (Machado et al. 2014 and Khatami et al. 2016), supplemented by field survey, where appropriate (Laliberte et al. 2004). Here, we used an existing database, comparing accuracy with land cover classes identified in 2012. The overall accuracy in the Malé Karpaty Mts. on the 4th hierarchical level was determined at 93.6% with a kappa coefficient of 0.81. These values have the same or greater accuracy compared to other authors' results, where for example: Bock et al. (2005) reported 86.19% overall accuracy and 0.80 Kappa; Vieira et al. (2012) results were 94% and

0.87; Hussain et al. (2013) recorded 93.99% and 0.87; Machado et al. (2014) had 71.4% and 0.68 and Meng´s (2015) results were 90% with Kappa close to 1.

In a detailed view of each class of land cover the highest accuracy of 100% was achieved in open cast mine and water areas. Forest areas follow with an accuracy of more than 98%, permanent crops and grasslands with an accuracy of 85%. Natural forest young stand's accuracy was 76%. The accuracy limited to 50% was achieved in urban and industrial areas, whereas the highest error was involved in permanent crops, which showed abnormal improvement in our case and associations of family houses with gardens were created. The lowest accuracy of 10% was achieved in arable lands, because it occurs in research areas partially.

While Fig. 3 herein highlights very close border correlations on 1st and 2nd hierarchical levels, the 3rd and 4th levels reveal deviations in similar classes caused by differences in image quality and almost identical spectral features in these classes. In this case, we could not use other features. Subjective evaluation is very interesting because manual interpretation led to 22 experts compiling different land cover maps (Albrecht 2010).

The classification algorithm was applied also to delineate land cover units in ranges with a similar climate and topography throughout the Western Carpathians. The best results are listed in Tab. 2 and selected land cover maps are shown in Fig. 4.

Tab. 2. Accuracy assessment of selected Western Carpathians Mountain ranges (in %)

Western Carpathians mountain ranges	1st hierarchical level	2nd hierarchical level	3rd hierarchical level	4th hierarchical level
Malé Karpaty Mts.	97.8	96.3	95.3	93.6
Slanské vrchy Mts.	88.7	87.8	81.8	78.4
Tríbeč Mts.	88.4	88.3	85.6	74.2
Považský Inovec Mts.	88.6	82.2	79.7	73.1

The advantages of semi-automated object-based classification (OBIA) are precision and repetition where one set of input data can successively delineate land cover borders without algorithmic change, whereas manual interpretation is dependent on the level of image interpretation knowledge and ability. This varies not only among authors (Albrecht 2010), but it is possible in repeated one researcher´s interpretation. Semi-automated methods also provide a detailed division of land cover legend and information on each hierarchical level while manual interpretation delivers non-hierarchical classification.

The overall accuracy in the following test was lower because the rule set was calibrated for the Malé Karpaty Mts. For higher accuracy, it is necessary to convert rule set for the selected mountain.

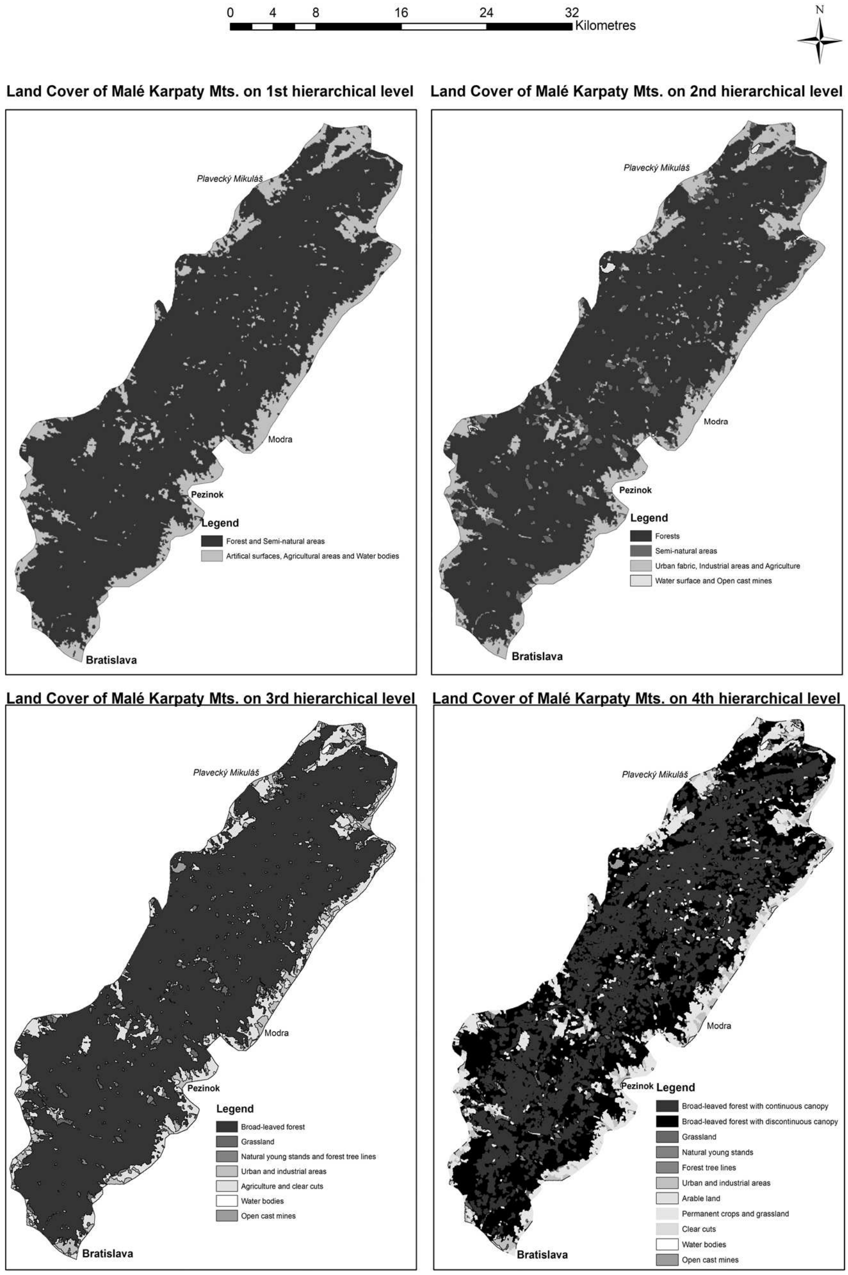

Fig. 3. Land cover maps of the Malé Karpaty Mts. on four hierarchical levels

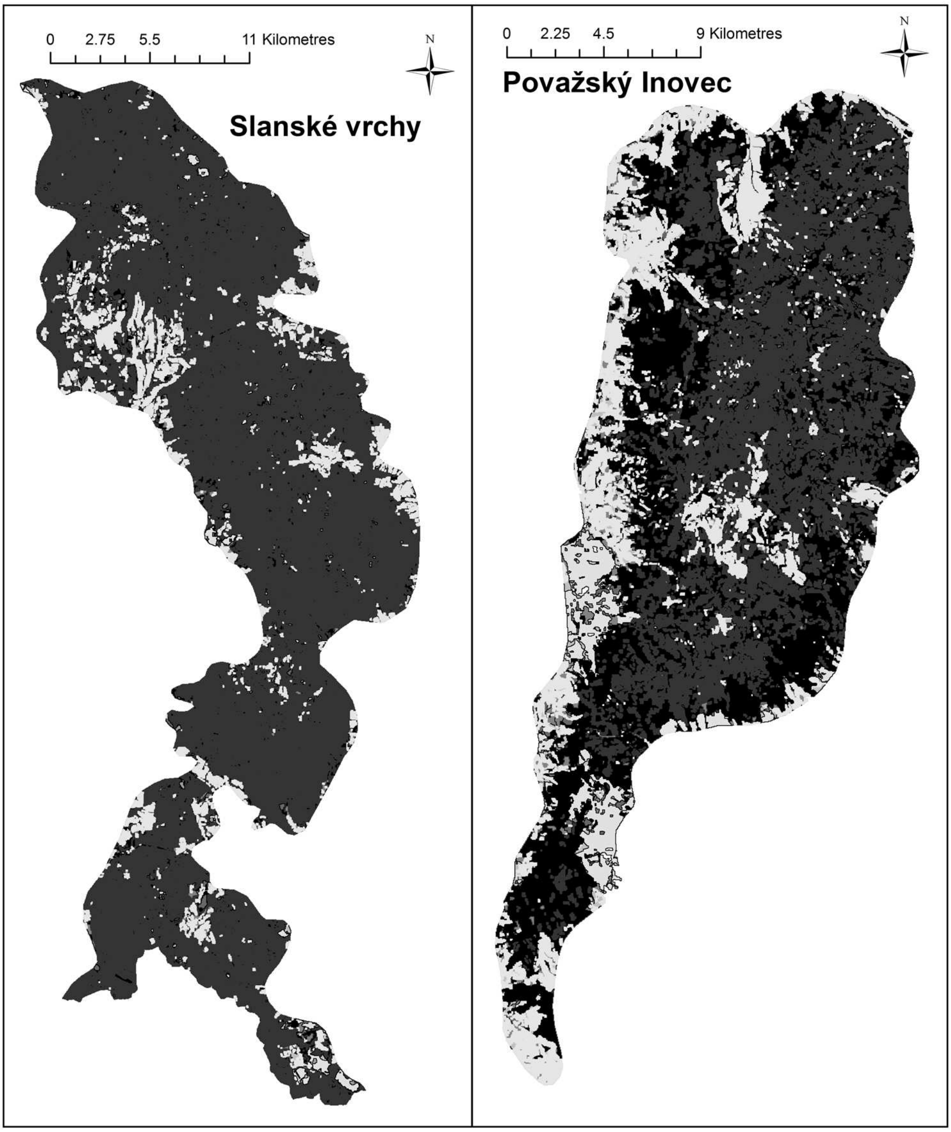

Fig. 4. Land cover maps of selected mountains on 4th hierarchical level, the legend is same with Fig. 3 (right below)

The OBIA approach has several individual steps in assigning defined parameters. Using a number of defined parameters to set up a set of classifying rules with the goal of gaining required results that are necessary for further analysis. On the other hand, it is necessary to realize that the flexibility of parameterization could cause the inability of applying a given set of rules on other datasets. This is caused by the fact that the performance of the spectral index depends on the spectral response functions of land cover characteristics. This characteristics vary from one region to another, due to climatic and topographic changes (Bouzekri et al. 2015). OBIA is reproducible but there are certain limits when a set of segmenting and classifying rules could be used. However, to preserve the accuracy of the results it is necessary to adapt some of the limit values of these rules and carefully approach to dataset selection for which we are planning to apply created rules. We agree with this statement of Khatami (2016): „Land-cover mapping is a complicated process with numerous factors influencing the quality of the final product. Some of these factors such as landscape complexity, target classes, and scale are usually predetermined by the project's requirements".

CONCLUSION

The article presents the semi-automatic OBIA method of mapping land cover from the Landsat 8 satellite image. OBIA classification was successfully achieved for four hierarchical levels of land cover. This methodology was employed in the summer of July/August 2015 imaging, when spectral, textural and contextual classification algorithms was developed for the classification of land cover without in situ data for training/calibration. OBIA designed for landscape of the Malé Karpaty Mts. achieved 93.6% overall accuracy (on the 4^{th} level), and it was also tested with positive results for other Western Carpathian mountain ranges with similar land use, geomorphology and bioclimate. This semi-automated method with its four hierarchical levels successfully classified from satellite image was compared to ortophoto imaging. The OBIA algorithm was subsequently tested in the Považský Inovec, Slanské vrchy and Tríbeč mountain ranges with satisfactory results. The use of spectral indexes (NDVI, SRI, BAEI) was appropriate and extremely beneficial in delineation of land cover classes.

In conclusion, the ability to divide the semi-automated object-based image classification approach into easy successive steps of data preprocessing, hierarchical legend creation, spectral index calculation and subsequent land cover class classification is its most attractive utility. The OBIA method thus provides the effective creation of more detailed maps which will improve land use and environmental planning.

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Marián G á b o r, Lukáš K a r l í k, Vladimír F a l ť a n, František P e t r o v i č

IMPLEMENTÁCIA POLOAUTOMATIZOVANEJ OBJEKTOVO ZALOŽENEJ METODOLÓGIE KLASIFIKÁCIE KRAJINNEJ POKRÝVKY NA PRÍKLADE POHORIA MALÉ KARPATY (SLOVENSKO)

Existujú dva hlavné metodické prístupy klasifikácie krajinnej pokrývky – tradičná (manuálna) a poloautomatizovaná, ktorú môžeme rozčleniť na pixelovú a objektovo orientovanú. Základným predpokladom analýzy krajinnej pokrývky prostredníctvom spektrometrických procesov je fakt, že rôzne typy krajiny pohlcujú slnečnú energiu rôznym spôsobom a ich spektrálne vyžarovanie sa preto líši. Objektovo orientovaná klasifikácia je založená na klasifikácii takzvaných objektov: zgrupovaní pixelov na základe spektrálnych, priestorových, textúrnych, vzťahových a kontextuálnych metód. Cieľom predkladanej práce bolo priblížiť nové trendy pri mapovaní krajinnej pokrývky použitím poloautomatizovanej objektovo orientovanej analýzy obrazu získaného satelitným snímkovaním LANDSAT-8 na príklade pohoria Malé Karpaty.

Tvorba legendy bola zameraná na čo najdetailnejšie možné zachytenie tried krajinnej pokrývky vyskytujúcich sa na území podľa legendy Corine Land Cover na 4. hierarchickej úrovni. Na identifikáciu jednotlivých tried krajinnej pokrývky boli formulované a aplikované viaceré spektrálne indexy (NDVI, SRI a BAEI), ktoré sú schopné v porovnaní so samostatnými kanálmi efektívnejším spôsobom vyhraničiť jednotlivé triedy krajinnej pokrývky.

Klasifikácia tried krajinnej pokrývky OBIA pozostáva z troch hlavných krokov, a to segmentácie, klasifikácie, overenia výsledkov a eliminácie chýb, pričom všetky tri kroky sme využívali na každej hierarchickej úrovni s cieľom maximalizovať presnosť výstupov. Na všetkých úrovniach práce bol zvolený algoritmus tvorby objektov známy v anglickej terminológií ako *multiresolution segmentation*, čo je proces spájania pixelov zdola-nahor. Uvedený algoritmus umožňuje spájať najpodobnejšie regióny až po situáciu, keď sa nedosiahne už prahová hodnota vnútornej heterogenity objektov definovaná faktorom mierky. Segmentácia bola vykonaná s ohľadom na parametre mierky, farby a tvaru požadovaných objektov, ktorý v sebe zahŕňa parametre kompaktnosti a hladkosti.

Výsledkom práce sú štyri mapy krajinnej pokrývky z územia Malých Karpát, pričom každá predstavuje jednu hierarchickú úroveň. Preukazujú využiteľnosť satelitných snímok pri tvorbe rôznych klasifikácií a databáz bez toho, aby bolo nutné vykonať terénny výskum. Presnosť klasifikácie bola porovnávaná s modifikovanou databázou CLC, ktorá bola použitá ako vstupná TTA maska.

Metodika bola pôvodne vytvorená na území Malých Karpát (celková presnosť klasifikácie na štvrtej hierarchickej úrovni 93,6 %), avšak pozitívne výsledky boli dosiahnuté aj v prípade ďalších pohorí s podobnými geomorfologickým a klimatickými vlastnosťami a podobným charakterom využívania krajiny.