Forest Mapping Through Object-based Image Analysis of Multispectral and LiDAR Aerial Data

Martin Machala* and Lucie Zejdová

Department of Geoinformation Technologies, Faculty of Forestry and Wood Technology,
Mendel University in Brno, Zemědělská 3, 613 00 Brno, Czech Republic
*Corresponding author, e-mail address: xmachala@mendelu.cz

Abstract
The objective of this research was to establish a set of rules for using Object-based Image Analysis (OBIA) to semi-automatically map a given densely forested area. Aerial images (RGB and NIR bands) and LiDAR elevation data provided the raw data and were analysed using eCognition Developer 8 software. All the non-forested areas, including built-up areas, water surfaces or agricultural land, were identified first. The forested areas were then classified as stands composed principally of broadleaf trees, coniferous trees, mixed forest or clear-cuts, which was achieved with an accuracy of almost 90%. Subsequently the stands were classified on the basis of height, using 5 metres intervals, and this was achieved with an accuracy of just over 70%.

Keywords: Object-Based Image Analysis (OBIA), eCognition Developer, image segmentation and classification, forest division mapping, LiDAR.

Introduction
The ever-growing amount of information acquired by remote sensing technologies requires increasingly sophisticated methods for its analysis. To extract the required information efficiently, several different approaches can be applied. Besides the classical visual interpretation followed by manual classification of the image data it is usually a widely-used per-pixel analysis [Ceccarelli et al., 2013]. Nevertheless, this conventional method is often found to be not sufficient, especially when applied on a Very High Resolution (VHR) imagery [Fisher, 1997; Towonshend et al., 2000; Kim and Madden, 2006; Myint et al., 2011]. With the continuously growing availability of the VHR imagery with the spatial resolution having pixel sizes significantly smaller than the average size of the object of interest, there grows also the need for reliable methods capable to classify them efficiently. As proved already in many studies, object-oriented approach offers an optimal solution for classifying such data [Marangoz et al., 2004; Kamagata et al., 2006]. This approach brings the ability to group relatively homogenous pixels into meaningful objects based on their radiometric values and then extract useful extra information such as size, shape, texture or contextual information. The human visual system can interpret high resolution data very easily and accurately, so if a truly accurate and robust automated land-use classification system is to be achieved, it must draw from
research in the area of cognitive psychology and attempt to model how we as humans interpret aerial imagery. This is the aim of research in the area of Object-based Image Analysis (OBIA) [Hay and Castilla, 2006; Corcoran et al., 2010]. Since the approach to image objects interpretation is highly subjective even for different skilled human operators [Gardin et al., 2011], the ascertained ordinarily used approaches of human visual interpretation have to be studied and tested so that their principles can be implemented subsequently into the OBIA algorithms and tools.

In forestry, as well as in many other fields of human activity, the Light Detection and Ranging (LiDAR) technology finds a place as a very powerful tool for data acquisition. Besides the traditional airborne or spaceborne remote sensing images which for decades serve mainly as a source of radiometric information about the woodlands, LiDAR and especially Airborne Laser Scanning (ALS) technology brings an exceptional amount of information about the forest structure in recent years [Corona et al., 2012]. In comparison to traditional photogrammetry ALS offers new ways of describing the forest structure in 3D since this active remote sensing technique can measure the location of objects in 3-dimensional (x, y and z) inside the canopy and not only model its upper surface [Montaghi et al., 2013].

While it was originally used primarily for digital terrain mapping, more recently LiDAR has proved to be very useful for examining vegetation in native and plantation forests [van Aardt et al., 2008; Kim et al., 2009]. By knowing the direction of the beam and the distance between the instrument and the target, the device builds a three-dimensional data set representing the forest in the scanned area. This enables forest managers to measure forest structure with unprecedented detail and provides a permanent record of a forest’s three-dimensional structure at any given growth stage. From such data an amount of biometric information about the forest and even about individual trees can be measured and derived, such as the height of the trees or diameter of the tree crowns, stem density or stock of the wood and amount of dendromass.

The information about the woodland gained from the ALS can be significantly extended when the LiDAR spatial data are combined with the radiometric information of the traditional images. Hudak et al. [2009] describe that calculated height, cover, or other vegetation metrics within the cells can be output as two-dimensional raster layers. These raster outputs are analogous to the bands in a multispectral image, but with the LiDAR outputs indicative of structural features rather than spectral. The distribution of canopy height values within a defined bin is effectively a “structural signature” analogous to the “spectral signature” of a hyperspectral image pixel. Hudak et al. [2002] and Wulder and Seemann [2003] used Landsat images with LiDAR data to estimate forest stand heights, and Chen and Hay [2011] studied the possibilities of using QuickBird images in combination with laser scan data for the same purpose. All three studies are emphasizing the benefits of mutual combination of these two data sources and are looking for the dependence of the forest heights and the pattern of the multispectral images. After applying the developed regression models the authors proved the possibility to estimate the stand heights even from the satellite imagery with satisfactory results (accuracies about 6 metres) and also propose the use of algorithms for LiDAR transect selection suitable for very large areas of land.

Ke et al. [2010] have also utilized laser scanner data together with QuickBird image data, for object-based image analysis of forest areas. They have proved that the combination of both, LiDAR and multispectral data can significantly increase the accuracy of segmentation process and the subsequent classification, compared to using either dataset as the input separately. The utilization of these two data sources together is therefore an advisable approach for improving the amount of information which can be extracted from the data and for helping to delineate the forest stands’ borders as well as the borderlines between groups of different tree species in the forest.
Radoux and Defourny [2006] tried to quantitatively assess the effect of segmentation parameters on the quality of image-objects prior to classification. Their study was made on pan-sharpened IKONOS images, and their classes of interest were deciduous forest, coniferous forest and non-forested areas. The results showed that when changing a shape parameter, compactness often improved the overall segmentation quality. However, the separation of deciduous and coniferous forests, which was the lowest of all classes, did not significantly improve with the scale parameter. A small scale parameter seemed therefore to be advisable. The inspiration how to find the suitable scale parameters can be found in Ke et al. [2010] where on the QuickBird data combined with LiDAR data the scale parameter of 250 for spectral/LiDAR-based segmentation has given the most accurate results, whereas for the only spectral-based segmentation the value of 200 and for the purely LiDAR-based segmentation the value of 100 were found to provide the best results. Antonarakis et al. [2008] have utilized OBIA principles to analyze ALS data without additional multispectral imagery, whereas combining data from LiDAR and images processed with object-based analysis has been carried out by Tiede et al. [2006], Kressler and Steinnocher [2006]. As it is obvious combination of multispectral and LiDAR remote sensing data and use of object-oriented image analysis belong to the contemporary approaches to highly effectively study woodlands as well as many other environments. Application of such an approach, focused on looking for the appropriate set of rules in eCognition suitable for reliable classification of forest area was therefore the main goal of this study.

Data and methods

Area of interest
The area of interest is situated in the Czech Republic, in the region of South Moravia near the north-east edge of the City of Brno (Fig. 1). The research area covered 8 km² (i.e. 800 ha) of land and included a large part of the town of Bílovice nad Svitavou. 77% of the area is covered by forest, the rest consists mainly of urban and agricultural areas. The height above sea level varies between 212 and 432 metres, and so the maximum variation in elevation is 220 m.

Figure 1 - Site of the research area (red rectangle) in the context of the City of Brno and the Czech Republic. (Source of maps: WMS server of http://geoportal.cenia.cz).
Forests in the research area consist of broadleaf as well as coniferous trees. The following tree species are found here: oak (*Quercus* sp.), hornbeam (*Carpinus* sp.), pine (*Pinus* sp.), larch (*Larix* sp.), lime (*Tilia* sp.), beech (*Fagus* sp.), spruce (*Picea* sp.), fir (*Abies* sp.), douglas fir (*Pseudotsuga* sp.), ash (*Fraxinus* sp.) and maple (*Acer* sp.).

**Data**

Image data were acquired by an aerial digital camera. The image is composed of four optical bands - Red, Green, Blue and Near-Infrared, with spatial resolution of 0.6 x 0.6 metres and radiometric resolution of 16 Bits. Additionally, the Digital Terrain Model (DTM) and Digital Surface Model (DSM), both derived from an airborne LiDAR scanner and having spatial resolutions of 1 x 1 metre and radiometric resolutions of 32 Bits, were used (Fig. 2). The LiDAR device used to obtain this data was Leica ALS50-II and the average point density was 2.5 points / m². All the data used in this study were positioned using the S-JTSK Krovak EastNorth Coordinate System. Both, multispectral as well as LiDAR data were captured 13. 6. 2009 which is during the vegetation (leaf-on) season.

![Figure 2 - Different data types of imported image layers. Left: RGB image, right: DSM.](image)

**Methods**

eCognition Developer 8.64 software (formerly Definiens) of Trimble Germany GmbH (München, Germany), which was specifically created as a powerful instrument for object-oriented image analysis [Benz et al., 2004], was chosen for the purposes of this study. The classifications were made on the basis of all three source datasets (multispectral image, DSM and DTM). The classes vegetation and non-vegetation were distinguished first, using a Normalised Difference Vegetation Index (NDVI). This classification was done on objects created by multi-resolution segmentation using these parameters: Scale parameter - 40, Shape criterion - 0.15, and Compactness criterion - 0.65. Those mainly empirically gained parameters ensured,
that all the various objects of interest were delineated properly. More than 80,000 individual objects were created with this segmentation. Non-vegetated areas were then classified into three further classes: water, clear-cuts (not all yet which were present in the whole area) and built-up areas. The delimitations of objects were improved by mathematic morphology algorithms in some cases (pixel-based object re-sizing - tools included in eCognition).

A new level of segmentation was created to classify the vegetated areas, and the results of both segmentations were synchronised at the end. Specific segmentation settings had to be created. The Image layer weights were tailored for the best differentiation of forested areas, with the emphasis being put mainly on the NIR band. The weight of DSM was multiplied too, because of the much smaller differences in its value range in comparison with the other bands. In contrast, the value of DTM was decreased to zero, since the height of terrain was not supposed to improve the segmentation results. The scale parameter was set to 80, the shape criterion was set to 0.55 and the compactness criterion to 0.75. All those parameters were empirically found to ensure the best results for delineation of desired classes.

The single broad class of vegetation was re-classified into forest and non-forest (which included fields, meadows, gardens, solitary trees, etc.). A supervised Nearest Neighbour (NN) classification was then used for a detailed classification of the forest areas, and this was the main aim of this study. In doing so, one slight complication in the image data used for the classification became apparent. The data contained unnaturally different brightness values in parts, so that the image appeared to be significantly brighter in the north compared to the south. This was probably caused by the uneven illumination of the terrain during the aerial imaging. The result was that coniferous trees, which are usually darker than broadleaf trees in the NIR band, had much higher brightness values in the northern part of the image than the broadleaf trees in the southern part (Fig. 3).

![Figure 3 - Examples of broadleaf and coniferous forests appearance on different parts of the source image. The false-colour composition of Near-Infrared, Red and Green bands (4-3-2 synthesis) displayed with 7% linear stretching equalization.](image-url)
For this reason, the traditional features such as brightness, mean values or standard deviations of appropriate image layers, which would usually be considered for a NN Classification, would not have been effective enough in this case since their particular values have been highly variable even for the similar surfaces in northern and southern parts of the image. To circumvent this problem, a series of customized arithmetic features (equations) were created. These equations worked with the standard features (e.g. mean values etc.), putting them into mutual relationships such as sums, differences and especially ratios. This partially resolved the problem of the inequality in brightness, since the mutual ratios of defined features are a more stable and relevant property (more characteristic for different examined surfaces) than their sum (e.g. brightness).

The input features for the formulas were selected partly on the basis of their characteristics, discovered empirically by observing the properties of forest image objects, and partly more or less randomly. Together 73 customized arithmetic features were created and tested. Since they all worked with a limited number of input features and all were based on a combination of just 6 image layers (RED, GRN, BLU, NIR, DSM and DTM), naturally there was a degree of correlation between these derived arithmetical features.

The statistical correlations between customized features were computed by STATISTICA 9.0 software of StatSoft, Inc. (Oklahoma, USA). Since the number of values in the exported eCognition file was enormous (the table consisted of 73 columns for features and approx. 6600 rows for all image objects), the common mathematical correlation matrix did not provide clear and useful information. Factor analysis was found to be the most suitable method to obtain the required information. 32 statistically significant features were then tested with the feature space optimization tool within eCognition. It was discovered that 26 features used in the NN Classification gave results comparable to the previous 32, therefore just those 26 arithmetic features (Tab. 1) were selected for defining the feature space.

When defining the feature space, some textural features were also tested (Textures after Haralick - GLCM Homogeneity and GLCM Contrast). It was observed that when using these features, the NN Classification took a much longer time (hours instead of minutes on a PC: Intel Core2 Duo 2.26 GHz, 3GB RAM, Ati Radeon HD 3400, MS Win XP Pro SP3), but the results were not significantly better. Therefore to save computing time it was decided not to use any textures as dimensions of the feature space.

When the definition of feature space was complete and the training sites were selected for each particular class, the NN classification was performed. The following classes were used: broadleaf; coniferous; mixed (image objects containing broadleaf as well as coniferous trees in approximately equal number); young (for forest areas which had been recently deforested - these areas were either not yet re-afforested but covered by some kind of vegetation (e.g. grass or weeds), or were afforested but the young trees were too small to be identified); plantation (in one area the trees were planted strictly according to a square grid, with large distances between them); clear-cuts (the rest of the clear-cuts present in the research area, subsequently merged with those delineated already before); bare ground (referring to areas which were not fully covered by any type of vegetation, but were not clear-cuts); and shadow (a temporary class, later to be re-classified into one or other of the other classes). The whole classification flow chart is shown in Figure 4 and the visualization of the final classification results can be seen in Figure 5.
Table 1 - List of 26 customized arithmetic features used for defining the feature space for the Nearest Neighbour Classification.

| Arithmetic feature | Description or Equation |
|--------------------|-------------------------|
| Mean NIR           | Mean value of the Near Infra-red band |
| St Dev NIR         | Standard deviation of the Near Infra-red band |
| St Dev DSM         | Standard deviation of the DSM layer |
| NDVI 1) * Means   | [NDVI] * ([Mean NIR] + [Mean RED] + [Mean GRN] + [Mean BLU]) |
| Max Diff 2)        | Maximal Difference |
| Four-bands ratio   | ([Mean NIR] + [Mean RED]) / ([Mean BLU] + [Mean GRN]) |
| CHM 3)             | [Mean DSM] - [Mean DTM] |
| Combined ratio 1   | ([Mean NIR] / [Mean RED] + [Mean GRN] / [Mean BLU]) * ([DSM - DTM] / [St Dev DSM]) |
| Combined ratio 2   | ([St Dev RED] * [Mean NIR]) / ([St Dev BLU] * [Mean BLU]) |
| NIR / BLU ratio    | [Mean NIR] / [Mean BLU] |
| Three-bands ratio  | [Mean NIR] / [Mean RED] / [Mean GRN] |
| Combined ratio 3   | ([St Dev NIR] * [Mean NIR]) / ([St Dev BLU] * [Mean BLU]) - ([St Dev GRN] * [Mean GRN]) / ([St Dev RED] * [Mean RED]) |
| CHM * St Dev DSM   | ([Mean DSM] - [Mean DTM]) * [St Dev DSM] |
| NDVI * St Dev NIR  | [NDVI] * [St Dev NIR] |
| NDVI * St Dev DSM  | [NDVI] * [St Dev DSM] |
| NIR / RED St Devs  | [St Dev NIR] / [St Dev RED] |
| NIR * DSM St Devs  | [St Dev NIR] * [St Dev DSM] |
| Three St Devs ratio| ([St Dev NIR] * [St Dev DSM]) / [St Dev RED] |
| Combined ratio 4   | ((((St Dev NIR) * [St Dev DSM]) / [St Dev RED]) * [NDVI] * ([Mean DSM] - [Mean DTM])) |
| BLU ratio          | [Mean BLU] / ([Mean RED] + [Mean GRN] + [Mean BLU]) |
| NIR / RED St Dev rati| ([Mean NIR] * [St Dev NIR]) / ([Mean RED] * [St Dev RED]) |
| Max. Diff. * CHM   | [Max diff] * [DSM-DTM] |
| GRN ratio          | [Mean GRN] / ([Mean RED] + [Mean GRN] + [Mean BLU]) |
| Combined ratio 5   | ([Mean NIR] / [St Dev NIR]) * ([BLU ratio] / [Mean RED]) |
| Combined ratio 6   | ([Mean NIR] - ([Mean RED] + [Mean GRN] + [Mean BLU])) / ([Mean NIR] + ([Mean RED] + [Mean GRN] + [Mean BLU])) * [DSM-DTM] |
| GRN / BLU ratio    | [Mean GRN] / [Mean BLU] |

1) Normalized Difference Vegetation Index, calculated as ([Mean NIR] - [Mean RED]) / ([Mean NIR] + [Mean RED]);
2) Maximal difference between Means of all values belonging to an object, subsequently divided by the brightness;
3) So called Canopy Height Model.
In the next step, a new classification working solely with elevation data was carried out. The layers of the DTM and the DSM were used to determine the heights of the forest stands. Several customized arithmetical features were also created and tested. These features worked with mean values of DSM and DTM as well as with the minimum and maximum pixel values of these layers, counted for each object.

Since the segments used during this work were not small enough to distinguish all height divergences in the forest areas, the methods using these arithmetical features were found to be unsuitable. The problem when using maximum pixel values appeared, for instance, in cases where an object was composed of a young stand with generally low heights of trees, but nevertheless contained a few much taller trees. Such an object was then wrongly shown as having the height of these tall trees. On the other hand, when using the minimal pixel values the results were also often misleading. This problem was probably caused in some cases by the fact that in objects composed of very dense forest, the LiDAR laser did not penetrate to the real surface of the ground. This then caused the minimum pixel value of DSM to be much higher than the minimum pixel value of DTM of the same object. Calculations based on the difference of these values would therefore have shown a large error too. Also customized features containing equations using different ratios and other mutual relations of mean values of DSM and DTM and their minimum and maximum pixel values were tested, but no universally applicable equation was found. In the end, the use of the simple difference between mean DSM and mean DTM values (so called Canopy Height Model - CHM, arithmetic feature [mean DSM] - [mean DTM]), was found to be the best solution, as far as possible eliminating the problems just described. Execution of this process ensured that all image objects were classified according to the difference in mean values of DSM and DTM, using 5 metres intervals. The results of this second classification are shown in Figure 6.
Figure 5 - Visualization of the results of the main classification showing different kinds of forest and non-forested areas. Based on heights from the DTM.

Figure 6 - Visualization of results of elevation-based classification showing forest height levels in metres. Displayed on the surface of the DSM.
Results
A total of two maps, gained purely on the basis of information contained in the remote sensing data, represent the main result of this work. The first map shows the results of assigning the forested areas to one of the following seven groups: Broadleaf, Coniferous, Mixed, Young, Plantation, Clear-cuts and Bare Ground (Fig. 5). In addition, the non-forested areas were delimited and assigned to one of these classes: Water, Non-Forest and Built-up Areas.

The maps are also linked to an attribute table containing the areas of each delineated object. The proportional areas calculated based on the results of both classifications are summarized in Figures 7-9.

The accuracy of the classification was verified by collecting ground truth data, for which more than 300 observations were made. Information including the heights and composition of forest stands was gathered and entered into a GPS device. For this purpose the GPS Juno ST from Trimble Navigation Limited, using TerraSync software, was used. Two devices were employed for the measurement of tree heights: a Mechanical Altimeter “Blume-Leiss” and a Laser Distancemeter DISTOTM lite5 from Leica Geosystems AG.
The overall accuracy of the forest NN classification was calculated to be nearly 90% (Tab. 2). The value of the Kappa Index of Agreement (KIA) was calculated to more than 85% in this case.

Table 2 - Error matrix showing the accuracy of the main forest area classification.

| Accuracy | Clear-cuts | Broadleaf | Coniferous | Mixed | Bare ground | Young | Plantation |
|----------|------------|-----------|------------|-------|-------------|-------|------------|
| Producer | 0.733      | 0.951     | 0.848      | 0.811 | 0.697       | 0.935 | 1.000      |
| User     | 0.988      | 0.897     | 0.944      | 0.721 | 0.722       | 0.923 | 0.984      |
| Overall  | 0.895      |           |            |       |             |       |            |
| KIA      | 0.853      |           |            |       |             |       |            |

Relatively low accuracy can be observed, for instance, in the case of the Mixed class, when many pixels were confused with either Coniferous or Broadleaf classes. Low user as well as producer accuracy is shown by the Bare Ground class, because this class was represented by a number of usually small objects spread across the research area. This is the exact opposite of the situation with the Plantation class, which was represented by just one large and symmetrical area, and therefore had the highest level of accuracy.

The overall accuracy of classified height levels came out slightly over 70% (Tab. 3) in this case and the Kappa Index (KIA) was calculated to be 63%. In general, both user and producer accuracies decreased rapidly with increasing height of forest.

Table 3 - Error matrix showing the accuracy of the forest stands’ height classification.

| Accuracy | 0 - 5 m | 5 - 10 m | 10 - 15 m | 15 - 20 m | 20 - 25 m | 25 + m |
|----------|---------|----------|-----------|-----------|-----------|--------|
| Producer | 0.900   | 0.874    | 0.694     | 0.772     | 0.597     | 0.318  |
| User     | 0.949   | 0.693    | 0.449     | 0.656     | 0.552     | 0.959  |
| Overall  | 0.701   |          |           |           |           |        |
| KIA      | 0.632   |          |           |           |           |        |

It is also obvious from the matrix that the forests were commonly assigned to a lower height class than they should have been. Furthermore, the higher the forest stand really was, the higher the probability that it would be wrongly classified into one of the lower categories. This is also confirmed by the very high user accuracy in the case of the highest tree class (25m +) which at the same time has a producer accuracy of only 32%.

Discussion and Conclusion

The objective of this research was to find appropriate methods using Object-Based Image Analysis principles for the purposes of mapping areas of forest. Using eCognition Developer software and working with different up-to-date types of remote sensing data, an aggregate of suitable rules in the form of linked processes was created.

In the first instance, it should be mentioned that since only one specific dataset covering one particular area was used during this work, all rules and processes were created to fit this data and have not been tested on other data sets. Although the idea was to develop rules which would have general applicability, and could be applied to any other dataset, the
practical testing and application of these will have to be the subject of further studies. The classification of forest areas as being principally composed of broadleaf or coniferous trees had an accuracy of almost 90%, which could be considered to be a very good result. However, it could also be asked why this value was not even higher, and there are several possible reasons. For instance, it is never completely clear which forest stands are mainly composed of broadleaf and coniferous trees, and which should be considered as being mixed forest. Since the decision to assign a given forest area to the mixed class is very subjective, either when selecting samples of objects for NN Classification or when collecting ground truth data during the field survey, the final results can be greatly influenced by both these operations.

A method to increase the classification accuracy could be found, for instance, by incorporating ancillary information into the analytical process. This has been demonstrated by Kim et al. [2008], who improved overall accuracy by using topographic variables during the image segmentation procedures. It should be pointed out that the ancillary data has naturally got to be current to be useful. Additional vector layers containing land-cover information can also be used for the final accuracy assessment, as described by Radoux and Defourny [2006]. When looking at the overall accuracy of the classification of tree stand heights, the value of 70% may seem to be low at first sight, but the actual form of the segments used for classification should be taken into consideration. When looking at the error matrix, the tendency to underestimate the heights of forest stands is apparent in almost all instances. There could be several reasons for this. First of all, the image objects used in the classification process usually contained anything from just a few individuals up to a few tens of individual trees. The method used to calculate the heights of these areas did not include the maximum heights of trees, but used only mean values of DSM (and DTM). Since the mean value of DSM is calculated from all the values contained in the object, including both the tree tops (first laser returns) and often the ground as well (last laser returns), with many values in between, the results can hardly ever correspond to the actual heights of the tree tops, as measured in the field, when using such large segments for a classification.

This inaccuracy naturally increases as the forests get older since stands are often thinned and the vegetation becomes sparser. The mean value of DSM is then significantly decreased by the fact that the laser scanner reaches the ground more often and hits tree crowns less often. This problem could probably have been avoided by using smaller segments for the classification, and ideally, there should be one segment for each tree crown, as some studies have shown [Tiede et al., 2006; Goulding et al., 2009]. However, since this would require a fundamentally different approach it does not form a part of this particular study, but could certainly be the subject of future studies. Such an approach could possibly achieve better accuracy in assessing the height of tree stands.

The values for heights produced by the classification system used in this work say more about the average height of the canopy than the maximum height of the stand, which is what is usually measured. Furthermore, the younger the forests are, the better the results correspond with ground truth data. Also, in some cases the inaccuracy can arise from the fact that the trees have grown a little in the time between when the remote sensing data was acquired and the time when reference data was collected. Finally, it must be acknowledged that some of the variation may also be due to mistakes made when measuring the heights of trees during the field survey.
Acknowledgements
Data sets were provided by GEODIS BRNO, spol. s r.o.
The paper was prepared within the framework of research project of the Ministry of Education of the Czech Republic “Forest and Wood - Support to a functionally integrated forest management”, grant of Ministry of Education No. MSM 6215648902.
Mr. Malcolm Russell kindly proof-read the manuscript and assisted with the final draft in English.

References
Antonarakis A.S., Richards K.S., Brasington J. (2008) - Object-based land cover classification using airborne LiDAR. Remote Sensing of Environment, 112 (6): 2988-2998. doi: http://dx.doi.org/10.1016/j.rse.2008.02.004.
Benz U., 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: 239-258. ISSN 0924-2716.
Chen G., Hay G.J. (2011) - An airborne lidar sampling strategy to model forest canopy height from Quickbird imagery and GEOBIA. Remote Sensing of Environment, 115: 1532-1542. doi: http://dx.doi.org/10.1016/j.rse.2011.02.012.
Ceccarelli T., Smiraglia D., Bajocco S., Rinaldo S., De Angelis A., Salvati L., Perini L. (2013) - Land cover data from Landsat single-date imagery: an approach integrating pixel-based and object-based classifiers. European Journal of Remote Sensing, 46: 699-717. doi: http://dx.doi.org/10.5721/EuJRS20134641.
Corcoran P., Winstanley A., Mooney P. (2010) - Segmentation performance evaluation for object-based remotely sensed image analysis. International Journal of Remote Sensing, 31: 617-645. doi: http://dx.doi.org/10.1080/01431160902894475.
Corona P., Cartisano R., Salvati R., Chirici G., Floris A., Di Martino P., Marchetti M., Serinzi G., Clementel F., Travaglini D., Torresan C. (2012) - Airborne Laser Scanning to support forest resource management under alpine, temperate and Mediterranean environments in Italy. European Journal of Remote Sensing, 45: 27-37. doi: http://dx.doi.org/10.5721/EuJRS20124503.
Fisher P. (1997) - The Pixel: a Snare and a Delusion. International Journal of Remote Sensing, 18 (3): 679-685. doi: http://dx.doi.org/10.1080/014311697219015.
Gardin S., van Laere S.M.J., van Coillie F.M.B., Anseel F., Duyck W., de Wulf R.R., Verbeke L.P.C. (2011) - Remote sensing meets psychology: a concept for operator performance assessment. Remote Sensing Letters, 2: 251-257. doi: http://dx.doi.org/10.1080/01431612010516280.
Goulding C.J., Fritzsche M., Culvenor D.S. (2009) - Improving Forest Inventory: Integrating Single Tree Sampling With Remote Sensing Technology. In: IUFRO Division 4: Extending Forest Inventory and Monitoring over Space and Time, McRoberts R.E., Fournier R. (Eds.), 19-22 May 2009, Quebec City, Canada.
Hay G.J., Castilla G. (2006) - Object-Based Image Analysis: Strengths, Weaknesses, Opportunities and Threats (SWOT). In: First International Conference on Object-based Image Analysis (OBIA 2006), XXXVI (4/C42), Salzburg, Austria.
Hudak A.T., Evans J.S., Smith A.M.S. (2009) - LiDAR Utility for Natural Resource Managers Remote Sensing, 1: 934-951. doi: http://dx.doi.org/10.3390/rs1040934.
Hudak A.T., Lefsky M.A., Cohen W.B., Berterretche M. (2002) - *Integration of lidar and landsat ETM+ data for estimating and mapping forest canopy height.* Remote Sensing of Environment, 82: 397-416. doi: http://dx.doi.org/10.1016/S0034-4257(02)00056-1.

Kamagata N., Hara K., Mori M., Akamatsu Y., Li Y., Hoshino Y. (2006) - *A new method of vegetation mapping by object-based classification using high resolution satellite data.* In: First International Conference on Object-based Image Analysis (OBIA 2006), XXXVI (4/C42) Salzburg, Austria.

Ke Y., Quackenbush L.J., Im J. (2010) - *Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification.* Remote Sensing of Environment, 114: 1141-1154. doi: http://dx.doi.org/10.1016/j.rse.2010.01.002.

Kim M., Xu B., Madden M. (2008) - *Object-based Vegetation Type Mapping from an Orthorectified Multispectral IKONOS Image using Ancillary Information.* In: GEOBIA 2008 - GEOgraphic Object Based Image Analysis for the 21st Century, Calgary, Alberta, Canada, Hay G.J., Blaschke T., Marceau D. ISPRS (Eds.), XXXVIII (4/C1). ISSN 1682-1777.

Kim M., Madden M. (2006) - *Determination of optimal scale parameter for alliance-level forest classification of multispectral IKONOS image.* Commission IV, WG IV/4 on Proceeding of 1st OBIA Conference, 4-5 July, Salzburg, Austria.

Kim S., McGaughhey R.J., Andersen H.E, Schreuder G. (2009) - *Tree species differentiation using intensity data derived from leaf-on and leaf-off airborne laser scanner data.* Remote Sensing of Environment, 113: 1575-1586. doi: http://dx.doi.org/10.1016/j.rse.2009.03.017.

Kressler F.P., Steinnocher K. (2006) - *Image Data and LiDAR - an Ideal Combination Matched by Object-Oriented Analysis.* available at: First International Conference on Object-based Image Analysis (OBIA 2006), XXXVI (4/C42), Salzburg, Austria.

Marangoz A.M., Oruç M., Büyüksalih G. (2004) - *Object-Oriented Image Analysis and Semantic Network for Extracting the Roads and Buildings From Ikonos Pan-sharpened Images.* In: Proceedings of the XXth ISPRS Congress, Istanbul, Turkey, 12-23 July 2004, XXXV (Part B3), p. 4.

Montaghi A., Corona P., Dalponte M., Gianelle D., Chirici G., Olsson H. (2013) - *Airborne laser scanning of forest resources: An overview of research in Italy as a commentary case study.* International Journal of Applied Earth Observation and Geoinformation, 23: 288-300. doi: http://dx.doi.org/10.1016/j.jag.2012.10.002.

Myint S.W., Gober P., Brazel A., Grossman-Clarke S., Weng Q. (2011) - *Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery.* Remote Sensing of Environment, 115 (5): 1145-1161. doi: http://dx.doi.org/10.1016/j.rse.2010.12.017.

Radoux J., Defourny P. (2006) - *Influence of image segmentation parameters on positional and spectral quality of the derived objects.* In: First International Conference on Object-based Image Analysis (OBIA 2006), XXXVI (4/C42), Salzburg, Austria.

Tiede D., Lang S., Hoffmann Ch. (2006) - *Supervised and forest type-specific multi-scale segmentation for one-level representation of single trees.* In: First International Conference on Object-based Image Analysis (OBIA 2006), XXXVI (4/C42), Salzburg, Austria.

Townshend J.R.G., Huang C., Kalluri S.N.V., Defries R.S., Liang S., Yang K. (2000) -
Beware of Per-pixel Characterization of Land Cover. International Journal of Remote Sensing, 21 (4): 839-843. doi: http://dx.doi.org/10.1080/014311600210641.

Van Aardt J.A.N., Wynne R.H., Scrivani J.A. (2008) - Lidar-based Mapping of Forest Volume and Biomass by Taxonomic Group Using Structurally Homogeneous Segments. Photogrammetric Engineering & Remote Sensing, 74 (8): 1033-1044. doi: http://dx.doi.org/10.14358/PERS.74.8.1033.

Wulder M.A., Seemann D. (2003) - Forest inventory height update through the integration of LIDAR data with segmented Landsat imagery. Canadian Journal of Remote Sensing, 29: 536-543. doi: http://dx.doi.org/10.5589/m03-032.

© 2014 by the authors; licensee Italian Society of Remote Sensing (AIT). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).