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FAKULTA LESNICKÁ A ENVIRONMENTÁLNÍ

KATEDRA HOSPODÁŘSKÉ ÚPRAVY LESŮ

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AUTOMATED CLASSIFICATION OF TREE SPECIES COMPOSITION FROM REMOTE SENSING DATA

PhD Thesis

Praha 2007

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AUTOMATIZOVANÁ KLASIFIKACE LESNÍ DRUHOVÉ SKLADBY Z OBRAZOVÝCH DAT DPZ

DISERTAČNÍ PRÁCE

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Preface

This PhD thesis is about automated classification of tree species composition from remotely sensed imagery. As the entire field of geoinformatics has been rapidly enhancing during the last decade, new digital sensors collecting images of very high spatial resolution were introduced, demanding modern processing approaches. Classification techniques based on analysis of individual pixels are no longer suitable for VHR imagery such as from IKONOS, QuickBird, or OrbView-3. However, there is an evident need for more accurate and more effective methods of forest inventory data collection.

The study was initiated Doc. Lena Halounová from Remote Sensing Lab, Czech Technical University Prague, who kindly suggested such interesting and relevant forestry topic. Her previous work about the object-oriented classification of black&white aerial photographs served as a key inspiration to determine the main principles of developed methodology. The study would not have been possible without the financial support of the National Agency for Agricultural Research (project code QG50097). Besides, the IKONOS imagery and digital aerial photos were provided for purpose of the dissertation by companies GISAT s. r.o. and GEODIS Brno free of charge. Moreover, I would like to thank to my supervisor Prof. Jan Kouba who widely assisted with many valuable opinions and ideas.

Many thanks to all of you. Your faith and support are most appreciated.

In Prague, March 2007   Filip Hájek

1 Index

2 Introduction

Monitoring of forest environment has the fundamental meaning for sustainable resource management. The increasing demands on the level of inventory precision, information resolution and repeatability involve new methods to the forestry management. For several decades, various remote sensing (RS) techniques and instruments has been utilised for purposes of forest inventories, forest mapping, as well as acquisition of some quantitative stand and tree estimates.

The first aerial image ever was acquired from an air-balloon in Paris in 1856 by F. TOURNACHON (Flygbildsteknik och Fjärranalys, 1993). Then beginnings of research in field of forestry remote sensing go back in 1920s, when the aerial photographs were integrated into forest inventory in Canada and the first photogrammetric methods were utilised. Since 1950s, a number of authors from Western Europe (BAUMANN 1958), Russia (SAMOILOVIČ 1953, BĚLOV 1959), USA (SPURR 1960) and later also Czechoslovakia (ČÍHAL 1969) dedicated their work to photo interpretation techniques for forestry. Besides traditional panchromatic (B&W) aerial photo interpretation, infrared and multispectral photography were being tested for qualitative assessment. Although aerial photos continue to be important to forest monitoring and management, the rapid pace of sensor development and information needs in the past three decades has led in to an explosion of forestry remote sensing research and multispectral satellite imagery, radar data hyperspectral images and laser scanning forestry applications have been intensely examined. So far, the satellite data have been used mainly for global forest monitoring and inventories of broader extent. However, the increasing improvement in spatial resolution will soon allow estimation of stand and tree characteristics as well (ŽÍHLAVNÍK and SCHEER 2000).

The significant fields of forestry remote sensing application include forest management, forest protection, forest ecosystem biodiversity assessment, forest planting and silviculture, biology, game management etc. Specifically working at a tree scale has a potential to extend digital remote sensing into many new areas (HILL and LECKIE 1999) such as detailed assessments of forest stands, forest regeneration (GOUGEON 1997), logging practices, forest health (LECKIE et al. 1992) and susceptibility to invasive pests.

When evaluating potential of RS for intensive forest management, it is rather adequate to mention that such methods are meant to facilitate the assessment of forest state using appropriate combination with ground measurements, not to replace it completely.

3 Aim of thesis

The aim of this dissertation was to utilize the entire knowledge gained through the process of studying various forestry remote sensing aspects in order to create an automated technique of tree species estimation from the remotely sensed (RS) images. The process involved literature survey, field investigations, skills of working with image analysis software and practical experience with various types of the remote sensing images. The resulting study then covers several topics for which partial objectives were formulated:

1. utilization of very high resolution (VHR) aerial and satellite images in forestry
2. benefits of image pre-processing and GIS data fusion
3. aspects of object-based image analysis and the result interpretation
4. acquisition of field reference data

Ad 1) The three different types of RS images were involved in the research – IKONOS-2 satellite images, color and infrared film aerial photos and aerial images acquired by medium-format digital camera. These represent the accessible alternatives of VHSR data sources, which were considered suitable for the intended methodology. However, each data type differs in spectral, radiometric and temporal resolution, as well as the availability and cost. The objective was to apply the method consistently to such different images, so the individual results could be obtained and discussed.

Ad 2) Various image channels were calculated from the original datasets to enlarge the classification feature space. These involved spectral ratios and vegetation indices (NDVI), Tasseled cap and IHS transformation layers, low-pass filters, Sobel edge detection and GLCM texture measures calculated in pre-processing phase. In order to use proper features, the contribution of different layers to class separability was then evaluated by means of graphical and statistical methods. The objective was to study an impact the various image channels to the classification feature space enlargement. Besides, the contribution of some existing GIS layers (DEM, forest management database) to classification result was also to be examined.

Ad 3) The main study objective was to create a classification rule base, which could be transferred and applied over the series of images to automatically obtain the tree species estimates. The concept is based on object-oriented classification presented in the commercial image analysis software Definiens Professional (a.k.a. eCognition, Definiens Imaging Germany). The aspects of using algorithms for multi-resolution image segmentation, complex object description (spectral, geometric, textural and contextual), relations within hierarchical image object network and classification procedures based on fuzzy rule sets were to be explored and demonstrated. Furthermore, the issues of accuracy assessment and the result interpretation within object-oriented analysis environment emerged. There statistical measures commonly used in pixel-based techniques e. g. Producer, Accuracy, User Accuracy, or Kappa Index of Agreement (KIA) can be applied also to evaluate object classification, however, the interpretation of the result may be problematic. Some of the issues were intended to be covered.

Ad 4) Apart from the main topic of forest image classification, the problem of reference (ground truth) data acquisition was also examined. Since the only data source available to evaluate the classification results may be the forest management planning GIS database LHPO (ÚHÚL, Czech Republic), there is often a need to obtain more accurate and updated information by own field-work measurements. The objective was to develop a simple and cost-effective method based on mobile GIS mapping, which would suit the requirements for reference sampling and accuracy assessment.

Structure and sections of thesis

The presented thesis is divided into 10 chapters (see index). The chapter *Results* consists of four research papers and one technical article. The individual papers are indicated by roman numerals (**I – V**) in further text. For purpose of proper grasp, the references are listed at the end of *Literature survey* chapter, as well as at the end of each publication. The final chapter *References* (chapter 10) lists all references and literature sources included in the dissertation.

Note:
By the time of the thesis printout, the three research papers were already reviewed and approved for publishing (**I**, **II** published, **IV** in print), the paper **V** was positively reviewed and returned for the minor corrections.

4 Literature survey

Selected applications of remote sensing in forestry management

Extraction of height information

Various tree and stand characteristics can be interpreted from a single image, stereo-pair of large scale aerial photography, or VHR satellite imagery respectively. For detailed extraction of 3D information, the stereogram needs to be obtained either from imagery with sufficient continuous overlay (one metric camera), or it can be derived from the synchronized photography using two metric cameras. Then the standard stereo-photogrammetry procedures are applied to calculate estimates such as tree height, canopy width, tree count, in-between distance, canopy closure, or a stand density. Due to poor visibility of the stem at a breast-height, the measurements of stem volume are extremely difficult and therefore rather experimental within condition of very low-stocking broadleaved forests during season of vegetation calm (SCHEER and RAČKO 1987).

Height approximation from the length of cast shadow

The shape of shadows is important attribute for the tree species identification, but shadow length can be also used for tree height assessment (MURDYCH 1976). In the flat terrain, the height is calculated as

$$h = s * tg\alpha$$

where s is length of the shadow (Figure 1a, b)

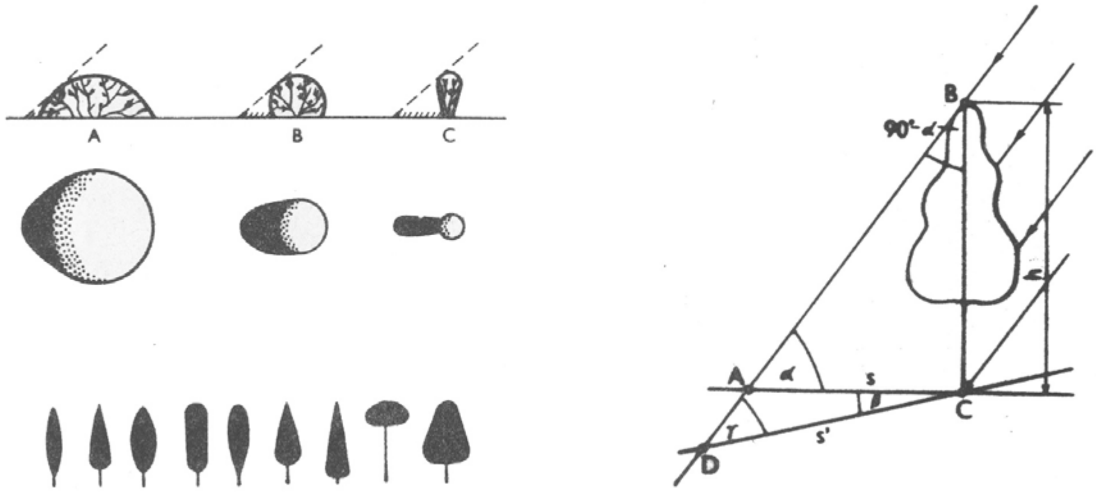

Figure 1. Shape of self and cast shadows for different types of bushes and trees (a). Scheme of tree height assessment from the shape length feature (b) (from MURDYCH 1976)

However, the practical assessment of tree height from the cast shadow is complicated due to shadow length variability associated with season and the day time. Very course estimates can be made at the forest boundaries and open spaces.

Parallax measurements from stereoscopic imagery

Based on the measurements of horizontal parallaxes between the tree foot and top in image stereo-pair, the tree height can be calculated:

$$h = p * \frac{H}{b}$$

where p - difference of horizontal parallaxes between the tree foot and top

H - height of the aeroplane

b - stereoscopic base

Although the most widespread, this method is has also a number of constraints mainly associated with the poor bottom visibility in the high canopy closure stands. The measurements of few heights can be acquired at the forest boundaries and gaps. These are not representative for heights of individual trees, but often sufficient to estimate mean stand height. ŽÍHLAVNÍK and SCHEER (2000) suggested a method of height profiles, where the mean stand height is calculated from the profile of forest stand and terrain profile measurements. Such approach enables measuring of relatively high number of trees within selected row, but requires enough flat terrain between the positions of measurements.

Airborne laser scanning

The advanced and extremely relevant might be the extraction of height information from the airborne laser scanning (ALS) so-called LiDAR. The system originally designed for topographical mapping provides a dense 3D point cloud of the forest structure at the very high resolution and hence can provide accurate estimates of stem density and tree crown density. The main task is classification of the individual pulses into different object classes. For example, laser pulses (Figure 2) reflected by the ground must be distinguished from non-terrain points to derive digital terrain model (DTM). This is by using filtering algorithms, which highlight spatial distribution and geometric characteristics of points relatively to their neighbourhood. Besides the height and location measurements, accurate species discrimination can be achieved by combination of co-registered laser data and VHR optical imagery.

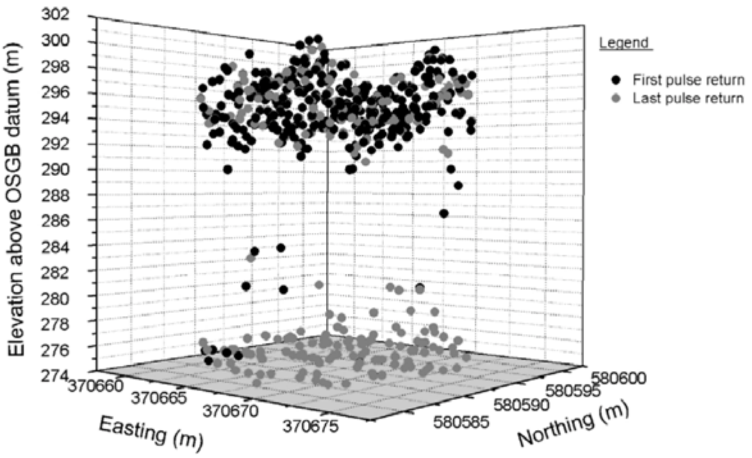

Figure 2. Distribution of first and last LiDAR pulses (from DONOGHUE et al. 2006)

In connection to topic of 3D information extraction, it is rather adequate to mention the step of orthorectification - connection of image to the specific coordinate system. As noted by WARNER et al. (1998), any image data must be georeferenced and directly applicable in GIS to be most useful for forestry users. The digital orthorectification requires a high resolution digital terrain model. The DTM can be produced either from an existing cartographic information, or also derived from a stereo-pair of aerial photos by semi-automated or automated correlation procedure. These methods are still rare in practical forestry and remain in the domain of research (ŽÍHLAVNÍK 1998). However, such data are then suitable for vectorisation in the range of mapping and registration tasks.

Identification of tree species composition

The correct identification of basic landuse /landcover types (forest, grass, agriculture, urban) from both aerial and satellite images is usually an easy task, but is necessary for the further detailed classification of forest tree species composition. Various interpretation characteristics can be used for visual or digital automated recognition methods. The canopy shape is one significant feature often associated with bio-sociologic location in the stand, density of canopy closure, differences in the canopy growth space, etc. Two types of shape are common in Czech condition - round shape represents coniferous and irregular shape represents broadleaved tree species. In aerial photos, these basic canopy shapes are often modified by the position of projection centre and the sun angle at the moment of exposition (Figure 3). The very recent technique of crown shape recognition is based on canopy modelling from raw LiDAR point data (DONOGHUE et al. 2006).

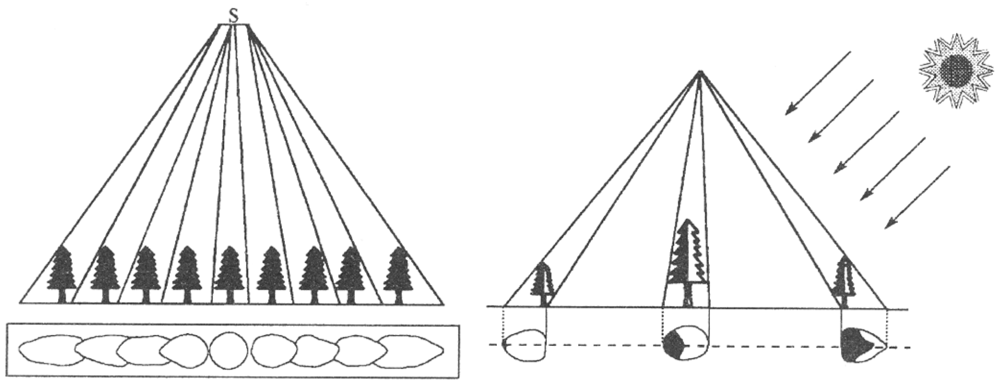

Figure 3: Canopy shape in connection to position in the image and the sunlight direction (ŽÍHLAVNÍK and SCHEER, 2000)

Among the other characteristics to recognize forest type is texture, where broadleaves have coarser and conifers have smoother appearance. Looking at the individual trees, some species have also specific canopy texture (spotted beech, radial texture for fir). However, only large scale aerial photos allow observing such details.

Much better results can be obtained by the interpretation of imagery with infrared band, such as colour infrared (CIR) aerial photos, or multispectral satellite imagery. IR images make use of the reflectance attributes of different tree species associated with the chlorophyll content in leaves and needles. Whereas in panchromatic image conifers and broadleaves appear similar, there is huge increase in their reflectance in the near infrared band (Figures 4 and 5). Further, colour composites derived from multispectral images are especially useful to distinguish different tree species within the stand structures. The proper band combination is chosen based on the optimal grey level differentiation for individual species. The common band combinations used for both visual and automated interpretation are true color (true RGB representation) and false color (NIR band represented by red) composites.

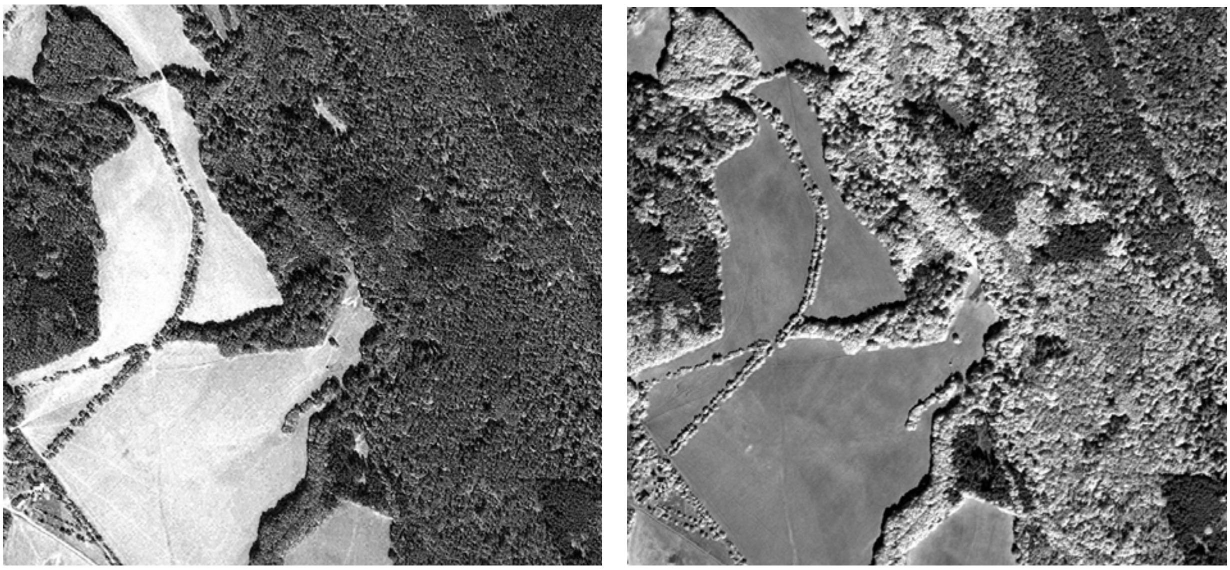

Figure 4. Spectral reflectance of mixed forest stands in green (left) and NIR (right) band

In the automated analysis of species distribution, the most important is to determine the correct spectral signature for individual species. However, the differentiation itself can be problematic as their spectral curves sometimes overlap. Moreover, the crown reflectance is always a complex interaction of foliage spectral properties with other sources of variability including atmospheric effects, shadow pattern, back ground composition and instrument noise (STONE and COOPS 2004).

In cases of small scale projects, where accurate the information for individual trees is not required, the forest classification focuses rather on the estimation of area occupied by the species. The assessment of prevailing forest type (conifer, broadleaved, mixed) from remotely sensed data can be also used for the effective methods of forest stratification (ŽÍHLAVNÍK and SCHEER 2000).

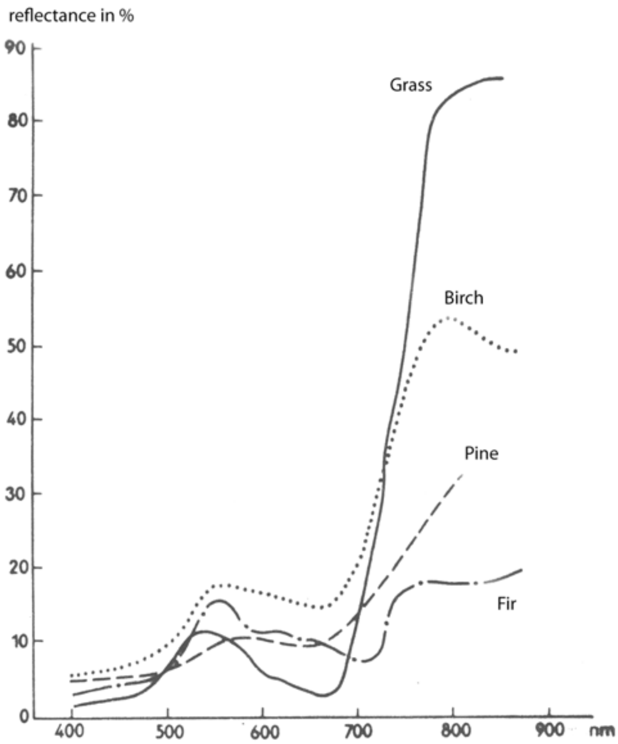

Figure 5. Spectral reflectance curves of different forest species (Sborník přednášek ČVST - FEL 1977)

Lately, the methods of tree species identification from satellite imagery have been widely explored. Some studies (BUCHA 1998) aimed to estimate forest species composition using moderate resolution data, such as Landsat TM, Spot HRV. MALENOVSKÝ (2001) tested satellite images from Spot 4-Xi and found that spatial resolution of 4 m could be sufficient for forest vegetation mapping. The relevant studies on VHR satellite imagery (Ikonos, QuickBird) seem promising for the species identification at the individual tree level. The recent advances in image processing allow delineation of individual tree crowns and enable extraction of crown reflectance for both modelling and classification (CULVENOR 2002). Besides, spectral analysis combined with the additional information from e.g. terrestrial measurements or laser scanning, and the integration of GIS within the automated classification procedures has been characteristic up-to-date approaches for the species identification.

Monitoring of forest change

Besides estimating forest stand parameters, an evaluation of structural characteristics of forested landscapes is also considered an important application of remote sensing data. The influence of forest management on forest landscapes requires evaluating changes to landscape patterns, since these changes can have also impacts on wildlife habitats and forest-dwelling species (ELKIE and REMPEL 2000).

Observation of forest health and detection of logging and regeneration are of the most important application in change detection methods. Changes are generally expressed as a large spectral contrast in a multi-temporal image dataset. For the monitoring of environmental change, moderate resolution imagery e. g. Landsat and Spot were found sufficient by most authors (STOKLASA 1995, WOODCOCK et al. 2001). Also clearcut logging can be readily detected using Landsat data. Fore example, SADER and WINNE (1992) analysed multiple dates of Landsat TM imagery using RGB-NDVI classification methods to identify clearcuts and partial cuts with the high efficiency results. Some studies in change monitoring were based on visual image interpretation using one, or a pair of images. The recent computer-based methods (OLSON et al. 2004) involve texture analysis, image transforms, tasselled cap analysis and/or vegetation indexing (NDVI) within the fully digital image analysis workflow.

Assessment of forest health condition is probably the most significant remote sensing application in forestry. As explained by ŽÍHLAVNÍK and SCHEER (2000), the reason is the increasing damage of forest ecosystems and also interpretation of qualitative forest characteristics is easier and less complex then quantitative tree and stand estimation. The advantage of RS methods is the ability to asses the current extent of damage, but also to detect its latent initial phases. In this aspect, infra red images are especially useful to expose so-called extravisual changes of forest diseases. MURTHA and MCLEAN (1981) used CIR aerial photos to monitor coniferous forests damaged by SO_2. SCHEER (2000) developed method to classify degree of forest damage using channels of PCA, IHS transformation and R-G band subtraction derived from digitized aerial photos. However, satellite images are currently considered the main source of forest state information, due to their better radiometric, spectral and temporal resolution. Also, the greater scene coverage allows health monitoring of areas of global extent.

Some studies (KIRBY 1980, GOUGEON and LECKIE 1999) also explored methods of evaluation of forest regeneration using RS images. The optimal data for regeneration assessment (both natural and plantations) should be CIR aerial photos acquired with consideration to vegetation season and seedling phenology. KIRBY (1980) found that images from early spring and late autumn season allow high level of contrast to distinguish between conifers seedlings and the ground cover by dead grass.

Utilisation of forestry remote sensing in Czech Republic

Estimation of tree and stand characteristic

Methods of forest state assessment using remotely sensed data have been utilised for several decades in Czech Republic. Considering the traditionally high level of forest inventories, studies of Scandinavian and central-european authors (ARDÖ 1992, STOKLASA 1995, SCHEER 1996, REESE and NILSSON 2000, BUCHA 2004) were the most relevant sources of inspiration for Czech forestry remote sensing. The extensive research focused mainly at the assessment of location, but also other attributes, such as volume, height, age, structure and health condition using remotely sensed data (aerial, satellite).

From the beginning, mainly visual interpretation of aerial photos was found useful in forestry. The typical application represented a drawing of basic map elements in Forest Management maps 1:5000 over aerial photos, lately transformed into production of overview management maps using simple overlay with LHP raster layers within the geographic information systems (Figure 6).

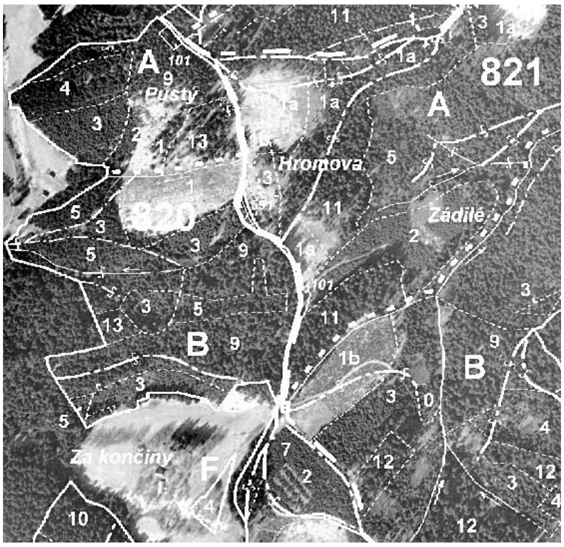

Figure 6. Panchromatic aerial photograph overlaid by raster GIS layer from Forest management planning LHP database (UHUL Map Server 2005)

Another application of exceptional significance is the use of traditional photogrammetric methods for purposes of forest mapping. TICHÝ (1949) worked on the task of "how well to utilise aerial photogrammetry in forest practice" to acquire fast and cost effective forest inventories already in the late 1940s. The proposed method was considered an efficient alternative to creation of the management plans and maps, but also the elevation contour maps. He also set a number of screening conditions and calculated costs at the half of the geodetic terrestrial measurements. ŽÍHLAVNÍK (1998) refers that demands on mapping extent, maximal rationalization and difficult conditions for terrestrial works in mountainous areas cased the photogrammetric assessment prevailing method of forestry mapping in Slovakia. Nevertheless, the b&w photos successfully used for acquisition of basic location and height attributes are less suitable for forestry mapping of specific thematic content.

Valuable information for vegetation mapping can be acquired from multispectral aerial images. The first forestry oriented experiments with MS material were done within the international cooperation program Interkosmos in 1978. TOLLINGER and HUSÁK (1982) aimed to evaluate multispectral images for purpose of forest health assessment and tree species identification, but also explored different band combinations suitable for thematic interpretation. The multispectral satellite images of moderate resolution (Landsat, Spot) were found too coarse for Czech forestry. Such data might be suitable for mapping of extensive areas in countries such as USA, Canada and Scandinavia, but the operational use in the Czech environment is rather complicated, as the level of forest information is typically very high here. Unfortunately, neither the aerial photo interpretation was not applied in broader extend as a technology of production of forest management plans in Czech Republic (FRYML, 2005 pers. communication).

The advanced techniques of the tree top detection and crown delineation are not very often used in Czech forestry research. Still, some activities occurred recently in this field. Following approaches of different authors (GOUGEON 1995, DRALLE and RUDEMO 1997, LARSEN and RUDEMO 1998, BRANDTBERG 1999), ŠUMBERA and ŽÍDEK (2003) aimed to locate individual trees from scanned multispectral aerial photos. The algorithms e.g. finding local maxima, template matching and edge detection were tested and implemented into a special program to automatically create maps to be used in a range of forestry applications.

Assessment of forest health

Assessment of forest health condition using remote sensing data was one broadly studied application in Czech forest sector. The research cooperation program between Czechoslovakia and NDR (since late 1970s) utilised infrared aerial images to locate trees damaged by smog emissions in Krušné Hory Mts. (VINŠ and PELZ 1981). The level of forest damage was assessed by combination of terrestrial and aerial survey and then profiles of selected trees were analysed in the age ring analysis. VINŠ and PELZ (1981) deduced that infrared aerial photos are suitable to expose different levels of forest damage and consequently perspective method to assess yield losses in polluted forest areas. Their report extended results of evaluation of various aerial photo materials in Krušné Hory studied by HAUTKE in 1978. Besides, multispectral aerial images were studied with the objective to identify trees damaged by frost, dry rot, or bark insects (TOLLINGER and HUSÁK 1982).

Since 1984, series of satellite imagery from Landsat TM and ETM+ sensors have been continuously analysed to obtain evaluation of forest damages. The 30-m multispectral data allow extraction of mixed information about the amount of needles (leaves) and its condition in terms of water content and withering level. Based on this information, two different classification scales of forest mortality and defoliation can be acquired (STOKLASA 1995):

A. "Level of damage and forest stand mortality" is connected to classification of coniferous forest damage caused air pollution (O, O/I, I, II, IIIa, IIIb, IVa, IVb). Mainly decrease in leave amount with its condition as secondary factor are represented by this scale.

B. "Defoliation and mortality of coniferous forests" evaluates mean defoliation of coniferous species within forest stand in 10% steps. Such finer scale provides higher agreement of the image classification with terrestrial data, basically due to better correlation of spectral information and the defoliation attribute.

Maps of actual forest health condition and maps of long-term development are then processed. Consequently, maps of endangered coniferous forests representing areas of the poor actual condition and unsatisfying development are produced.

The image analysis methodology itself has some application constraints. The most important are the minimum canopy closure of 70% and homogeneity in tree species composition (higher than 80%). This is mainly due to the spectral influence of understorey and the problematic classification of mixed pixels in the heterogeneous stands. Considering the image spatial resolution of 30m, the similar problems may also occur at the forest boundaries. The maximum quadratic errors of 10% of the terrestrially acquired classification scale are achieved for the standard conditions (VÚLHM 2004). The classifier is trained separately for homogenous spruce stands and general broadleaved forests.

Assessment of forest health condition by remote sensing is the joint project of Forest Management Institute, Help Service Group and STOKLASA Tech. The produced satellite maps are incorporated into forest health condition information system to enable operational evaluation and support decision process of the Ministry of Agriculture of the Czech Republic.

Besides, the database is used by institutions such as Forest Management Institute (ÚHÚL), Forestry and Game Management Research Institute (VÚLHM) and State Forests of Czech Republic (LČR, s.p.)

Image interpretation

Each pixel in the satellite data has a DN (digital number) specifying a spectral reflection of the sensed object in a specific spectral band. Different feature types manifest different combinations of DNs based on their inherent spectral reflectance and emmitance properties (LILLESAND et al. 2004). Spectral pattern refers to the set of radiance measurements obtained by the various wavelength bands for each pixel. We can also recognize the spatial pattern of objects when trying to interpret remotely sensed data. That typically involves the categorization of image pixels on the basis of their spatial relationship with pixels surrounding them. Spatial classifiers consider aspects such as texture, feature size, shape directionality and content.

Digital image processing is an extremely broad subject and it often involves procedures that can be mathematically complex. The idea behind the subject is that digital image, fed into computer on the pixel basis, enters an equation or a series of equations and the changes are stored to be used for the analysis or may itself be further manipulated by additional programs (LILLESAND et al. 2004). These procedures typically involve image rectification and restoration (radiometric and geometric correction), image enhancement, image transforms and filtering techniques. Methods of image enhancement can be divided into 3 main groups:

1. Radiometric enhancement — enhancing images based on the values of individual pixels
2. Spatial enhancement — enhancing images based on the values of individual and neighboring pixels
3. Spectral enhancement — enhancing images by transforming the values of each pixel on a multiband basis

Spectral analysis

Since there is a relationship between forest stand parameters and the particular spectral bands, the analysis of multispectral imagery such as Landsat TM requires selection of an appropriate band according to the intended forestry application. The near-infrared band is usually preferred for generic forest inventory (although the green band can also work effectively), while the blue band may be more appropriate for defoliation assessment. From five Landsat TM bands studied by BROCKHAUS and KHORRAM (1992), TM5 and TM7 were found significantly correlated with age class and basal area. According to ARDÖ (1992), there is a strong negative correlation between the stem volume of the forest compartments and the spectral radiance in all bands except TM4. The shortwave infrared spectral region (SWIR) seems to be particularly sensitive to forest vegetation density, especially in the early stages of clearcut regeneration (HORLER and AHERN 1986).

Apart from the direct application of certain bands, it is also possible to generate an illumination image from various band combinations and different image transform processes - arithmetic operations such as addition, subtraction, multiplication and division. These enhancements derived from multispectral and multi-temporal imagery should ideally utilize multi-resolution image data to reduce acquisition costs, manage computational expense, narrow the spatial extent of areas in consideration, and provide a manageable workflow (OLSON et al. 2004).

Band rationing and vegetation indices

Ratio images are enhancement resulting from division of DN values in one spectral band by the corresponding values in another band. Derived images clearly portray variations in the slopes of the spectral reflectance curves between the two bands involved, regardless of the absolute reflectance observed in the bands. In other words, spectral characteristics of image objects are preserved and represented without respect to variations in scene illumination conditions (LILLESAND et al. 2004). Indices can be used to minimize shadow effects in satellite and aircraft multispectral images. Further, as ratio images are derived from the absorption/reflection spectra of the material of interest, the ratio often gives information on the chemical composition of the target. This is useful in vegetation analyses to bring out small differences between various vegetation classes.

Since the concept of between-bands differences and ratios was broadly accepted by the image interpretation community, numerous forms of linear data transformation have been developed for vegetation monitoring. In many cases, reasonably chosen indices can highlight and enhance differences which cannot be observed in the display of the original color bands. The differential reflectance in these bands provides a means of monitoring density and vigour of green vegetation growth using the spectral reflectivity of solar radiation. This can utilize in many tasks such as classification of land cover or detection of vegetation stress

Normalized difference vegetation index (NDVI) is a frequently used index that provides a standardized method of comparing vegetation greenness between satellite images. While most authors (BOONE et al. 2000, CHEN 1998) studied NDVI as an indicator of relative biomass and greenness, other studies used indexes to derive further transforms. TUOMINEN and PEKKARINEN (2004) extracted NDVI and three channel ratios NIR/R, NIR/G, and R/G to calculate different texture features from digital aerial images. SOUZA et al. (2005) proposed a new Normalized Difference Fraction Index (NDFI) spectral index for enhanced detection of forest canopy damage caused by selective logging activities and associated forest fires.

Principal component analysis

Problems of extensive interband correlation in the multispectral imagery often cause that individual wavelength bands appear similar and convey essentially the same information. Principal components analysis (PCA) is used as a method of data compression allowing to reduce such redundancy in multispectral data. The bands of PCA data are non-correlated and independent, and are often more interpretable than the source data (JENSEN 1996). As stated in LILLESAND et al. (2004), the first principal component describes majority of the variance in the original dataset, for example 98% for Landsat imagery. If used for purpose of automated analysis, the reduction of data dimensionality can generally increase the computational efficiency of the classification process.

IHS transformation

The color monitors used for image display on image processing systems have three color guns corresponding to additive primary colors of red, green, and blue (R, G, B). When displaying three bands of mulispectral imagery, the viewed image is said to be in RGB space. However, it is possible to define an alternate color space that uses Intensity (I), Hue (H), and Saturation (S) as the three positioned parameters.

IHS enhancement operations benefit from the ability to vary each IHS component independently. After the conversion from RGB to IHS, a contrast stretch can be applied to the intensity component without affecting hue and saturation of the image pixels (FOLEY et al. 1990). The other way of using IHS transform is combining co-registered images of different resolutions (sources). For example, Ikonos 1-m panchromatic data (used in the intensity component) can be merged with 4-m multispectral (hue and saturation components) to get pan-sharpened multispectral imagery.

Tasseled cap analysis

Tasseled Cap transformation offers a way to optimize data viewing for vegetation studies. These transformations were originally derived for Landsat images to highlight differences in vegetation and soil. As shown by COHEN and SPIES (1992) who used a combination of Tasseled Cap spectral indices and textural features of Landsat TM and SPOT HRV imagery, the transform can be well utilised also for estimating of forest attributes. HORNE (2003) suggested the method of tasseled cap calculation for multitemporal analysis of Ikonos data. Tasseled Cap transform was calculated as an average of principal components (used as a new orthonormal basis for the four bands) across a large number of Ikonos images in his study.

Texture analysis

Texture is one of the most important defining characteristics of an image. It is characterized by the spatial distribution of gray levels in a neighborhood (JAIN et al., 1995). Many studies proved that RS classification methods based solely on spectral classification are insufficient for mapping of complex forest structures from high resolution digital imagery (ZHANG 2001, WACK and STELZL 2005). Particularly young succession stages and heterogeneous mature stands are characterised not only by the spectral but also their textural (spatial) properties. Similarly non-forested areas and regenerating areas be eliminated based on their different texture characteristics. However, automated recognition of objects based on these characteristics is still difficult. Various methods have been employed for automated extraction of texture information in forestry. This includes local statistical measures (HSU 1978), grey level co-occurrence matrix (ANYS et al. 1994), semivariogram (ST-ONGE and CAVAYAS 1997), and neural network approaches (DREYER 1993).

ZHANG (2001) tested several texture algorithms and found that local variance extraction, edge detection and some co-occurrence matrix texture measures can well separate trees from lawn and other objects with similar spectral properties. The result of texture integrated classification gained almost 30% of agreement over the multispectral only method. The use of textural and spectral features of SPOT HRV imagery in classifying forest and other vegetation types has been studied by PEDDLE and FRANKLIN (1991). TUOMINEN and PEKKARINEN (2005) assessed performance of selected textural features derived form digital aerial photos and stated that optimal image spatial resolution is dependent on the object size. HAUTA-KASARI et al. (1999) applied different HARALICK features on the multispectral images to perform texture segmentation. Another evaluation of spatial information (semivariance range and sill, co-occurrence texture) in spectrally unmixed image fractions of vegetation, shadow and wood was done by Le'VESQUE and KING (2003) who found it useful in forest structure and health modelling. NARASIMHA et al. (2002) found textural features GLCM Entropy and Correlation optimal for Landover classes discrimination from IRS-1D pan data with achieved accuracies over 80%.

Automated classification methods

The methods with some degree of automation that use the existing knowledge to increase the practical efficiency (benefit/cost ratio) were the important topic lately. The main goal is to fully or partly replace the human image interpreter by a seeing computer, capable of making many decisions on its own, with a minimum of human intervention during the image processing and analysis. As stated by COHEN et al. (1998), automated classification methods provide sufficient accuracies when mapping forestry harvest activities. Further, methods based on generalization require less time and effort than conventional methods and as a result may allow monitoring of larger areas or more frequent monitoring at reduced cost (WOODCOCK et al. 2001). BALTSAVIAS (2004) clarifies the term automated and semi-automated methods. As these always involve some kind of interactions, either during preprocessing or postprocessing stage, should be viewed as knowledge-based methods. In BENZ at al. (2004), the four main requirements for successful knowledge-based object extraction were highlighted:

- understanding of the sensor characteristics
- understanding of appropriate analysis scales and their combination
- identification of typical context and hierarchical dependencies
- consideration of the inherent uncertainties of the whole information extraction system, starting with the sensor, up to fuzzy concepts for the requested information.

The commercial systems that allow to use our knowledge to extract desired objects from aerial and satellite imagery include photogrammetric, GIS and remote sensing software. Typically, the different programs are usually designed for particular tasks, which leads to the complex software workflow - one program is used for data preparation and image pre-processing (PCI Geomatica, Erdas Imagine), followed by the classification procedures (eCognition, ENVI) and then result is exported for the final post-classification improvement and accuracy assessment to the GIS (ArcGIS, Geomedia).

The automated classification procedures, as stated in LILLESAND et al. (2004), can be basically divided to supervised and unsupervised classification. In supervised classification, an image analyst specifies various land cover types for the computer in a categorization process. Training areas (sample sites of known cover type) are used to compile a numerical “interpretation key” that describes the spectral attributes for each feature type of interest. Each pixel in the data set is then compared numerically to each category in the interpretation key and labelled with the name of category it “looks most like” (LILLESAND et al. 2004). Unsupervised classification involves data aggregation into natural spectral groupings (clusters) in the first step, while the image analyst identifies these spectral groups as certain land cover types using ground reference data in the second step.

Feature selection

Considering the supervised classification, success of classification stage is determined by the quality of the training process. This is often done by selecting training pixels or training areas, which well represent desired cover classes. LILLESAND et al. (2004) suggest to involve several training sites in the analysis, which increases the change of having representative sample of each cover type. In the training set refinement process, quality of candidate training areas and their spectral separability is assessed. The gaps and redundancies (overlap regions) in signature distributions are identified. Further, areas that include more than one spectral class are identified and recompiled, extraneous samples may be deleted from the selection. Definition of representative training set is normally an iterative process with the revision of class statistical description until they are sufficiently spectrally separable. Hence, the class separability is logically associated with the class spectral signatures. The inherently similar spectral response patterns often need the ancillary information from GIS layers, visual interpretation or the field check, as well as multitemporal and spatial pattern recognition procedures to be discriminated.

Graphical representation of class separation

The nature of classified objects can be very heterogeneous, so various types of features must be integrated into feature space to achieve a good recognition rate. The relevant features may include many such as color, texture or context, and then their selection for optimal and efficient class separation is needed.

The distribution of training area response patterns can be graphically displayed by means of histograms and two-dimensional scatterograms. Histograms well illustrate distribution of one class, but do not provide comparisons between different cover types. The scatter plots indicate response in various bands (features) with distribution overlaps for several categories. Based on such feature space representation, the least correlated features can be selected for improved class separation.

Besides the scatterogram visualisation, some commercial image analysis software also allows computing divergence for every class pair within each feature, or band. The separability listing contains every divergence value for the bands studied for every possible pair of signatures. The separability listing also contains the average divergence and the minimum divergence for the band set. (Erdas FieldGuide).

Quantitative expressions of class separation

Two measurements are basically used for a quantitative estimation of class separation. Transformed divergence is a measure of statistical separation between category response patterns. This measure evaluates the difference between all pairs of classes and can be presented in the form of matrix. The technique requires that the measurements on samples of classes are distributed in multivariate normal form (MATHER, 2004).

Discriminant Analysis was found a simple and powerful technique to project data into a reduced dimensional space in which the data are optimally separated given a set of labelled images. The implicit effect of the transformation is to assign various weights to each feature dimension depending on their relevance to discriminate each class (FAUQUEUR et al. 2005). Discriminant Analysis is generally used as a description of group (class) separation with linear functions of variables used to describe or elucidate the differences between two or more groups. The goal is to identify relative contribution of the *p* variables to separation of the groups and finding the optimal plane on which the points can be projected to best illustrate the configuration of the groups (Rencher 2002).

BUCHA (2004) successfully applied discriminant analysis to find optimal variables and derived discriminant model for distinction of different stand structures. The contribution of variables was assessed (F-test) and the best feature combination was found using Wilks Lambda statistics in stepwise procedure. Hotelling's T^2-tests and MANOVA test are other commonly used multivariate tools. Some authors (FAUQUEUR et al. 2005) suggest projection the data with Principal Component Analysis before discriminant projection to avoid matrix singularity problem in cases, when the number of samples is lower than the feature dimension.

Accuracy assessment

Maps derived from remotely sensed data are often judged to be of insufficient quality for operational applications. In order to derive quality of a classifier and to evaluate classification with respect to their suitability for specific application, results are compared on the basis of other classification. This data can be obtained with different methods, e. g. *in-situ* ground measurements and is considered as a reference data set. Disagreements between the two data sets are typically interpreted as errors in the land cover map (CONGALTON, 1991).

The most commonly used method of representing the degree of classification accuracy is to build a k x k confusion matrix. Such table is derived by counting how many of the pixels assigned to a class A in the result classification are of the corresponding class in the reference classification. As a simple cross-tabulation of the mapped class label against that observed in the ground or reference data for a sample of cases at specified locations, it provides an obvious foundation for accuracy assessment (CAMPBELL 1996; CANTERS 1997). The confusion matrix provides the basis on which to both describe classification accuracy and characterize errors, which may help refine the classification or estimates derived from it (FOODY 2002).

Sample areas

The test areas are representative and uniform plots with distinctive characteristics for specific class. Beside the typical use during the training stage of supervised classification, the plots can serve the post-classification accuracy assessment. The important aspect is the definition of an appropriate sample size and sampling design as well as specification and use of a measure of accuracy appropriate to the specific application.

The sample size must be selected with care and be sufficient to provide a representative and meaningful basis for accuracy assessment (FOODY, 2002). The size recommendations went through a complex development and several researchers proposed approaches to determine appropriate sample size. To fill an error matrix, some broad guidelines suggested that a minimum of 50 samples of each vegetation or land cover category are to be included. According to CONGALTON and GREEN (1999), the minimum number of samples should be increased to 75 or 100 per class, "if the area is especially large (more than a thousand hectares), or the classification has a large number LULC classes (i.e. more than 12 classes). The number of samples should also be adjusted based on relative importance of certain class for particular application, and the sampling allocated with respect to the variability within each class (LILLESAND et al. 2004).

The issue of sampling design and appropriate sample unit are also broadly discussed, as it maybe individual pixels, clusters of pixels, or polygons. As stated by some authors (LILLESAND et al. 2004, MATHER 2004), homogenous test areas might not provide a valid indication of accuracy at the individual pixel level of land cover variability. Basic random sampling can be appropriate if the sample size is large enough to ensure that all classes are adequately represented. However, it may be extremely difficult to use randomly located sites to assess the accuracy of a map covering a very large area. The ground data collection is frequently constrained by a problematic physical access and consequently, selection of a sampling design is influenced by budget or other practical reasons.

Methods of automated forest information extraction on stand and tree level

The increasing demands on the level of accuracy, timeliness, completeness, and cost-effectiveness of forest information extraction cause that traditional methods of visual image interpretation are being gradually replaced by the semi-automated and automated techniques. This fact is further supported by the improved computing power together with the availability of high spatial resolution (10-100 cm/pixel) multispectral aerial or satellite images, allowing the digital analysis on the stand and individual tree crown level.

GOUGEON and LECKIE (2003) recognise three different streams in field of individual tree crown (ITC) analysis, tree location, tree location and crown dimension parametrization, and full crown delineation. According to BRANDTBERG (1999b), tree delineation approaches can be categorized into three classes:

a. detection of a local intensity maximum assumed to represent the apex of the tree
b. contour based methods that find edges of objects
c. template-based matching methods that match generalized shapes of trees to the image patterns.

However, the results promising for forestry practice were rather obtained when combining the individual approaches. Various geometric-optical models and the template matching algorithms to locate tree tops of individual trees from aerial photographs were presented in DRALLE and RUDEMO (1997). Detection of image local maxima for coniferous stands using smoothing filters of scales appropriate for the tree sizes and the image resolution were proposed by GOUGEON and Moore (1989). Similarly, ŠUMBERA and ŽÍDEK (2003) used Gaussian smoothing to delimit number of detected trees followed by the tracing spectral minima algorithm to segment individual crowns. WALSWORTH and KING (1998) declared the peak-shadow combination "fundamental" in recognizing individual trees and CULVENOR *et al.* (1998) found that the combination of local maxima and minima, representing respectively crowns centres and boundaries, was particularly effective in delineating individual *Eucalyptus* trees. KORPELA (2000) determined tree tops using 3D matching from an aerial image stereopair. As a method of crown delineation, GOUGEON (1995) suggested a system based on following valleys of shade (Figure 7) and contouring rules to automatically delineate individual tree crowns from high spatial resolution aerial photographs. A rule based system following the tree edges was then used in order to outline and further refine the tree isolation (GOUGEON 1995, 1999). The developed method was locally adaptive, so it can switch from open to dense stand procedures.

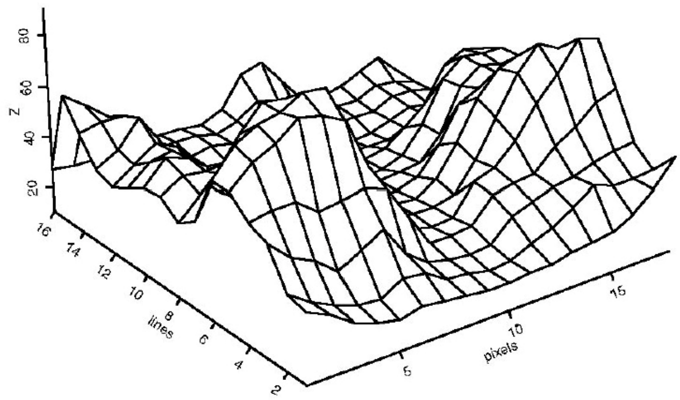

Figure 7. 3D view of image subset showing the brighter tree crowns as mountains often separated by valleys of shade (from GOUGEON 1999).

BRANDTBERG (1999) studied dependence of two-dimension variograms for detection of texture features. The presented algorithm followed edges created by the gradient operator and the edge curvatures were analyzed. The crown delineation based on edge detection was also examined by ŠUMBERA and ŽÍDEK (2003). Besides, method so-called Cost surface generation, where the primarily located tree tops serve as a starting point to crown filling and delineation was tested.

Automated methods of tree crown delineation have been successfully applied to coniferous plantations using high resolution imagery (GOUGEON 1993, 1995, 1997a), but deciduous forests appear to be a greater challenge. COOPS et al. (1998) suggested that the terms "canopy object" or "tree cluster" are preferable to "tree crowns" for this work, because few sub-dominant trees are visible from above, and the boundaries of trees in natural environments can be so complex (BRANDTBERG 1999a).

Recently, a number of researchers aimed to delineate tree crowns using various segmentation algorithms. The one considered useful was developed by BAATZ and SCHÄPE (1999) and introduced in the first commercial object-oriented analysis software eCognition (Definiens Inc. 2000). The segmentation studies focused stand delineation and area-based species distribution (HALOUNOVÁ 2003), as well as delineation of individual trees. The approach of local maxima detection followed by simultaneous object-growing (similar to Cost surface generation, Figure 8) was lately proposed by TIEDE and HOFFMANN (2006).

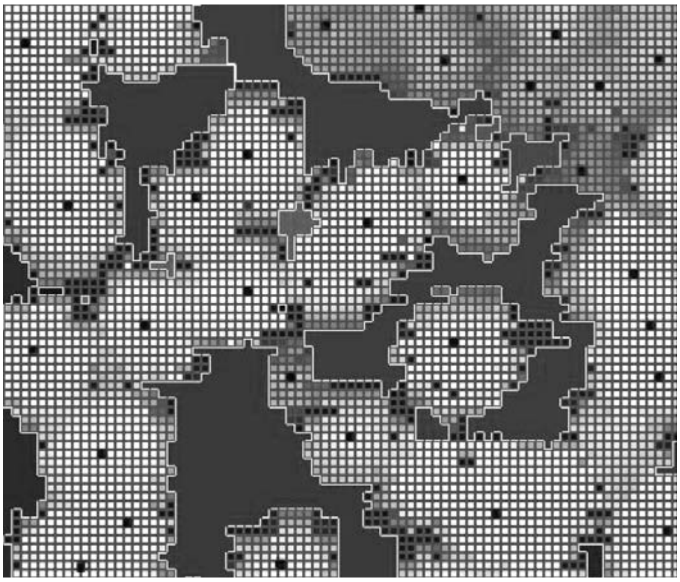

Figure 8. Chessboard segmentation with tree tops detected by local maxima (TIEDE and HOFFMANN 2006)

Object-oriented analysis of VHR image data

The automated classification of highly textured image data such as aerial photos and VHR satellite imagery is a complicate task (HALOUNOVÁ 2003). The extreme image heterogeneity cause the objects representing one thematic class (tree crown) are actually consisted of number of pixels with diverse digital values. The traditional pixel-based classification procedures (supervised and unsupervised) consider the DNs of the individual pixels, but not their spatial distribution so called image texture. The different approaches can be applied to solve this problem:

a) Enlarging the classification signature space by the calculation of additional channels (e.g. texture)
b) Image segmentation followed by object classification of the original dataset
c) Object-oriented image analysis using enlarged signature space (combination of the two former)

The topic of signature space enlargement is connected to the multiple image matching and contribution of various image transforms and derivatives to classification result, and was already covered in chapters *Image pre-processing* and *Feature selection*. The problematic of image segmentation and classification of meaningful objects refers to term Object-oriented image analysis. According to BALTSAVIAS (2004), the methods for extraction of image objects show some typical tendencies in the recent years:

- increasing number and variety of sensor data such as laser scanners, digital cameras and high-resolution satellites an their combinations are used
- semantic and Bayesian nets, artificial neural networks (ANNs), evidence theory and fuzzy logic are frequently employed
- increased use of a priori knowledge
- object-oriented, hierarchical and multiscale approaches are often used in both processing and object modelling
- more use of context and the relations between neighbouring objects
- small steps towards semi-automation and generation of operational systems
- reliability and completeness of automated results together with their automatic evaluation remain the major problem

The object-oriented image analysis is considered revolutionary in viewing content of the digital dataset. The idea behind object classification approach is to employ multi-scale object relations typically observed in form of the real world dependencies. Similarly, the concrete local relation of different data types might be of use when dealing with the multi source data fusion. Such relations can be preserved only for meaningful image objects and thus image segmentation must be done. The increased uncorrelated feature space using shape (e.g. length, number of edges, etc.) and topological features (neighbour, super-object, etc.) improves the value of final classification (BENZ et al. 2004). BURNETT and BLASCHKE (2003) concluded that the multi-scale segmentation/object relationship modelling can be a vehicle for a theory driven exploration of different types of landscape heterogeneity. Delineation of objects of high heterogeneity and complex structure represents the other motivation to perform segmentation.

Also many forest researchers agreed that the segmentation of the individual tree crowns is required to estimate the tree species composition from high spatial resolution images and it has been an ongoing research field for several years. The techniques employ template matching, valley following, local maximum filtering, edge detection, spatial clustering. Many algorithms utilize combinations of these (BRANDTBERG & WALTER 1998, CULVENOR 2002, GOUGEON 1995, PINZ 1989, POLLOCK 1996). The results from many of these methods are rather good, although more research can probably improve the result. When it comes to classification of the tree crowns into species, less research has been done. BRANDTBERG (2002) developed a method for classification of the tree crowns using fuzzy sets and GOUGEON et al. (1998) a method using spectral signatures. LECKIE et al. (2003) have developed a method for classification at stand level.

Image segmentation

The task of creating meaningful objects equates to searching for changes in image object heterogeneity/homogeneity. The number of segmentation techniques were developed e.g. HARALICK and SHAPIRO (1985), RYHERD and WOODCOCK (1996) and BAATZ and SCHÄPE (2000). The common approaches use thresholding or region growing algorithms and different types of texture segmentation algorithms and knowledge-based approaches are also used in operational applications.

Multi-scale analysis

Same type of object appears differently at different scales and thus definition of scale of interest is crucial. Studying the scene in different levels of scale enables to understand relations within the image and its better interpretation. Consequently, employing these hierarchical scale dependencies enhance the automated classification methods (BENZ et al. 2004). The purpose of a hierarchical structure is to reduce redundancy and complexity in the class descriptions (BAATZ et al. 2003). Practically classifying the upper level, each object e.g. forest stand can be analyzed based on the composition of its classified sub-objects (tree species). The context information and semantics can be used to distinguish between trees within a forest or within an urban area and more.

Fuzzy classification

Besides the hard classifiers commonly used in automated techniques (maximum likelihood), fuzzy logic together with neural networks (GOPAL and WOODCOCK 1996) present soft classifiers. The soft classification allows for data ambiguity being especially useful when describing transition properties and variations in boundary sharpness.

As JENSEN (1996) notes, there needs to be a way to make the classification algorithms more sensitive to the imprecise (fuzzy) nature of the real world. Instead of being assigned to on specific class, the pixels can have a multiple and (or) partial class membership (FOODY 1996). Fuzzy classification takes into account the existence of mixed pixels that doesn't belong strictly to one class, allowing creation of inhomogeneous spectral response patterns with relation to other objects. The method determines wherein a pixel's value is closer to one class than another using a membership function. The classification result ten does not have definite boundaries and each pixel can belong to several different classes (JENSEN 1996).

The basic idea behind Fuzzy logic is to quantify uncertain statements. The two boolean logical statements "true" and "false" are replaced by the continuous range of [0,. . .,1], where 0 means ''false'' and 1 means ''true'' and all values between 0 and 1 represent a transition between true and false. Avoiding arbitrary sharp thresholds, fuzzy logic is able to approximate real world in its complexity much better than the simplifying boolean systems (BENZ et al., 2004). Moreover, the fuzzy classification systems can handle significant problems of remote sensing expert analysis, such as uncertainty in sensor measurements, parameter variations due to limited sensor calibration, vague (linguistic) class descriptions and class mixtures due to limited resolution (TSATSOULIS 1993). Working in a high-dimensional feature space with different feature value ranges and features of various types, e.g., backscatter from different sensors, geographic information, texture information and hierarchical relations is also easier. Finally, the important advantage of fuzzy logic compared e.g., to neural networks is a transparent and adaptable set of classification rules that can be applied on other datasets for a high level of automation.

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5 Main methodical principals

In this chapter, important features of the intended methodology are overall reviewed. The actual procedures are further described in the publications in chapter *Results* (**I – V**).

The methodology pay interest on the most up-to-date and promising approaches in the image analysis and remote sensing data interpretation. Firstly, the very high resolution digital multispetral imagery are only involved and processed. The IKONOS satellite images and color infra-red (CIR) aerial images were considered to fulfill the needs of the detailed forest assessment at reasonable cost. Secondly, the methodology put emphasis on the initial enlargement of classification signature space during the pre-processing phase. Thus, many additional channels such as spectral ratios and vegetation indices (NDVI), Tasseled cap and IHS transformation, low-pass filters, Sobel edge detection and GLCM texture measures are calculated from the original dataset. The whole concept is then integrated into process of the object-oriented classification presented in the commercial image analysis software Definiens Professional (a.k.a. eCognition, Definiens Imaging Germany). Nowadays, it is the only program on the market, that implements object analysis with enhanced algorithms for multi-resolution image segmentation, complex capability in object description (spectral, geometric, textural and contextual), relations within hierarchical image object network and fuzzy rule-based classification. In such manner, the knowledge of either forestry or RS interpretation experts may be employed. The effort was utilize the features to create a powerful tool for automated forest management applications.

Material – very high resolution (VHR) digital imagery

The advantage of VHR images (with pixel size less than one meter) is that individual trees are often visible, especially when the forest is mature and not too dense. Such imagery can potentially be used for individual tree-based forest inventory and planning. Features of particular interest include the tree crown size, and spectral characteristics, stem position, and stem number per hectare. The tree species estimates are also important, both for the species area distribution and timber volume calculations.

Lately, a number of new sensors and systems were developed and introduced to remote sensing experts and the potential is gradually approaching operational applications. The very high resolution (VHR) digital images acquired by spaceborn sensors such as IKONOS, and QuickBird fulfil much of demands on large scale multitemporal analysis. Also digital aerial cameras for photogrammetry have developed significantly since they were first introduced in 2000 and today, frame based as well as linear array cameras are available on the market (e.g. Leica Geosystems, Z/I Imaging, DiMAC systems, Vexcel Imaging). Their main advantages over traditional aerial photos are a completely digital data flow, a significantly improved radiometric image quality, together with the possibility to simultaneously acquire panchromatic, colour and near infrared (NIR) imagery. In addition to aerial photography, very high spatial resolution aerial data are available from airborne imaging spectrometers (e.g. AISA, CASI, DAIS 7915, ROSIS and HyMap), active sensors such as airborne laser scanners (e.g. TopoSys, Optech ALTM and Leica ALS50) and airborne radars (e.g. CARABAS and GEOSAR). This implies a situation, when the technology and research with applications have to be well coordinated.

In this study, the three different types of remotely sensed images were selected for further analysis: IKONOS-2 satellite images, color and infrared film aerial photos and aerial images acquired by medium-format digital camera.

IKONOS-2 satellite data

The IKONOS satellite was launched in September 1999 as the first commercial high resolution imaging satellite. The high geometric accuracy, stable radiometry, and 11-bit dynamic range of IKONOS images make them an excellent mapping tool and enable significant automated feature extraction. The panchromatic sensor with 82-centimeter imagery provides imagery for civilian applications such as urban planning and mapping. The 3.28-meter multispectral sensor provides spectral-radiometric measurements for the scientific community with promising applications in land-use classification, environmental monitoring and resource development (DIAL and GRODECKI 2003). Moreover, stereo imagery enabling terrain and 3-D feature extraction is available for operational use.

Sensor Characteristics

The IKONOS satellite orbits the Earth every 98 minutes at an altitude of approximately 680 kilometers. IKONOS was launched into a sun-synchronous orbit, passing a given longitude at about the same local time daily. IKONOS can produce 1-meter imagery of the same geography every 3 days. IKONOS images data are available in 8-bit radiometry, or full dynamic range 11-bit format. The Blue, Green, Red, and NIR bands approximate Landsat TM 1-4 bands (Figure 9):

- blue: 0.45 - 0.52 mm
- green: 0.51 - 0.60 mm
- red: 0.63 - 0.70mm
- near IR: 0.76 - 0.85 mm

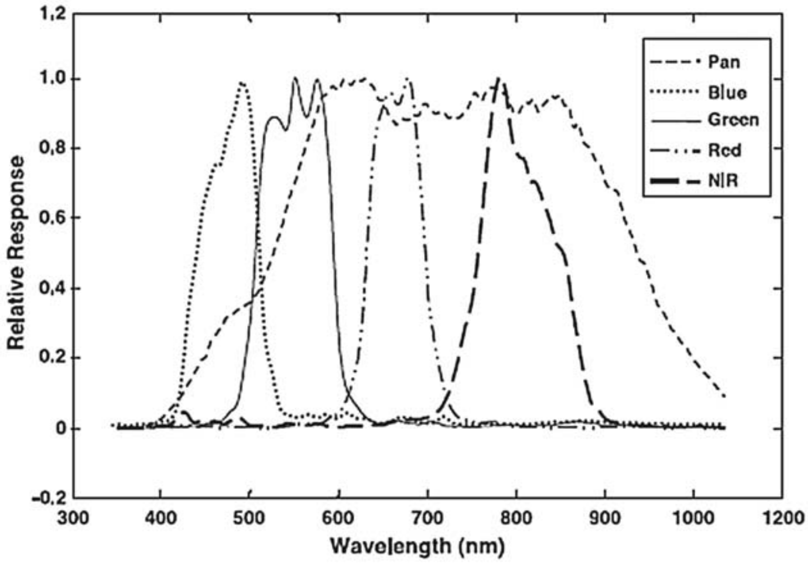


Figure 9. The relative radiometric response of the IKONOS multispectral imagery

Standard products include 1-meter panchromatic, 4-meter multispectral (all bands), 1-meter color (true color, false color, or 4-band), and a 1-meter and 4-meter data bundle. All products are radiometrically corrected by rescaling the raw digital data transmitted from the satellite. The product range includes *IKONOS Geo, Geo Ortho Kit, Reference, Pro, Pro plus, Precision and Precision plus* positional accuracy image levels. Besides, *IKONOS Stereo* images distributed in epipolar projection are available for 3-D applications.

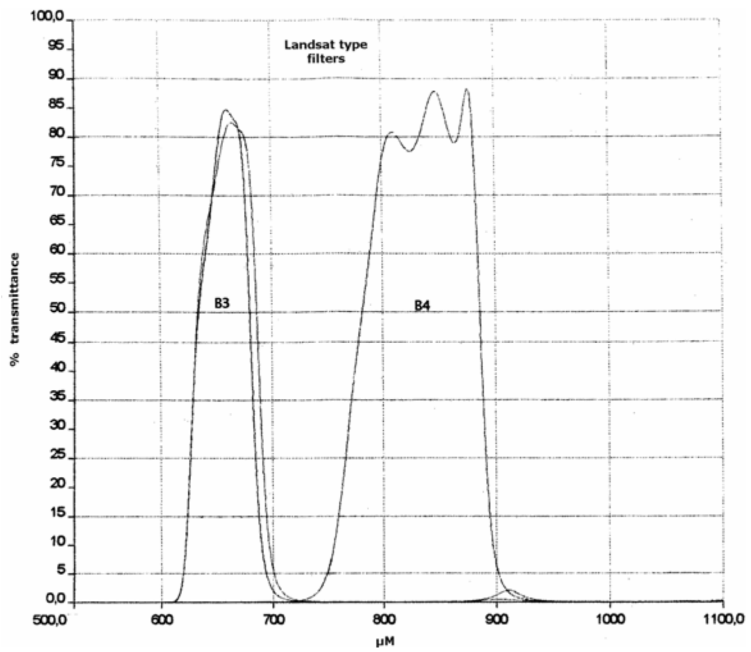
The actual imagery used in the study was delivered in a geo-registered UTM projection (zone N33) with 11-bit radiometric resolution at Standard Geometrically Corrected processing level - IKONOS *Geo*. *Geo* images are rectified to a map projection at a constant height without the use of a Digital Elevation Model (DEM). Such product is suitable for image analysis where a high degree of positional accuracy is less important than correct radiometry.

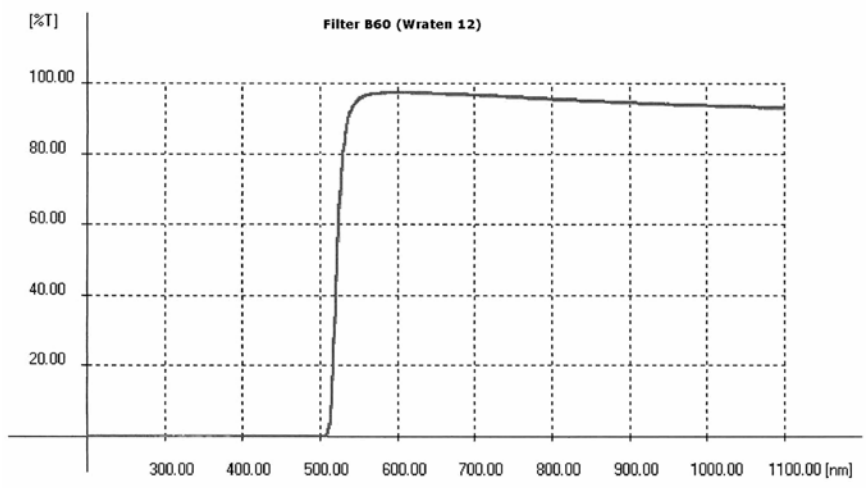
Medium–format digital aerial photos

Aerial images from medium-format camera Hasselblad H1 with lens of 50.4 mm focal length and PhaseOne P25 (Figure 10) digital back were another image format analyzed in this study. Hasselblad H1 is a medium format SLR camera with a number of unique features that support digital backs and provide similar handling and functionality as an integrated digital camera. Image format is 6 x 4.5 cm (actual size 56 x 41.5 mm). Phase One P25 digital back incorporates 22 megapixel CCD chip with size of 48.9 x 36.7 mm, 9 x 9 µm pixel pitch, 4:3 ratio and 16 bits per pixel ADC.

Figure 10. Hasselblad H1 medium- format camera with PhaseOne P25 digital back

The images were sensed using custom-made optical filters to obtain three multispectral bands with spectral properties similar to Landsat TM bands (Figures 11a, 11b).





Figures 11a, 11b. Transmitance custom-made optical filters: Landsat type B3 and B4 and B60 (Wraten 12) (Optical research workshop AV Turnov 2002)

The analyzed images acquired as testing material by company GEODIS™ Brno were delivered as a raw data in with radiometry restricted to 8-bit per pixel. The imagery was geo-registered to the reference GIS in UTM projection (WGS 1984 zone 33N) using a rational polynomial function model with the total RMSE 2.3 m and pixel size resampled to 0.5 m, before further pre-processing and classification.

Color and infrared film aerial photos

Aerial imagery acquired on color and infrared film material by aerial camera ZEISS LMK 2015 (Figure 12) and delivered by different companies were the third data source analyzed in this study. The camera produces images in format 23x23 and features an anti-erase technology, built-in exposure meter and gyroscopic suspension.

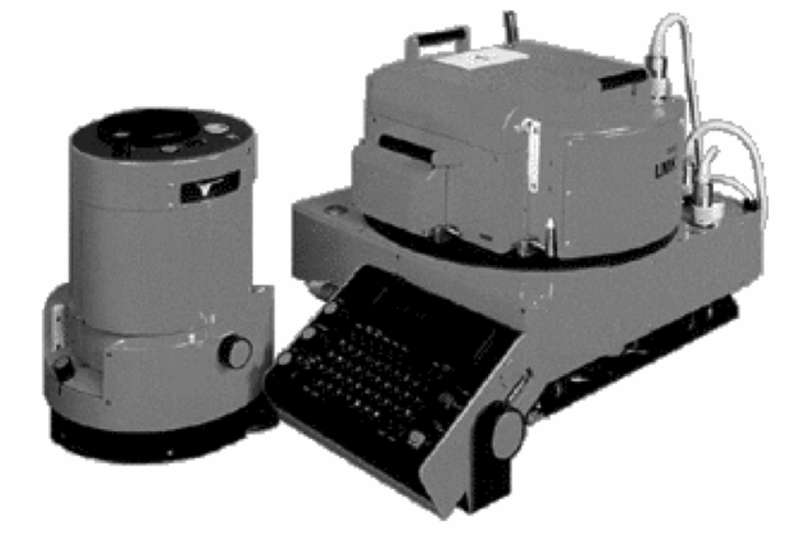


Figure 12. Aerial camera ZEISS LMK 2015

Color aerial photographs were acquired in three visible spectral bands with 8-bit depth. Infrared (a. k. a. color IR) images were acquired on IR sensitive film Kodak AEROCHROME 2443. In this film, the dye-forming layers are sensitive to green, red, or near-infrared wavelengths. It must be used with a yellow or minus-blue filter (e. g. Wratten. 12) to eliminate the blue light. After reversal development, three dyes are formed (yellow, magenta and cyan). When viewed with transmitted light, the dyes act to subtract light and consequently show images in false colours.

The actual photographs used in the study were delivered both as orthophoto, and scanned unprocessed raw data. These were geo-registered to the reference projection (WGS 1984 zone 33N) and then all images resampled to spatial resolution of 0.42 m/pixel.

Signature space enlargement

Many studies (HALOUNOVÁ 2003, OLSON et al. 2004, DeKOK 2006) showed that image classification may greatly benefit of using various channels and illumination layers calculated from the original image datasets. These derivatives are often represented by different band combinations and image arithmetic operations such as addition, subtraction, multiplication and division. The objective is to find information not much correlated to the original bands – channels that are highly enlarging signature space of intended classes. There are many of the image transforms proposed in RS literature, only the channels tested for purpose of forest classifications in this study are further described.

NDVI

Normalized difference vegetation index (NDVI) is a frequently used index that provides a standardized method of comparing vegetation greenness between satellite images. The formula to calculate NDVI is:

$$NDVI = \frac{(IR - R)}{(IR + R)}$$

Vegetation NDVI typically ranges from 0.1 up to 0.6, with higher values associated with greater density and greenness of the vegetation canopy. Surrounding soil and rock values are close to zero while the differential for water bodies have the opposite trend to vegetation and the index is negative. A range of errors such as scattering by dust and aerosols, Rayleigh scattering, subpixel-sized clouds, plus large solar zenith angles and large scan angles all act to increase channel 1 with respect to channel 2 and reduce the computed index.

In this study, NDVI calculated from Ikonos and medium-format digital images were examined in ability to distinguish between different LULC and vegetation classes.

PCA

The principal components analysis (PCA) is often used to reduce unnecessary dimensionality of multispetral images. To perform PCA, the axes of the n-dimensional spectral space are rotated, changing the coordinates of each pixel in spectral space, and the data file values as well. The new axes are parallel to the axes of the ellipse. The first principal component shows the direction and length of the widest transect of the ellipse (Figure 13). The direction of the first principal component is the first eigenvector, and its length is the first eigenvalue (TAYLOR 1977).

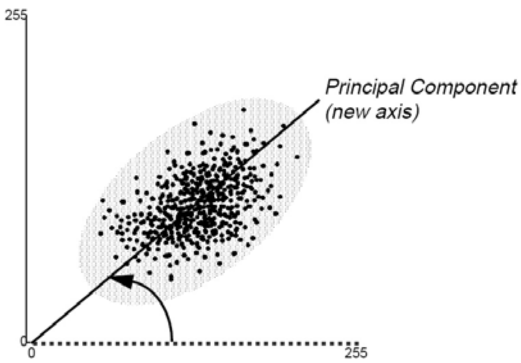


Figure 13. First principal component

If used for purpose of automated analysis, the reduction of data dimensionality can generally increase the computational efficiency of the classification process. In this study, first PCA component derived from multispectral Ikonos images served as a basis for further texture calculations.

IHS transforms

When displaying three bands of mulispectral imagery, the viewed image is said to be in RGB space. However, it is possible to define an alternate color space that uses Intensity (I), Hue (H), and Saturation (S) as the three positioned parameters. This system is advantageous to present colors more nearly as perceived by the human eye. The three components of the IHS transform are:

- *Intensity* is the overall brightness of the scene (like PC-1) and varies from 0 (black) to 1 (white).
- *Saturation* represents the purity of color and also varies linearly from 0 to 1.
- *Hue* is representative of the color or dominant wavelength of the pixel. It varies from 0 at the red midpoint through green and blue back to the red midpoint at 360 to define the entire sphere (BUCHANAN 1979).

IHS enhancement operations allow analyzing each IHS component independently. In this study, IHS components derived from Ikonos XS and Pan data were assessed for the contribution to forest classes separation.

Tasseled cap analysis

Tasseled Cap transformation offers a way to optimize data viewing for vegetation studies. It is considered to rotate the image data space to obtain its "invariant transformation" that does not change from one image to another. These rotations are sensor-dependent, but once defined for a particular sensor (e.g. Landsat 4 TM), the same rotation will work for any scene taken by that sensor. Research has produced three data structure axes which define the vegetation information content (CRIST and KAUTH 1986):

- *Brightness* — a weighted sum of all bands, defined in the direction of the principal variation in soil reflectance.
- *Greenness* — orthogonal to brightness, a contrast between the near-infrared and visible bands. Strongly related to the amount of green vegetation in the scene.
- *Wetness* — relates to canopy and soil moisture (LILLESAND et al. 2004).

Tasseled Cap transformations were originally derived for Landsat images to highlight differences in vegetation and soil. The method was later suggested also for Ikonos data (HORNE 2003). In this study, Tasseled Cap axes derived from Ikonos data were tested for the contribution to separation of forest classes.

GLCM texture measures

Gray-level co-occurrence matrix (GLCM) is the two dimensional matrix of joint probabilities between pairs of pixels, separated by a distance in a given direction. It is popular in texture description and based on the repeated occurrence of some gray level configuration in the texture; this configuration varies rapidly with distance in fine textures, slowly in coarse textures (HARALICK et al. 1973). Most of the texture measures are computed from GLCM directly. In addition, some texture measures are computed from a grey level difference vector (GLDV) which itself is derived from a GLCM.

Various texture features are calculated from the gray-level co-occurrence matrix based upon the grey values of one selected layer (eCognition UserGuide, 2004). Hence, every GLCM needs to be normalised according to following operation:

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$$

where i - row number and j is the column number

i,j - value in the cell i,j of the matrix

Pi,j - normalized value in the cell i,j

N - number of rows or columns

Homogeneity

Homogeneity, also known as the Inverse Difference Moment, measures image homogeneity as it assumes larger values for smaller grey tone differences in pair elements. Hence homogeneity is very sensitive to the presence of near diagonal elements in the GLCM.

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$$

Contrast

Contrast is a measure of spatial frequency, the difference between the highest and the lowest values of a contiguous set of pixels. A low contrast image presents a GLCM concentrated around the principal diagonal. This means that high contrast values imply high coarse texture.

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$$

Dissimilarity

Dissimilarity, akin to contrast, tells about the heterogeneity of the grey levels. Higher values of dissimilarity in GLCM indicate coarser textures.

$$\sum_{i,j=0}^{N-1} P_{i,j} \left| i - j \right|$$

Mean

Mean is an indicator of the distribution of grey levels with respect to the central position. Interpretation of this feature in association with variance will provide textural information.

$$\mu_{i,j} = \frac{\sum_{i,j=0}^{N-1} P_{i,j}}{N^2}$$

Standard Deviation

Standard deviation or variance of GLCM denotes dispersion of the grey levels as defined by the sum of the squares. Generally, coarse textured features associate with higher standard deviations. It is similar to contrast or dissimilarity.

$$\sigma_{i,j}^2 = \sum_{i,j=0}^{N-1} P_{i,j} \left(i,j - \mu_{i,j} \right)$$

Entropy

Entropy measures the disorder of an image. When the image is not texturally uniform, many GLCM elements have very low values implying that entropy is very large. Conceptually, homogeneity and entropy are inversely correlated.

$$\sum_{i,j=0}^{N-1} P_{i,j} \left(-\ln P_{i,j} \right)$$

Correlation

Correlation is a measure of grey tone linear dependencies in the image. High correlation values imply a linear relationship between the grey levels of pixel pairs.

$$\sum_{i,j=0}^{N-1} P_{i,j} \left[\frac{\left(i - \mu_i \right)\left(j - \mu_j \right)}{\sqrt{\left(\sigma_i^2 \right)\left(\sigma_j^2 \right)}} \right]$$

Angular Second Moment

Angular Second Moment is also called Energy and Uniformity and is a measure of textural uniformity, i.e., pixel pair repetition. High ASM values occur when the grey level distribution has either a contrast or a periodic form.

$$\sum_{i,j=0}^{N-1} P_{i,j}{}^{2}$$

Edge detection

Edge detection techniques determine pixels in the image with correspondence to the object boundaries in the scene. The method commonly used for edge detection produce also excellent texture features similar to those of local variance (ZHANG 2001). The commonly used Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that correspond to edges. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The operator consists of a pair of 3x3 convolution kernels designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations:

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

The magnitude of the gradient is then calculated using the formula:

$$|G| = \sqrt{G_X^2} + \sqrt{G_y^2}$$

Utilization of the texture features for differentiation between vegetation classes in addition to their spectral properties was already proposed by several authors (ZHANG 2001, NARASIMHA et al. 2002, HALOUNOVÁ 2003). In this study, selected GLCM features and edge layers were tested and found useful to distinguish between young succession stages, heterogeneous mature stands and other vegetation classes.

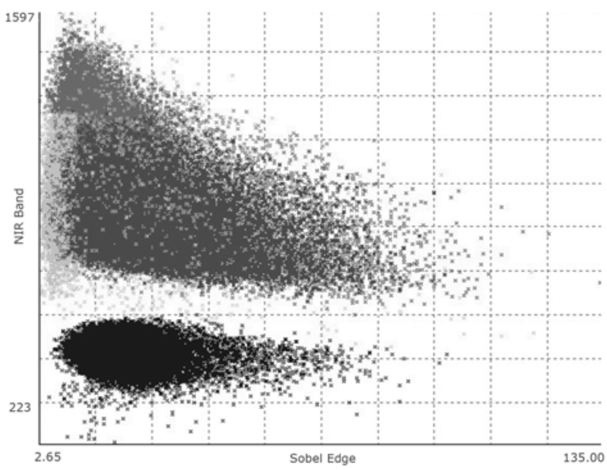
Feature selection

Due to increasing volume and dimensionality of datasets being used in image classification, methods of the dimensionality reduction for are required. The relevant features may include those of the original image bands, but also number of layers calculated during the image pre-processing. Thus, proper feature selection for the optimal and efficient class separation is needed.

The objective is to find set of statistics (features) that describe the patterns of individual objects to be classified. Firstly, the sets of samples are assigned to the corresponding class based on the reference data (manual classification). The quality of the sample objects and their spectral separability are assessed in this step. The term separability usually stands for a statistical distance between two class signatures. It can be calculated for any combination of bands used in the analysis, allowing to rule out any bands not contributing to class-by-class separation. In this study, the feature contribution was evaluated by a combination of two techniques. Various characteristics (e.g. spectral, textural, and geometrical) of the sample objects were compared using graphical statistical methods.

Graphical representation of class separation

The distribution of sample response patterns within the classification feature space can be graphically displayed by means of histograms and two-dimensional scatter diagrams (Figures 14a and 14b). Based on such feature space representation, the least correlated features can be selected and used in order to improve the class separation.



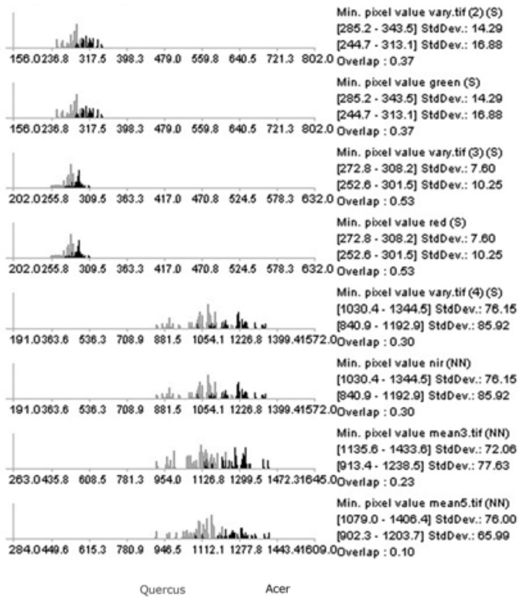


Figure 14a, 14b. Two-dimensional scatter diagram plotting Sobel Edge (horizontal axis) versus NIR band (vertical axis) Histogram representation of two different classes for various classification features.

Discriminant Analysis

Discriminant Analysis is generally used as a description of class separation with linear functions of variables used to describe or elucidate the differences between two or more groups. The goal is to identify relative contribution of the *p* variables to separation of the groups. The method used in this study was based on comparison of coefficients a_r , $r = 1, 2, \ldots, p$, in the discriminant function

$$z = a'y = a_1 y_1 + a_2 y_2 + \ldots + a_p y_p$$

Mean observation vectors **y** for 15 selected variables were calculated and the discriminant function coefficient vectors **a** were derived from variance-covariance matrix $\mathbf{S}_{\mathrm{pl}}$ as

$$\mathbf{a} = \mathbf{S}_{\mathrm{pl}}^{-1}\left(\overline{\mathbf{y}}_1 - \overline{\mathbf{y}}_2\right)$$

Since the y's were not commensurate, coefficients applicable to standardised variables **a*** had to be calculated. The relative contribution to separation of the analysed classes was then assessed by comparison of absolute values of coefficients standardized by square roots of the diagonal elements of $\mathbf{S}_{\mathrm{pl}}$:

$$\mathbf{a}^* = \left(\mathrm{diag}\ \mathbf{S}_{\mathrm{pl}}\right)^{1/2}\mathbf{a}$$

The output of the statistical method was always compared with the results of visual interpretation ("Feature View" in Definiens Professional software) and graphical methods, where histograms of the candidate features for every two competing classes were compared (Figure 14b).

Object-based image analysis

The key point of the proposed methodology is to analyse the entire image layer stack (various features selected out of original bands and the derived channels) using the object-oriented classification approach. Therefore, the main principals of the object-based analysis will be described further in this chapter.

The idea behind object classification approach is to employ multi-scale object relations typically observed in form of the real world dependencies. Similarly, the concrete local relation of different data types might be of use when dealing with the multi source data fusion.

Such relations can be preserved only for meaningful image objects and thus initial image segmentation must be done. Besides, the objects of high heterogeneity and complex structure can be delineated using proper segmentation technique. As the term indicates, the object classification involves two elemental steps:

I. Image segmentation into several hierarchical object levels based on spectral and textural properties

II. Classification of the objects according to their characteristics (spectral, textural, contextual…). These typical features are defined by mathematical functions and stored in the classification rule-base.

Image segmentation at multiple levels

Generally, the task of creating meaningful objects equates to searching for changes in image object heterogeneity/homogeneity. The segmentation algorithm developed by BAATZ and SCHÄPE (1999) considers object spectral and textural properties, but also their size and behaviour on the different level of scale. The underlying idea is the minimization of the weighted heterogeneity of image objects. In each step adjacent objects that define the smallest growth in heterogeneity are merged, but only if the heterogeneity growth is smaller than a user-defined scale parameter. The increase of heterogeneity *f* is defined as:

$$f = w_{color} \Delta h_{color} + w_{shape} \Delta h_{shape}$$

where w_{color} E[0; 1]; w_{shape} E[0; 1]; $w_{color} + w_{shape} = 1$

By mixing the spectral heterogeneity criterion w_{color} with a spatial criterion w_{shape}, one can actually smooth the resultant object, thereby eliminating branched segments or fractal shaped borderlines. The user defines the scale parameter (heterogeneity criterion), single layer weights, and mixing of spectral and shape criteria. This process is simultaneously applied across the whole image to obtain objects of comparable size and quality (BAATZ and SCHÄPE 2000, WILLHAUCK et al. 2000, SCHIEWE 2002).

As already mentioned, the objective is to perform such segmentation on several hierarchical levels, so the multi-scale relations can be used to improve the classification result. The multi-scale concept is represented by Multiresolution segmentation procedure implemented into Definiens Professional software package (Definiens Germany). In this approach, objects created on different scales - segmentation levels - can be linked together to a hierarchical object network (Figure 15) introducing several advantages:

- Structures of different scales can be represented simultaneously and thus classified in relation to each other
- Different hierarchical levels can be segmented based on different data
- Object shape correction based on regrouping of sub-objects is possible

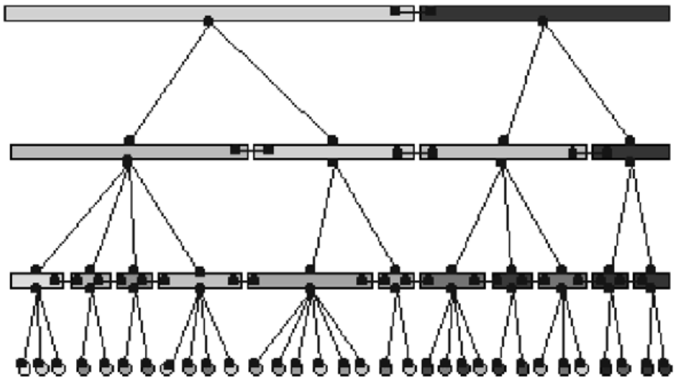


Figure 15. Four-level hierarchical network of image objects in abstract illustration (BENZ et al. 2004)

In the hierarchical image object network, class descriptions are being passed down from parent classes to their child classes. Child classes can inherit descriptions from more than one parent class.

Fuzzy rule-based classification

The classification process is controlled by a rule-base that describes the characteristics of output object classes in the form of fuzzy membership functions. Each class description consists of a set of fuzzy expressions and their combinations allowing the evaluation of specific features.

Mathematically, Fuzzy classification consists of an n-dimensional sequence of membership degrees, which describes the degree of class assignment μ of the considered object obj to the n considered classes:

$$f_{class,obj} = [\mu_{class1}(obj), \mu_{class2}(obj), \ldots \mu_{classn}(obj)]$$

The basic idea behind Fuzzy logic is to quantify uncertain statements. The two boolean logical statements “true“ and “false” are replaced by the continuous range of [0,. . .,1], where 0 means ‘‘false’’ and 1 means ‘‘true’’ and all values between 0 and 1 represent a transition between true and false. Avoiding arbitrary sharp thresholds, fuzzy logic is able to approximate real world in its complexity much better than the simplifying boolean systems (BENZ et al., 2004). Working in a high-dimensional feature space with different feature value ranges and features of various types, e.g., backscatter from different sensors, geographic information, texture information and hierarchical relations is also easier. Finally, the important advantage of fuzzy logic compared e.g., to neural networks is a transparent and adaptable set of classification rules that can be applied on other datasets for a high level of automation.

The fuzzy sets defined by membership functions will identify those feature values regarded as typical, less typical, or not typical for a class, according to their high, low, or zero membership degree (Figure 16).

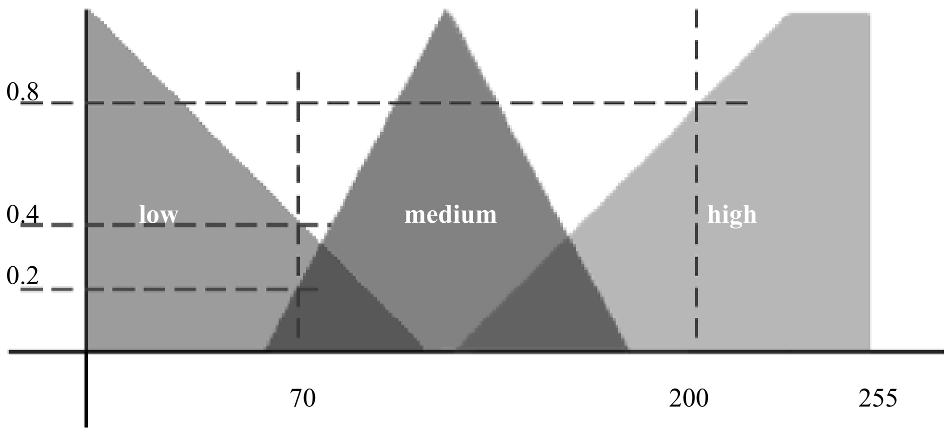


Figure 16. The three fuzzy sets on feature x defined by membership functions as low, medium and high for this feature (BENZ et al. 2004)

Further, the rules for individual features can be combined by using the logical operators ‘‘and’’, ‘‘or’’ and ‘‘not’’ (Figure 17).

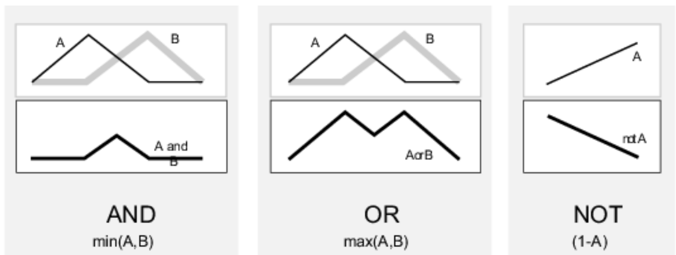


Figure 17. Logical operators in multi-valued fuzzy sets (MathWorks website 2006)

Each object in the analysis typically competes to be assigned to a certain class. Equal membership degrees of an object to several classes indicate an unstable classification. Also, the threshold for maximum membership degree needs to be set. If the class membership degree is below this threshold, no classification is performed and the object remains "unclassified" (eCognition User Guide 2003).

In this study, the workflow of multi-scale segmentation followed by object classification was consistently applied. The classification rules sets and process sequences often involved primary classification based on multiple object features (employing original and calculated channels and their combinations) and followed by relational classification and class border improvement.

Accuracy assessment

The automated classification output in form of thematic map must be evaluated with respect to the suitability for specific application. This is usually done by comparing results with the other classification. The data serving as a reference set can be obtained by terrestrial measurements, visual image interpretation, or other existing "ground truth" information (GIS).

In this study, the disagreement between automated analysis result and the reference dataset was assessed by assembling an error matrix and calculation selected measurements widely used in pixel-based approaches: *Overall accuracy*, *Producer's accuracy*, *User's accuracy* and *COHEN's kappa coefficient* (a.k.a. Kappa Index of Agreement KIA). Besides, statistics specific for fuzzy classification e.g. *Classification Stability* and *Best Classification Result* were used.

Confusion matrix

The most commonly used method of representing the degree of classification accuracy is to build a k x k confusion matrix. Such table is derived by counting how many of the objects assigned to a class A in the result classification are of the corresponding class in the reference classification. The confusion matrix provides the basis on which to both describe classification accuracy and characterize errors, which may help refine the classification or estimates derived from it (FOODY 2002).

Class/ Ref	A	B	C	D	row ∑
A	n_{AA}	n_{AB}	n_{AC}	n_{AD}	n_{A+}
B	n_{BA}	n_{BB}	n_{BC}	n_{BD}	n_{B+}
C	n_{CA}	n_{CB}	n_{CC}	n_{CD}	n_{C+}
D	n_{DA}	n_{DB}	n_{DC}	n_{DD}	n_{D+}
column ∑	n_{+A}	n_{+B}	n_{+C}	n_{+D}	n

Table 1. Five class confusion matrix for data obtained by simple random sampling. The highlighted elements represent the main diagonal of the matrix that contains the cases where the class labels depicted in the image classification and ground data set agree, whereas the off-diagonal elements contain those cases where there is a disagreement in the labels.

Derived statistics

Although all information about relations between classification and reference classification is stored in the error matrix, various measures are often calculated to simplify the output of the accuracy assessment:

Overall accuracy is the proportion of all reference pixels which are classified correctly (the percentage of cases correctly allocated). It may be derived from the confusion matrix by relating the number of pixels correctly allocated to the class to the total number of pixels of that class. This measure gives no information on what classes are classified with good accuracy.

$$\text{Percentage correct} = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$$

Producer's accuracy is calculated by dividing the number of correctly classified pixels in each class by the number of training set pixels of that class (the column sum). This indicates how well the training set pixels of the given cover type are classified. It gives, however, no information about how well the classification predicts a class.

$$\text{Producer's accuracy} = \frac{n_{ii}}{n_{+i}}$$

User's accuracy is computed by dividing the number of correctly classified pixels in each class by the total number of pixels that were classified in that class (the row sum).This figure is a measure of commission error and indicates the probability that the pixel classified into a given class actually represents that class on the ground (LILLESAND et al. 2004).

$$\text{User's accuracy} = \frac{n_{ii}}{n_{i+}}$$

COHEN's kappa coefficient has often been used and adopted as a standard measure of classification accuracy (SMITS et al. 1999). Considering compensation for chance agreement and variance, it enables the statistical testing of the significance of the difference between two coefficients and to compare different classifications or matrices.

$$\text{Kappa coefficient} = \frac{n \sum_{k=1}^{q} n_{kk} - \sum_{k=1}^{q} n_{k+} n_{+k}}{n^2 - \sum_{k=1}^{q} n_{k+} n_{+k}}$$

Whereas overall accuracy checks count of all pixels correctly classified (assuming that the reference classification is true), here it is assumed that both classification and reference classification are independent class assignments of equal reliability. The actual agreement is what is measured. The big advantage of the kappa coefficient over overall accuracy is that it takes chance agreement into account and corrects for it. Chance agreement means here the probability that classification and reference classification agree by mere chance (eCognition User guide 2004).

Fuzzy classification assessment

In the process of definition complex hierarchies of many classes, the class descriptions often do overlap. The fuzzy concept of class description cause that objects can belong to several classes but with different degrees of membership. Thus, to evaluate the reliability and stability of classes it is necessary to survey the different membership degrees of the classified objects.

Classification Stability

The measure of classification stability can be described as difference between the best and the second best class membership of specific object. Such analysis of class assignments gave evidence about the ambiguity of an object's classification. The value evaluated for each image object ranged from 1.0 (non-ambiguous) 0.0 (absolutely ambiguous). In other words, the higher value the more stable was the classification.

Best Classification Result

The classification with the highest assignment value was taken as the best classification result while the statistical output of the best classification result was evaluated per class. The value evaluated for each image object ranged from 1.0 (maximum degree of membership) 0.0 (no membership). Thus it was possible to evaluate how the objects of a class fulfil the class description.

Acquisition of reference data

An important task connected to the automated image analysis is to obtain reference information also known as "ground truth" data. These are often representative and uniform plots with distinctive characteristics for specific class to be used during the training stage of supervised classification. Besides, the plots can serve the post-classification accuracy assessment. The right choice of an appropriate sample size and sampling design are therefore substantial. Moreover, the ground data collection is frequently constrained by a problematic physical access. Selection of a sampling design is often influenced by budget or other practical reasons.

For purposes of this study, the custom technique of ground truth data acquisition was developed. The method was based on the application of the field GIS software by ESRI™ (Environmental Systems Research Institute), where spatial data from the analysed imagery and vector information available from the forest management planning GIS database LHPO (ÚHÚL, Czech Republic) were stored in. From this existing forest database, twenty 400m^2 plots covering areas with 100% species composition were located as reference sample plots. The sample plots were selected according to the size and species distribution to provide a representative basis for the accuracy assessment. The boundaries of each plot were then determined in the field by mobile GIS procedure.

The main objective was to develop a simple and straightforward method using available technology and digital data to substitute the outdated "paper and pen" inventory approaches. Further details on the processing workflow are given in chapter *Results*, publication **III**.

6 Results

The chapter consists of four reviewed research papers a one un-reviewed technical article. The individual papers are indicated by roman numerals (**I – V**) in further text.

Besides the presented papers, the results of the proposed methodology were also published in form of the following papers and conference contributions:

HÁJEK, F., 2004. Zkušenosti s programem eCognition pro identifikaci lesní druhové skladby z obrazových dat DPZ. Sborník z konference COYOUS 2004, December 3th 2004, Praha: pp. 11

HÁJEK, F., 2004. Object-oriented classification of remote sensing data for the identification of tree species composition – eCognition software skills. Sborník semináře Aktuální problémy fotogrammetrie a DPZ, December 12th 2004, Praha

HÁJEK, F., 2005. Object-oriented classification of remote sensing data for the identification of tree species composition. Proceedings of ForestSat 2005 conference, May 31 - June 3th 2005, Boras, Sweden: pp. 16 - 20

HÁJEK, F., 2005. Lesnické mapování a evidence porostních veličin v ArcPad 6.0.3.
ArcRevue 3/2005, Praha: s. 13 - 15

HÁJEK, F., 2005. Automated classification of tree species composition from VHR satellite data. Proceedings of JRC Workshop at Climate Change conference, October 19 – 20th 2005, Silenica, Slovakia: pp. 136

HÁJEK, F., 2006. Prospect of automated classification of tree species composition from IKONOS satellite imagery. Proceedings of international workshop 3D Remote sensing in Forestry, , Feb 14 - 15 2006, Vienna

HÁJEK, F., 2006. Automatická extrakce porostních údajů z obrazových dat DPZ. Lesnická práce 85, 4: 22 - 23

HÁJEK, F., 2006. Object-oriented classification of Ikonos satellite data for the identification of tree species composition. Journal of Forest Science 52, 4: 181 – 187

HÁJEK, F., 2006. Object analysis of Ikonos XS and pan-sharpened imagery in comparison for purpose of tree species estimation. In: S. Lang, T. Blaschke and E. Schöpfer (eds.): Proceedings of the 1st International Conference on Object-based Image Analysis, July 4-5, 2006, Salzburg (pages pending).

HÁJEK, F., 2006. Comparison of 4-m and pan-sharpened Ikonos satellite imagery for purpose of automated tree species composition. Scientia Agritulturae Bohemica 37, 3: 122 – 127

HÁJEK, F. Vyhodnocení odumírání horského smrkového lesa na Trojmezné (NP Šumava) metodou automatické klasifikace leteckých snímků. 02/2007 accepted in print in Silva Gabreta (Czech Republic)

HÁJEK, F. Process-based approach to automated classification of forest structures using medium format digital aerial photos and ancillary GIS information. 10/2006 submitted in European Journal of Forest Science (Germany), (03/2007 returned for corrections)

I

OBJECT-ORIENTED CLASSIFICATION OF IKONOS SATELLITE DATA FOR THE IDENTIFICATION OF TREE SPECIES COMPOSITION

F. Hájek

OBJECT-ORIENTED CLASSIFICATION OF IKONOS SATELLITE DATA FOR THE IDENTIFICATION OF TREE SPECIES COMPOSITION

ABSTRACT

This paper describes the automated classification of tree species composition from Ikonos 4-meter imagery using object-oriented approach. The image was acquired over a man-planted forest area with proportion of various forest types (conifers, broadleaved, mixed) in the Krušné Hory Mts., Czech Republic. In order to enlarge class signature space, additional channels were calculated by low-pass filtering, IHS transformation and Haralick texture measures. Employing these layers, image segmentation and classification were conducted on several levels to create hierarchical image object network. The higher level separated image into smaller parts regarding the stand maturity and structure, the lower (detailed) level assigned individual tree clusters into classes for the main forest species. The classification accuracy was assessed by comparing automated technique with the field inventory using Kappa coefficient. The study aimed to create a rule-base transferable to other datasets. Moreover, appropriate scale of common image data and the utilisation in forestry management are evaluated.

Keywords: Automated image analysis, eCognition, median filters, texture, forestry management

INTRODUCTION

Remote sensing and image interpretation have been utilized in forestry management for many years. These methods can be applied in various tasks ranging from forest thematic mapping to the detailed tree or stand characteristics survey. Besides the advancement in digital aerial methods, high-resolution satellite sensors (e.g. Ikonos, QuickBird) are now available for operational use. However, the automated classification of such data is still problematic due to greater spectral variation within one class (Halounová 2003).

Previous studies on high-resolution data (Blaschke & Strobl, 2001) proved that traditional spectral-based methods result in rather poor or incorrect classification. Much information is contained in spatial relations of pixels and a few studies already showed the object oriented approach promising when classifying VHR data (Baatz & Schäpe, 1999, Leckie et al. 2003). The contribution of textural and structural information was also examined (Haralick &

Shapiro 1992, Brandtberg 1999) and various algorithms, such as co-occurrence matrix were applied to extract texture characteristics of trees (Zhang 2001). Neural networks (Gopal & Woodcock 1996) and fuzzy classification improved modelling of real-world dependencies (Benz et al., 2004). Furthermore, increased use of a priori knowledge and information extraction become important with the rapid development of GIS.

This paper explores and demonstrates capability of object-oriented image analysis software eCognition (Definiens Imaging, Germany) for the tree species classification from 4-meter Ikonos imagery. Combination of complex object description, hierarchical image object network and fuzzy system makes eCognition a challenge to knowledge-based image interpretation in a range of forestry management applications. Next project objective is to determine appropriate scale and accuracy of species composition estimation using common image data. The prospect of rule-base creation for the high level automation in operational forestry is also discussed.

SITE AND FIELD DATA COLLECTION

The research was conducted in man-planted forests nearby the town Hrob (50°40'N, 13°43'E) in the Krušné Hory Mts., Czech Republic. This submontane area consists of patches of mature Spruce (*Picea Abies L.*) and Beech (*Fagus Silvatica L.*) forest, with the substantial proportion of Larch (*Larix deciduas Mill.*) and also young plantations of Beech, Birch (*Betula pendula L.*) and *Picea pungens* often mixed with *Larix* and *Betula Pubescens*. The planted mature stands are mostly of the same age, but very heterogeneous in species composition, stocking density and canopy structure. The natural regeneration in addition to the planted trees sometimes occurs. Silviculture practices range from clear cutting to seed felling with heavy thinning on some spots.

Based on the previous information from LHPO forest inventory, twenty 400m^2 plots covering areas with 100% species composition were located as a reference data. Sample plot selection put emphasis on size and class purity to provide representative basis for accuracy assessment. The boundaries of each plot were determined with differential GPS SX Blue™ and PDA with ESRI ArcPad™ mobile GIS.

IMAGERY PREPROCESSING

The Ikonos (Space Imaging, USA) image was acquired on 17th September 2003. Except for some hardwood species, most vegetation was still green and fully foliaged. Data were delivered in a geo-registered UTM projection (zone N33) with 11-bit radiometric resolution.

The image contained significant amount of clouds and atmospheric haze, so a 3x3 km subset of forested area with clear sky conditions was chosen for the analysis. There is also important amount of shadow fraction throughout the scene associated with solar and observation angles (Table 1)

View Azimuth	View Elevation	Sun Angle Azimuth	Sun Angle Elevation
330.30 degrees	71.78 degrees	170.58 degrees	41.51 degrees

Table 1. *Ikonos viewing and illumination geometry*

In the next step, class signature space was enlarged by the calculation of additional channels. Foremost the single principal component from original bands was derived and then Median filter (kernel sizes 3x3 and 5x5) was applied in order to suppress spatial frequency. Several Haralick (GLCM) texture measures were calculated and the contribution to class separability was tested. Measures Mean, Variance and Homogeneity with window sizes of 3x3 and 5x5 were chosen. Further, layers calculated by IHS transformation and edge detection (Sobel operator) were also applied in the classification.

OBJECT ORIENTED ANALYSIS

After the signature space enlargement, image segmentation was performed to further handle high spectral variation and overlapping values of classes. In this phase, image was split into smaller regions (object primitives) to simplify thematically complex data content. The classification was then performed using segments instead of single pixels.

Multiresolution segmentation

In the segmentation process, size and shape of desired objects are defined by the calculation of heterogeneity between adjacent pixels, where Scale is the main input parameter. Shape factor (colour/shape ratio) and spatial properties (smoothness/compactness ratio) are other variables to define homogeneity of object primitives.

Segmentation was conducted stepwise on several levels using different scales to construct the hierarchical image object network. The primary level was created using Scale parameter of 15. After preliminary classification, objects were merged by classification-based segmentation and the result (basic landuse classification) was re-imported into eCognition as a thematic layer. The sublevel was then segmented only within the area of interest (class Forest) using Scale parameter equal to 5. The finest objects with the Scale value of 3 were calculated at the third level applying the same approach.

The Shape factor was set to higher value for the coarse segmentation and lower value at finer scale (higher influence of spatial properties). The two lower levels were processed using four Ikonos bands and median filtered channel of kernel size 3x3, the coarse landuse segments were made based only on thematic layer. Layer weights were set in relation to their standard deviations.

Class definition

The three level hierarchical image object network was used to delimit classes. Level 3 comprised basic "Landuse" types - Urban, Fields and Forest. This served to mask all non-forest areas. The lower level 2 "Forest" aimed to separate forest regions into Dense (young and mature stands with more less closed canopies), Sparse areas and Clearcuts. Sparse forests mostly consisted of low stocking mature beech trees with presence of visible ground. The detailed level 1 "Stand" was set to distinguish four main forest species in the area - Fagus, Picea, Larix and Betula. Further, structures of shadows and bare ground were classified on this level.

All classes of "Forest" level were also recognised at the lower "Stand" level for purpose of post classification improvement.

Classification

In order to create distinct and fully transferable rule base, fuzzy logic membership functions were used to define object features. Fuzzy description enables classes to be assigned according to membership degree rather than crisp threshold values. Following features were applied:

a) Object features: mean layer values (blue, red, NIR, brightness, GLCM mean 3x3, IHS, Sobel NIR), ratio layer values (blue, red), area generic shape feature,

b) Class-related features: relative border to neighbour objects, relative area of sub-objects, existence of sub-objects (super-objects)

c) Customised features: NDVI, (red-green) vegetation index, IHS/ brightness index

Besides MF classification, preliminary nearest neighbour classification was done on the lowest level and features suitable to separate tree species were evaluated using sample editor (histogram comparison). The masking technique of determining foremost the easy classes (ground, beech trees) and moving on to more difficult ones was often applied. Then the class boundaries were improved using class-related features and finally corrected by means of classification-based segmentation.

RESULTS

The classification accuracy was evaluated using field reference data. Sample areas were imported into project by means of TTA mask (Definiens Inc. 2003) and the corresponding classes were linked to form confusion matrix (Table 2). Several measurements such as Producer's, User's, Overall accuracy and Kappa index of agreement were derived for each class. Besides, classification reliability (Best classification result) and stability within fuzzy concept were assessed.

User \ Referer. Class	Larix	Betula	Fagus	Picea	sparse	ground	shadows	fields	urban	Sum
Larix	211	104	2	5	0	0	0	0	0	322
Betula	25	322	5	0	35	0	0	0	0	387
Fagus	93	14	685	0	2	0	0	0	0	794
Picea	34	0	0	444	0	0	107	0	0	585
sparse	10	0	0	0	317	0	0	0	0	327
ground	0	0	0	2	17	207	0	0	0	226
shadows	0	0	0	37	0	0	216	0	0	253
fields	0	0	0	0	0	0	0	5849	0	5849
urban	0	0	0	0	0	0	0	0	1334	1334
unclassified	17	17	5	3	1	0	17	0	0	60
Sum	390	457	697	491	372	207	340	5849	1334	
Producer's	1	0.541	0.705	0.983	0.904	0.852	0.635	1	1	
User's	0.916	0.655	0.832	0.863	0.759	0.969	0.854	1	1	
KIA Per Class	1	0.526	0.693	0.981	0.898	0.847	0.626	1	1	

Table 2. Error matrix of classification accuracy assessment. The Overall Accuracy is 0.945 with the Kappa index of agreement equal to 0.914

***Figure 1**. Ikonos image (false colour composite)*

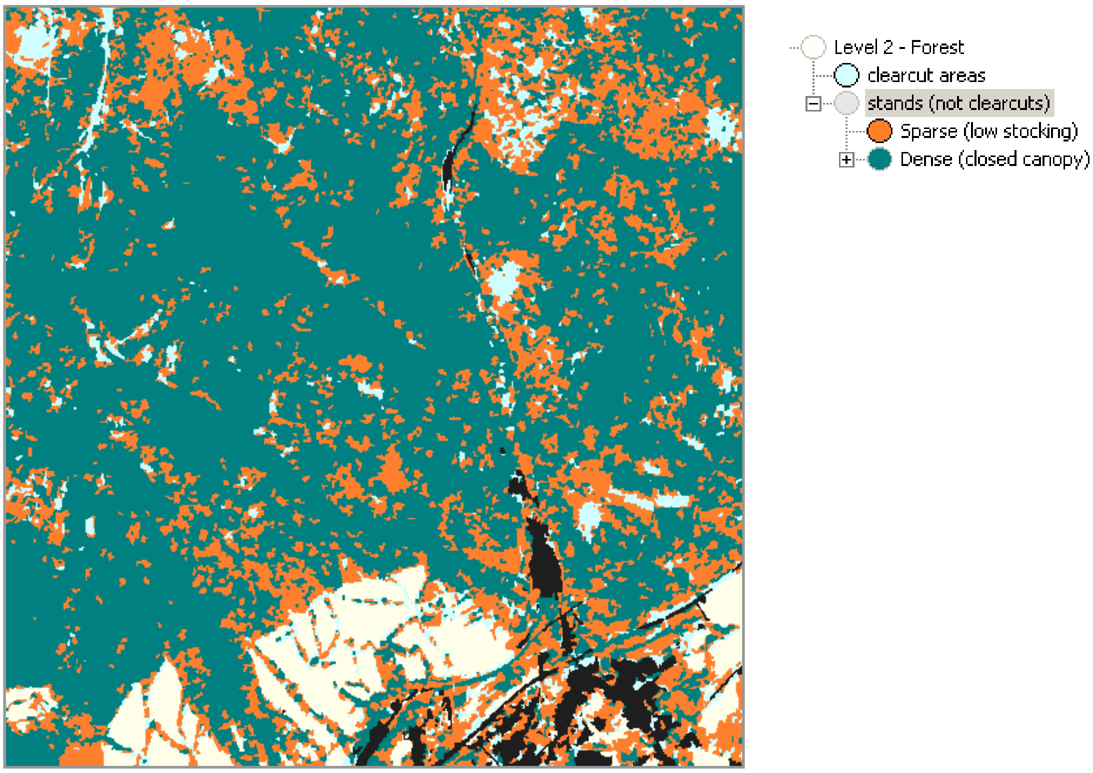


***Figure 2.** Higher level classification*

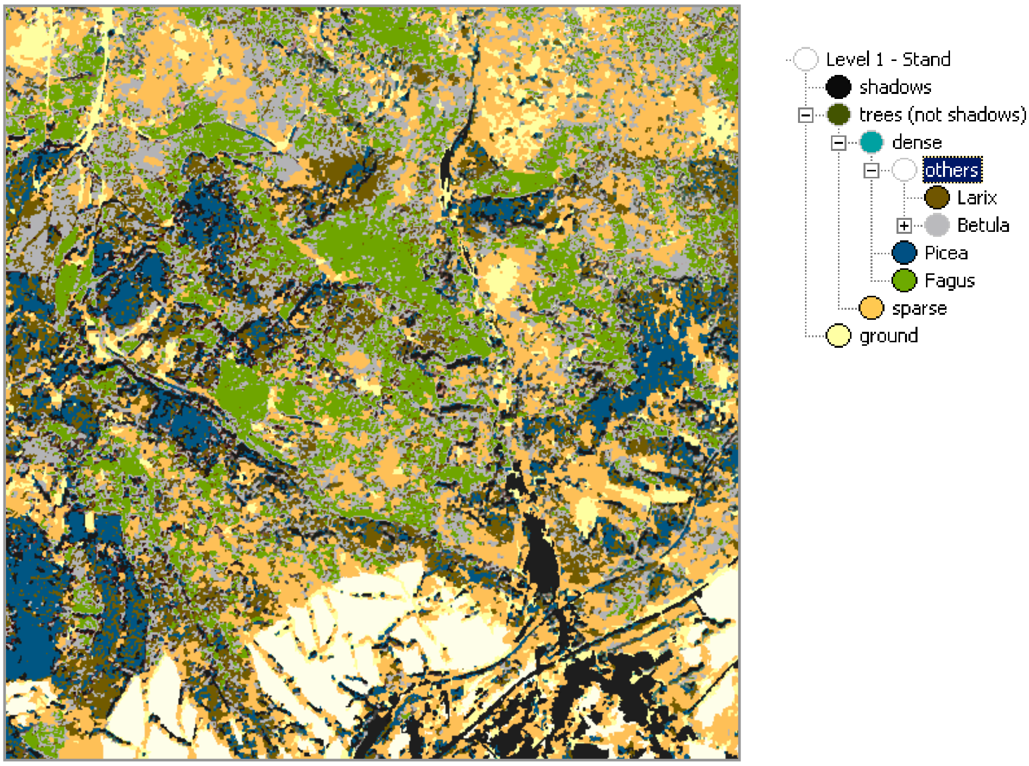


Figure 3. *Classification at the lower level*

Figure 1 shows the original image, Figure 2 shows classification on higher "Forest" level. The result of classification at lower "Stand" level is on Figure 3.

As indicated in the confusion matrix, proposed method offered very good overall results. Both Picea and Larix conifer species were classified with accuracy over 90%. Fagus achieved accuracy about 70%, which was caused by confusion with class Sparse (high proportion of beech trees). The most problematic tree class was Betula, not only by means of error matrix, but also classification reliability and stability. This tool estimating differences in membership degrees between the best and second best class assignment shows that class Betula and Larix often act as ambiguous. The two species have similar spectral and textural characteristics, especially at young age. Besides, shadows are frequently being confused or mixed with Picea pixels. Best results were obtained for all non-forest classes.

CONCLUSSION AND FINAL DISCUSSION

The results showed that classification of 4-m Ikonos data can be performed with relatively high accuracy. The image allows to estimate tree species composition at the sufficient scale. To get satisfying outcome, additional channels must be calculated in the pre-processing phase and then included in segmentation and subsequent object-oriented classification. The object shape attributes are influenced by the kernel size and layer weight in the process of segmentation, the contribution of additional layers to classification was high for Sobel Edge detector, IHS transformation and low-pass filters. Other textures measures had lower impact using on such spatial resolution data. The classification rules based on fuzzy membership functions are highly convertible, eCognition protocols developed in this project can be transferred and applied (with some threshold modification) to other datasets. To normalize imagery band ratios can be employed, yet data acquired under fixed viewing and solar geometry is recommended to use for the automated analysis.

Previous studies indicated that variations in image acquisition (different projection centres) become more problematic when analysing multitemporal aerial photos. Lower spectral, radiometric and temporal resolutions are also a drawback comparing to VHR satellite data. However, the current lower price at higher spatial resolution still account for aerial photography when developing knowledge base for the method utilization in forestry management. The necessary conditions to obtain good results are standardised screening plan and introduction of photography on IR material. The object-oriented analysis of aerial photos will be examined in the further research.

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Objektově orientovaná klasifikace satelitních snímků Ikonos pro účely identifikace lesní druhové skladby

Abstrakt: Studie popisuje automatizovanou metodu klasifikace dřevinné skladby ze satelitních snímků Ikonos s prostorovým rozlišením 4 metry za použití objektově orientovaného přístupu. Snímek zobrazuje oblast hospodářského lesa s podílem různých porostních typů (jehličnany, listnáče, smíšené) v Krušných horách, ČR. Z důvodu problematické klasifikace dat s velmi vysokým rozlišením (VHR) bylo třeba nejdříve zvětšit příznakový prostor jednotlivých tříd vypočtením dodatečných kanálů pomocí mediánové filtrace, transformace IHS a Haralickových texturálních měr. Tyto vrstvy byly poté použity k segmentaci obrazu a následné klasifikaci na několika úrovních hierarchické sítě objektů. Vyšší úroveň měla za cíl rozčlenění obrazu na menší části podle věkové a prostorové struktury porostu, na nižší úrovni byly klasifikovány skupiny stromů do kategorií podle hlavních lesních dřevin. Přesnost klasifikace byla stanovena porovnáním výsledků s referenčními údaji z terénních šetření a výpočtem Kappa koeficientu. Studie měla za cíl vytvoření přenositelné znalostní báze, kterou bude možné využít pro automatizovanou klasifikaci snímků Ikonos 4-m. Dále bylo posouzeno rozlišení a měřítko vhodné k analýze dostupných typů obrazových dat DPZ a jejich použití v praxi Hospodářské úpravy lesa.

Klíčová slova: Objektově orientovaná analýza obrazu, eCognition, mediánová filtrace, textura, Hospodářská úprava lesa

Interpretace obrazových dat dálkového průzkumu země slouží již řadu let jako cenný nástroj v Hospodářské úpravě lesa. Využití zahrnuje zejména lesní inventarizace, lesní tematické mapování, zjišťováni stromových a porostních charakteristik, zdravotního stavu apod. Vedle rozvoje na poli digitální fotogrammetrie se do popředí dostávají také VHR satelitní snímky s velmi vysokým rozlišením (Ikonos, QuickBird). Automatizovaná klasifikace těchto dat je však z důvodu vysoké heterogenity v rámci zvolené třídy stále problematická.

Tradiční metody založené na analýze jednotlivých pixelů ignorují texturu a prostorové vztahy v obrazu. Přitom důležitou sémantickou informaci nepředstavují pixely, ale smysluplné objekty s jejich vzájemnými vztahy a tudíž segmentace a následná klasifikace obrazových objektů může být klíčem k úspěšné interpretaci. Práce navrhuje využití objektově orientované analýzy ke klasifikaci vysoce texturovaných obrazových dat (Ikonos 4-m) pro účely identifikace lesní druhové skladby. Představený software eCognition umožňuje komplexní popis vlastností objektů (spektrální, geometrické, texturální a kontextuální), tvorbu klasifikačního schématu pro segmentaci obrazu a klasifikaci na několika úrovních hierarchické sítě objektů a definici příznaků pomocí „fuzzy" pravidel.

Dosažené výsledky ukazují, že uvedená metoda umožňuje klasifikaci snímků Ikonos 4-m s relativně vysokou přesností (Celková přesnost 0.945 a Kappa koeficient 0.914). Data disponují dostatečným prostorovým rozlišením k určení dřevinné skladby lesa ve vhodném měřítku. Předpokladem pro úspěšnou klasifikaci je výpočet dodatečných kanálů v přípravné a fázi a jejich využití v následných fázích segmentace a klasifikace obrazových objektů. Tvar a velikost objektů při segmentaci je ovlivněna velikostí posuvného filtračního okna a stanovenou vahou, detekce hran (Sobel operátor), IHS transformace a mediánová filtrace zase výrazně přispívá ke zvětšení příznakového prostoru během klasifikace. Texturální míry lze při tomto rozlišení využít jen omezeně. Klasifikační „fuzzy" pravidla vymezená funkcemi členství jsou velmi flexibilní, po úpravě prahů lze znalostní bázi přenést a celé klasifikační schéma aplikovat na jiná data pomocí vytvořených protokolů. Z důvodu normalizace lze doporučit použití poměrů pásem, nicméně pro automatizovanou analýzu je stále důležité, aby byly snímky pořízeny za obdobných akvizičních a světelných podmínek.

Satelitní snímky s velmi vysokým rozlišením představují nový obzor DPZ a oproti leteckým snímkům mají řadu výhod (vyšší spektrální, radiometrické a temporální rozlišení) pro využití v praktickém lesnictví. Navíc odpadá problém s odchylkami snímacích center při analýze dat v časových řadách. Cena za zobrazené území je však poměrně vysoká a proto zůstávají barevné letecké snímky i nadále nejdostupnějším zdrojem obrazových informací. Předmětem další činnosti bude vytvoření objektově orientované metody pro analýzu leteckých snímků, konkrétně znalostní báze pro využití v HÚL. Nezbytným předpokladem k uspokojivých výsledků je přechod na snímkování podle standardizovaného plánu a zavedení spektrozonálního materiálu.

II

COMPARISON OF 4-M AND PAN-SHARPENED IKONOS SATELLITE IMAGERY FOR PURPOSE OF AUTOMATED TREE SPECIES COMPOSITION

F. Hájek

COMPARISON OF 4-M AND PANSHARPENED IKONOS SATELLITE IMAGERY FOR PURPOSE OF AUTOMATED TREE SPECIES IDENTIFICATION

ABSTRACT

Forest inventories conducted on large areas with laboured manual RS data interpretation increasingly call for a development of knowledge-based classification methods. Considering multitemporal image analysis, VHR satellite data have many advantages over traditional aerial photos for such purposes. This study explores and demonstrates technique of automated identification of tree species composition from Ikonos imagery using object-oriented classification approach. Methodology developed to process 4m/pan data emphasizes the pre-processing phase, when the additional channels are calculated and their contribution to class separation assessed by Discriminant analysis. Then the image segmentation and classification is conducted on several levels to create hierarchical image object network, where the higher level aim to separate image into smaller parts regarding stand maturity and canopy structure and the lower (detailed) level assign individual tree clusters into classes for the main forest species. The developed rule-base was applied on datasets of different resolution and the results were compared by means of classification accuracy (KIA). Further, the utilization of 4-m and 1-m images in different forestry management tasks is discussed.

Key words: object image classification; VHR satellite data; texture analysis; forest management

INTRODUCTION

Methods of forest state assessment using remotely sensed data have been tested for several decades, with the visual aerial photo interpretation as the main tool widely utilised in practical forestry. Nevertheless, the automated classification of such textured data is still problematic due to enormous class spectral variation (Halounová 2003). The methods of tree species identification from satellite imagery have been also explored lately. Some studies aimed at estimation of forest species composition using moderate resolution data such as Landsat TM, Spot HRV, while the relevant studies on VHR satellite imagery such as Ikonos (Bucha, 2004) and QuickBird seem promising for the species identification at the individual tree level. As demonstrated by several authors (Brandtberg 1999, Leckie et al. 2003), working at a tree scale has a potential to extend digital remote sensing into many new areas such as forest stand extraction, forest regeneration, logging practices, etc. In the same time, however, many studies proved the RS methods based solely on spectral classification insufficient for detailed forest mapping (Wack and Stelzl 2005). The enhanced height information from LiDAR and its integration with the tree species estimates from optical data are nowadays in the main focus for purpose of detailed 3D stand modelling.

In the environment of the Czech forest sector, the estimation of species distribution is traditionally based on the area coverage acquired by terrestrial methods. Even manual interpretation of aerial photos never quite met the needs of forest inventories, as reported by the official authorities. Nevertheless, the increasing demands on the level of inventory precision, information resolution and repeatability call for the development of practical application based on automated image analysis to be utilised in forest management. This study deals with the automated method of tree species composition estimation from Ikonos imagery using object-oriented approach. The presented methodology was tested on both 4-meter and pan-sharpened Ikonos images with the aim to compare and describe the two datasets to meet the forestry needs. Besides, the prospect of the knowledge-based classification using VHR data in operational forestry was suggested.

MATERIAL AND METHODS

VHR imagery and additional input data

IKONOS

The proposed methodology was tested on VHR satellite data from sensor Ikonos-2. The sensor delivers multispectral (XS) images with spatial resolution of 4m and 1m images using panchromatic mode. The imagery acquired on 7th June 2003 was delivered in a geo-registered UTM projection (zone N33) with 11-bit radiometric resolution at Standard Geometrically Corrected processing level. The nominal Collection azimuth and elevation were 105.4862^{o} and 76.79404^{o}, the Sun angle azimuth and elevation were 155.8632^{o} and 61.15952^{o}.

The subset of 4 x 4km representing an industrial forest area close to town Žlutice (50^{o}05’N, 13^{o}12’E), Western Bohemia was selected. The predominantly flat site comprised large patches of old Norway spruce (*Picea abies L.*) often mixed with Scots pine (*Pinus sylvestris L.*), extensive mature Pedunculate oak (*Quercus robur L.*) forests and also Birch (*Betula pendula L.*), European larch (*Larix decidua Mill.*) and young plantations of Pine and Oak.

Besides, smaller proportions of Sycamore maple (*Acer pseudoplatanus L.*) could be found inside forest stands and along the margins. In both areas, planted mature stands were mostly of the same age, but very heterogeneous in species composition, stocking density and canopy structure. The natural regeneration in addition to the planted trees sometimes occurred.

DTM

The digital contour map from ZABAGED® GIS database produced by the Czech Office for Surveying, Mapping and Cadastre (COSMC) in scale of 1: 10 000 were used as a source of height information. Then the DEM was created with resolution 2m/pixel (Figure 1). Lambertian Reflection Model was initially tested in order to reduce topographic effects. However, the transformed image was unsuitable to use due rapid radiometric shift and so the shade layer was instead calculated to normalise the image for varying illumination. Besides, the height information was used as an additional input during the classification phase.

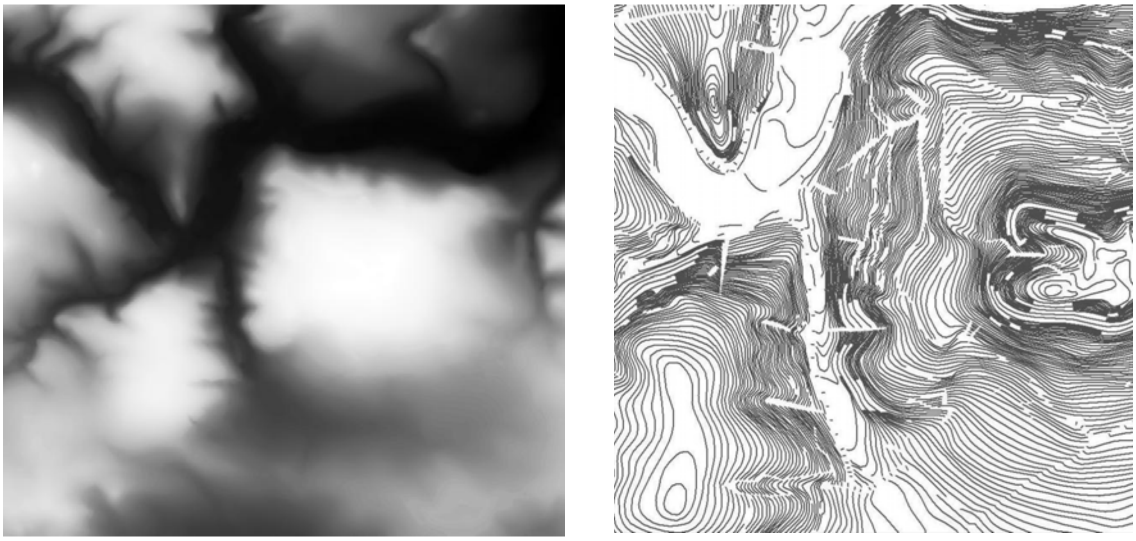

Figure 1. High resolution digital elevation model (left) calculated from ZABAGED® (COSMC) digital contours (right)

Field GIS

Based on the previous information from forest management planning database LHPO provided by the Forest Management Institute (ÚHÚL), twenty 400m^2 plots covering areas with 100% species composition were located as a reference data. Sample plot selection put emphasis on size and class purity to provide representative basis for accuracy assessment. The boundaries of each plot were determined with differential GPS SX Blue™ and PDA with ESRI ArcPad™ mobile GIS.

Image analysis

Object-oriented classification in software eCognition (Definiens Imaging, Germany) was the main image analysis method. This approach features an enhanced technique of multi-resolution image segmentation, complex capability in object description (spectral, geometric, textural and contextual), hierarchical image object network and fuzzy rule base classification.

SEGMENATION

Segmentation was conducted stepwise on three levels using different scales to construct the hierarchical image object network. The primary level was created using large Scale parameter and after preliminary classification was done for basic landuse classes. Other two sublevels were segmented only within the forested area using smaller Scale parameter and using classification-based segmentation (Table 1)

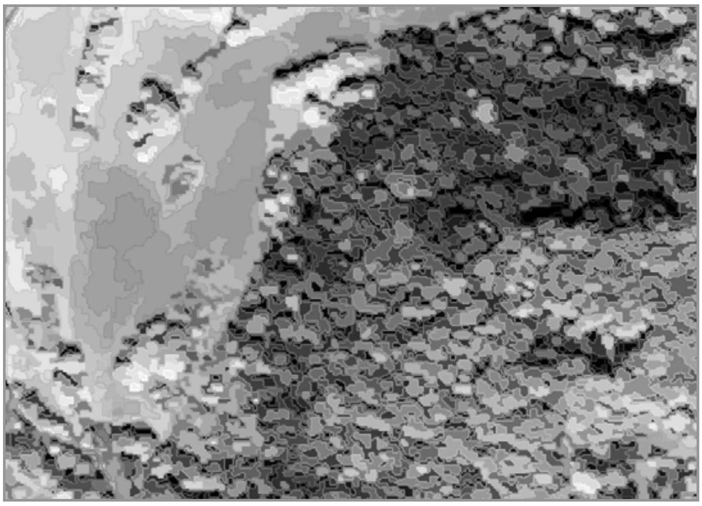

Figure 2. Detailed segmentation at the lowest level of hierarchical image object network

Segmentation level	Scale 4m/pan	Homogeneity criterion			
		Color	Shape	Shape settings (Compact/Smooth)	
Level I – Landuse	25 / 60	0.8	0.2	0.5	0.5
Level II – Forest	18 / 45SB	0.7	0.3	0.5	0.5
Level III - Stand	5 / 12 SB	0.7	0.3	0.7	0.3

Table 1. Segmentation parameters for analysis of Ikonos 4-m and Ikonos pan-sharpened images

SIGNATURE SPACE ENLARGEMENT AND FEATURE SELECTION

In order to enhance class separability, the signature space was enlarged by the calculation of additional channels in pre-processing phase in Erdas Imagine 8.7. Various spectral features based on original channels and also derived band rationing were calculated as “Customised features” in eCognition 4.0.6. Considering all relevant features (color, texture, and context), the dimensionality of dataset increased and therefore methods of feature selection were needed. Layers tested for the significant contribution included: spectral ratios and vegetation indices (NDVI), Tasseled cap and IHS transformation, low-pass filters, Sobel edge detection and GLCM texture measures (Haralick and Shapiro, 1992).

In each class, 30 sample objects were manually classified based and the reference field data and then the visual and statistical techniques of feature contribution were tested. Discriminant analysis (Rencher, 2002) was used to find optimal variables for distinction of different stand structures. The assessment was based on comparison of coefficients a_r , r = 1, 2, …, p, in the discriminant function

$$z = a'y = a_1 y_1 + a_2 y_2 + \ldots + a_p y_p \quad (1)$$

Mean observation vectors **y** for 15 selected variables were calculated and the discriminant function coefficient vectors **a** were derived from variance-covariance matrix $\mathbf{S}_{pl}$ as

$$\mathbf{a} = \mathbf{S}_{pl}^{-1}\left(\bar{\mathbf{y}}_1 - \bar{\mathbf{y}}_2\right) \quad (2)$$

Since the y's were not commensurate, coefficients applicable to standardised variables **a*** had to be calculated. The relative contribution to separation of the analysed classes was then assessed by comparison of absolute values of coefficients standardized by square roots of the diagonal elements of $\mathbf{S}_{pl}$:

$$\mathbf{a}^* = \left(\mathrm{diag}\ \mathbf{S}_{pl}\right)^{1/2}\mathbf{a} \quad (3)$$

Further, the result of the statistical analysis was reviewed using the visual assessment of the feature distribution comparing histograms of two selected classes at the time. The significant contribution to class separation was found for these features:

- Mean spectral values of visible Green and NIR Ikonos bands together with the Customized features such as NIR/Red, Green/NIR, NDVI ratios and their derivatives normalized by Shade layer were predominantly used for the classification of tree species based on spectral information
- Sobel Edge layer calculated for IR Ikonos band, 2nd (saturation) channel of IHS transformation and GLCM texture feature Variance of window size 3 x 3 were applied to separate agriculture and vegetation areas of different textures and to differentiate forested areas, regenerating areas and clearcuts
- DEM values served to separate forest/agriculture bare soil areas

Besides the classification stage, channel of Median filter with kernel 3 x 3 was tested and used during initial segmentation of highly textured pan sharpened data.

FUZZY RULE-BASED CLASSIFICATION

The classification process was controlled by a rule base describing characteristics of individual classes by means of fuzzy membership functions (Baatz et al., 2003). Each class description consisted of a set of fuzzy expressions allowing the evaluation of specific features and their logical operation.

The three levels of hierarchical image object network were used to delimit classes (Figure 3). Level 3 comprised basic "Landuse" types – Water, Urban, Fields and Forest. This served to mask all non-forest areas. The lower level 2 "Forest" aimed at separation of forest regions into areas of bare ground, mature stands and young stands, where classes "plantation (transition)" and young stages of conifers, broadleaves and other were further distinguished. "Other" young forests were mostly consisted of Larch and Birch trees. The detailed level 1 "Stand" was set to distinguish four main forest species in the area - Quercus, Acer, Picea, Larix and Betula. Further, structures of shadows and bare ground were classified on this level. All classes of "Forest" level were also recognised at the lower "Stand" level for purpose of post classification improvement.

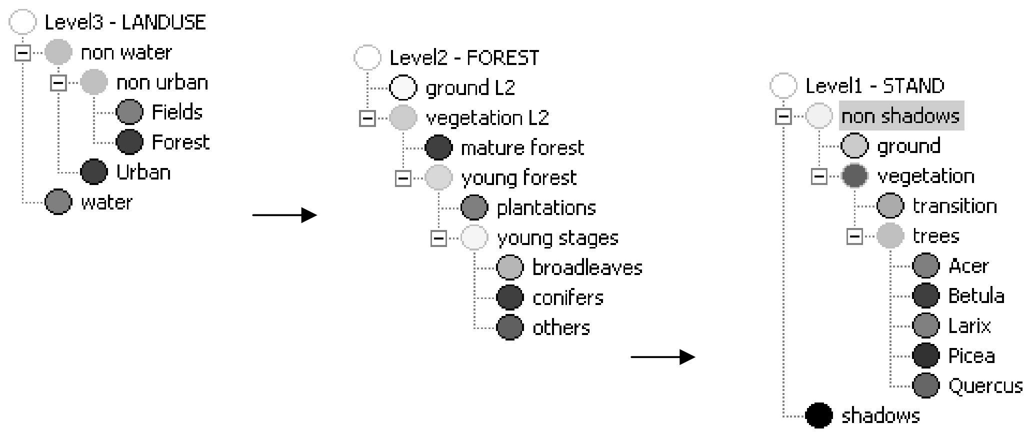

Figure 3. Classification rule-base of image analysis at three levels

RESULTS

The knowledge base initially created for 4m image was also applied with minor threshold modifications to the pan-sharpened data, so the comparative results were achieved. Then 20 samples for each class of the “Forest” and “Stand” classification levels were selected in accordance with the GIS field reference data and the common accuracy statistics were calculated from the assembled error matrix.

The overall classification results at the lowest “Stand” level were very similar for both tested datasets. As deduced from the accuracy assessment (Table 2), there is no crucial difference between 4-meter and pan-sharpened Ikonos imagery in ability of identifying tree species composition in terms of area coverage. The very good result of more than 90% was obtained for classes Acer and Picea, and class ground with approx. 80 %. The lower agreement (around 75%) was achieved for Betula and Larix and for the class transition (60%). Besides, some differences linked the image resolution occurred. This was most evident for shadows, where pan Ikonos gained nearly 30% in accuracy for over 4-m image.

Cover type / Stats	shadows	ground	transition	Acer	Querc	Picea	Betula	Larix
KIA per class (4m)	0.68	0.85	0.63	0.92	0.92	0.92	0.70	0.77
KIA per class (pan)	0.94	0.78	0.58	1.00	0.77	0.94	0.82	0.61
Overall acc (4m/pan)	0.83 / 0.83							
KIA (4m/pan)	0.80 / 0.81							

Table 2. Selected accuracy measures for “Stand” level of Ikonos 4m / pan classification. The statistics were derived for each class, Overall Accuracy and the Kappa index of agreement represent aggregated results

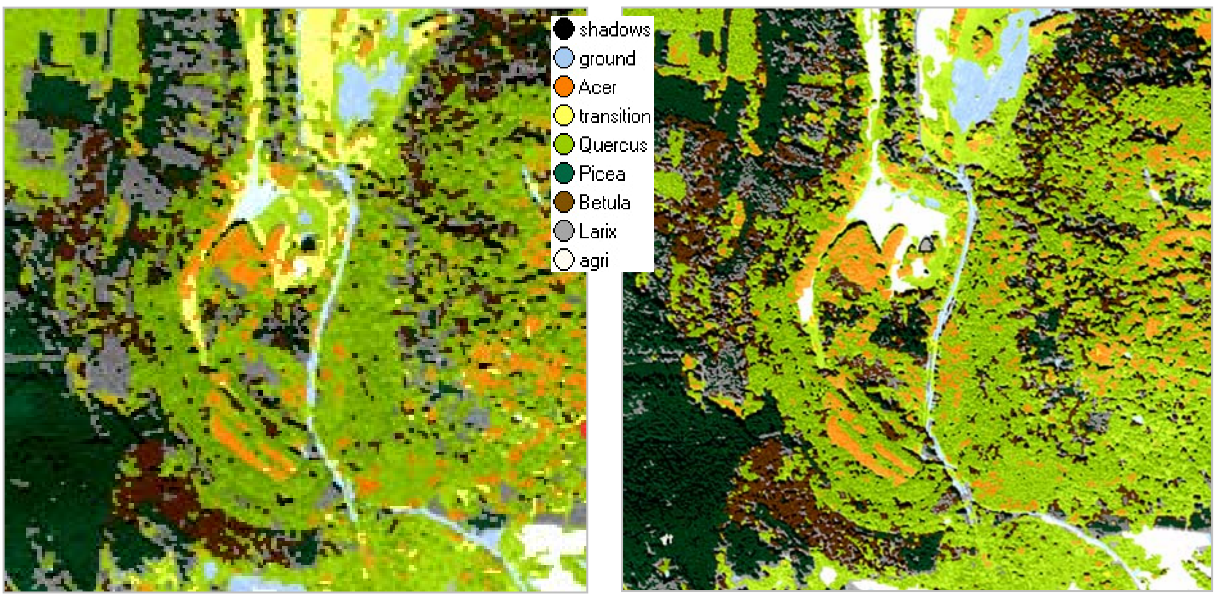

Figure 4. Forest species classification from Ikonos 4m vs. pan-sharpened imagery

The result of classification at the “Forest” level was also evaluated and the datasets of 4m/1m spatial resolution compared. The statistical measures (Table 3) indicate the overall accuracy improvement of nearly 10% when analysing pan sharpened Ikonos data. This was especially evident for delineation of the stand boundaries of young forest stages (conifers, broadleaves, other). Classes ground and plantation (transition), on the other hand, were better identified in 4-meter data. The fact is possibly connected to the different influence of textural information, as it was substantial for classification at this level.

Cover type / Statistics	ground	plantat	mature	Y conifer	Y broadl	Y other
KIA per class (4m)	0.63	0.64	0.74	0.36	0.30	0.76
KIA per class (pan)	0.48	0.36	0.87	0.61	0.88	0.82
Overall accuracy (4m/pan)	0.63 / 0.71					
KIA (4m/pan)	0.57 / 0.66					

Table 3. Selected accuracy measures for "Forest" level of Ikonos 4m / pan classification. The statistics were derived for each class, Overall Accuracy and the Kappa index of agreement represent aggregated results.

DISCUSSION

As showed in several previous studies, the standalone optical RS methods are insufficient for classification of complex forest structures. This is particularly true for young succession stages and heterogeneous mature stands. For purpose of tree species identification, however, very good results can be achieved by the combination of object-oriented approach and the topo-corrected VHR (both 4m and pan) Ikonos data with derived image transforms. The OO classification rules based on fuzzy membership functions are highly convertible and the knowledge-base can be transferred and applied to other data by means of recorded protocols. Among the calculated layers contributing to the classification, ratios of Green and NIR bands, Sobel edge and GLCM Variance are the most significant. The spectral signatures normalised with the high resolution DEM can further enhance the classification. Besides, the segmentation of pan-sharpened images can benefit from the use of median filtering. The ability of delineation of young stands is dependent on the amount of texture information, thus the analysis of 1-m spatial resolution imagery is suggested. Such data require careful determination of object scale with the perspective of broader context. However, the higher amount of detail brings the new opportunities in object description, where the multilevel mutual relations are of special advantage.

CONCLUSIONS

This study aimed at comparing of classification results of 4-m and 1-m resolution Ikonos imagery. Both data types have their benefits and should be utilised in different forest management tasks with respect to the price. As reported by Hájek (2005), the 4-m Ikonos imagery allows to estimate percentage distribution of the tree species at sufficient scale. The pan-sharpened data has further potential to expose detailed structures within forest stands but also canopies of individual trees. Classification of tree species composition with such high level of detail and accuracy would be suitable to combine with LiDAR data for advanced 3D stand modelling. Still, the prospect of the method utilisation is dependant on the existence of capable knowledge-based system, sufficiently robust for high level of automation. The further research will focus on object analysis of CIR digital aerial photos.

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Srovnání družicových snímků Ikonos 4-m a pansharpened z hlediska automatizované klasifikace dřevinného složení lesa

Lesní inventarizace prováděné na rozsáhlých územích tradičně terestrickými metodami s vysokým podílem manuální práce stále více vyžadují usnadnění v podobě znalostně orientované aplikace pro automatizovanou klasifikaci obrazových dat DPZ. S přihlédnutím k analýze časových řad mají satelitní data s velmi vysokým rozlišením (VHR) pro tento účel řadu výhod oproti klasickým leteckým snímkům. Tato studie zkoumá možnost automatizované klasifikace družicových snímků Ikonos XS (4-m) a pan-sharpened s rozlišením 1-m pomocí objektového přístupu. Metodika klade důraz na přípravnou fázi obrazové analýzy, kdy jsou z originálních dat vypočteny dodatečné kanály, které jsou dále statisticky testovány z hlediska rozšíření příznakového prostoru a přispění k separabilitě dílčích tříd klasifikace. Mimoto je do analýzy zahrnuta také výšková informace v podobě vysoce podrobného DMT. V dalším kroku jsou tyto vrstvy použity k segmentaci obrazu a následné klasifikaci na několika úrovních hierarchické sítě objektů, kdy vyšší úroveň rozčleňuje obraz podle věkové a prostorové struktury porostu, na nižší úrovni jsou pak klasifikovány skupiny stromů do kategorií podle hlavních lesních dřevin. Vytvořená znalostní báze byla aplikována na data s různým prostorovým rozlišením a správnosti klasifikace stanoveny výpočtem indexu shody (KIA). Výsledky klasifikace dat Ikonos 4-m a 1-m byly dále porovnány z hlediska uplatnění v rozličných úlohách HÚL.

Klíčová slova: objektově-orientovaná analýza, satelitní data VHR, texturální analýza, HÚL

III

LESNICKÉ MAPOVÁNÍ A EVIDENCE POROSTNÍCH VELIČIN V ARCPAD 6.0.3.

F. Hájek

LESNICKÉ MAPOVÁNÍ A EVIDENCE POROSTNÍCH VELIČIN V ARCPAD 6.0.3

ABSTRACT

Geographical Information systems have been utilized in forestry management for several years. Besides advancement in the desktop GIS, mobile GIS technology is getting more into the operational use. The methods of GIS based field data acquisition can be applied in various tasks ranging from forest thematic mapping to the detailed tree or stand characteristics survey. With the rapid development in fields of mobile computers and GPS, the technology is also easily accessible to the broad forestry community. This paper aimed to test ESRI ArcPad mobile GIS software installed onto mobile computer connected to GPS receiver for purposes of basic forest inventories with the registration of selected stand variables. The proposed method focused mostly on simplicity of the processing workflow and overall technology accessibility.

ÚVOD

Vedle četných GIS aplikací pro kancelářskou praxi zaznamenáváme v posledních letech rozvoj také na poli tzv. mobilních GIS. Tyto systémy lze s výhodou uplatnit v řadě úkolů hospodářské úpravy lesů (HÚL) jako jsou lesní inventarizace, lesní tématické mapování, zjišťováni stromových a porostních charakteristik apod. V důsledku neustálého zvyšování výkonu hardware, zpřístupnění pozičního systému DGPS a také zdokonalování samotných aplikací se navíc přístroje stávají dostupné široké lesnické veřejnosti.

Při tvorbě rozsáhlých a komplexních lesních evidencí se kladou vysoké nároky na technologii sběru terénních dat. Příkladem je nástroj Field-Map, který byl uplynulých letech používán Ústavem pro hospodářskou úpravu lesů při Národní inventarizaci lesů ČR. Field-Map se skládá z přijímače GPS, elektronického kompasu, optického a laserového dálkoměru a terénního počítače se speciálním software. Vzhledem k rozsahu, požadované kvalitě a množství měřených dat je taková technologie zřejmě nezbytná a také její cena je poměrně vysoká.

V mnoha případech však chceme získat data pouze v omezeném rozsahu (jednorázové terénní šetření, sběr referenčních dat k analýze DPZ) a proto hledáme dostupnější řešení. Cílem této práce bylo testovat možnosti využití běžného PDA s aplikací ArcPad od firmy ESRI pro evidenci vybraných údajů o porostních skupinách a jednotlivých stromech. Kromě příznivé pořizovací ceny software je nespornou výhodou plná kompatibilita se stolním ArcGIS a také značné možnosti rozšíření a přizpůsobení konkrétnímu úkonu.

Koncepce programu a přístrojové vybavení

Software svou koncepcí vychází ze stolních GIS firmy ESRI, které účelně rozšiřuje o možnost sběru venkovních dat. Nepředstavuje tudíž software pro samostatné použití. Metodický postup prací zahrnuje přípravu dat v ArcGIS desktop, terénní šetření a zpětný převod dat do stolního GIS. Následné zpracování může zahrnovat vše od tvorby porostních map až po import naměřených veličin do růstového simulátoru typu SILVA.

ArcPad ve verzi 6.0.3. byl nainstalován do PDA FSC Pocket LOOX 420 se systémem Windows Mobile 2003. Počítač byl propojen s bluetooth GPS SX Blue a přes sériový port RS232 (je zapotřebí redukce) s laserovým dálkoměrem ForestPro a elektronickým kompasem MapStar od společnosti LTI.

Obr. 1: Laserový dálkoměr ForestPro

Příprava dat v ArcGIS

Podkladem pro terénní mapovaní bývá často stávající projekt ve stolním počítači, ArcPad tento předpoklad zcela splňuje. Po instalaci programu na desktop i PDA a aktivaci ArcPad Tools extension v ArcGIS je vše nastaveno pro vzájemnou synchronizaci dat z obou systémů. Příprava podkladů k terénnímu šetření zahrnuje:

1. Extrakce požadovaného výřezu dat
2. Převod dat do formátu podporovaného programem ArcPad
3. Reprojekce do podporovaného souřadnicového systému
4. Příprava tabulek pro atributové informace a posouzení přesnosti jejich pořízení

Hlavní operace lze v ArcGIS provézt automaticky pomocí průvodce ArcPad Map, který převede stávající ArcMap projekt na mapu pro ArcPad (*.apm). Průvodce vyexportuje soubory typu geodatabase a coverage do shapefile, rastry převede na formát MrSID, uzpůsobí symbologii venkovní práci, příp. vytvoří výřez cílové oblasti. Další možností je manuální konverze, kdy provedeme konkrétní operaci pro každou zvolenou vrstvu zvlášť pomocí sady nástrojů ArcToolbox. Tímto způsobem je vhodné provést např. export obrazového souboru ve formátu TIFF do komprimovaného souboru MrSID pomocí nástroje Raster to MrSID.

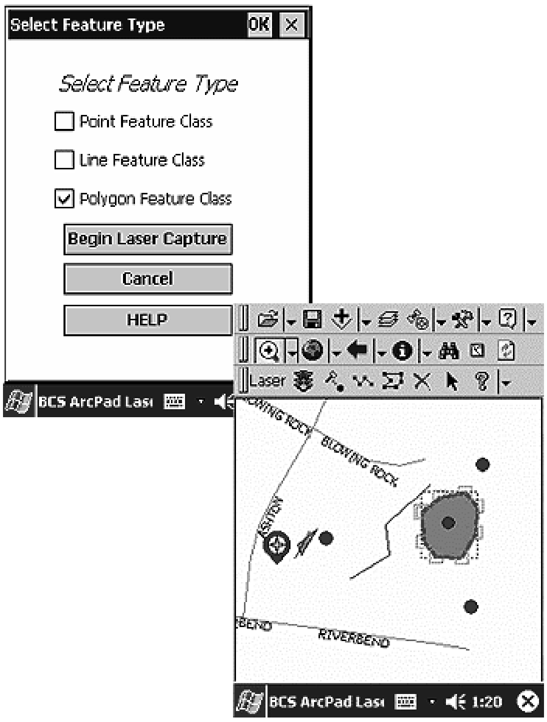
Pro usnadnění venkovních prací lze z webu ESRI stáhnout Tree Inventory Mobile Application (TIMA) – applet speciálně navržený pro lesní inventarizace. Rozšiřuje běžné způsoby pořízení dat o možnost „Přidat strom" buďto pomocí GPS, nebo pomocí existující informace v mapě pokud není GPS k dispozici. Navíc obsahuje již předpřipravené formuláře pro sběr atributových informací jako druh, výčetní průměr DBH (diameter at breast height), šířka koruny, stanovištní podmínky a doporučené hospodářské opatření. Pro účely popisu charakteristik jednotlivých stromů byla tato atributová pole importována do nové bodové vrstvy. Polygony porostních skupin a zkusných ploch byly nadefinovány vybranými atributy z tabulky ZastDRV numerické části databáze LHPO.

Poznámka:

Všechny vrstvy v mapovém souboru (*.apm) musí mít stejnou mapovou projekci, vrstvy v jiné projekci se neotevřou. Co se týče rastrových souborů, ArcPad primárně podporuje komprimované rastry ve formátu MrSID a dále zobrazuje soubory typu JPEG, Windows Bitmap a CADRG. Všechny musí mít připojen příslušný lokalizační soubor formátu (*.jgw pro JPEG), příp. soubor kartografického zobrazení (*.prj).

Komunikace s přídavnými zařízeními

ArcPad 6.0.3 přímo podporuje pouze připojení přijímače GPS. V možnostech programu se nastaví komunikační parametry GPS - typ protokolu, porty, přenosovou rychlost a paritu připojení. Z důvodu posouzení využití software ke sběru stromových charakteristik na dálku, byla testována také možnost propojení s laserovým dálkoměrem a elektronickým kompasem. Tato funkce není přímo podporována, nicméně program ve své architektuře nabízí komunikační objekt AUX, který lze nakonfigurovat pro příjem signálu z dalších přístrojů. Požadavek byl konzultován s lidmi z podpory ESRI (ArcData Praha) a následně byl poskytnut vhodný skript napsaný v minulosti jedním z uživatelů. Zkopírováním souborů skriptu do programové složky Applets umožní software pracovat s informacemi GPS, ale také odstupovou (offset) vzdáleností a azimutem jednotlivých bodů. Jiným řešením je pořídit komerční nadstavbu od americké firmy *Bradshaw Consulting Services*.



Obr. 2: Nadstavba pro propojení ArcPad s laserem od BCS, inc.

Případné problémy komunikace s některými přijímači GPS lze řešit instalací rozšíření FindGPS (http://arcscripts.esri.com/details.asp?dbid=12637), které automaticky detekuje NMEA nebo TSIP protokol přijímače GPS, otestuje dostupné porty a nastaví optimální parametry připojení.

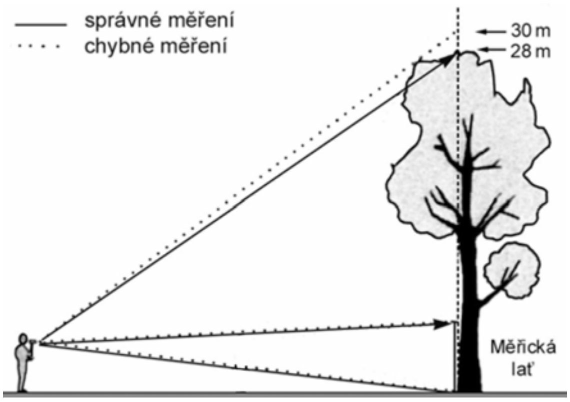
SBĚR TERÉNNÍCH DAT

Samotné venkovní práce lze koncipovat v zásadě dvěma způsoby:

A. Mapování porostu a sběr stromových atributů popocházením k jednotlivým objektům

B. Nepřímé odečítaní stromových atributů z místa o známé zeměpisné poloze

První způsob znamená postupný pohyb od jednoho stromu k druhému s tím, že u každého změříme polohu a příslušné veličiny přímo na místě. K měření potřebujeme pouze přenosné zařízení s GPS přijímačem, odečet tloušťek a výšek se realizuje tradičními pomůckami (Silva, Vertex, mechanická průměrka, příp. pásmo). Takový postup je však poměrně náročný na organizaci a nevýhodou může být také slabý signál GPS v místech se souvislým korunovým zápojem. Druhý přístup z velké časti řeší zmíněné problémy. Jedná se o metodu, kdy v porostu vybereme místo s přesně danou zeměpisnou polohou a souřadnice a výšky okolních stromů stanovíme výpočtem (trigonometricky) na základě měření horizontální vzdálenosti a příslušného úhlu pomocí laserového dálkoměru a elektronického kompasu. Tloušťky změříme buďto elektronickou průměrkou, pásmem, příp. lze využít nitkový dalekohled a tloušťky odečíst také nepřímo. Tento způsob je přímočarý a elegantní, představuje však nevýhodu v podobě vysokých přímých nákladů na pořízení přístrojů.

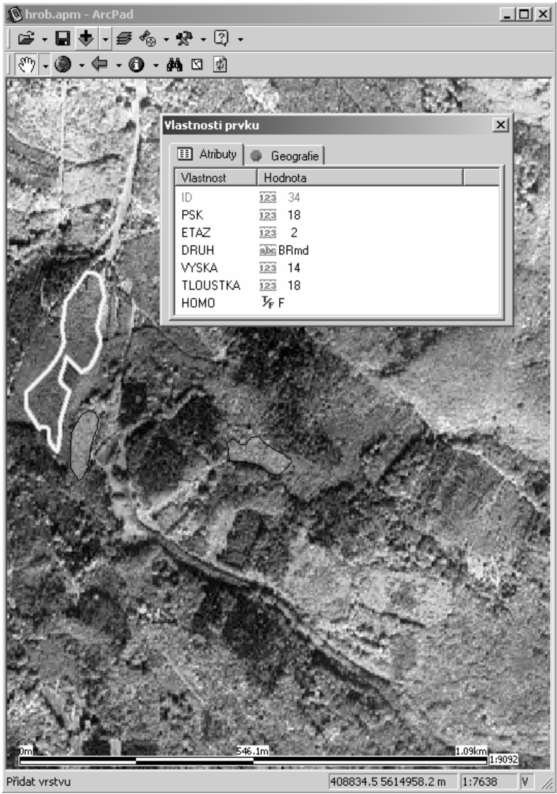


Obr.3: Trigonometrické měření výšek stromů

Tvorba bodových a polygonových prvků pomocí GPS

Pro účely studie byl zvolen postup, kdy sběru stromových atributů předcházelo mapování hranic porostních skupin tvorbou polygonů pomocí GPS. Byla vytvořena nová polygonová vrstva se základními atributy LHP jako ID porostní skupiny, Etáž, Dřevina, Zastoupení, Věk, průměrná Výška a Tloušťka. Vlastní mapování představuje sled několika kroků:

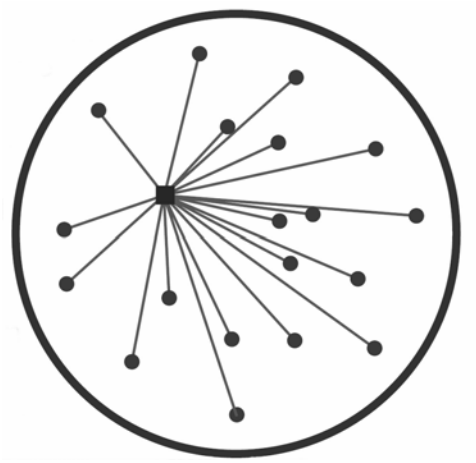
Po připojení GPS k mobilnímu zařízení a navázání komunikace, zvolíme v menu Polohovací okno „Aktivovat GPS“, tlačítkem Polygon zapneme vrstvu (musí být v editačním modu), zvolíme možnost GPS „Sejmout vrcholy“ a vlastní hranice pak vytvoříme prostou obchůzkou po okraji cílové skupiny. Opětovným sepnutím tlačítka Polygon ukončíme tvorbu prvku, po němž se automaticky nabídne tabulka k vyplnění atributů. Po krátkém zaučení se jedná o rychlý a jednouchý postup, vhodný k běžným samostatným pochůzkám (analogie terénního zápisníku). Pro práci v lese se velmi osvědčil GPS přijímač SX Blue, který ve většině případů držel signál na úrovni 3D DGPS a to i v porostech s hustým korunovým zápojem.



Obr. 4: Jednoduchý pochůzkový zápasník pro sběr referenčních dat k analýze obrazu DPZ

Offsetové měření polohy stromů v porostu

Následně byla testována možnost připojení přístrojů pro nepřímé stanovení některých stromových veličin. V rámci studie byly měřeny pouze pozice jednotlivých stromů v porostu, nicméně sestavu lze použít také k měření výšek, evidenci korunových projekcí, resp. mapování hranic porostů z místa se známou GPS polohou. Pro záznam pozice jednouše namíříme dálkoměr na patu stromu a kliknutím na přístroji sejmeme bod (záznam odstupové vzdálenosti). Po pípnutí přidá kompas MapStar do řetězce azimut a ArcPad zaznamená GPS pozici. Jedná se opět o rutinní postup, kdy výsledkem je bodový shapefile. Testovaný skript neumožňuje záznam liniových a polygonových prvků, nicméně vývojáři ESRI slibují, ze ArcPad ve verzi 7 bude připojení laserů již plně podporovat.



Obr. 5: Schéma záznamu zeměpisné polohy stromů v porostu

ZÁVĚR

Naplní článku nebyla tvorba komplexních lesnických evidencí. Cílem bylo spíše testovat přímočaré a dostupné řešení, které bude může sloužit široké škále uživatelů pro jednorázová venkovní šetření, sběr referenčních dat pro podporu výzkumu, příp. taxaci na malých lesních celcích. Základní programové rozhraní nabízí intuitivní ovládání a snadné propojení s obecně rozšířeným ArcGIS desktop. V případě specifických požadavků lze využít řady hotových nástaveb a skriptů vytvořených početnou rodinou uživatelů GIS software od ESRI. Další možností je pak ArcPad Application Builder, který nabízí široké možnosti konfigurace stávajících a tvorby nových nástrojů.

IV

VYHODNOCENÍ ODUMÍRÁNÍ HORSKÉHO SMRKOVÉHO LESA NA TROJMEZNÉ (NP ŠUMAVA) METODOU AUTOMATIZOVANÉ KLASIFIKACE LETECKÝCH SNÍMKŮ

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VYHODNOCENÍ ODUMÍRÁNÍ HORSKÉHO SMRKOVÉHO LESA NA TROJMEZNÉ (NP ŠUMAVA) METODOU AUTOMATIZOVANÉ KLASIFIKACE LETECKÝCH SNÍMKŮ

ABSTRAKT

The aims of this paper were: (1) to present preliminary results on bark beetle damage in Trojmezná old-growth forest (Bohemian Forest NP) and (2) to test possible application of automated classification of aerial photographs to survey this damage. The extent of undamaged forest area decreased about 16 % during the analyzed period. Based on our results, we conclude that methods of automated classification of bark beetle damage from remotely sensed data are useful and efficient. The problems of using aerial photos in terms of image quality (geometric properties, spectral and spatial resolution) and data accessibility are discussed. Moreover, the technological recommendations for practical processing of bark beetle damage surveys on large areas are presented.

Klíčová slova: aerial photos, *Ips typograhpus*, survey, Norway spruce forest, object-based analysis

ÚVOD

Monitorování změn stavu lesa pomocí interpretace obrazových dat dálkového průzkumu Země (DPZ) má u nás i ve světě poměrně dlouhou tradici. Jednou z nejvýznamnějších aplikací DPZ v lesnictví je analýza zdravotního stavu (ŽÍHLAVNÍK & SCHEER 2000). Pro tento účel jsou nejčastěji využívané zdroje údajů infračervené letecké snímky (MURTHA & MCLEAN 1981), případně multispektrální satelitní data (STOKLASA 1995, WOODCOCK et al. 2001). Zcela aktuální jsou pak snahy o využití družicových snímků s velmi vysokým prostorovým rozlišením (VHR) jako IKONOS a QuickBird. Vyhodnocení poškození lesa podkorním hmyzem ze snímků VHR bylo hojně testováno například v Kanadě. WHITE et al. (2005) úspěšně analyzoval data Ikonos metodou neřízené klasifikace ISODATA za účelem detekce stromů napadených druhem *Dendroctonus ponderosa*. Využití snímků z různých senzorů k mapování poškození lesa s ohledem na velikost sledovaného území dále rozebírá WULDER et al. (2006).

V České republice byly od konce 70. let minulého století testovány infračervené letecké snímky za účelem hodnocení poškození lesů v Krušných horách. Již HAUTKE (1978) studoval možnosti využití různých materiálů leteckého snímkování. Snímky z družice Landsat byly použity pro vyhodnocení rozsahu odumírání lesa v důsledku žíru lýkožrouta smrkového v NP Šumava (ZEMEK et al. 2001, ZEMEK et al. 2003). Podle ZEMKA et al. 1999 je možno využít satelitní snímky tohoto typu k hodnocení rozsahu kalamity způsobené žírem lýkožrouta smrkového, ale uvedená metoda má některé nevýhody. Jde především o časovou dostupnost snímků a jejich prostorové rozlišení. Z tohoto důvodu byly pravděpodobně při analýze rozsahu lesa napadeného žírem lýkožrouta smrkového v sousedním NP Bavorský les využity snímky letecké (HEURICH 2001). V NP Bavorský les je v současnosti tato metoda využívána jako standardní nástroj pro vyhodnocení rozsahu a průběhu odumírání lesa.

S potřebou vyhodnocení dat v časových řadách ustupují techniky založené čistě na vizuální interpretaci stále častěji automatizovaným metodám. Bohužel automatizovaná klasifikace vysoce texturovaných dat, jakými jsou letecké a satelitní snímky VHR, zůstává stále poměrně problematická. Plochy představující jednu tématickou třídu (např. koruna stromu) jsou ve skutečnosti tvořeny skupinou většího počtu pixelů se značným rozsahem hodnot stupňů šedi. Tradiční techniky klasifikace obrazu pracují pouze s digitálními hodnotami těchto jednotlivých pixelů a ignorují jejich prostorové rozmístění neboli texturu snímku (HALOUNOVÁ 2003). Zmíněná úskalí lze do značné míry řešit klasifikací založenou na objektovém přístupu. Objektová klasifikace se během poslední doby stala předmětem celé řady studií a mnohé z nich potvrzují, že lze tímto způsobem dosáhnout značného zpřesnění klasifikace. BENZ et al. (2004) poukazuje, že správnost klasifikace je podmíněna porozuměním typickému kontextu a hierarchickým vztahů na různých úrovních měřítka. Využití těchto vztahů umožňuje analýzu a hlubší pochopení různých typů krajinných struktur (BURNETT & BLASCHKE 2003). Přínosy objektové klasifikace byly s úspěchem testovány v rozličných úlohách jako mapování porostních struktur a druhového zastoupení lesa (HALOUNOVÁ 2003, HÁJEK 2006), identifikace a vymezení korun jednotlivých stromů (BRANDTBERG 1999, HAY et al. 2005, TIEDE & HOFFMANN 2006). Díky definované prostorové návaznosti umožňuje objektová klasifikace také snadné napojení na geografické informační systémy (GIS), například využitím stávajících tématických vrstev pro klasifikaci lesních porostů (FÖRSTER & KLEINSCHMIT 2006), či aktualizací údajů o porostních skupinách v databázi LHP (HÁJEK, in press). TIEDE et al. (2006) uplatnili přístup sekvenční objektové analýzy leteckých snímků k identifikaci stromů napadených lýkožroutem smrkovým v NP Bavorský les.

Cílem tohoto příspěvku je vyhodnocení rozsahu odumírání lesa v důsledku žíru lýkožrouta smrkového pomocí metody automatizované klasifikace časové řady leteckých snímků.

Časová řada leteckých snímků z oblasti I. zóny Trojmezná Národního parku Šumava (Trojmezná, NP Šumava) byla vybrána jako testovací území z několika důvodů. Přestože v dané oblasti dochází k odumírání lesa již od roku 1996, neexistuje do současnosti žádná objektivní studie řešící tuto problematiku. Existují pouze odhady rozsahu odumírání provedené v minulosti pracovníky parku, které ale byly pravděpodobně velmi nepřesné (SVOBODA 2005a). Tato studie si tedy klade za cíl otestovat současné moderní přístupy automatizované klasifikace obrazu k problému vyhodnocení odumírání lesa a zároveň prezentovat předběžné výsledky tohoto odumírání.

METODIKA

2. 1 Popis lokality

2.1.1 Historické poměry a současná situace

Do současné I. zóny Trojmezná (Trojmezenský prales) patří cca 600 ha lesa v rozdílných přírodních podmínkách a s různou minulostí využívání člověkem. Zatímco některé části pralesa nebyly v minulosti nikdy intenzivně využívány, zbytek území byl v 19. st. ovlivněn těžbou dřeva. Historické prameny z roku 1720 uvádějí lesy této oblasti jako jedny z nejzachovalejších z celé Šumavy (PRŮŠA 1990). V druhé polovině minulého století došlo k uzavření hranice a následujících čtyřicet let se vyvíjelo prakticky bez vlivu lidské činnosti (MAŠKOVÁ et al. 2003).

Po propuknutí kalamity způsobené lýkožroutem smrkovým v NP Šumava se odumírání a rozpad lesa nevyhnuly ani oblasti Trojmezné. Vizuální hodnocení leteckých snímků z roku 2005 z dané oblasti ukazuje Trojmeznou jako mozaiku odumřelých a přežívajících skupin stromů. V současné době se aktivně zasahuje proti lýkožroutu smrkovému v cca 200 m širokém pásu lesa podél státní hranice s Rakouskem a Německem, které má ochránit tamní lesy před šířícím se lýkožroutem smrkovým z NP Šumava (SVOBODA 2005b, SVOBODA & KŘENOVÁ, 2006). Terénní monitoring rozsahu odumírání lesa byl zastaven a v současnosti neexistují objektivní data o rozsahu odumírání lesa v této první zóně.

2.1.2 Přírodní podmínky

Trojmezná se rozkládá v hlavním šumavském hřebenu ve skupině Třístoličníku. Zahrnuje původní pralesovité zbytky porostů v pásu od Třístoličníku po Trojmezí, dále oblast od Trojmezí po Plechý podél hranice s Rakouskem. Území leží v nadmořské výšce 970 – 1380 m n.m. Roční úhrn srážek se pohybuje mezi 1200 mm – 1500 mm, roční průměrná teplota se pohybuje od 3,5 do 4 °C (KOPÁČEK et al. 2002). Půdy jsou hlinitopísčité, písčitohlinité, skeletovité, typu rankru, podzolu a kryptopodzolu (KOPÁČEK et al. 2002, SVOBODA 2003).

Z lesních společenstev převládá přirozená kyselá smrčina středního vzrůstu s přechodem k jeřábové smrčině v hřebenových polohách. V nižších polohách se nacházejí bukové smrčiny, případně smrkové bučiny (PRŮŠA 1990). Vzhledem k heterogenním přírodním podmínkách a rozdílné historii využívání se charakter lesa v rámci celého území Trojmezné výrazně liší. Struktura lesa byla popsána v práci SVOBODA (2005c) a SVOBODA (2005d).

2.2 Obrazová data a jejich předzpracování

2.2.1Barevné a barevné infračervené (IČ) letecké snímky

Letecké snímky byly v rámci případové studie analyzovány jako archivní data. Vzájemně se lišili obdobím pořízení, použitým materiálem, v případě předzpracovaných dat navíc nebyly k dispozici žádné informace o způsobu vyhotovení ortofotosnímků.. Proto je třeba zdůraznit, že kvalita snímků nebyla pro daný úkol optimální.

Pro klasifikaci byly použity snímky ze čtyř období - barevné infračervené letecké snímky z let 1995 a 2006, a barevné letecké snímky z let 2001 a 2004 (Tab. 1). Ke snímkování na bylo použito analogových kamer ZEISS LMK 15 a 2015. Barevné letecké snímky byly pořízené ve třech spektrálních pásmech viditelné části spektra elektromagnetického záření s radiometrickým rozsahem 8 bitů (256 úrovní jasu). Barevné infračervené (color infrared - CIR) byly pořízené na film Kodak AEROCHROME 2443, který má zvýšenou citlivost v IČ pásmu. K eliminaci záření v modré části viditelného spektra byl použit filtr Kodak WRATTEN č. 12. Aplikací tohoto filtru se jednotlivé vrstvy IČ filmu stanou citlivé pouze k zelené, červené a infračervené části spektra a snímky se pak zobrazují v nepravých barvách (www.kodak.com).

Zdroj	Rok	Datum snímkování	Typ snímku	Kamera	Měřítko
AOPK	1995	25.10. 1995	infračervený (IR)	LMK 15	1:10000
NP Šumava	2001	04.11. 2001	barevný (RGB)	LMK 2015	1:14000
Gefos a.s.	2004	18.6. 2004	barevný (RGB)	LMK 2015	1:15000
NP Šumava	2006	17.7 .2006	infračervený (IR)	LMK 2015	1:15000

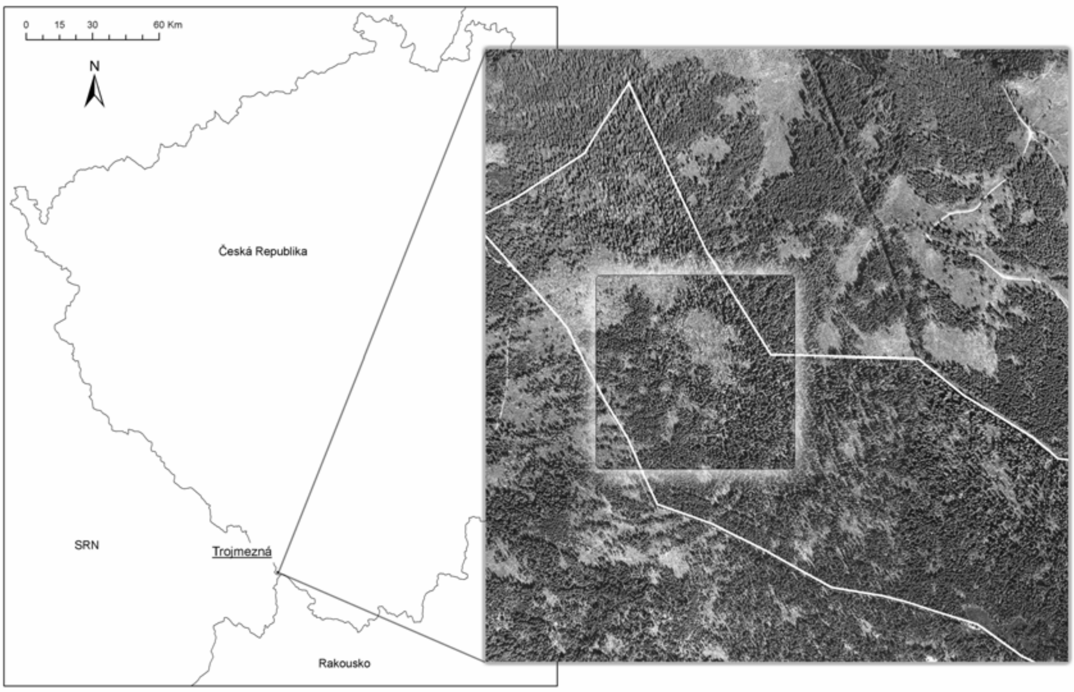
Tabulka 1. Přehled použitých snímků a jejich základní charakteristiky

Letecké snímky z let 2001 a 2004 byly získány již jako připojené do souřadnicového systému (WGS 84 zóna 33N) a ortorektifikované; snímky z roku 1995 a 2006 pak pouze jako skenované a dále nezpracované obrazové soubory. Při skenování pozitivu infračervených snímků se jednotlivé složky spektra – zelená, červená a infračervená – zobrazily do kanálů RGB v nepravém barevném podání. Tyto snímky byly koregistrovány pomocí afinní transformace a společně s ostatními snímky resamplovány na prostorové rozlišení 0,42 m/ pixel pomocí interpolační metody nejbližšího souseda (LILLESAND et al. 2004).

2.2.2 Volba zájmového území

Za účelem klasifikace lesa postiženého odumíráním hlavního stromového patra byla ze snímků vybrána čtvercová oblast cca 600 x 600 metrů. Tato plocha splnila požadavky definované pro následné vyhodnocení, a to na všech čtyřech snímcích: (1) podstatná část záběru uvnitř hranic první zóny NP, (2) území s evidentním vlivem lýkožrouta smrkového, (3) území v blízkosti středu snímku, (4) území, které je z hlediska stavu porostu charakteristické pro celou oblast, (5) minimální podíl území, kde byla prováděná úmyslná asanace lýkožrouta smrkového.

Poslední zmíněné kriterium bylo dodrženo jen částečně, protože v části analyzovaného území byly některé stromy napadené lýkožroutem smrkovým asanovány. Platí to především pro levý dolní roh analyzované oblasti (Obr. 1), která leží na území Německa a částečně také v pásmu kolem hranice, kde dochází k asanaci i na českém území uvnitř první zóny.



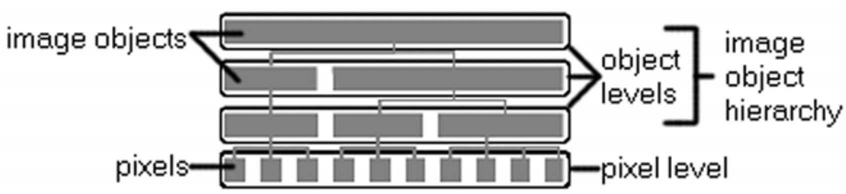
Obr. 1. Lokalizace studované oblasti. Bílá čára značí hranici první zóny NP Šumava. Čtvercový polygon označuje testovanou oblast.

2.3 Objektově-orientovaná klasifikace leteckých snímků

Multitemporální analýza leteckých snímků byla založena na objektovém klasifikačním přístupu. Při objektově orientované analýze je obraz nejprve rozdělen do tzv. primitiv - souborů více pixelů, které se co možná nejvíce podobají smysluplným objektům. Klasifikace pak probíhá nad těmito objekty, a nikoliv nad samotnými pixely, jako je tomu u běžných metod automatizované klasifikace. Segmentace originálních dat může být provedena do několika úrovní podle požadované velikosti cílových tříd (koruny stromů, porostní skupiny), čímž umožníme využití vzájemných vazeb mezi objekty na jedné nebo více úrovních. Vhodně nastavená segmentace navíc do jisté míry řeší vysokou heterogenitu některých tříd ve snímcích s velmi vysokým prostorovým rozlišením. V rámci následné klasifikace lze pro jednotlivé třídy definovat nejrůznější klasifikační pravidla, založená na spektrální a texturální charakteristice objektů, jejich geometrickém tvaru a kontextu v rámci jedné úrovně (sousedství), či hierarchickém vztahu mezi úrovněmi. Zapojení multi-úrovňových vztahů mezi objekty (Obr. 2) představuje zásadní posun oproti pixelovým automatizovaným metodám. Analýza tedy zahrnuje dva základní kroky:

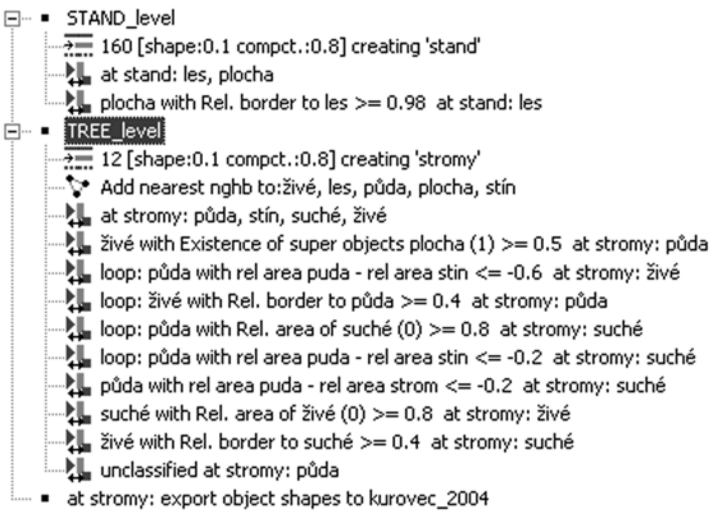
I. Obrazová segmentace do několika hierarchických úrovní objektů založená na spektrálních a texturálních znacích. Velikost a tvar segmentů vychází z výpočtu maximální povolené heterogenity (uživatel definuje velikost měřítka cílových segmentů tzv. Scale parameter) (BAATZ & SCHÄPE, 1999).

II. Klasifikace objektů podle jejich charakteristických vlastností. Příznaky tříd jsou definovány buď funkcemi členství a na základě číselně vymezených hodnot příznaků se provádí klasifikace, nebo se klasifikuje pomocí klasifikátoru nejbližšího souseda, který porovnává příznaky vybraných vzorků (segmentů vybraných zpracovatelem) a příznaky všech segmentů obrazu a provádí vlastní zatřídění segmentu do jedné nebo většinou více tříd.



Obr. 2. Multi-úrovňové vztahy objektové hierarchie. Struktury (objekty) různých měřítek mohou být reprezentovány simultánně a tudíž klasifikovány pomocí vzájemných vztahů (DEFINIENS PROFESSIONAL 5 USER GUIDE. 2006).

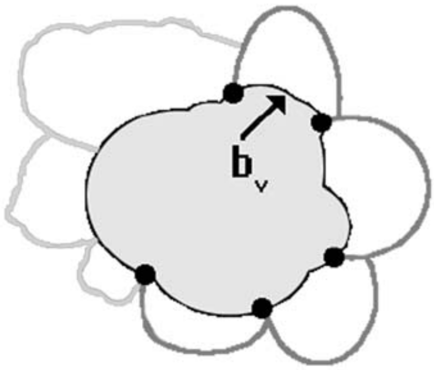
V této studii bylo vyhodnocení leteckých snímků bylo provedeno aplikací sekvence procesů v prostředí Definiens Professional 5.0.10. (DEFINIENS IMAGING Germany, 2006). Byla vytvořena základní zákonitá posloupnost procesů, která zahrnovala segmentaci snímků do dvou hierarchických úrovní objektů, klasifikaci podle definovaného souboru příznaků, opravy hranic jednotlivých tříd pomocí kontextuální klasifikace a nakonec export tématické vrstvy do GIS (Obr 3.). Sekvence procesů byla formou znalostní báze (rule-base) přenesena a postupně aplikována na snímky ze všech čtyřech časových období.



Obr. 3. Znalostní báze jako zákonitá sekvence procesů obrazové analýzy v Definiens Professional 5.0.10.

Základní segmentace na vyšší úrovni rozdělila obraz na velké polygony zapojeného lesa a polygony bezlesí (s ležícími suchými kmeny), případně polygony se stojícími suchými stromy. Na nižší úrovni byla provedena detailnější segmentace veškerého území mimo plochy bezlesí, kde byly klasifikovány jednotlivé koruny a skupiny stromů, a to na stromy živé a stromy suché. Dále byly vylišeny kategorie volná plocha a stín. Pro potřeby studie byly tedy na vybrané lokalitě vymezeny čtyři základní kategorie klasifikace: (1) živý les, (2) suchý les, (3), volná plocha, (4) stín. Do kategorie živý les byly zařazeny stromy, které v době pořízení leteckého snímku měly převážnou část asimilačních orgánů v zelené barvě. Do kategorie suchý les byly zařazeny: a) stromy u kterých v době pořízení leteckého snímku asimilační orgány ztratily zelenou barvu, b) stromy bez asimilačních orgánů s korunou tvořenou suchými větvemi v různém stádiu rozpadu koruny. V případě že došlo ke zlomení stromu a převážná část suché koruny na stojícím pahýlu chyběla, byly tyto stromy klasifikovány jako volná plocha. Do kategorie volná plocha byly zařazeny plochy bez zjevných stojících živých nebo suchých stromů na kterých nově odrůstající stromové patro nebylo identifikovatelné.

Klasifikace byla primárně řízena výběrem vzorků (segmentů), jejichž příznaky byly porovnávány klasifikátorem nejbližšího souseda a představovaly vzorové plochy pro zatřídění segmentů do tříd. Kategorie objektů byla definovány pomocí průměrných hodnot příznaků (typického projevu) v jednotlivých spektrálním pásmech a jejich odvozeninách. Tyto zahrnovaly především rozdíly a podíly spektrálních pásem u barevných a infračervených snímků. Výsledky spektrální analýzy byly následně přehodnoceny a zpřesněny zapojením (definicí) vztahů kategorií na dvou úrovních objektové hierarchie, jakožto i v rámci sousedství (Obr 4). Tímto způsobem bylo možné odlišení spektrálně identických tříd (vzrostlé stromy a nárost v barevných snímcích), úpravy plochy korun v zástinu, případně klasifikaci ležících a stojících suchých kmenů.



Obr. 4. Příznak „relativní hranice k" určuje poměr délky hranice objektu sdílené se sousedním objektem konkrétní třídy $\mathbf{b}_v$ *k celkové délce hranice objektu (Definiens Professional5 - Reference Book. 2006).*

Správnost klasifikací v jednotlivých letech byla posouzena především na základě vizuální interpretace. Pro roky 2004 a 2006 byly výsledky posouzeny také na základě terénních šetření. Pro každou kategorii bylo manuálně klasifikováno 45 rovnoměrně rozmístěných referenčních objektů, byla sestavena chybová matice (CONGALTON & GREEN, 1999) a vypočten standardní statistický ukazatel správnosti klasifikace Index shody Kappa (KIA) (SMITS et al. 1999). Na základě automatizované klasifikace byla vytvořena vrstva tématických GIS výstupů (Obr. 5) a plochová tabulka zastoupení tříd v čase (Tab. 2).

VÝSLEDKY A DISKUZE

3.1 Vyhodnocení rozsahu odumírání automatizovanou klasifikací

Správnost klasifikace v jednotlivých letech byla posuzována především na základě indexu KIA. V tomto ukazateli bylo dosaženo hodnot 0,94 (1995), 0,85 (2001), 0,90 (2004), 0,93 (2006) KIA. Výsledky lze považovat za velmi dobré, míra shody v rozmezí 85 % - 94 %

odpovídá výsledkům analýz leteckých snímků řešených objektovým přístupem v dalších pracích (HALOUNOVÁ 2003, TIEDE et al. 2006).

Změna v zastoupení a rozsahu jednotlivých analyzovaných kategorií během let 1995 až 2004 je znázorněna na Obr. 5. V roce 1995 byl podíl jednotlivých kategorií v analyzované oblasti následující: živý les 41,0 %, suchý les 3,7 % a stín 54,8 % (Tab. 2). Zjistit, kdy došlo k odumření stromů interpretovaných jako kategorie suchý les na leteckém snímku z roku 1995 není zatím s použitím analyzovaných dat možné. V časové řadě, která byla vyhodnocena zatím chybí kvalitní barevný snímek pořízený před rokem 1995. Podle jedné z mála studií, která se zabývala rozpadem smrkového lesa po odumření v důsledku žíru lýkožrouta smrkového se do deseti let od odumření porostu 75 % stromů zlomí, z toho 50 % stromů se zlomí ve výšce 0 – 10 m (KUPFERSCHMID et al. 2003). S využitím výsledků této studie je pravděpodobné, že většina stromů klasifikovaných v roce 1995 jako suché odumřela v rozmezí let 1985 – 1995. Jaká byla prvotní příčina odumření těchto stromů, zda to bylo pouze v důsledku žíru lýkožrouta smrkového, nebo kombinací více faktorů, a co bylo případně zdrojem lýkožrouta smrkového není možné na základě současných dat zjistit.

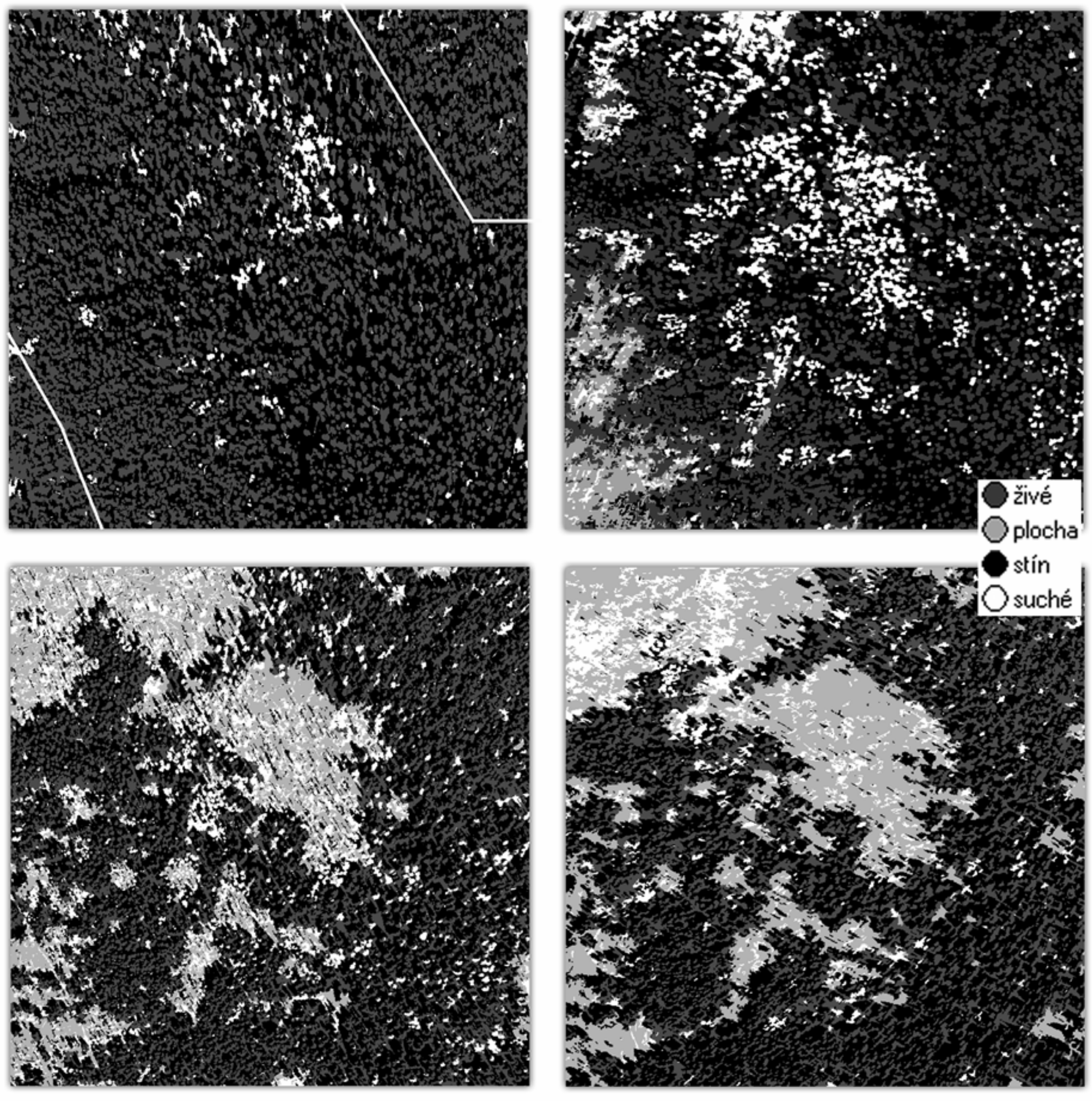
Rozloha v letech/ Typ třídy	**1995**		**2001**		**2004**		**2006**	
	Rozloha		Rozloha		Rozloha		Rozloha	
	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)
Živý les	14,80	41,00	11,76	32,48	9,83	27,15	9,26	25,41
Suchý les	1,33	3,67	4,13	11,40	4,74	13,09	2,88	7,91
Volná plocha	0,00	0,00	1,89	5,21	4,99	13,78	7,99	21,94
Stín	19,77	54,77	18,23	50,36	16,45	45,42	16,09	44,19
Suma	36,10	100,00	36,20	100,00	36,21	100,00	36,42	100,00

Tabulka 2. Zastoupení jednotlivých tříd klasifikace (v ha a %) z celkové rozlohy analyzované oblasti v jednotlivých letech časové řady.

Mezi roky 1995 a 2001 došlo k výraznému nárůstu plochy kategorie suché les a ke snížení rozlohy kategorie živý les. Podíl kategorie suchý a živý les v roce 2001 byl 11,4 a 32,5 %, tj. nárůst v případě suchého lesa o 7,7 % a pokles v případě živého lesa o 8,3 %. Pravděpodobnou příčinou odumření stromů byl žír lýkožrouta smrkového. Zdrojem lýkožrouta smrkového byly pravděpodobně lokality suchého lesa identifikované v roce 1995. Z Obr. 5 je zřejmé, že suché stromy v roce 2001 jsou koncentrovány v okolí suchých stromů z roku 1995. V roce 2001 bylo 5,3 % rozlohy analyzované oblasti zařazeno do kategorie volná plocha. Největší podíl této kategorie byl zjištěn v levém dolním rohu analyzované oblasti (Obr. 5). Tato část analyzovaného území již není součástí Trojmezné (NP Šumava), ale jedná se o německý lesní majetek. V těchto porostech dochází k asanaci lýkožrouta smrkového.

Proto v této oblasti nedošlo k nárůstu rozlohy suchého lesa, ale k zvýšení rozlohy kategorie volná plocha, která vznikla jako důsledek asanační těžby. Mezi roky 2001 a 2004 došlo k dalšímu poklesu rozlohy kategorie živý les na 27,2 %. Rozloha kategorie suchý les se v tomto období zvýšila na 13,1 %. Rozloha kategorie volná plocha mezi roky 2001 a 2004 také zvýšila na 5,2 %. Rozloha kategorie suchý lesa a volná plocha spolu navzájem souvisí. Jak dochází postupně k rozpadu stojících suchých stromů, dochází i k nárůstu plochy, která je klasifikována jako kategorie volná plocha. Z Obr.5 je opět zřejmá koncentrace suchých stromů na snímku z roku 2004 v okolí suchých stromů klasifikovaných v roce 2001. Na první pohled je patrný nárůst kategorie volná plocha ve střední a levé horní části snímku, kde došlo ke kompletnímu odumření horního stromového patra. Při interpretaci výsledku je nutno vzít v úvahu jeden důležitý fakt. Levá část snímku spadá do cca 200 m širokého pásu lesa podél státní hranice s Rakouskem a Německem, kde se i přestože se jedná o první zónu národního parku provádí asanace lýkožrouta smrkového pokácením a odkorněním napadených stromů. Z tohoto důvodu může být nárůst kategorie volná plocha způsoben nejen rozpadem stojících suchých stromů, ale i asanační těžbou. S použitím dostupných dat není možné tyto dva procesy od sebe zatím přesně odlišit. Mezi roky 2004 a 2006 se rozloha kategorie živý les snížila na 25,4 %. Nárůst byl menší něž v předchozích obdobích. Rozloha kategorie suchý les se mezi roky 2004 a 2006 snížila na 8,0 % a rozloha kategorie volná plocha v tomto období vzrostla na 22,0 %. V období 2004 až 2006 tedy došlo k mírnému zpomalení odumírání horního stromového patra, naopak pokračoval výrazný rozpad odumřelých suchých stromů.

Celkově se tedy v období mezi roky 1995 a 2004 snížila rozloha kategorie živý les z 14,80 ha na 9,26 ha. Rozloha kategorie suchý les kolísala mezi jednotlivými analyzovanými roky a rozloha kategorie volná plocha se zvýšila z 0 ha v roce 1995 na 21,94 ha v roce 2006. Samostatnou analyzovanou kategorii při klasifikaci tvořila třída stín. Rozloha této kategorie postupně klesala v jednotlivých letech z 19,77 ha na 16,09 ha. Stíny na obrazových datech obecně představují jeden z problémů automatizované klasifikace leteckých snímků. ASNER & WARNER (2003) poukazují, že podíl stínů ve snímcích vzrostlé vegetace je vždy podstatný a zvyšuje se s hustotou porostu. V případě souvislých lesních oblastí je množství stínu dále ovlivněno velikostí a tvarem korun, hustotou porostu, indexem listové plochy, optickými vlastnostmi asimilačních orgánů, a v neposlední řadě také geometrií slunečního záření a samotného snímkování (GERARD & NORTH 1997, GILABERT et al. 2000). Při vyhodnocení snímků z různých období se proto na množství stínů zásadně projeví různorodost vegetace, ale také odlišnosti v technologii leteckého snímkování. V případě této studie lze množství stínů v jednotlivých letech interpretovat ze dvou hledisek: (1) Datum snímkování. Snímky z let 1995 a 2001 byly pořízené na konci října (respektive začátkem listopadu), podíl stínů k celkové ploše je tedy ve srovnání s daty z letního snímkování (roku 2004 a 2006) vyšší. (2) Hustota porostu a množství asimilačních orgánů. Podíl stínů k celkové ploše se dále snižuje v důsledku postupného prořeďování lesa žírem lýkožrouta smrkového a chřadnutí napadených stromů.



Obr. 5. Změna v rozloze jednotlivých klasifikační tříd na leteckých snímcích v řadě let 1995 (2a), 2001 (2b), 2004 (2c) a 2006 (2d).

ZÁVĚR

V průběhu studie byla testována možnost využití automatizované klasifikace obrazu leteckých snímků při vyhodnocení odumírání horního stromového patra smrkového lesa v důsledku žíru lýkožrouta smrkového. Zároveň byly prezentovány předběžné výsledky tohoto odumírání ve vybrané části území. Pomocí automatizované klasifikace byla zjištěna změna v rozloze živého lesa v analyzované oblasti, která se snížila z 41 % na 25 %. Na základě získaných zkušeností je možné konstatovat, že přístupem tvorby zákonité sekvence procesů lze klasifikovat obrazová data s poměrně vysokou mírou automatizace. Nejedná se totiž o jeden konkrétní algoritmus či příznak kategorie, nýbrž o posloupnost typizovaných algoritmů přenositelnou ve formě znalostní báze. Prahové hodnoty jednotlivých procesů (příznaků) lze upravit pro další snímky v bloku, příp. pro odlišné podmínky snímkování. Metoda tudíž představuje jeden z potenciálně efektivních nástrojů, který bude pravděpodobně možné po dalším testování prakticky využít při opakovaném vyhodnocování rozsahu odumírání lesa. Posouzení možnosti aplikace získaným poznatků na celé území Trojmezenského pralesa bude předmětem dalšího výzkumu.

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V

PROCESS-BASED APROACH TO AUTOMATED CLASSIFICATION OF FOREST STRUCTURES USING MEDIUM FORMAT DIGITAL AERIAL PHOTOS AND ANCILLARY GIS INFORMATION

F. Hájek

PROCESS-BASED APROACH TO AUTOMATED CLASSIFICATION OF FOREST STRUCTURES USING MEDIUM FORMAT DIGITAL AERIAL PHOTOS AND ANCILLARY GIS INFORMATION

ABSTRACT

The methods of forest inventory data acquisition based on the analysis of remotely sensed images have been well tested and implemented during the last decade. The predominately visual interpretation and pixel-based automated techniques are now being gradually replaced by the object-based image classification at multiple levels. This paper explores and demonstrates the prospect of using medium-format digital aerial imagery for purpose of automated updating of the existing GIS forest management database (LHPO). The method put emphasis on the pre-processing phase, where various image transforms and additional channels such as spectral ratios and vegetation indices (NDVI), low-pass filters, Sobel edge and GLCM texture measures are derived from the original dataset. The layer stack is then imported into the object-oriented classification environment together with the exiting thematic vector layer and analysed on three hierarchical object levels. The classification involves recognition of the successional stage of forest compartments and the estimation of tree species composition in terms of area coverage. Further, age information in the GIS forestry management map can be updated and the spatial distribution of classes corrected using the multiscale object relations of the former analysis. The advances of the automated procedure based on sequential processing of image objects are partially covered. Moreover, aspects of utilisation of the medium-format CIR images as an alternative to traditional aerial photos and VHR satellite data, were also discussed.

Keywords: medium format digital images, GLCM texture, object-based image analysis, tree species

INTRODUCTION

The increasing demands on the level of accuracy, time, completeness, and cost-effectiveness of forest information extraction are causing traditional methods of visual image interpretation to be gradually replaced by the semi-automated and automated techniques. This fact is further supported by the improved computing power together with the availability of very high spatial resolution (VHR) multispectral aerial and satellite images. The advantage of VHR imagery is that individual trees are often visible allowing the forest classification on the stand and also on individual tree crown level. Such imagery can potentially be used for individual tree-based forest inventory and planning. Features of particular interest include the tree crown size and spectral characteristics, stem position, and stem number per hectare. Tree species estimates are important in forest management and it is also needed to estimate timber volume.

A number of newly developed sensors and systems with the capability of individual tree crown analysis are now approaching operational applications. VHR satellite data (SPOT 5, Formosat, IKONOS, QuickBird, OrbView-3) fulfil much of demands on large scale, multitepmoral LULC analysis. Also digital aerial cameras for photogrammetry have developed significantly since they were first introduced in 2000 and today, frame based as well as linear array cameras are available on the market (e.g. Leica Geosystems, Z/I Imaging, DiMAC systems, Vexcel Imaging). The main advantages over traditional aerial photos are a completely digital data flow, a significantly improved radiometry, together with the possibility to simultaneously acquire panchromatic, colour and near-infrared imagery.

Obeying the technological development, various methods of tree species identification from aerial and satellite imagery have been explored by researchers. Many studies on aerial photos aimed to delineate and identify individual tree species based on different algorithms e.g. finding local maxima, template matching and edge detection (Gougeon, 1995; Dralle and Rudemo, 1997; Larsen and Rudemo, 1998; Brandtberg 1999). Šumbera and Žídek (2003) followed these authors and implemented selected procedures into a special programmme to automatically create maps for a range of forestry applications. Other authors (Bucha, 1998) aimed to estimate forest species composition using moderate resolution data such as Landsat TM, and Spot HRV. Malenovský (2001) tested a combination of simulated HQSR (High Quality Spatial Resolution) and Spot 4-Xi satellite images and found that spatial resolution of 4 m could be sufficient for forest vegetation mapping. The most recent studies based on image segmentation and multiscale object representation focuses both on stand delineation and area-based species distribution (Halounová, 2003; Hájek, 2006), as well as delineation of individual trees (Burnett et al., 2003; Hay et al., 2005). The approach of local maxima detection followed by simultaneous object-growing was lately proposed by Tiede and Hoffmann (2006). Besides, spectral analysis, combined with the additional information from e.g. terrestrial measurements or laser scanning, and the integration of GIS within the automated classification procedures, has been characteristic up-to-date approaches for mapping of forest structures (Förster and Kleinschmit, 2006).

METHODS

Object-based classification

As stated by Hay et al. (2005), the significant cost savings may be realized through an inclusion of automated processes to an increasingly digital interpretation environment. Nevertheless, the traditional automated procedures based on the analysis of individual pixels ignore their spatial distribution (texture) and are often inaccurate (Willhauck et al., 2000). Similarly to automated classification of other landscape structures, the important point is to determine spectral, textural and geometric signatures of forest species. The differentiation itself can be problematic as their spectral curves sometimes overlap. Moreover, the crown reflectance is always a complex interaction of foliage spectral properties with other sources of variability including atmospheric effects, shadow pattern, back ground composition and instrument noise (Stone and Coops, 2004). Besides, the extreme image heterogeneity of VHR data itself, cause the objects representing one thematic class (e.g. tree crown) consist of a number of pixels with different digital values. Thus the automated classification of such highly textured image data still remains a complicated task (Halounová, 2003).

To overcome the problem of high variance, image segments representing meaningful objects can be calculated out of the pixels and then classified. The initial segmentation based on automatically extracted spatial measures explicitly related to the varying sized, shape and spatial distribution of image-objects within a scene, is essential.

Image segmentation

The task of creating meaningful objects equates to searching for changes in image object heterogeneity/homogeneity. The number of segmentation techniques were developed e.g. Haralick and Shapiro (1985), Ryherd and Woodcock (1996) and Baatz and Schäpe (2000). The common approaches use thresholding or region growing algorithms and different types of texture segmentation algorithms and knowledge-based approaches are also used in operational applications. The algorithm so-called Multiresolution segmentation, was developed by Baatz and Schäpe (1999) and introduced in the first commercial object-oriented image analysis software eCognition (Definiens Imaging, Germany). The classification procedure considers not only object spectral and textural properties, but also their size and behaviour on different levels of the scale. The underlying idea behind the step of building image objects is the minimization of their weighted heterogeneity. The process can be simultaneously applied across the whole image to obtain objects of comparable size and quality (Baatz and Schäpe, 2000; Willhauck et al., 2000; Schiewe, 2002). The very late approaches are based on creation of initial object primitives and their stepped rebuilding using the supervised region-specific processes at multiple levels (Definiens Professional 5.0).

Multi-scale analysis

Interpretation of earth observation data typically requires determining what greater structures exist in the landscape and the level of variability within these units (Hay et al., 2005). According to Benz at al. (2004), also the successful knowledge-based object extraction is much dependent on understanding of appropriate analysis scales and their combination, identification of typical context and hierarchical dependencies. Burnett and Blaschke (2003) concluded that the multi-scale segmentation/object relationship modelling can be a vehicle for a theory driven exploration of different types of landscape heterogeneity.

There is no single (spatial) scale being optimal for characterizing the multitude of different scene components (Baatz and Schäpe, 2000). The same type of object appears differently at different scales and thus the definition of the target scale is crucial. Studying the scene at different levels and consequently employing the multi-scale dependencies enhance the automated classification (Benz et al., 2004). Objects created on different scales - segmentation levels - can be linked together to a hierarchical object network (Figure 1). Different hierarchical levels can be segmented using different data. Further, the initial object borders can be corrected based on regrouping of their sub-objects. Practically classifying the upper level, each object e.g. forest stand can be analyzed based on the occurrence of its classified sub-objects e.g. tree crowns, gaps and shadows. The context information and semantics can be used to distinguish between trees within a forest or within an urban area etc.

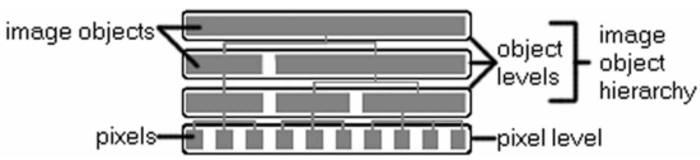

Figure 1: Multi-scale relations. Structures of different scales can be represented simultaneously and thus classified in relation to each other

Utilisation of existing forest inventory data

European countries such as Germany or the Czech Republic pursue their forest management traditionally at a very high level. The forest inventory data and the knowledge about processes of the forested landscapes are abundantly available and have been recorded for long decades here. According to Förster and Kleinschmit (2006), the task is to integrate this ancillary data into the image analysis with certain benefits.

The characteristics of forest types based on remote sensing data interpretation (as texture, spectral value, and object shape), have typically very broad ranges of occurrence, causing mixtures in the classification process. Besides, the existing information in the form of maps or GIS layers is often outdated, not spatially accurate, or missing. The integration of the two data sources enables enhanced separation of thematic classes (narrowing the possible mixtures) and consequently updating of the class borders based on RS imagery.

DATA AND STUDY SITE

Digital aerial imagery

Aerial images from medium-format camera Hasselblad H1 with lens of 50.4 mm focal length and PhaseOne P25 digital back were analysed in this study. Hasselblad H1 is a medium format SLR camera with a number of unique features that support digital backs and provide similar handling and functionality as an integrated digital camera. Image format is 6 x 4.5 cm (actual size 56 x 41.5 mm). Phase One P25 digital back incorporates 22 megapixel CCD chip with size of 48.9 x 36.7 mm, 9 x 9 µm pixel pitch, 4:3 ratio and 16 bits per pixel ADC.

The images were sensed using custom-made optical filters to obtain three multispectral bands with spectral properties similar to Landsat TM bands (Figure 2).

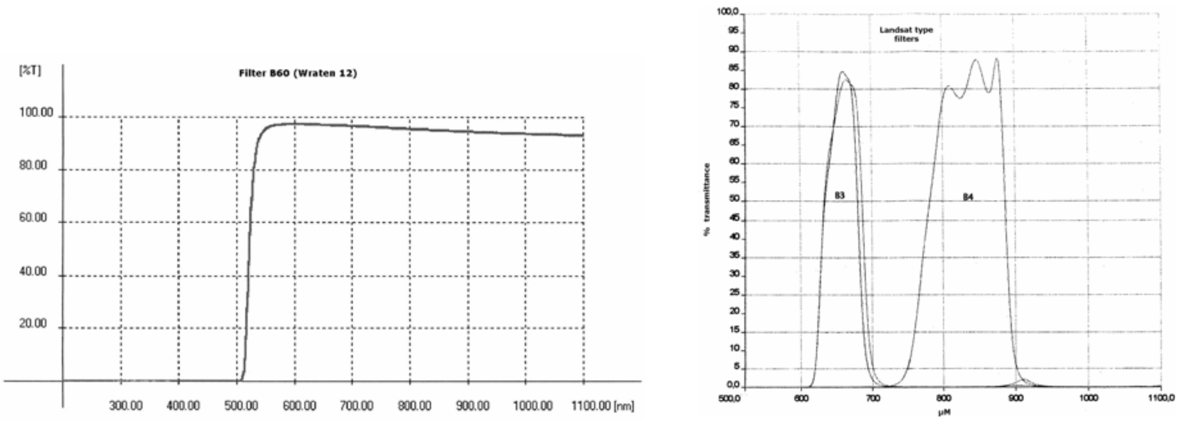

Figure 2. Transmitance custom-made optical filters B60 (Wraten 12) and Landsat type B3 and B4 (Optical research workshop AV Turnov 2002)

The imagery was experimentally acquired over the lowland flat forested area close to town of Židlochovice (49° 0’ N, 16° 38’ E) in southern Moravia, Czech Republic. The flat site comprised regular compartments of even-aged extensive mature Pedunculate oak (*Quercus robur L.*), European Ash (*Fraxinus excelsior*), Poplar (*Populus sp.*), Willow (*Salix sp.*), Norway spruce (*Picea abies L.*) and young plantations of Pine and Oak. Besides, smaller proportions of Large-Leaved Lime (*Tilia platyphyllos*) could be found inside forest stands and along the margins. The planted mature stands, with poor natural regeneration, had uniform stocking density and canopy structure.

LHPO vector data

Polygons from the existing forest management planning GIS database so-called LHPO provided by the Forest Management Institute (ÚHÚL, Czech Republic) were used for the thematic segmentation on the level of forest stands (Figure 3). Besides the vector layers, the database contains a detailed description of forest stands which is being continuously updated. Thematic attributes such as “Age step” were used as additional information for the relational classification of the forest compartments.

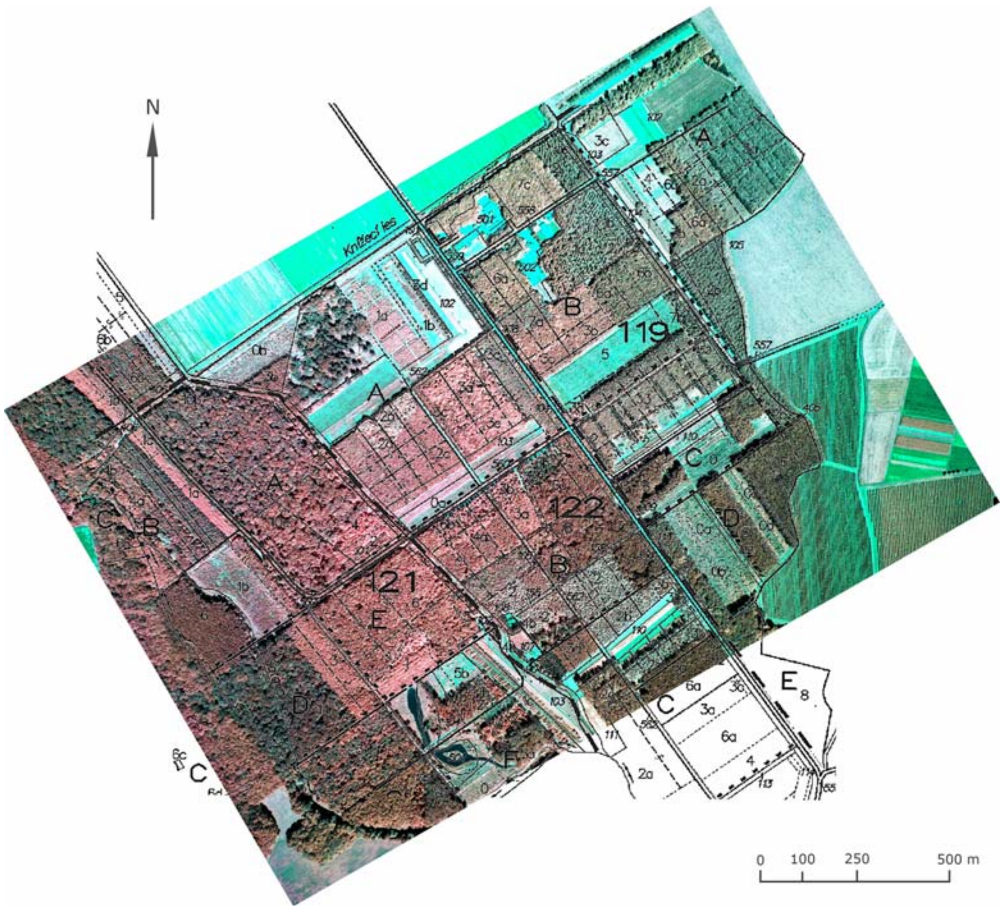

Figure 3. Digital aerial image (false color composite) overlaid with corresponding tile of LHPO vector database

Field GIS

Based on the previous information from LHPO forest inventory database, twenty $400 m^2$ plots covering areas with 100% species composition were located as reference data. Sample plot selection put emphasis on size and class purity to provide a representative basis for accuracy assessment. The boundaries of each plot were determined with differential GPS SX Blue™ and PDA with ESRI ArcPad™ mobile GIS.

Image pre-processing

Some authors such as Zhang (2001) and Wack and Stelzl (2005) stated that image classification methods based solely on spectral analysis are insufficient for the mapping of complex forest structures from high resolution digital imagery. Particularly young succession stages and heterogeneous mature stands are characterised not only by the spectral but also their textural (spatial) properties. Similarly non-forested areas and regenerating areas should be eliminated based on their different texture characteristics.

Various methods have been employed for the automated extraction of texture information in forestry. Zhang (2001) tested several texture algorithms, and found that local variance extraction, edge detection and some co-occurrence matrix texture measures can well separate trees from lawn and other objects with similar spectral properties. The result of texture integrated classification gained almost 30% of agreement over the multispectral only method. Tuominen and Pekkarinen (2005) assessed the performance of selected textural features derived from digital aerial photos and stated that optimal image spatial resolution is dependent on the object size. Hauta-Kasari et al. (1999) applied different Haralick features on the multispectral images to perform texture segmentation. Another evaluation of spatial information (GLCM texture measures) in spectrally unmixed image fractions of vegetation, shadow and wood was done by Le'Vesque and King (2003) who found it useful in forest structure and health modelling.

FEATURE SPACE ENLARGEMENT

In this study, the delivered raw image initial was geo-registered to the reference GIS in UTM projection (WGS 1984 zone 33N) using a rational polynomial function model with the total RMSE 2.3 m and pixel size resampled to 0.5 m. Afterwards, a number of additional channels were calculated out of the original data in order to enhance the class-by-class separability. The image pre-processing was done in external programmes (PCI Geomatica 9.1, Erdas Imagine

8.7), and involved calculation of first principal component from which the GLCM texture measures Homogeneity, Mean and Standard Deviation (Haralick et al., 1973), as well as the Sobel edge layer, were derived. Besides, various spectral features and transforms such as NDVI and NIR/Green band ratios were calculated as customised features in "Definiens Professional". Due to the issue of large data handling, the project was based on 1800 x 1700 pixels data subset.

CLASS SEPARABILITY ASSESSMENT AND FEATURE SELECTION

A frequent task in image analysis is to reduce the number of features utilized for classification to the essential ones. In this project, the in-between correlation of pre-processed layers was visually assessed using 2D features space plot (Figure 4). From each pair of highly correlated features, one was deselected and omitted in the classification.

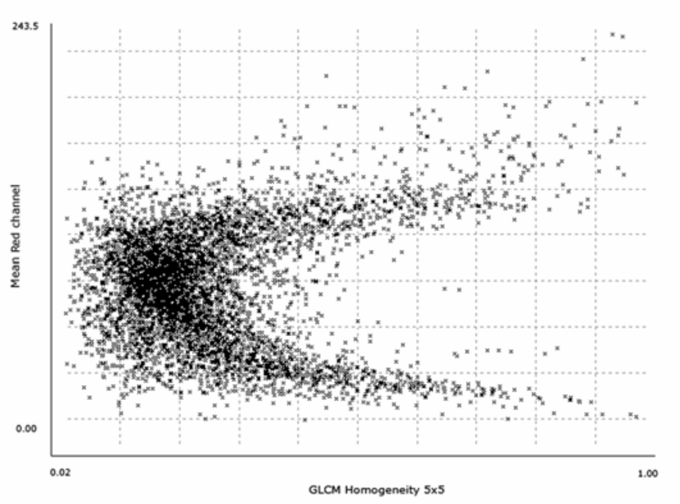

Figure 4. 2D Feature space plot. Correlation analysis of two image channels - Mean Red and GLCM Homogeneity

Furthermore, the 30 sample objects in each class were manually classified based and the reference field data and the class-by-class separability with the feature contribution, were tested using the Definiens internal tool called "Feature Space Optimization". Then histograms of the candidate features for every two competing classes were compared.

Automated analysis based on sequential processing of image objects

The approach of process-based image analysis as provided by commercial software Definiens Professional 5.0.10 was tested in this study. The programme enables the building of a rule-base out of single processes (algorithms), which can be executed on a specific image object domain. The resulting rules-set is a sequence of individual processes providing a solution to a specified image analysis problem in the predefined order (Definiens User Manual, 2005). The available algorithms are many e.g. Segmentation, Classification, Reshaping operation algorithms, Vectorization, Export algorithms. Besides, individual objects or object domain can be assigned to a target thematic class according to description within single or multi-dimensional feature space. As in the earlier software version, features include various object characteristics, class related and context related features.

The concept of object domain allows adapting selected algorithms to individual initial regions and treating the different thematic classes independently. Analyzing VHR data in such manner is advantageous for instance for the single tree crown delineation as shown in Tiede et al. (2006). The processes run on target domain enables improved object building (merging, splitting) as well as advanced classification techniques e.g. searching for objects enclosed by specific class, searching an extrema of certain feature within this domain and more. Furthermore, this functionality enables generating complex workflows, restricting child processes to certain domains or tying child processes to conditions. De Kok (2006) found the process approach an advance towards the fully automatic classification.

SEGMENTATION OF OBJECT PRIMITIVES

There are many ways to perform multi-level segmentation using different algorithms and segmentation parameters. The bottom-up approach of building object hierarchy using multiresolution segmentation with thematic vector layer was tested in this study. Setting the scale parameter is important to obtain object primitives most suitable for target classes. According to Radoux and Defourny (2006) the higher scale parameter increases the class-by-class separation and using of the shape factor improved the overall segmentation quality. Still, the process of finding optimal segments was a matter of testing. The resulting segmentation parameters are shown in Table 1. The segmentation process sequence included a calculation of very fine objects (tree parts), higher level segmentation of forest compartments and vector-based segments created in between the two levels (Figure 5). The object primitives calculated by multiresolution algorithm were later refined by multi-level contextual processes. In such manner, the existing vector border of compartments was updated by the information from the aerial image.

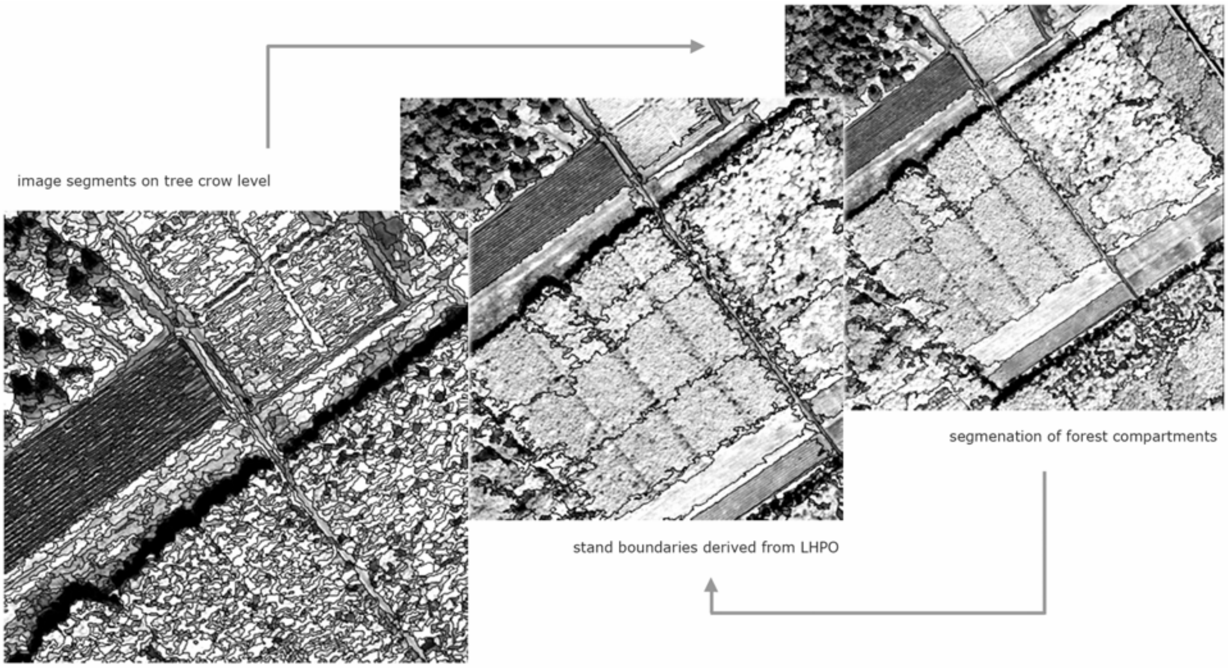

Figure 5. Bottom-up segmentation at three image object levels - tree crowns, GIS-based stands and forest compartments.

Segmentation level	Scale par.	Homogeneity criterion			
		Color	Shape	Shape settings (Compact/Smooth)	
Level 1 – Compartm	130	0.8	0.2	0.9	0.1
Level 2 – LHP	1000 TM	1	0	0	0
Level 3 – Crowns	15	0.7	0.3	0.3	0.7

Table 1. Segmentation parameters for 8-bit digital imagery resampled to pixel size of 0.5 meters.

THEMATIC AND OBJECT-BASED CLASSIFICATION

The idea behind the automated procedure was to formulate the expert knowledge into processes. The two different algorithms were used to classify objects on the lower (detailed) and upper GIS-based levels. The polygons of the thematic forest stands were simply assigned to eight age classes according to definite (Boolean) threshold of LHP attribute. The classes included: non_forest, plantation (1 to 10 years), young_stand (11 – 20 years), young_stand (20 – 40 years), premature_stand (40 – 60 years), premature_stand (60 – 80 years), mature_stand (80 - 100 years) and mature_stand (over 100 years). The object primitives on the level of tree parts were organized in a hierarchical structure and analysed by means of hierarchical classification. The process was controlled by a rule-base describing the class characteristics in the form of fuzzy membership functions allowing definition by multiple fuzzy expressions - rules for individual features were combined by using the logical operators ‘‘and’’, ‘‘or’’ and ‘‘not’’. The features based on mean spectral values of objects and various band ratios were mostly applied. The classes differentiated at the tree-crown level were:

(1)shadow, (2)bare_soil, (3)grass, (4)planted, (5)spruce, (6)willow, (7)oak, (8)lime and (9)other broadleaves (*Fraxinus, Populus*)

Finally, the multiresolution segments of forest compartments were also classified using hierarchical structure - assigning the easy classes and moving to more difficult ones (so-called masking technique). In contrast to species identification at the bottom level, the very large objects allowed to utilise more textural features, so different successional stages could be recognised. The classes involved: unplanted, plantation, young_conifers, young_broadleaves, mature_conifers, mature_broadleaves, sparse_stand, and shadowed_ground

The analysis workflow

The image classification workflow was defined by a sequence of individual processes as described by the process tree showed on Figure 6. The analysis started with the segmentation, where large objects build above the detailed level using the MS algorithm were cracked-down following the LHPO vector file. Then, the classes could be classified according the thematic attribute at this level. Another step involved the initial classification of tree species and forest types based solely on the object features (spectral, geometrical, textural).

In the next phase, the classification was gradually refined using advanced contextual relations – within one level and between levels. This required several process cycles. The resulting class distribution was further adjusted by means of border optimisation and objects fused by the domain-merging algorithms to prepare the thematic map for export into the preferred GIS layer format.

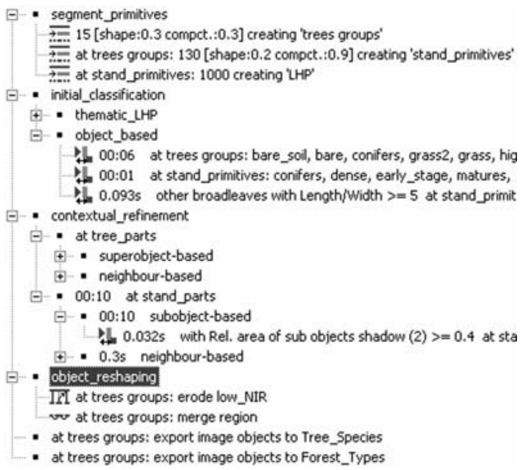

Figure 6. The image analysis workflow in form of process tree: The initial multi-level segmentation followed by “crisp” and fuzzy classification algorithms and class-related refinement. The last phase represents improvement of the object border and conversion into GIS thematic layer.

RESULTS AND DISCUSSION

The thematic classification was obtained for the two levels of tree-crowns and forest compartments and the results were evaluated by means of common accuracy measures. 20 samples for each class were selected in accordance with the GIS field reference data and the accuracy statistics (such as Producer's, User's, Overall accuracy, as well as Kappa Index of Agreement (KIA)) were derived from the assembled error matrix. Selected statistics calculated per class, and for all assigned classes, are shown in Tables 2a and 2b.

As the statistical measures indicate, the proposed method offered satisfactory results when applied to medium-format digital aerial images. In both tasks, the recognition of successional stage of forest compartments as well the ability of identifying tree species composition in terms of area coverage were fulfilled with the overall accuracy above 75%. The very good result of more than 90% was obtained for classes of oak, bare_soil, shadow and grass and class planted with approx. 80%. The lower agreement between 66 to 78% was achieved for willow, lime and other broadleaves (Ash and Poplar). The KIA for spruce was only 33%. The fact referred to the spectral limitation of the tested imagery. On the other hand, the textural characteristics represent significant contribution and the analysis of prevailing forest types was very advantageous at this site. The most of given age classes were assigned with the agreement over 75%. The classes mature_conifers and mature_broadleaves were often mixed, which was also caused by the problematic spectral discrimination.

Cover type / Stats	shadow	bare	grass	planted	spruce	willow	lime	oak	other
KIA per class	1.00	0.89	0.90	0.78	0.33	0.66	0.77	0.98	0.67
Overall accuracy	0.79								
KIA	0.76								

Cover type / Stats	unplant	planted	y_conif	y_broadl	m_conif	m_broadl	sparse
KIA per class	1.00	0.89	0.90	0.78	0.33	0.66	0.77
Overall accuracy	0.88						
KIA	0.85						

Tables 2. Selected accuracy measures evaluating classification at "tree-crown" (2a) and "forest compartment " (2b) levels. The statistics were derived for each class, Overall Accuracy and the Kappa index of agreement represent aggregated results

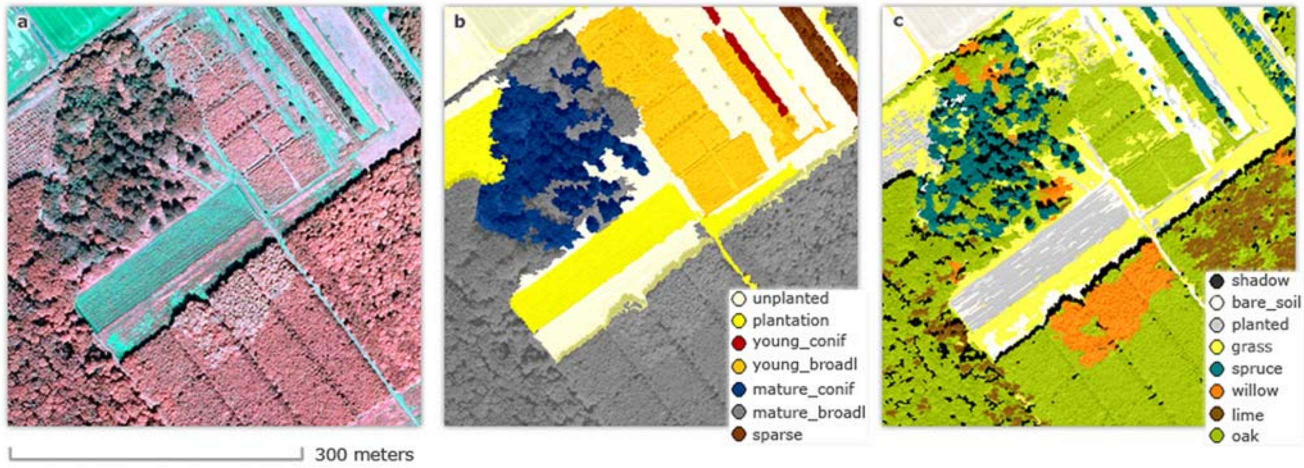

Figure 7. Subset of digital aerial imagery in false color composite (a), thematic age classification on the level of forest compartments (b) and the spatial distribution of main forest species at the tree-crown level (c)

The next part of the result demonstrated the ability of utilisation of the former image analysis for updating the existing GIS forestry management map. Using the object relations to level above and under thematic classification, the areas being previously wrongly mapped and areas with outdated age information were corrected (see Figure 8). The developed logical sequence can be adopted to apply the workflow onto the other imagery.

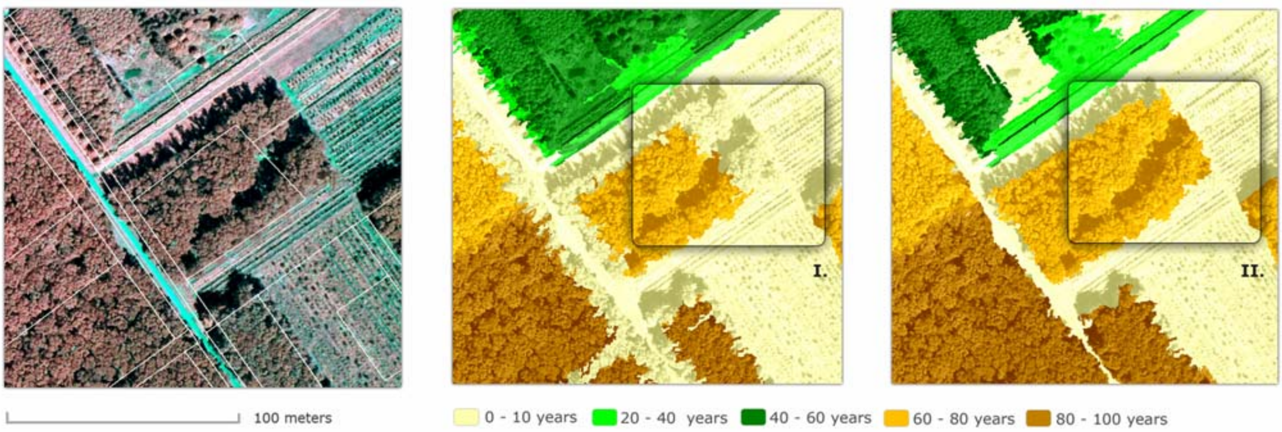

Figure 8. The process of subsequent update of existing GIS layer. Image segmentation and classification based on thematic input (I.) and the class boundary improvement resulting from the multilevel class relations

The sequential processing of objects derived from VHR aerial imagery using Definiens Professional version 5.0.10 was the objective of testing in this study. The transferable protocols from previous eCognition versions were replaced with the rule-set in the form of a process tree, which alone represents progress towards the automation of the image analysis. This process can be modified to suit other datasets or tasks. Besides, the concept of algorithms targeted to the specific domain (class, scale), improves the capability of hierarchical classification (De Kok, 2006). The programme also offers advanced segmentation techniques and procedures based on the creation of object primitives, as well as the stepped region-specific object rebuilding. However, the setting of important segmentation 'scale parameter' still remains a matter of extensive (often, very time consuming) testing. As noted by Hay et al. (2005), this can represent a serious limitation for some users and thus the problem of automate selection of the scale parameter needs to be solved. Moreover, interpretation of the results using site-specific accuracy assessment methods may be problematic when applied to object-based classification, as already mentioned by Tiede et al. (2006). The topic of the positional quality of objects derived by segmentation was further discussed by Radoux and Defourny (2006). Since we deal with spatial objects, the geometrical accuracy of borders should be taken into account. Therefore object-specific techniques, as proposed by Shöpfer and Lang (2006), must be considered for further evaluation of the results.

CONCLUSIONS

The effort to replace visual methods of remote sensing data interpretation with the automated techniques has been obvious for several years. As the radiometric and spatial resolution have improved over the time, the predominately pixel-based automated methods need to be substituted by object-based image classification. Apart from the application on the highly textured images from (e.g. IKONOS), the procedures seem well suited also for other less common image data. The presented methodology proved that images obtained by a medium-format digital sensor might be an interesting alternative to other Earth observation data such as traditional aerial photos and VHSR satellite imagery. The results showed the particular benefit is a very high spatial resolution, which allows for an enhanced utilisation of the contained textural information. The spectral properties are rather influenced by use of the optical filters and do not have the quality of multiresolution and CIR images. Also the radiometry of the 8-bit / pixel can hardly compete with 11-bit Ikonos data, or Digital Mapping Camera (DMC, Z/I Imaging) with 12-bit per pixel. However, the cost of images with the very low primary investment should be considered for selected management tasks, especially on non-extensive forest areas. The one application would be the updating the existing information about distribution of age classes, where the valuable textural information is very useful, as demonstrated in this study. Besides, the process design can be applied on multispectral Ikonos imagery (4 meters per pixel), which were found sufficient for estimation of forest species in previous work (Hájek, 2006). Generally, utilisation of remotely sensed images in similar manner might be the way to preserve long-standing tradition of acquiring numerous forest parameters in the central Europe.

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7 Conclusions

Based on the results of image classifications and the experience with the imagery interpretation, several conclusions in connection to the key issues of this study were made.

Utilization of very high resolution (VHR) aerial and satellite images in forestry

IKONOS-2 multispectral imagery with 4-meter pixel size: The original image bands are equivalent Landsat TM (ETM+) bands, so number of common spectral calculations can be used to extract different vegetation types. In order to enhance the classification of forest structures, additional channels calculated from the original bands are required. However, the benefits of involving texture analysis are less significant due to lower spatial resolution (4m/pixel). The image geometry, radiometric stability, dynamic range were excellent. The sensor represents a robust source of image data that allows extraction of the tree species composition at sufficient scale.

IKONOS-2 multispectral images pan-sharpened to 1-meter spatial resolution (XS pan bundle): The imagery features excellent sensor characteristics (as described above). The improved spatial resolution of 1 meter per pixel enables to expose detailed structures within forest stands, further, the canopies of individual trees can be analysed. Consequently, the increased textural content allowed for better discrimination of different vegetation structures such as young succession stages and heterogeneous mature stands. Due to the higher amount of detail, the careful determination of object scale with respect context on multiple levels was required. The classification result may greatly benefit of image analysis within the object-oriented environment.

Color and infrared film aerial photographs: As a part of the thesis, images acquired by analog aerial survey camera were tested in ability to distinguish between green living spruce trees and trees damaged by bark beetle insect. Although the satisfactory results of forest classification were obtained, several problems of using such data in automated analysis were recognized. The limited spectral and radiometric resolutions cause the imagery to be unable for the tree species discrimination. Besides, the differing image geometry caused by non-consistent acquisition procedures (variations in viewing and solar angles, and screening centers) determine the data source more suitable for the visual interpretation tasks.

Medium–format digital aerial photographs: The alternative to common RS data takes advantage of the enormous progress in field of digital imaging. The imagery features excellent radiometry of 16-bit per pixel and very good spatial resolution corresponding to 22 megapixel CCD sensor. The spectral properties are dependant on the quality of used optical filters. In this study, the image did not offer quite the spectral output of the multiresolution, or CIR aerial photos, which might have been partially caused by the restricted bit depth (to 8-bit only) of the delivered imagery. However, the contained textural information was considered very useful in succession stage classification. The geometric problems were in consequence of principles of the aerial remote sensing.

Benefits of image pre-processing and GIS data fusion

The hypothesis of enlarging class signature space to improve classification results was positively acknowledged. The most significant contribution was found for channels calculated from multispectral image bands, where NDVI and ratios of Green and NIR were especially useful for better forest species recognition. The layers derived based on texture calculations e. g. GLCM Variance, GLCM Mean, GLCM Entropy, or Sobel edge operator enhanced separation of forest areas at different succession stages. Besides, the image smoothing filter (Median) was approved to refine segmentation results of pan-sharpened IKONOS images, as well as the highly textured digital aerial photos.

Apart from the image derivatives, existing GIS data were also considered to enhance the classification. The application of DEM and forest management planning GIS database LHPO were only tested in this study. The DEM raster dataset calculated from map contours was used to reduce topographic effects of varying image illumination. The "elevation" thematic attribute allowed separating classes of typically different altitude (pastures vs. mountain meadows). The GIS attribute "age_step" of LHPO was similarly used to classify the age distribution of forest compartments (PSK), while the existing stand boundaries could be sequentially updated by the output of image analysis.

In connection to the increased signature space dimensionality, the issues of class feature selection had to be solved. The two techniques of selection the significant class characteristics were implemented in this study. Both the graphical and statistical method helped the decision, however, none of the tested procedures were considered enough sufficient and straightforward.

Aspects of object-based image analysis and the result interpretation

Results of the thesis showed that analysis of very high spatial resolution (VHSR) imagery using the object-based classification approach can be performed with relatively high accuracy.

Depending on the image pixel size and bit depth, proper segmentation parameters to create meaningful objects of the target class were set. The process of searching and setting the important ‘scale parameter’ was found quite complex and time consuming task. The idea of creating different segmentation levels to construct multilevel object hierarchy (landscape / forest / stand / tree_crown) allows to employ semantic relations between these levels, and represents a totally new perspective in RS data classification.

The capability of class definition using “fuzzy” descriptions and their combination with logical operators were found very useful. In such manner, the specific characteristics of different classes (tree species for instance) were recorded and formed into classification rule-base. The rule-base can be applied onto different dataset and the image, assuming data from the identical sensor, classified with the minor modifications of fuzzy function into the same thematic map. Further enhancement in the analysis automation was recognized when using the sequence of individual processes as introduced in Definiens Professional 5.0.10. The logical sequence of algorithms targeted to the specific domain (class, scale) were found easy to modify to suite other datasets and tasks.

The object classification delivered solid thematic output. Comparing to results of pixel-based methods (typically salt & pepper appearance), these maps looked very coherent and unbroken, with no need of post-classification improvement. Further, the software allowed exporting results into preferred GIS format. The visual map evaluation and accuracy assessment proved the high level of classification agreement of more than 80% using common accuracy measures such as Producer Accuracy, User Accuracy, and Kappa Index of Agreement (KIA). However, the result interpretation became more complex with the object-based image analysis. The object quality and positional accuracy of object borders were not considered, since the topic was found beyond the scope of this thesis.

Acquisition of field reference data

In connection to classification data sampling and accuracy assessment, method of field reference data acquisition to ensure reliable and updated ”ground truth” information was developed. The method focused on simplicity and efficiency utilizing the widely available equipment (hardware / software present at the department). The system based on mobile GIS technology was intended for an individual as a modern version of field notepad. In the office, the field GEO data can be imported and edited within the desktop GIS, or directly used in the image analysis environment. Apart from the basic system configuration (handheld PC with

GPS receiver), the capability of extension using laser rangefinder was tested. The technology allowing measurements of reference points was considered useful for classifications of individual trees, as well as techniques of sub-pixel image analysis.

8 Final Discussion and outlook

This study demonstrated that the acquisition of selected stand and tree characteristics, commonly done by terrestrial methods (or visual interpretation of aerial photos respectively), can be facilitated and gradually replaced by semi-automated and automated classification of remotely sensed images. When estimating tree species composition, the approach based on analysis of image objects offers considerably higher level of accuracy and thematic agreement comparing to pixel-based classification procedures. Nevertheless, there are several problems of object-oriented image analysis that need to be solved to utilize the method in operational forest management.

Many questions are connected to accuracy assessment of object classification. The accuracy measures Producer, Accuracy, User Accuracy, or Kappa Index of Agreement (KIA) widely used in the RS studies were developed for classification “per pixel”. The application of such statistics to evaluate objects is problematic, since the object borders created by the segmentation algorithm may be of different geometric accuracy. Therefore, new methods of accuracy measures considering the segmentation quality need to be investigated.

Another controversial topic would be the contribution of fuzzy logic to transferability and the full autonomy of classification system. The definition of classes using “fuzzy” membership of feature mean and the rule-base building as hierarchy of these classes is enormously demanding and time consuming process. In the further development, such class hierarchy might be possibly replaced by a logical sequence of processes, while searching rather for extremes (minimum / maximum) of class features.

Further, there are significant issues about segmentation procedures as the basis of the object-oriented classification concept. The algorithm so-called “Multiresolution segmentation” (DEFINIENS Imaging, Germany) provides very good results in terms of geometric accuracy. However, the process of setting proper segmentation parameters remains a matter of extensive testing, which alone represents a limitation for most users. The other segmentation techniques introduced in the latest version of Definiens Professional software (Chessboard and Quadtree segmentation) allow for advanced object creation within the process sequence, still the system lacks a definite and universal workflow suggestion.

Generally, the study showed that availability of RS image data of consistent quality is the most important prerequisite to develop the automated classification system. The current price of the VHR imagery properly pre-processed for further analysis remains the biggest constraint in the forest management sector in Czech Republic. Besides, the availability of VHR satellite data is also limited by the sensor acquisition capabilities. The analog film aerial images were considered less suitable for automated and multitemporal classification due to the variations in acquisition geometry, and also limited spectral and radiometric resolution. However, there are several new airborne digital sensors with improved features (radiometry of 12 -16 bit per pixel, parallel image collection using single perspective center) that should be tested and utilized in the automated processes. In consequence to rapid technological development on the field of remote sensing data acquisition and processing, the most of present problems are assumed to be solved within the next few years.

List of abbreviations

3D	Three-dimensional
ADC	Analog-to-Digital Converter
AISA	Airborne Imaging Spectroradiometer
ANOVA	ANalysis Of Variance
ALS	Airborne laser scanning aka LiDAR
ASCII	American Standard Code for Information Interchange
B&W	Black and white (photographic material)
CASI	Canadian Aeronautics and Space Institute
CIR	Colour infrared (photographic material)
DEM	Digital Elevation Model
DTM	Digital Terrain Model
ESRI	Environmental Systems Research Institute
GIS	Geographical Information System
GLCM	Grey Level Co-occurrence Matrix
GLDV	Grey Level Difference Vector
GPS	Global Positioning System
IFER	Institute of Forest Ecosystem Research
IFOV	Instantaneous Field Of View
ITC	Individual Tree Crown
IHS	Intensity Hue Saturation (image composition)
ISODATA	Iterative Self-Organizing Data Analysis Techniques

KIA	Kappa Index of Agreement
LAI	Leaf Area Index
LANDSAT 7 ETM+	Land remote sensing satellite Enhanced Thematic Mapper Plus
LČR	State Forests of Czech Republic – Lesy České Republiky (in Czech language)
LHP(O)	Forest management planning GIS database (ÚHÚL Czech Republic)
LULC	Landuse /Landcover
NDFI	Normalized Difference Fraction Index
NDVI	Normalized Difference Vegetation Index
NIR	Near Infra-Red (part of the electromagnetic spectrum)
NP	National Park
PCA	Principal Component Analysis
RGB	Red Green Blue (colour composition)
RMSE	Root Mean Square Error
RS	Remote Sensing
SNR	Signal to Noise Ratio
SO_2	Sulphur dioxide
SPOT	Systeme pour l'Observation de la Terre satellite with High Resolution Geometric instruments
SWIR	Shortwave Infrared (part of the electromagnetic spectrum)
TM	Thematic Mapper
ÚHÚL	Forest Management Institute - Ústav pro Hospodářskou Úpravu Lesů (in Czech language)
UTM	Universal Transverse Mercator (geographic projection)
VH(S)R	Very High (Spatial) Resolution imagery
VNIR	Visible and Near Infra-Red (part of the electromagnetic spectrum)
VÚLHM	Forestry and Game Management Research Institute - Výzkumný Ústav Lesního Hospodářství a Myslivosti (in Czech language)

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