

SUPERVISED AND FOREST TYPE-SPECIFIC MULTI-SCALE SEGMENTATION FOR A ONE-LEVEL-REPRESENTATION OF SINGLE TREES

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1st International Conference on Object-based Image Analysis (OBIA 2006)

KEY WORDS: Segmentation, LiDAR, object-based, laser scanning, crown delineation, region growing, OLR, region-specific segmentation

ABSTRACT:

In this paper a supervised approach for the object building / segmentation process utilizing a priori knowledge about the specific scale domain of the target features is proposed. One premise was that the result should finally represent the entire scene content in a spatially contiguous one-level-representation (OLR, Lang & Langanke, 2006). High-level segmentation and pre-classification of multi-spectral line scanner data were used to generate an initial set of regions, characterised by their spectral behaviour and height information and accordingly assigned to image object domains (i.e. forest types). Five different forest types were distinguished: coniferous spacious vs. coniferous non-spacious forest, deciduous-spacious vs. deciduous non-spacious forest, and mixed forest. All types were treated independently: optimized multi-scale segmentation was used to build up objects in a region-specific two-level hierarchy. The sub level objects correspond to single trees or tree crowns. The region-specific segmentation is controlled by a combination of rule-sets as being developed by Tiede & Hoffmann (2006) for single tree crown delineation on laser scanning data, taking into account the forest characteristics (i.e. deciduous vs. coniferous or spacious vs. non-spacious) of the respective types. Since working below the initial (super-) level, OLR is finally accomplished. The approach was realised using Cognition Network Language (CNL) for the Definiens Developer Software. CNL offers possibilities to address single objects and to manipulate and supervise the process of building new region-specific scaled objects. The results concerning single tree crown delineation are promising due to the fact that instead of applying one single algorithm for the entire scene a sequence of adapted algorithms for each initial region is performed.

1. INTRODUCTION

Recent technology of very high spatial resolution (VHSR) optical sensors and laser scanning enables imaging of a broad range of possible target features in human-related scale domains. But the comfort of an 'H-res' situation (Strahler et al., 1986), where the pixel size is significantly smaller than the average size of the object of interest, goes at the expense of an overload of spatial detail. Region-based segmentation techniques provide powerful, yet intuitive means for reasonably re-aggregating this detailed information and reducing scene complexity. Using multi-scale segmentation we arrive at a hierarchical set of scaled representations, which can be adapted to the required level of detail. In forest and other environment-related applications, we usually aim at scaled representations of the entire scene content – other than at feature extraction. However, for a full representation of the scene content, one specific parameterization may be inappropriate and a product of a trade-off between over- and under-segmentation. Consequently, as Lang (2002) has pointed out, specific structural arrangements of target features may require feature-specific multi-scale segmentation. One approach to achieve this is to perform scale-space analysis and derive specifics of how image objects move through scale (e.g. Hay et al., 2005). The approach introduced in this paper is complementary: we propose a supervised approach for the object building / segmentation process utilizing human pre-knowledge about the

specific scale domain of the target features. One premise of the study was that the result should finally represent the entire scene content in a spatially contiguous one-level-representation (OLR, Lang & Langanke, 2006).

2. STUDY AREA AND DATA SETS

2.1 Study area

The study area is located in the National Park Bavarian Forest in south-eastern Germany along the border with the Czech Republic (cf. Fig. 1). It covers almost 270 ha of near natural forest stretching from the mixed mountain forest zone in the National Park to the spruce forests of the valleys zones. Different forest structures occur including spacious / closed forests, multiple tree canopy layers as well as varying tree size and species.

2.2 Data

For this study we used data from the Toposys airborne laser scanning (ALS) system (see Wehr & Lohr, 1999). Surveying of the study area was done at three dates: leaf-off (March and May, 2002) and leaf-on (September 2002). Both first and last returns were collected during the flights and the average point density is 10pts per m². The datasets were processed and

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classified using TopPit (TopoSys Processing and Imaging Tool) software. The resulting surface model (DSM) and terrain model (DTM) were subtracted to create a normalised crown model (nCM) with 1 m resolution. Simultaneous to the LiDAR range measurements, image data were recorded with the line scanner camera of Toposys. The camera provides four bands: B (440-490 nm), G (500-580 nm), R (580-660 nm) and NIR (770-890 nm) and a ground resolution of 0.5 m.

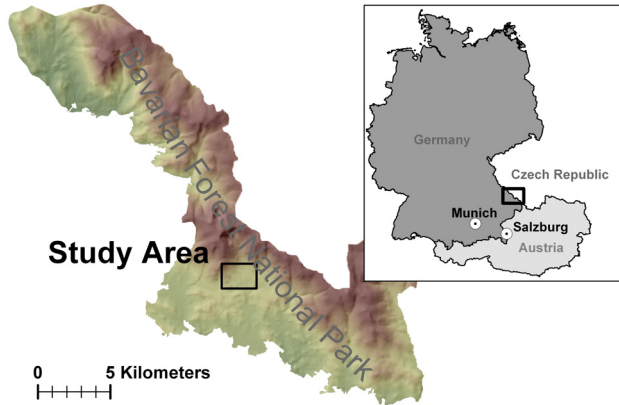


Figure 1. Study area within the Bavarian Forest National Park

3. METHODOLOGY

The approach presented in this paper was realised by developing a ruleset using Cognition Network Language (CNL) for the Definiens Developer Software. CNL is a sort of a modular programming language allowing typical programming tasks like branching, looping and variable definition. Specifically, it enables addressing single objects and supports manipulating / supervising the process of building scaled objects in a region-specific manner (cf. Tiede & Hoffmann 2006). We used this flexibility for designing a workflow from scene specific high-level segmentation and classification to region specific multi-scale segmentation of single tree crowns (Figure 2).

3.1 High-level segmentation and classification

In a first segmentation step (high-level segmentation) a multiresolution segmentation with a scale parameter of 100 was used. This segmentation takes into account all five data layers (optical and nCM data), but weighting the nCM three times higher (cf. Tab. 1). The result is a rough delineation of single forest types, but also non-vegetated areas (roads, larger clearance areas etc.). These were characterised by their spectral behaviour and height information and accordingly assigned to image object domains (i.e. forest types).

L	SP	SW	CPW	Remarks
1	100	0.5	0.5	nCM was weighted by 300%

Table 1. High-level segmentation settings (L = Level, SP = scale parameter, SW = shape weighting, CPW = compactness weighting)

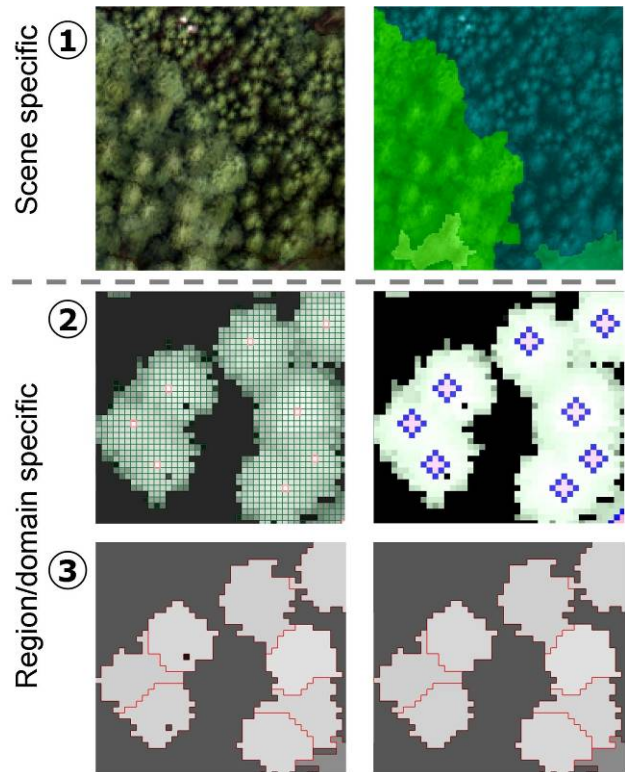


Figure 2. Workflow: (1) High-level segmentation and classification of forest types (2) Break down of pre-classified forest type domains to small objects (here: pixel level) and extraction of local maxima. Rebuilding of region-specific objects by using a region growing algorithm (local maxima taken as seed points) (3) Extracted single tree crowns - holes are mainly caused by the ALS data. Cleaning of the single tree crown objects using neighbourhood information (Tiede & Hoffmann 2006, modified).

Within forest, five types were differentiated using the NDVI and the standard deviation as an indicator of the forest structure:

- coniferous spacious,
- coniferous non-spacious
- deciduous-spacious,
- deciduous non-spacious
- mixed forest.

The coniferous and deciduous classes were further distinguished by adding two more sub-categories, namely young respectively old forests (depending on the height information of the nCM). This turned out to be a crucial information input for the following single tree delineation. Two additional classes, non-vegetated area and larger areas of dead trees (due to bark beetle attacks in the park's mountainous spruce stands) were included. The latter, non-vegetated and dead trees, have been used as masks for the following analysis steps and were therefore not redefined further. Instead, dead trees occurring within other forest types are not masked but included in the subsequent steps. Figure 3 shows the result for forest type classification in a subset (950 x 1000 meters) of the study area.

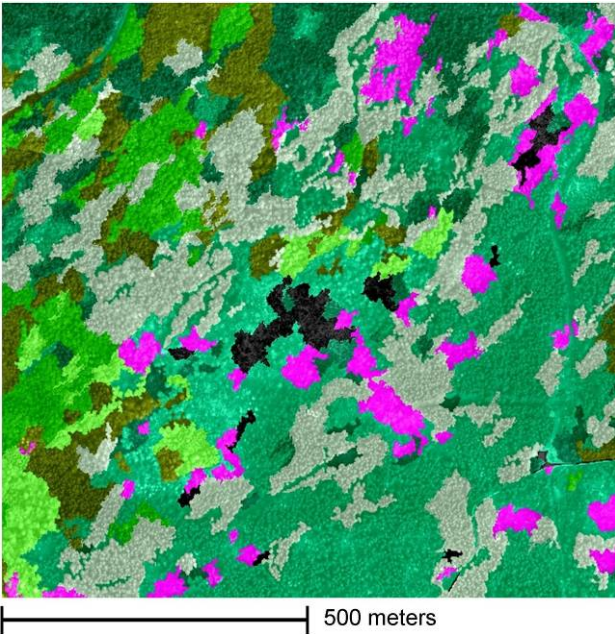


Figure 3. High-level segmentation and classification of forest types in a subset of the study area. Results serve as regions for the supervised multi-scale segmentation

3.2 Optimized multi-scale segmentation - objects build-up in a region-specific hierarchy

Recent studies concluded that, in case of single tree crown delineation, segmentation algorithms based on homogeneity (like the region-based, local mutual best fitting approach used in the high-level segmentation) is not suitable for addressing complex, inhomogeneous canopy representations in VHSR data (Tiede et al. 2004, Burnett et al. 2003). New developments seem to overcome that limitation through the use of scalable segmentation / object build-up algorithms which can be adapted to the very situation and applied within regions or domains. In the following the classified forest types (regions) served as spatial constraints for building a region-specific two-level hierarchy, inside which the scalable algorithms were embedded and optimized multi-scale segmentation was accomplished.

One core element of the approach is the possibility to break down the regions to pixel sized objects which still reside in the super object boundary that represents the very forest type. After the breakdown a new supervised build-up of objects can be performed, using specific rule-sets as being developed by Tiede & Hoffmann (2006) for single tree crown delineation on ALS data. In these rule-sets a region growing segmentation algorithm is programmed using a continuity constraint starting from tree tops (local maximum) as seed points (Figure 4).

The pre-classified forest types controls the parameterisation information (cf. Table 2) for each region-specific algorithm, which includes (1) The search radius for the local maximum method. This has to be adapted for every region depending on the assigned forest type: taller deciduous trees require a bigger search radius to avoid detecting false positives due to the flat and wide crown structure; dense coniferous stands require much smaller search radius for the local maximum search to detect even close standing tree tops. (2) A stopping criterion for the region-growing process, depending on the underlying nCM data. Candidate neighbouring objects are only taken into

account, if differences height between the respective objects not exceed a certain limit. These limits are variable in terms of different tree age (height) and tree type. (3) A crown width limit in the segmentation (region-growing) process. This should avoid uncontrolled growing of tree crown objects into other potential tree crowns. This might happen, if a local maximum was not recognized correctly, for example in dense deciduous stands due to very planar tree surface or missing tree top representations in the ALS data.

Parameter	Finer scale – smaller trees	Coarser scale – larger trees
Local maximum search radius	- to detect even tree tops in closed stands	+ to avoid false positives
Sensitivity of the stopping criterion value due to underlying nCM data (continuity criterion)	+ for small coniferous trees ++ for small deciduous trees	-- for large coniferous trees - for large deciduous trees
Crown width limit in segmentation process	-- for small coniferous trees - for small deciduous trees	+ for large coniferous trees ++ for large deciduous trees

Table 2. Generalised overview of region specific biased differences in object build-up processes. Plus (+) and minus (-) indicate higher or lower values

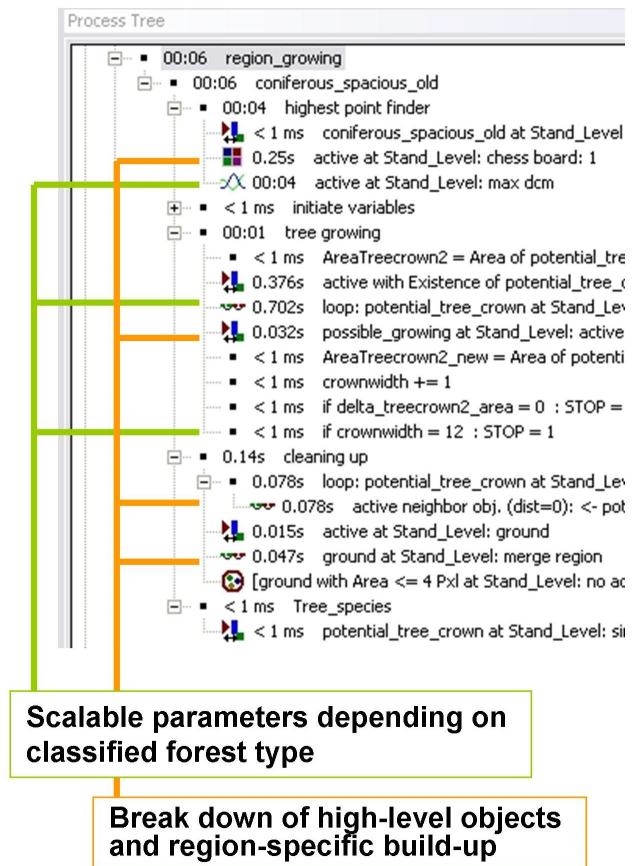


Figure 4. Process tree for single tree delineation in a “coniferous spacious-old” region showing scalable parameters and object-rebuild processes

The resulting objects correspond with single tree crowns. The occurrences of smaller holes were mainly caused by limitations of the ALS data. A cleaning process using neighbourhood information was applied to classify and fusion these holes with the surrounding objects. Finally, classification of the single tree objects was done based on NDVI and nCM height values. In this process, the classes assigned to the high-level objects were ignored in order to avoid confusion with the high-level classification. The following five classes were differentiated:

- coniferous trees
- deciduous trees
- dead trees
- non-vegetated area
- understorey (objects which could not be allocated to a tree crown because of the defined stopping criteria but which still show values indicating vegetated areas)

4. RESULTS AND DISCUSSION

Altogether, more than 73,600 dominant trees (> 10 meters tree height) were extracted, out of which 75% were classified as coniferous trees, 19% as deciduous trees and 6% as dead trees (cf. Figure 5).

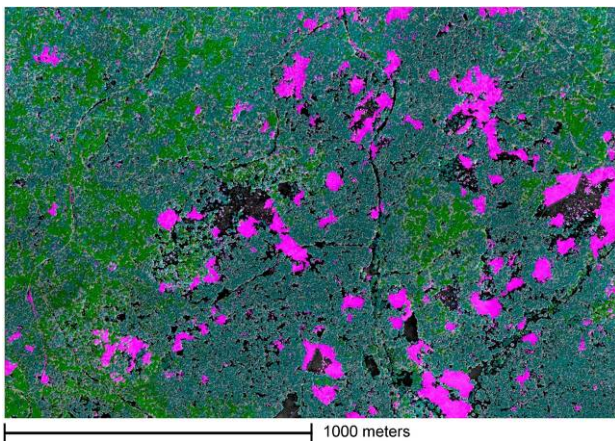


Figure 5. Result of the single tree segmentation and classification. Colours indicate classes as follows: coniferous trees (dark green), deciduous trees (light green), dead trees (magenta) understorey (grey) and non-vegetated area (black)

The rule-sets for single tree crown delineation on ALS data were already evaluated using ground-truth data on smaller subsets in the same region (Tiede & Hoffmann, 2006) but not exactly in the same study area. Since the local maxima method is mainly suited to find dominant trees (cf. Maltamo et al., 2004 and Pitkänen, 2001), the accuracy assessment was conducted only for this type. Best results were reached in well spaced conditions with a detection rate of more than 91% for dominant trees. In less spaced forest stands the identification rates drop noticeably. The average detection rate of dominant trees for all test areas was almost 81% with a quite low rate of false positives (detected but not validated) of approximately 3%.

Accuracy assessment in the study area was performed visually, because single tree ground truth information was not available. For this purpose, a reference data set was created by visual interpretation. A grid of 50 m cell-size was laid over the whole

study area and 20 cells were randomly selected for manually digitizing dominant trees (Figure 6). Three different types of trees were distinguished ending up in a point data set representing 847 coniferous trees, 302 deciduous and 138 dead trees.

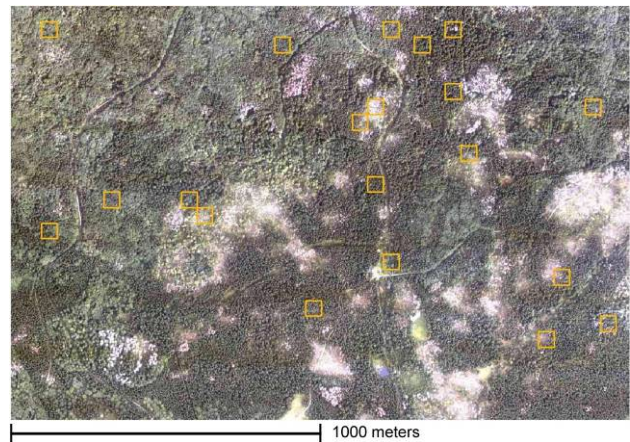


Figure 6. Random selection of 20 cells (50 m x 50 m) for point-in-polygon accuracy assessment in the study area

Table 3 shows the results of a point-in-polygon analysis: 730 coniferous trees, 132 deciduous trees and 109 dead trees were classified correctly. This results in an accuracy of approx. 75% for all classified trees, varying between 86% for coniferous and 79% for dead trees, dropping to 44% for deciduous trees. Taking in account detected but not correctly classified trees the detection rate for delineated trees increases to 90%.

	Coniferous	Deciduous	Dead trees	Overall
# of manually digitized dominant trees	847	302	138	1287
# of automatically classified dominant trees (point in polygon)	730	132	109	971
% of automatically classified dominant trees (point in polygon)	~ 86%	~ 44%	~ 79%	~ 75%
# of misclassified but detected trees	148	15	29	192
# of false positives	139	59	4	202
% of false positives	~ 16%	~ 19.5%	~ 3%	~ 16%

Table 3. Accuracy assessment results for the 20 randomly selected cells

These values come along with a high value of false positives (202 trees are detected but could not be validated). The low result for the detection of deciduous trees and especially the high amount of false positives was already mentioned by Tiede & Hoffmann (2006). There are known limitations for the local maxima method to find tree tops as seed points for crown delineation. Especially in dense and highly structured forest different problems appear. Next to the fact that the laser scanner might had missed the highest point, these problems are related to the specific shape and structure of the trees comprising (1) double crowns which can not be detected due to a non tree-specific local maxima search radius (cf. Tiede et al. 2005); (2)

understorey trees which are only partly visible; and (3) crowns (especially deciduous tree crowns) with more than one local maximum because of a flat rather than conical shape.

So far we applied site-specific accuracy assessment (Congalton & Green, 1999) in an object-based environment by using a point-in-polygon analysis. The comparison against visually interpreted tree types proved both thematic correctness of the automated tree classification and identification of a tree. In this respect we went one step further as compared to classical map-to-map comparison, as not only the assignment of classes, but also the tree detection as such has been assessed. However, applying object-specific accuracy assessment, as the name indicates, would even go beyond that (Lang & Langanke, 2006). When dealing with spatial objects, their geometrical accuracy needs to be assessed as well. More than assessing locational and semantic agreement, that means evaluating the way how an object was delineated. But this implies the issue of scale: whatever method we apply for tree delineation (automated, visually, mapping on the ground), we introduce scaled representations. A method for performing object-based accuracy assessment considering this issue is discussed by Schöpfer & Lang (this volume).

The idea of region-specific hierarchical representations is based on the notion of different hierarchical (i.e. 'vertical') compositions of the land cover classes to be addressed (Lang, 2002). 'Regions' are then considered spatially coherent areas of similar hierarchical characteristics. In this case we assume that we can discern these regions by a coarse segmentation. Classified regions allow for applying type-specific segmentation. Clearly, high-level segmentation and classification of forest types in the first step plays an important role concerning the effectiveness of the single tree algorithms. Especially in heterogeneous mixed forests it is difficult to segment regions representing more or less even scaled objects. But this is a crucial prerequisite for successfully applying an algorithm tailored to a specific scale. Nevertheless, a supervised approach for the object building / segmentation process utilizing a priori knowledge about the specific scale domain of the target features was successfully applied. Looking at the transferability of rule-sets this could be a step towards operability as it allows for selecting specific algorithms based on a first high-level segmentation and classification. Considering this, one could imagine to build up a sort of an algorithm library for scale-specific target features, different scenes or different data sets. The high-level segmentation and classification would then control (in an expert driven manner) which features may occur in the area. This again would be used to select, out of the library, the best fitting algorithms in terms of data sets used and expected features.

5. REFERENCES

Burnett, C., M. Heurich & Tiede, D., 2003. Exploring Segmentation-based Mapping of Tree Crowns: Experiences with the Bavarian Forest NP Lidar/Digital Image Dataset. Poster presented at ScandLaser 2003 Inter-national Conference and Workshop, Umeå, Sweden, September 2-4, 2003.

Congalton, R.G. & K. Green, 1999. *Assessing the accuracy of remotely sensed data: principles and practices*. Lewis Publishers, Boca Raton.

Hay, G. J., G., Castilla, M. A. Wulder, & J. R. Ruiz, 2005. An automated object-based approach for the multiscale image segmentation of forest scenes. *International Journal of Applied Earth Observation and Geoinformation*, Vol. 7, pp 339-359.

Lang, S. & T. Langanke, 2006. Object-based mapping and object-relationship modeling for land use classes and habitats. *PFG - Photogrammetrie, Fernerkundung, Geoinformatik*, Vol. 1, pp 5-18.

Lang, S., 2002. Zur Anwendung des Holarchiekonzeptes bei der Generierung regionalisierter Segmentierungsebenen in höchstauflösenden Bilddaten. – In: Blaschke, T. (ed.), *Fernerkundung und GIS: Neue Sensoren – innovative Methoden*, Wichmann Verlag, Heidelberg, pp 24-33.

Maltamo, M., Mustonen, K., Hyypä, J., Pitkänen, J., Yu, X. (2004). The accuracy of estimating individual tree variables with airborne laser scanning in boreal nature reserve. *Canadian Journal of Forest Research*, Vol. 34, pp.1791-1801

Pitkänen, J., (2001). Individual tree detection in digital aerial images by combining locally adaptive binarization and local maximal methods. *Canadian Journal of Forest Research*, Vol. 31, pp. 832-844.

Strahler, A.H., C.E. Woodcock & J. Smith, 1986. Integrating per-pixel classification cover classification. *Remote Sensing of the Environment*, Vol. 71, pp. 282-296.

Tiede, D. & Ch. Hoffmann, 2006. Process oriented object-based algorithms for single tree detection using laser scanning data. *EARSeL-Proceedings of the Workshop on 3D Remote Sensing in Forestry*, 14th-15th Feb 2006, Vienna, 151-156.

Tiede, D., G. Hochleitner & T. Blaschke, 2005. A full GIS-based workflow for tree identification and delineation using laser scanning. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. XXXVI, Part 3/W24, Vienna, pp. 9 - 14

Tiede, D., C. Burnett, & M. Heurich, 2004. Objekt-basierte Analyse von Laserscanner- und Multispektraldaten zur Einzelbaumdelineierung im Nationalpark Bayerischer Wald. In: S. Strobl, T. Blaschke, G. Griesbner (Hrsg.), *Angewandte Geoinformatik 2004*, Wichmann Verlag, Heidelberg, Germany, pp. 690-695.

Wehr, A. & U. Lohr, 1999. Airborne Laser scanning - an introduction and overview. *ISPRS Journal of Photogrammetry & Remote Sensing*, 54, pp. 68-82

ACKNOWLEDGEMENTS

We would like to thank the administration of the Bavarian Forest national park for the provision of the data used in this study.