CLASSIFICATION OF UNMANAGED FOREST RESERVES IN FLANDERS (BELGIUM) AT THE TREE CROWN LEVEL USING AIRBORNE HYPERSPECTRAL AND LIDAR DATA

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ABSTRACT:

Focusing on unmanaged forest reserves in Flanders (Belgium), we present an approach for the generation of tree species maps at the tree crown level using hyperspectral CASI imagery and full waveform LiDAR data. Unmanaged forest reserves are characterized by growth stage diversity, high crown closure, multi-layering of the canopy and the non-existence of a pre-ordered spatial tree distribution. To be able to classify trees at the tree crown level in these highly structured closed forests, an algorithm for delineating tree crowns need to be developed that can handle a) expansive crowns with large branches exhibiting a huge amount of within-crown shadow, and b) crowns belonging to the sub-canopy that are partially overtopped or shadowed by neighbours. Using the LiDAR-derived canopy height model (CHM), a tree detection algorithm based on a Directional Local Filtering (DLF) is applied prior to crown delineation to automatically locate individual tree crowns. Tree crowns are subsequently outlined using object-based decision rules developed in eCognition. Following tree crown delineation, the mean-lit spectra derived from the hyperspectral CASI data of individual tree crowns are extracted to identify tree species.

1. INTRODUCTION

In the framework of sustainable forest management, there is a need for reliable data on forest parameters such as tree species composition, stand diversity and forest vitality. These parameters need to be reported at regular intervals at national and international level. Currently, data acquisition in Flanders (Belgium) is done by time-consuming and labor-intensive field campaigns. In recent years, hyperspectral and Light Detection and Ranging (LiDAR) remote sensing techniques offer the potential to facilitate and improve this information acquisition.

The goal of our study is to generate tree species maps at the tree crown level based on an integrated use of airborne hyperspectral imagery and LiDAR data. The study focuses on unmanaged forest reserves that are the central entities of the monitoring programme of the Flemish Research Institute for Nature and Forest (INBO). The monitoring research in unmanaged forests in Flanders started in 2000 and is promoted by the Flemish forest administration. INBO is in favor of and would greatly benefit from a more efficient way of data acquisition in these forest areas, as they have to be monitored with a repetition of 10 years.

The tree crown delineation algorithms published in literature are usually developed and evaluated on images from different types of sensors and acquired over different forest types (Bai et al., 2005, Bunting and Lucas, 2006, Culvenor, 2002, Gougeon, 1995, Holmgren, 2004, Leckie et al, 2003,2005, Wolf and Heipke, 2007) (Larsen, et al., 2011). Most of them proving to be more successful within relatively simple forests, including natural or plantation forests and orchards. However, these approaches are less applicable in structurally complex and closed forests (Leckie et al. 2005). Therefore we propose to delineate tree crowns using a number of object-based decision rule sets based on the LiDAR-derived canopy height model (CHM). In a pre-processing step, trees are detected by applying a Directional Local Filter (DLF) to the CHM (Van Coillie et al., proceedings of GEOBIA 2012). Afterwards, the mean-lit spectra of individual delineated tree crowns derived from the hyperspectral CASI data can be used to identify tree species. As the structural complexity of the forest is a real challenge, the pressing question in this context is: are we able to discriminate between tree species at the tree crown level?

2. DATA

2.1 Study area

The study focuses on the oldest forest reserve in Flanders, Kersselaerspleyn. Kersselaerspleyn is part of the forest complex Sonian Forest, which is located in the south of Brussels (figure 1). Most of the Sonian Forest is located on a relative dry silt soil. Kersselaerspleyn covers 98 ha and was planted around the year 1788. From the year 1983 no management is performed. Since 1995 Kersselaerspleyn is protected as forest reserve. The forest is known for its cathedral aspect of very large and old closed beech stands, old scattered oak trees and almost non-existent understorey (figure 2).

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A lot of difficulties are associated with this forest type. First, there is the closed forest canopy (figure 3). Next, beech and oak tree crowns have a very similar reflectance spectrum. Finally, because of their age, most beech and oak trees have expansive crowns that are characterized by a number of large branches, each of which are associated with a cluster of smaller branches and leaves. When seen from above, these crowns exhibit a huge amount of within-crown shadow that looks similar to the between-crown shadow observed within clusters of smaller crowns, making it more difficult to discriminate between individual crowns and crown clusters. Moreover, this within-crown shadow strongly influences the spectral reflectance pattern of both species. These three properties significantly hamper species discrimination and render crown delineation and classification pretty challenging.

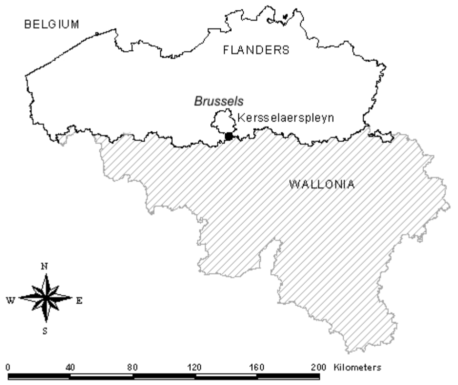

Figure 1. Geographical location of Kersselaerspleyn

Figure 2. Kersselaerspleyn: view from the ground

Figure 3. Kersselaerspleyn: view from above

2.2 Imagery

LiDAR data were flown over the study area on the 4th and 5th August 2010. The Riegl LMS Q560 full waveform laser scanner operates with a beam divergence of < 0.5 mrad, a point density of >10 points/m² and a wavelength of 1560 nm. The horizontal accuracy is < 0.5m and the vertical accuracy is < 0.15m. Absolute accuracy was checked using surveyed roof tops. Height percentiles were computed from terrain corrected point clouds by the Remote Sensing Laboratories (RSL, University of Zurich). The images were made available in the Belge Lambert 1972 projection system.

Hyperspectral CASI data were also acquired over the study area at the end of August 2010. The 1m spatial resolution data were acquired in 96 wavelength regions of the electromagnetic spectrum covering the visible to near-infrared components (368 – 1052 nm wavelength). The data were radiometric, atmospheric and geometric corrected by the image providers INTA and the Flemisch Institute of Technological Research (VITO). The images were provided in the Belge Lambert 1972 projection system. Image-to-image registration of the CASI to LiDAR data was performed by VITO.

2.3 Field data collection

Kersselaerspleyn has been monitored by INBO in the framework of the monitoring programme for the first time in the year 2000. In 2010 and 2011 a new intensive field survey was performed. More than 100 working days were needed to update the forest inventory in Kersselaerspleyn (K. Vandekerkhove, INBO). This proves again remote sensing can be a valuable tool for extracting accurate and fine-scale resource information in an efficient way.

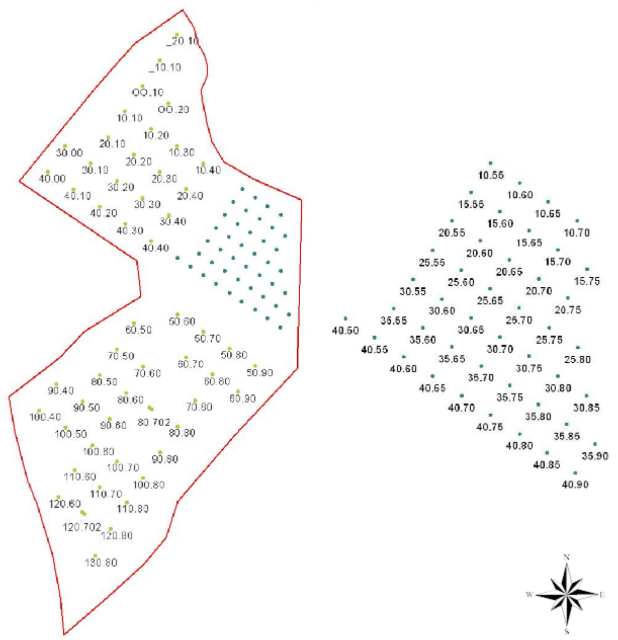

Figure 4. Sampling design for the core area (right) and circular plots (left) in Kersselaerspleyn

In the forest reserve a combination of a systematic grid of circular plots and a core area is used. The core area is 10.75 ha and is divided by a grid of 50 m by 50 m (figure 4). The circular plots are situated at two sides of the core area with a distance of

100 m between them. A circular plot covers an area of 0,28 ha (radius = upper tree height = 30 m). In the core area and circular plots, a full survey was performed of all trees over 10 cm diameter-on-breast-height (DBH). Species composition, DBH and tree positions are recorded for each of these trees (figure 5).

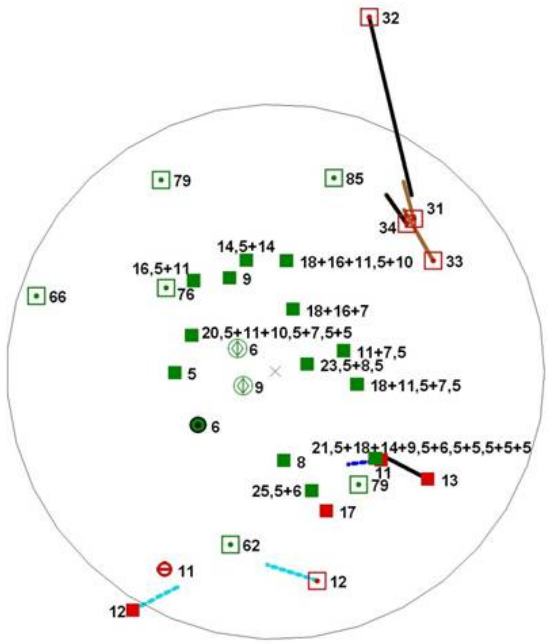

Figure 5. Circular plot with measurements of tree position, species composition and DBH

3. METHODOLOGICAL FRAMEWORK AND PRELIMINARY RESULTS

In order to generate tree species at the tree crown level, a Geographic Object-Based Image Analysis (GEOBIA) approach is adopted.

3.1 Tree crown delineation

The tree crown delineation technique is built on the algorithm of Bunting and Lucas (2006) designed for open forest and woodland environments in Australia and for hyperspectral CASI data. We present a variant of their technique based on full waveform LiDAR data and incorporating a novel tree detection technique, Directional Local Filtering (DLF). Hyperspectral analysis for crown delineation was found to be less effective in the highly structured closed forest of Kersselaerspleyn.

The working strategy exists of three main stages: the generation of a forest mask, tree detection with DLF and the actual tree crown delineation.

3.1.2 Discrimination of forest and non-forest: The first stage in the process is the generation of a mask to separate forest from non-forest (understorey and soil, whether shadowed or not). This stage is considered critical, as relatively small changes in the forest mask will influence the final delineation (Bunting and Lucas, 2006).
The threshold applied to separate forest from non-forest using the CHM is based on expert knowledge (K.Vandekerkhove, INBO). Tree crowns are located above a height of 10m. Below 10m only understorey and soil occur. This threshold is implemented in an eCognition decision rule set (figure 6). In a first step, a multi-resolution segmentation is performed on the CHM using a large scale factor. In a second step, sub-objects are created by decreasing the scale factor. These sub-objects are classified into forest and non-forest objects based on the assumed threshold. A refinement of the forest/non-forest classification is applied on the forest objects by chessboarding and reclassifying the resulting objects. In a next step, adjoining objects of the same class are merged. To create the final forest mask, the merging of forest and non-forest objects is followed by the merging of contained non-forest objects (< 5 pixels) into forest objects.

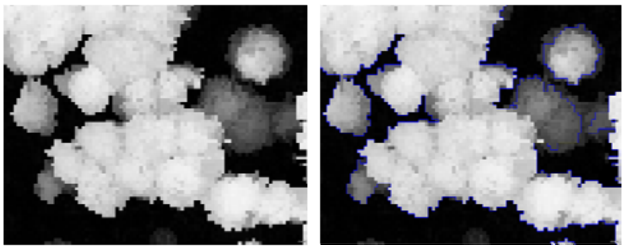

Figure 6. (left) LiDAR-derived CHM of forest and non-forest areas, (right) forest and non-forest areas separated using a threshold of 10 m .

3.1.2 Tree detection: As mentioned by Van Coillie et al. (proceedings of GEOBIA 2012), tree detection is considered as a necessary pre-processing step before tree delineation. Tree detection deals with locating trees. The Directional Local Filtering (DLF) uses a 1D window scanning the CHM line-wise in different viewing angles, looking simultaneously for local maxima and minima. If the central pixel of the 1D window has the highest or lowest value within the window, the pixel is assigned as respectively a maximum or a minimum. These maxima and minima correspond with respectively crown apexes and crown edges. Filtering line-wise offers the opportunity of finding an increasing amount of local extrema. Using different viewing angles has the advantage that not only more but also locally connected extrema are detected (figure 7). Moreover, the distance between two consecutive minima containing a maximum can be used as a condition for crown delineation. For more information about the DLF, see Van Coillie et al. (proceedings of GEOBIA 2012).

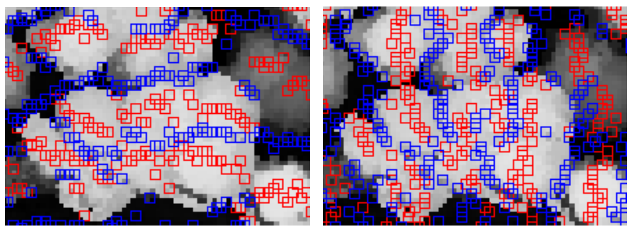

Figure 7. Detected maxima (red) and minima (blue) scanning CHM in (left) horizontal lines, (right) vertical lines

The detected maxima cannot be implemented for seeding in eCognition as only existing objects processed during previous segmentations can be used as seeds. As a consequence, local maxima are identified using the Local Maximum Filter (LMF) within eCognition (figure 8). The filter length of the LMF has to be tuned to the size of the tree crowns. The minima derived from the DLF are implemented in eCognition to bound the region growing process in the next tree delineation step.

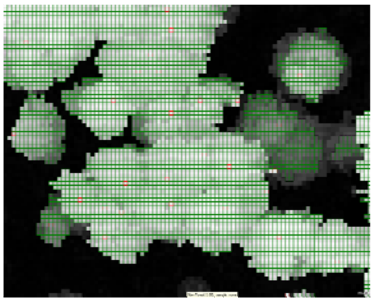

Figure 8. Local maxima (red pixels) detected by the LMF in eCognition

3.1.3 Tree delineation: In an iterative process, the maxima (seeds) within one forest object are expanded successively by one pixel such that adjacent pixels were captured. The process is terminated when the pixel selected for capture corresponds to a minimum detected by the DLF. Another approach to terminate the region growing process is by using the distance between two consecutive minima containing a maximum as a threshold condition.

A number of fragmented objects often result from this process, corresponding with small crowns in the sub-canopy overtopped by neighbouring trees in the upper-canopy. These trees have only a part of their crown visible in the image.

3.2 Classification of crowns

Within the delineated crowns, the reflectance within each is variable because of the differing degrees of illumination and contributions of reflectance from tree components, understorey and ground surface (Lucas et al., 2008). Therefore, as suggested by Leckie et al. (2005) the mean-lit spectra (i.e. the mean reflectance of all pixels that support a reflectance above the average of all pixels in the crown) are used to strive for increased classification accuracies. Compared to the full crown mean, the mean-lit spectra reduces variability associated with the inclusion of different proportions of the shaded area of the crown and adds consistency into the process of capturing pixels associated within the sunlit area (Lucas et al., 2008). The mean-lit spectra matches with the pixels associated with the sunlit portion of each tree crown.

For the association of delineated crowns with different tree species, only crowns are selected if there identification through reference to field data is certain and if the crowns are clear delineated (no small overtopped crowns in the sub-canopy). Using the mean-lit spectra derived from the CASI data of these selected crowns, a classifier is chosen that is able to exploit the wide amount of data provided by hyperspectral sensors. The supervised classifiers considered are a Lineair Discriminant Analysis, a Support Vector Machines and a Artificial Neural Network.

4. CONCLUSION

At the time of submitting the proceedings paper, the image analysis is not yet finished. Consequently, no definite conclusions can be drawn here. Preliminary results show that the presented GEOBIA approach is promising for the generation of tree species maps at the three crown level in highly structured closed forests. The DLF algorithm has proved to be successful for tree detection and stem density estimation using artificial and optical imagery (Van Coillie et al., proceedings of GEOBIA 2012). The first results regarding the use of DLF for tree detection based on the LiDAR-derived CHM are looking promising. The intended outcomes of the crown delineation using the minima detected by the DLF for bounding the region growing process and the following species classification will be presented at the GEOBIA 2012 conference.

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REFERENCES

References from Journals:

Bai, Y., Walsworth, N., Roddan, B., Hill, D.A., Broersma, K. and Thompson, D., 2005. Quantifying tree cover in the forest-grassland ecotone of British Columbia using crown delineation and pattern decision. *Forest Ecology and Management,* 212, pp. 92 – 100.

Bunting, P. and Lucas, R., 2006. The delineation of tree crowns in Australian mixed species forests using hyperspectral Compact Airborne Spectrographic Imager (CASI) data. *Remote Sensing of Environment*, 101, pp. 230 – 248.

Culvenor, D.S., 2002. TIDA: An algorithm for the delineation of tree crowns in high spatial resolution remotely sensed imagery. *Computers & Geosciences*, 28, pp. 33 – 44

Gougeon, F.A., 1995. A crown-following approach to the automatic delineation of individual tree crowns in high spatial resolution aerial images. *Canadian Journal of Remote Sensing,* 21, pp. 274 – 284.

Holmgren, J. and Persson, A., 2004. Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment*, 90, pp. 415 – 423.

Larsen, M., Eriksson, M., Descombes, X., Perrin, G., Brandtberg, T. and Gougeon, F.A., 2011. Comparison of six individual tree crown detection algorithms evaluated under varying forest conditions. *International Journal of Remote Sensing,* 32, pp. 3827 - 3832

Leckie, D.G., Gougeon, F.A., Walsworth, N. and Paradine, D., 2003. Stand delineation and composition estimation using semi-automated individual tree crown analysis. *Remote Sensing of Environment*, 85, pp. 355 – 369.

Leckie, D.G., Gougeon, F.A., Tinis, S., Nelson, T., Burnett, C.N. and Paradine, D., 2005. Automated tree recognition in old growth conifer stands with high resolution digital imagery. *Remote Sensing of Environment*, 94, pp. 311 – 326.

Lucas, R., Bunting, P., Paterson, M. and Chisholm, L., 2008. Classification of Australian forest communities using aerial photography, CASI and HyMap data. *Remote Sensing of Environment*, 112, pp. 2088 – 2103.

Van Coillie, F., Devriendt, F. and De Wulf, R., 2012. Directional Local Filtering assisting individual tree analysis in closed forest canopies using VHR optical and LiDAR data. *Proceedings of GEOBIA 2012.*

Wolf, B-M. and Heipke, C., 2007. Automatic extraction and delineation of single trees from remote sensing data. *Machine Vision and Applications*, 18, pp. 317 – 330.