Robust characterization of forest canopy structure types using full-waveform airborne laser scanning

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Paper Number: SL2012-041

1. Introduction

Forests cover almost one third of the total land surface of the Earth. Therefore, they play a pivotal role in the global biogeochemical and -physical cycles between atmosphere and the land surface (Ross 2011; Betts *et al.* 2001). Understanding, assessing and quantifying forest ecosystem goods and services and their underlying processes (De Groot *et al.* 2002), helps to project the development of biogeochemical cycles under changing climate conditions (Jonsson and Wardle 2010; Sierra *et al.* 2009) and to develop sustainable management strategies (Purves and Pacala 2008). Particularly the complex three-dimensional distribution of geometric objects and their topology within forests canopies, here termed *forest canopy structure* (Nadkarni *et al.* 2008; Disney *et al.* 2006), influences the fluxes of energy and matter between the atmosphere and forests (Xue *et al.* 2011; Yang and Friedl 2003) and is one of the critical variables to determine forest stand resistance to disturbances and to estimate the conservation potential for biodiversity (Kayes and Tinker 2012; Lindenmayer *et al.* 2006).
Assessing forest canopy structure is difficult: conventional fieldwork is time-consuming, subjective and mostly limited in its spatial extent (Foody 2010; Haara and Leskinen 2009; Strand *et al.* 2002), whereas traditional remote sensing methods are lacking information in the vertical dimension (Jones *et al.* 2012; Hall *et al.* 2011; Roberts *et al.* 2007). Airborne laser scanning (ALS) systems have been shown to be suitable for providing not only horizontal information on the forest canopy structure, but also explicit vertical information due to the canopy penetration of the emitted signal (Kaartinen *et al.* 2012, Leeuwen and Nieuwenhuis 2010). Canopy structure metrics derived by ALS include geometric variables such as canopy height, canopy volume and canopy base height, as well as biophysical variables such as the Plant Area Index (PAI) or the canopy cover (Hilker *et al.* 2010; Morsdorf *et al.* 2009). However, existing approaches mostly include manual processing steps or need additional data about stand characteristics (e.g. tree species, age) (Antonarakis *et al.* 2011; Korpela *et al.* 2010; Kim *et al.* 2009). Therefore, a robust and transferable method is basically needed to provide a more efficient monitoring of forest canopy structure, as well as to improve the robustness and reliability of derived structure variables as input for environmental modeling, e.g. for dynamic global vegetation models or forest gap models.
To meet these requirements, we utilized the concept of forest canopy structure types (CSTs). Each specific CST represents a unique set of forest canopy structural variables. Thus, areas with the same CST are assumed to be homogenous in terms of forest canopy structure. We developed a robust and physical based method using full-waveform ALS data under leaf-on/leaf-off conditions in a deciduous dominated forest stand to extract a set of forest structure variables (crown and canopy dimensions, tree position, tree types, and occurrence of understory) as input for the CST derivation. For the validation, we used Digital Hemispherical Photography (DHP), Terrestrial Laser Scanning (TLS), and forest inventory data.

2. Method

Forest structure variables characterize canopies at different spatial scales: for example on individual tree level (e.g. crown length), on stand level (e.g. mean canopy height) or on landscape level (e.g. proportion of canopy cover) (Shugart *et al*. 2009). In this study, forest canopy structure will be investigated on the individual tree level and based on a regular grid, representing the stand level.

2.1 Study area and data

In the approach presented in this study, we use full-waveform ALS data in a 300 x 300 m test site. The data acquisition was performed under leaf-on (using RIEGL's© LMS-Q680i scanner) and leaf-off (using RIEGL's© LMS-Q560 scanner) canopy conditions in a mainly semi-natural, deciduous-dominated forest stand in Laegeren (Swiss Jura; 47°28'N, 8°21'E), yielding in two independent datasets. The used sensor specifications are summarized in Table 1 and described more in detail in Wagner *et al.* 2008 and RIEGLs (2012) specific sensor documentations.

Table 1: Used sensor specifications of RIEGL's laser scanner LMS-Q560 and LMS-Q680i.

	LMS-Q560	LMS-Q680i
pulse repetition rate [Hz]	200 000 Hz	
scan angle [deg]	± 15 deg	
mean operating altitude above ground [m]	500 m	
date of acquisition	10.04.2010	01.08.2010

The dense forest stand is characterized by steep topographic relief (slope up to 60°) and high species diversity (mostly *Fagus sylvatica (L.)*, *Picea abies (L.) Karst*, *Fraxinus excelsior (L.)* and *Acer pseudoplatanus (L.)*), age (55-160 years), and diameter distribution (7-120 cm) (Eugster *et al.* 2007). For the investigated area, an extensive set of ground based reference data is available, mainly measured during field campaigns in September 2011: DHPs, TLS derived tree models, and forest inventory data. All field measurements were geo-referenced and co-registered based on traditional terrestrial land surveying by a total station and a GNSS real-time kinematic system.

2.2 Data pre-processing

The benefit of full-waveform data is the approximation of the entire backscattered signal by digitization, which facilitates the extraction of additional features of each reflecting object within the ALS footprint. To detect and extract specific object reflections, Gaussian pulse estimation was applied in order to obtain representative echo descriptions. In particular, this includes the derivation of the point cloud with its basic and established geometrical characteristics of reflectors but additionally the physical description of each reflector with information such as amplitude, width and intensity of each specific echo.
In a first step, we extracted the ground returns from the point cloud using the single and last echoes, their geometrical characteristics and echo width information (Mücke *et al.* 2010). Based on the method by Evans and Hudak (2007) we developed a new adaptive multi-scale filter algorithm. As part of the filtering, a kernel based query was applied to the selected ground return echoes to detect areas with high deviations in height values (≥ 100 % slope). Within these areas a combination of optimized spline function analyses (amount of local maxima) and a scale dependent multi-point triangulation (in a 3x3 and/or 5x5 kernel) was applied to exclude non-ground points from the point cloud. The spline function approach allows a reliable distinction between height deviations caused by the steep terrain and the less continuous height deviations caused by artificial objects or dense vegetation. The remaining points were

interpolated applying an ordinary kriging to a 1x1 m digital terrain model (DTM). Additional, a 1x1 m digital surface model (DSM) was processed using the first echo reflections and their corresponding echo width. Afterwards, the canopy height model (CHM) was calculated from the difference between DSM and DTM. Finally, for each point of the point cloud we determined the height above ground as well as the according DTM, DSM and CHM values.

2.3 Extraction of structure variables on tree level

The characterization of the crown structure of individual trees requires the segmentation of the full point cloud into specific point clouds of the single trees. As input for the point cloud segmentation a set of seed points is necessary, representing the position of the individual trees. To detect understory trees as well, we applied an iterative, three-dimensional grayscale dilation on the point cloud based on an ellipsoid-shaped structuring element S with a pre-defined domain D_S (Adams 1993). Accordingly, all resulting local maxima were used as initial seed points for a standard k-means clustering. The clustering with an Euclidean metric favors ball shaped clusters in a three-dimensional feature space. Due to the high variations in the vertical extent of the point cloud, a scaling of the height values (z-coordinates) was applied using the ratio of the respective CHM value to the height above ground of each specific point. Based on the resulting individual point clusters, we calculated the alpha shape (Vauhkonen *et al.* 2009) to be able to derive additional crown specific variables such as crown volume or crown diameter.
For all points within the individual alpha shapes, we investigated the variations in the point distribution between the leaf-on and leaf-off acquisitions (e.g. percentage distribution in vertical extent). Based on the differences (using a significance level of 5 %), we distinguished deciduous from coniferous trees. This attribute as well as the information about the unique point cloud membership was added to each point within the crown.

2.4 Determination of canopy structure types (CSTs)

To derive CSTs, we analyzed the vertical stratification and properties of the specific point clusters based on Cartesian grids with 1x1 m, 5x5 m and 50x50 m pixel size, respectively. Depending on the respective spatial scale, we extracted the common canopy variables mean canopy height, canopy cover, mean length of live canopy, mean height to canopy base, the occurrence and height of understory and the foliage distribution as well as their variations within the pixel (except for the 1 x 1 m grid). This includes information about the occurrence of various canopies in a vertical column and the species composition in terms of coniferous and deciduous trees. Figure 1 shows the concept of the vertical forest canopy stratification for the 5x5 m grid.

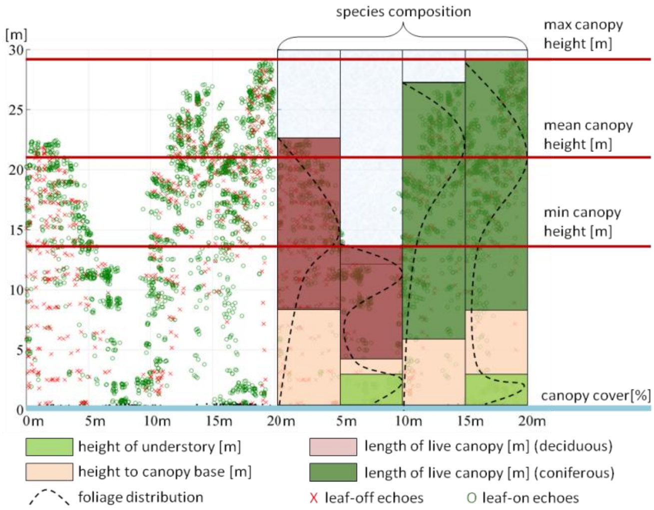

Figure 1: Example for the grid based vertical stratification of forest canopy structure (cell size 5x5 m).

For the 50x50 m grid, we applied the classic index by Clark and Evans (1954) for the statistical determination of distribution patterns based on the individual trees extraction (random, uniform, and clumped) as well as determined stand level parameters such as stand density and stand height. The resulting grid with the multi-dimensional feature space was then classified into a pre-defined amount of unique CSTs, representing structural homogeneous forest areas.
To evaluate the applicability of the derived CSTs for the estimation of bio-physical variables, we enhanced the method of Morsdorf *et al.* (2006) to calculate the PAI, the fraction of absorbed photosynthetically active radiation (fAPAR) and the canopy cover, utilizing the amount of vertical layers, the foliage distribution and the tree type of the specific CSTs. For the validation of the estimated parameters, both point measurements with DHPs and plot-wise TLS measurements were carried out, resulting in grid based PAI, canopy cover and fAPAR layers.

3. Results and discussion

The reconstruction approach on tree level results in a complete 3D representation of the forest area and the CST classification. Figure 3 shows a visualization of the 3D-scene and the result of the CST classification for the 5x5 m grid.

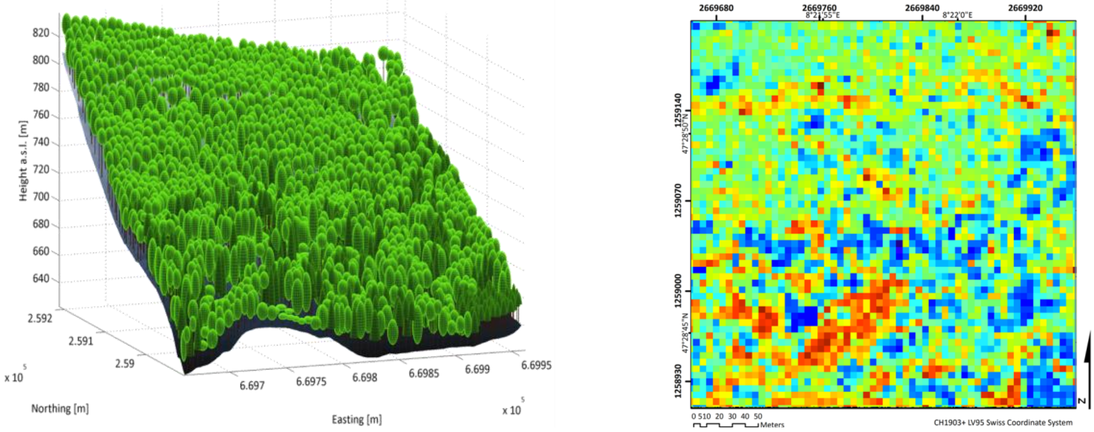

Figure 3: Visualization of the reconstructed three-dimensional forest scene and the 5x5 m CST map.

In the 3D representation, the complex alpha shapes of the canopies are simplified using geometrical primitives depending on the tree species (ellipsoids for deciduous; paraboloids for coniferous); whereas the stems are represented by uniform cylinders and placed at the specific local maximum position. In the map of the CSTs, each color is representative for a unique combination of the derived canopy structure variables.
The validation of the tree/ stem position was based on TLS measurements for two 30x30 m plots and leaf-off/on ortho-images outside these areas. The commission and omission errors for the delineation is 5.2% and 13.1%, respectively, whereby the omission errors have mainly been caused by the large amount of clustered and multi-stemmed trees due to former coppicing activities (Van Calster *et al.* 2008). The connected canopies of these clusters are even with field measurements nearly inseparable and show a similar shape as the crown of an individual tree. As the applied tree delineation method is based on the assumption, that each crown represents an individual tree/ stem, we underestimate the amount of trees/ stems particularly in the old beech stands. Thus, the estimation of the related biomass and stem volume information as well as the determination of the stand density are likely to be less accurate and were not further investigated in the context of this study. The distribution patterns of the individual trees were compared with the reference data based on a grid representation of the three classes “random”, “uniform”, and “clumped”, resulting in a mean r^2 of 0.56. However, this result is subject to the same limitations as the detection of the individual trees. The cross-comparison of the crown dimensions with the TLS measurements, ortho-images and forest inventory data shows a high consistency in the horizontal dimension, whereas a quantitative validation of the horizontal

crown dimensions and the crown volume/ crown surface is difficult and involves a high level of uncertainty (cf. tree detection). The results of the extraction of the vertical extent is shown in Table 2 for the individual tree level and the canopy level based on the specific CSTs, with slightly better results for the CST based dimension variables. The occurrence of understory was detected with an accuracy of 78% with a mean error in the vertical extent of 1.2 m.

Table 2: Accuracy assessment for the extraction of vertical crown/ canopy dimension variables.

mean error of	**individual tree level**	**canopy level**
crown height / mean canopy height [m]	0.6	0.5
length of live crown / mean length of live canopy [m]	2.8	1.2
height to crown base / mean height to canopy base [m]	2.6	1.6

The classification in coniferous and deciduous trees was compared to the forest inventory data and the ortho-images utilizing the common statistics metrics overall accuracy (OA), users accuracy (UA), producers accuracy (PA) and the kappa coefficient (Liu *et al.* 2007) (Table 3). In comparison to existing studies for species distinction (e.g. by Kim *et al.* 2009), we achieved similar accuracies using only the leaf-on/leaf-off point distribution varieties. Accordingly, the species distribution derived from the CSTs differs 10 to 15 % to the reference data. The major sources of uncertainty in the test area are the misclassification of *Larix decidua (Mill.)* and areas with structure changes in the canopy caused by wind and snow induced damages.

Table 3: Confusion matrix of the distinction between coniferous and deciduous trees.

	coniferous (ALS derived)	**deciduous (ALS derived)**	**PA [%]**
coniferous (reference)	430	79	84.5
deciduous (reference)	120	1300	91.5
UA [%]	78.2	94.3	
OA [%] / Kappa coefficient			89.7 / 0.74

The CST derived bio-physical variables show high correlations to the reference data derived from the DHPs (PAI r^2 = 0.57, fAPAR r^2 = 0.64, canopy cover r^2 = 0.78). However, the statistical base for the bio-physical variables of only 18 reference measurements is insufficient for a representative and quantitative validation. Therefore, we need to extend the ground measurements to a larger area within the future work. Nevertheless, the results are promising considering the robust, physical based approach of the CSTs. The derived foliage distribution information could not be validated yet directly. For this purpose a dense vertical sampling of the full canopy (e.g. leaf area density) is necessary, which will be carried out in future studies.

4. Conclusion

In this study, we developed a robust and transferable method for a physically-based extraction of canopy structure variables on the individual tree level as well as on the grid based level of the CSTs. The validation/evaluation shows that the determination of structure variables on the individual tree level can only be carried out with limitations due to the specific stand characteristics (former coppice management). Particularly the horizontal crown dimensions and the amount of stems cannot be extracted with sufficient accuracy. The vertical dimensions could be determined with a good reliability, whereby a direct comparison of these results to existing studies is problematic due to the different forest structure characteristics.

The detection of the occurrence and the height of understory as well as the classification into deciduous and coniferous trees were performed with high accuracies. For these investigations the availability of the leaf-on/leaf-off data with a high point density was significant. The determination of bio-physical parameters was possible to a certain extent; but for a sufficient

validation an extension of the reference data is necessary.
We conclude that the direct, physically-based extraction of forest structure variables at the individual tree level has some limitations, particularly for the derivation of the tree/ stem locations and the horizontal crown dimensions. The presented approach based on CSTs provides robust and transferable information on the vertical canopy dimensions (e.g. amount of canopy layers, mean canopy height, mean height to canopy base, length of live canopy), understory characteristics and species distribution. However, the derivation of forest structure variables at the tree level is subject to larger errors due to omission and commission (as e.g. for stand density). Still, the information contained in the CSTs can easily be applied to improve the indirect/ empirical derivation of forest structure variables, depending on additional available in-situ data and the forestry expertise of users.

Acknowledgements

ESA is greatly acknowledged for funding the 3D-VegetationLab project, where this study is embedded in.

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