POTENTIAL AND LIMITS OF AIRBORNE REMOTE SENSING DATA FOR EXTRACTION OF FRACTIONAL CANOPY COVER AND FOREST STANDS AND DETECTION OF TREE SPECIES

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ABSTRACT:

This study presents a methodology for derivation of fractional canopy cover, detection of main tree species, and extraction of forest stands using logistic regression, airborne remote sensing data and field samples. In a first step, canopy height models (CHMs) are generated using medium point density LiDAR DSM and DTM and a high-quality matching DSM. Then, fractional canopy covers are calculated using logistic regression models and explanatory variables from LiDAR and matching CHM, whereas the latter produced better results due to higher quality and was therefore further used in this study. Based on this fractional canopy cover, main tree species and forest stands are modelled using logistic regression and airborne digital sensor data ADS40 and CIR aerial image data as input variables. Good accuracy for the extraction of canopy cover, distinction between coniferous and deciduous trees and classification of five main tree species (kappa = 0.7 to 0.9) were obtained but classification of additional three deciduous tree species was less accurate. The extraction of forest stands produced visually satisfactory results but this method suffers from some limitations and further research is needed. The present study reveals that the extracted forest attributes may be helpful to support stereo-image interpretation and field surveys in the frame of the Swiss National Forest Inventory (NFI) and may also be useful for updating existing forest masks and forest management and protection task*s*.

1. INTRODUCTION

The present study was carried out in the framework of the Swiss Mire Monitoring Program and the Swiss National Forest Inventory (NFI). Since tree growth and expansion of forest areas impact the non-forest areas of a protected mire biotope, especially the extraction and modelling of the above mentioned forest attributes is essential (Küchler *et al.*, 2004, Waser *et al.*, 2008).

Recent progress in three-dimensional remote sensing mainly includes digital stereo-photogrammetry, radar interferometry and LiDAR (Watt and Donoghue, 2005, Baltsavias *et al.,* 2007). E.g. by subtracting a DTM from the corresponding DSM, canopy height models (CHMs) can be calculated that serve as basis for other forest attributes. Using digital photogrammetry, DSMs are generated via image matching, often using cross-correlation (Hyyppä *et al.,* 2000) or less frequently multi image-matching approaches (Zhang and Gruen, 2004). Meanwhile several LiDAR systems are commercially available (Naesset and Gobakken, 2005), enabling the derivation of DTMs from such data as well (Baltsavias, 1999). Several studies have integrated LiDAR with optical remotely sensed data to estimate forest attributes such as stand composition, tree height, crown diameter, basal area, and stem volume (e.g. Straub, 2003; St-Onge *et al.,* 2004, Baltsavias *et al.,* 2008). Combining some of these attributes can be useful to evaluate extent of forest area, detect changes in forest stands (Waser *et al.*, 2008b), and determine tree/shrub species (Holmgren and Persson, 2004). According to Scott *et al.* (2002) modern regression approaches have proven particularly useful for modelling spatial distribution of tree species and communities. Thus, high-resolution remote sensing data in combination with regression analyses are promising for modeling forest composition and tree species (e.g. Lamonaca *et al.,* 2008). The objective of this study is to develop a methodology for derivation of fractional canopy cover, detection of main tree species and derivation of forest stands using logistic regression, airborne remote sensing data and field samples.

2. MATERIAL AND METHODS

2.1 Test site

Models have been developed and tested for a representative forest ecosystem in the northern Pre-alpine zone of Switzerland. The test site “Breitmoos” (approx. 47°18’ N and 9°14’ E) has an extent of approx. 2 km^2 and is characterized by a varying terrain, mixed land cover and deciduous and coniferous forests with a core mire area (see Fig. 1).

2.2 Remotely sensed data

In this study, four different data-sets are available:

- Leica RC30 frame camera, 4 CIR (red, green, near-infrared bands) aerial images (1 strip) of 2005, scale 1:5,600 and an orthoimage that was generated with a spatial resolution of 0.25 m. Main disadvantage: The images are only available on request and do not cover entire Switzerland.

- A DSM that was generated automatically from the above images with a spatial resolution of 0.25 m.

- National raw LiDAR DSM and DTM data from 2003, leaves-on .

- Leica airborne digital sensor (ADS40) images Level 1 (rectified) of 2005, scale 1:30,000, RGB bands (16 bit), spatial resolution 0.25m. An orthoimage was generated using the LiDAR DSM. Main advantage: The image data is available for the area of entire Switzerland every three years.

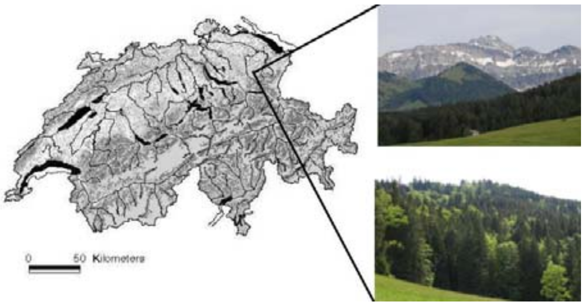

Figure 1. Test site "Breitmoos" with typical mixed forests (Pixelmap © 2006 Swisstopo JD052552)

Orientation of the CIR aerial images was performed in LPS and the following accuracies were obtained. The aposteriori sigma 0 was 0.32 pixel and the RMSE for the control points: X=0.06 m, Y=0.06 m, Z=0.17 m and RMSE for the check points are X=0.06 m, Y=0.06 m, Z=0.24 m. High-resolution DSM data is indispensable since accurate surface information of the forest area is very important for modelling forest composition, e.g. tree species. Thus, a matching method was applied that can simultaneously use any number of images (> 2). It is implemented in the operational, quasi-complete photogrammetric processing package Sat-PP which supports satellite and aerial sensors with frame and linear array geometry (for further details see Zhang (2005) and Zhang and Gruen (2004)). In principle, the matching method consists of three mutually connected components: an image pre-processing, a multiple primitive multi-image matching (MPM) and a refined matching procedure. This automated DSM generation provides high accuracy (1-5 times the ground sampling distance (GSD), depending on landcover and terrain roughness), and enables to produce very dense (grid spacing = 3-4 x GSD) and detailed DSMs that allow a good 3D modeling of trees and shrubs (see Fig. 2).

From the raw LiDAR data (first and last pulse), both a DTM and DSM were generated by the Swiss Federal Office of Topography (SWISSTOPO). The average density of the DSM data was 1-2 points / m^2 and the height accuracy (1 sigma) 0.5 m for open areas and 1.5 m for vegetation. The DTM has an average point density of 0.8 points / m^2 and height accuracy (1 sigma) of 0.5 m (Artuso *et al.*, 2003). The raw LiDAR data provided by SWISSTOPO were converted using SCOP++ V5.3 (INPHO) to a raster with 1 m resolution. For the interpolation of the LiDAR DTM the classic prediction method with default parameters, while for the LiDAR DSM the robust filtering with the so-called "LiDAR DSM parameter" was used. For comparison of the different input data, the matching DSM and the LiDAR DSM and DTM were co-registered using a point cloud co-registration procedure as described in Akca (2005) and Gruen and Akca (2005). This co-registration uses a 7-parameter 3D similarity transformation to remove systematic differences (bias) between the datasets, e.g. due to different image orientation. For the estimation of these parameters, control surfaces were used, i.e. DSM parts that did not change in the two datasets, i.e. bare ground, and large differences due to matching errors were removed with a robust filtering. After co-registration of the 2003 and 2005 DSMs, the Z component of the Euclidian distances (sigma a posteriori) was 2.8 m, showing a clear reduction of trees and other wooded plants from 2003 to 2005 (see Fig. 3 in the result section for details).

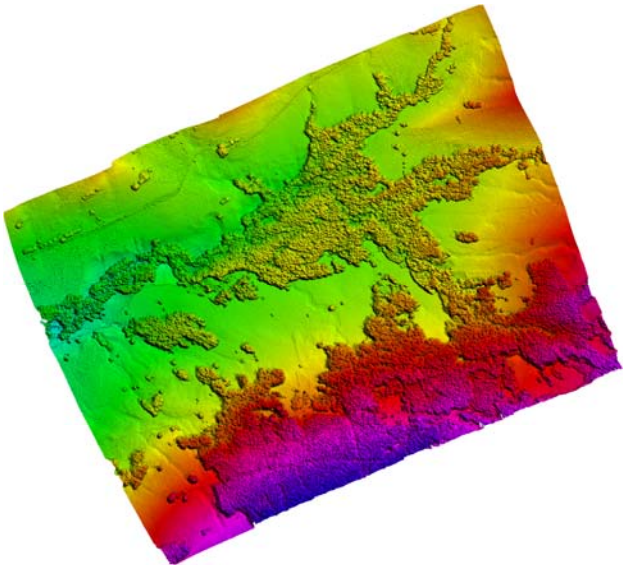

Figure 2. DSM of the entire test site generated by the SAT-PP matcher. The DSM is coded in color from light green (light In BW) to cyan (dark in BW) for lowest and highest elevations respectively.

2.3 Training and reference data-sets

A ground survey was carried out in summer 2006 and 2007 within the test site. Since the LiDAR data was acquired in 2003 and the image data in 2005 only trees which are visible in both data-sets were considered as training and reference objects. In total, for 480 trees we collected: i) tree positions using a sub-decimeter GPS with differential correction, ii) tree heights using a tachymeter and iii) determination of eight tree species. These are: *alder*, *maple*, *birch*, *beech*, *ash*, *sorbus* (all deciduous trees) and *white fir*, *spruce* (coniferous trees). This information was used for calibration and validation of the models.

2.4 Fractional canopy covers

The forest / non-forest decision is based on several steps: In a first step, two canopy height models (CHM) were produced (CHM1 = matching DSM – LIDAR DTM; CHM2 = LiDAR DSM –LiDAR DTM). Then both CHMs were used to extract potential tree areas according to the > 3 m height definition of trees in the Swiss national Forest Inventory (NFI) (Brassel and Lischke, 2001). In a second step, non-tree objects (buildings, rocks etc.) of both CHMs were removed using normalized difference vegetation index (NDVI) information (low values) obtained from the CIR aerial images. In a third step, based on the canopy covers two fractional shrub/tree covers were produced using a logistic regression approach (e.g. McCullagh and Nelder, 1983) with a probability for each pixel to belong to the class “forest”. The explanatory variables consist of five commonly used topographic parameters derived from the CHMs (slope, aspect, curvature, and two local neighbouring functions). This approach and the extraction of explanatory variables are described in detail in Waser *et al.* (2007) and Waser *et al.* (2008a). Using the fractional shrub/tree covers, various cover strata were computed using different probability ranges (see Table 1).

2.5 Forest composition

Forest composition is commonly regarded as a combination of degree of composition (i.e. separation on deciduous and coniferous trees) and tree species.

Before modelling the degree of composition, the tree species and forest stand results were smoothed using ArcGIS and segmentation of the ADS40 images was applied using the Definiens developer 7.0 software. The segmentation provides groups of trees and single trees with similar shapes and spectral properties. Distinction of coniferous / deciduous trees and distinction of main tree species is primarily based on the fractional canopy cover – all pixels with a forest probability of less than 0.2 were skipped.

2.5.1 Distinction of coniferous / deciduous trees

For each pixel within a segmented tree group or tree object, probability belonging to deciduous or coniferous trees was calculated using a logistic regression model. As explanatory variables we used 18 parameters derived from the ADS40 images and the RC30 images: original bands of RGB and CIR, the ratio of each band divided by the sum of the corresponding 3 bands, and the same ratios smoothed with a 3x3 local average filter. The last 12 parameters have shown a good performance based on empirical tests. 240 tree species (half of the field data) were used as training data.

2.5.2 Distinction of main tree species

Probability belonging to one of the eight main tree species was calculated using a second logistic regression model for each pixel within a segmented tree group or tree object. For this model we used 20 spectral variables, which consist of the 18 parameters used in 2.5.1 plus NDVI and smoothed ADS40 blue channel. Again, 240 tree species (half of the field data) were used as training data. As output, probabilities for each tree species within an image segment were obtained.

2.5.3 Forest stands

According to the Swiss NFI a stand can be defined by the three parameters *composition*, *diameter at breast height* (dbh) and *structure* (multi-layers of tree cover). *Composition* can be determined using the distinction of coniferous / deciduous trees and classification of the eight tree species as performed in 2.5.1 and 2.5.2.

Since it is not possible to obtain the diameter at breast height from the input data-sets tree height information and minimum tree area (500m^2) was used instead. Tree height is indirectly linked with the diameter of a trunk. Four tree height classes according to the definition by the NFI were built using the CHMs: 3-8m, 8-15m, 15-25m and > 25m. Minimum tree area and the dominating tree heights per segment (tree group or tree object) were calculated using moving window approaches. Since no full-waveform LiDAR data was available for this test site the third parameter multi-layer information (*structure*) could not be achieved.

3. RESULTS

3.1 Canopy covers

The predicted shrub/tree cover strata were validated using a pixel-to-pixel comparison on the 240 randomly sampled reference field measurements. For this validation the corresponding pixel clusters (5x5 pixel window) of the measured 240 tree/shrub samples and 150 non-tree samples, respectively were used. Table 1 presents the correspondence between the pixels of randomly sampled shrubs/trees that are > 3 m and the modelled individual shrub/tree cover strata. The following statistical measures were used: correct classification rate (*CCR*), consumer’s accuracy, producer’s accuracy, kappa coefficient and correlation coefficient (r^2). The accuracies for five different tree/shrub cover strata are given for both CHMs. Table 1 clearly shows that generally better accuracies are obtained by using the topographic parameters from the matching DSM as explanatory variables. The most accurate cover stratum also varies. Best correspondence between the models and field data is obtained for cover stratum 20-100% when using the matching DSM variables, and 30-100% when using the LiDAR DSM variables.

Cover stratum	**10-100%**	**20-100%**	**30-100%**	**40-100%**	**50-100%**
CCR	0.841 0.923	0.883 0.971	0.902 0.958	0.891 0.935	0.863 0.921
Cons. Ac.	0.801 0.817	0.861 0.965	0.902 0.954	0.865 0.956	0.836 0.938
Prod. Ac.	0.842 0.924	0.863 0.934	0.887 0.912	0.857 0.881	0.835 0.834
Kappa	0.721 0.802	0.786 0.915	0.823 0.903	0.782 0.883	0.761 0.856
r^2	0.765 0.832	0.782 0.924	0.821 0.908	0.812 0.891	0.747 0.864

Table 1. Accuracies of both canopy covers for five different strata. 1st lines are based on the Lidar DSM variables, whereas second lines were obtained from the matching DSM variables.

Fig. 3 clearly shows the different extent of canopy covers with tree height classes when a) using the LiDAR CHM and b) using the matching CHM. For comparison purposes the DSMs were resampled to 1m. The varying extent of forest area is due to quality differences of the LiDAR data and the matching DSM but also due to deforestation between 2003 and 2005.

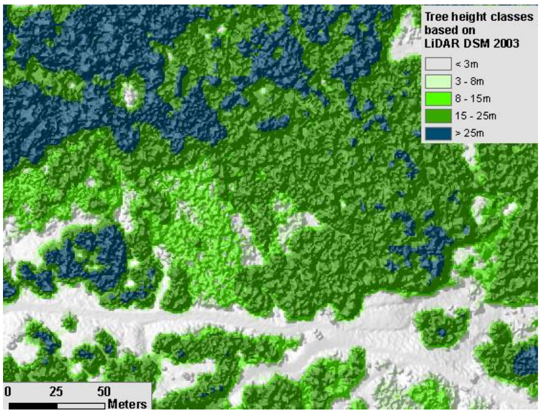

Figure 3a. Extracted forest area and tree height classes based on the LiDAR CHM of 2003.

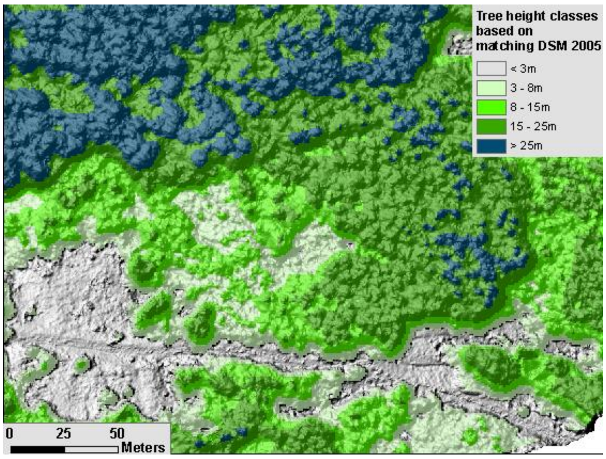

Figure 3b. Extracted forest area and tree height classes based on the CHM of the matching DSM of 2005. New deforestation is visible in the left part of the area.

Since the extracted vegetation obtained by the LiDAR DSM is less accurate and detailed as by the matching DSM data, for further investigation only the latter was used. Fig. 4 gives an example of the fractional canopy cover for a typical area within the test site using the matching DSM.

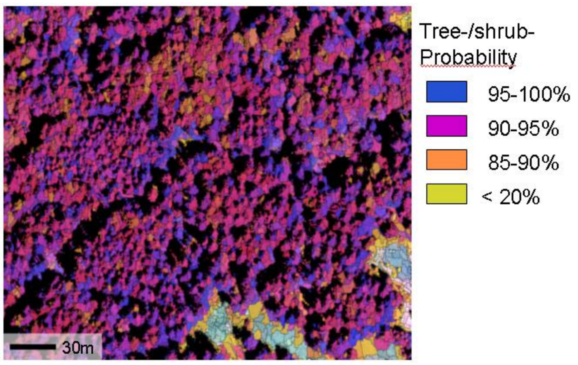

Figure 4. Calculated tree-/shrub probability as provided by the fractional canopy cover based on the matching DSM data. The range 20-85% is not shown as it covered a very small area.

3.2 Coniferous / deciduous trees

An example of extracted deciduous and coniferous trees is given for a typical area within the test site in Fig. 5. The corresponding accuracies are given in Table 2.

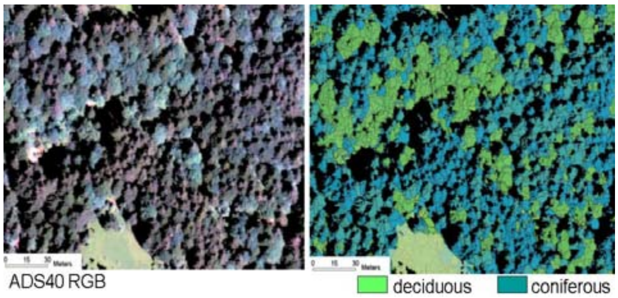

Figure 5. Left: ADS40 RGB image, right: the corresponding distinction of deciduous / coniferous trees using ADS40 input data.

Lowest accuracies are obtained when using CIR images only. Best results were obtained using both ADS40 images and CIR images as input data-sets. Table 2 also reveals an increasing percentage of coniferous trees (and a decrease of deciduous trees) when both image data-sets were used. Since this increase compared to the CIR results is about 10% it might be of interest for further analysis. However, the differences between using both datasets and ADS40 only is small.

Based on	*CCR*	*K*	% coniferous	% deciduous
CIR	88.1	0.78	57.1	42.9
ADS40	93.8	0.87	63.7	36.3
CIR + ADS40	94.8	0.90	64.3	35.7

Table 2. Accuracies (*CCR* and *Kappa*) of distinction between coniferous / deciduous trees.

3.3 Tree species

In general, best distinction is obtained when combining both ADS40 and CIR data as explanatory variables. Low classification rate (*CCR*) is obtained when considering all eight tree species. Therefore the focus was laid on five main tree species (spruce, white fir, ash, beech, birch). Table 3 reveals the accuracies using either CIR images, ADS40 images or a combination of both data-sets and shows that best results are obtained from the latter. Table 3 also shows that this improvement is less pronounced for deciduous trees.

based on	*spruce*	*w. fir*	*ash*	*beech*	*birch*	*K*
CIR	0.75	0.64	0.81	0.80	0.76	0.68
ADS40	0.86	0.85	0.84	0.82	0.78	0.75
CIR+ ADS40	0.92	0.88	0.91	0.86	0.84	0.86

Table 3. CCR values of the five main tree species as obtained by logistic regression. Kappa (*K*) values are the average for all 5 species.

3.4 Forest stands

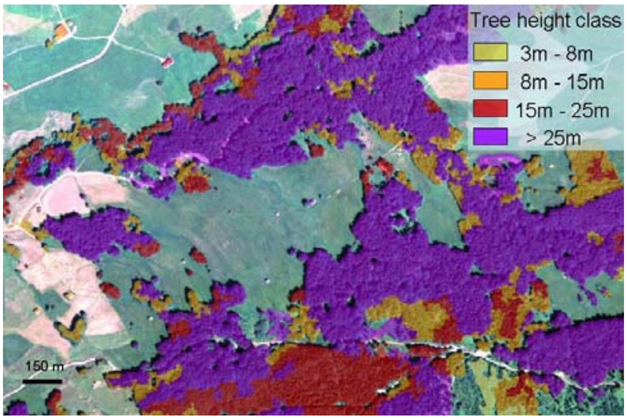

Figure 6a. Tree height classes according to the Swiss national forest inventory (NFI).

Fig. 6 shows that forest stand classes are a combination of tree heights and forest composition. However, since no forest stand maps exist from this region, the quality control of the different forest stands was performed visually using stereo-image interpretation. In general, the typical stand classes are well represented when accepting some discrepancies especially in stand classes with lower tree heights (3-8m).

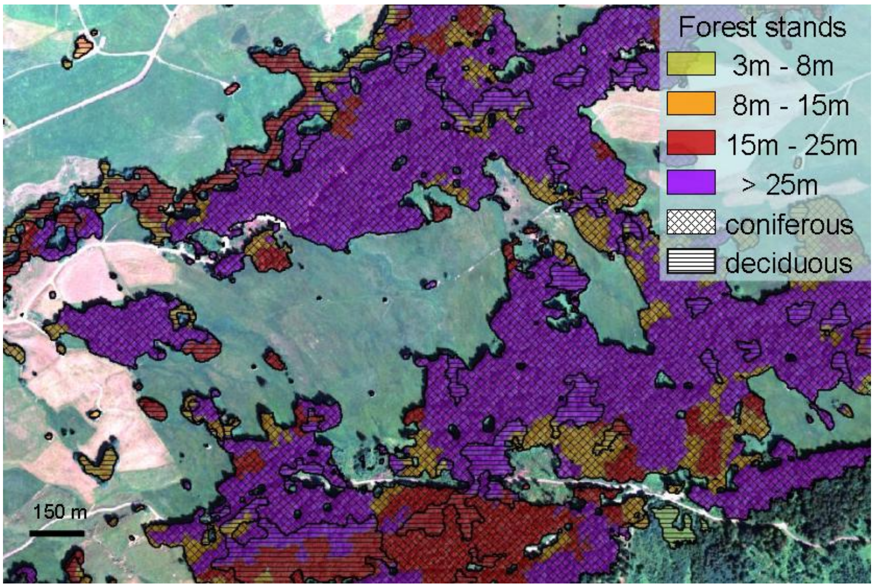

Figure 6b. Forest stand classes as obtained by combining tree heights and dominant tree type.

4. DISCUSSION AND FINAL REMARKS

This study highlights the potential of combining airborne remote sensing data with logistic regression models to obtained forest attributes such as area, tree species and stands on sub-pixel level. The usage of standard explanatory variables derived from the DSMs, as already applied in other studies (Küchler *et al.*, 2004, Waser *et al.* 2008a), proved to be a good approach for modeling fractional canopy covers. Accurate extraction of these forest attributes might be essential for tasks of the NFI (e.g. support for stereo-interpretation of aerial images), for forest owners and also forest management tasks.

The first objective, the extraction of forest area, was achieved semi-automatically with high accuracy using either LiDAR or matching DSM data. Generally, the usage of explanatory variables from the matching DSM produced better accuracies – especially regarding single tree detection. Highest correspondence between fractional canopy cover and field data was obtained for the fractional canopy cover strata of 20-100% using the matching DSM and 30-100% using the LiDAR DSM, respectively. However, this validation is based on trees > 3 m (according to the minimum tree height as defined by the NFI). It has to be kept in mind that accuracies for the strata may vary when considering also shrubs/trees < 3 m for validation. But detailed visual stereo-image interpretation confirmed that most small trees are then within the forest area when using the two canopy cover strata. Since this study clearly reveals that accuracy of fractional canopy covers strongly depends on the accuracy of the DSM data, newly developed, high-quality matching methods are indispensable. The usage of a dense and accurate DSM is an absolute prerequisite in order to be able to derive accurate topographic parameters which in turn are used to derive the fractional canopy covers. The LiDAR DSM as applied in this study has a lower point density than the matching DSM, and due also to partial canopy penetration (especially with leaves off) is less accurate for modeling vegetation canopy. In the future, we will be able to produce high-quality DSMs also from ADS40 data.

The second objective, the distinction of main tree species, was achieved semi-automatically and mediocre to high accuracies were obtained. First, simple distinction between deciduous trees and coniferous trees revealed higher accuracies than the distinction of several tree species. Second, better results were obtained when using ADS40 data, especially for coniferous tree species. Anyhow, distinction of tree species based on CIR aerial image information at least produced satisfactory results for *spruce*, *ash*, *beech* and *birch* and partly satisfactory for *white fir*. Best results were obtained when combining both sensors as input for the logistic regression models. However, both sensors failed to distinguish further deciduous trees with good quality. Possible reasons are that *alder*, *maple* and *sorbus* are often grouped, have smaller crowns (and are therefore partly covered from each other or from other more dominant species) and also have very similar spectral properties.

This study clearly reveals that spectral information of the blue band (428-492 nm) as provided by ADS40 is essential to distinguish between several deciduous tree species. Another advantage of the ADS40 sensor is that the three spectral bands are not overlapping. Two final remarks are given here: i) advantages of this approach are that only few training data is needed and this method can be applied semi-automatically – also for larger regions; ii) an important disadvantage is the availability of both image data, whereas the CIR aerial images are only available on request. Unfortunately, with this first generation ADS40 sensor, the NIR line CCD is placed far away from the RGB CCDs and thus the NIR image looks very different and cannot be combined with the RGB images

Therefore, in near future the focus will be laid on single usage of the 2nd generation ADS40 sensor where all four spectral CCDs are very close to each other. This will improve the results, by using also the NIR information. Another advantage will be the availability of newest ADS40 imagery for entire Switzerland every three years. In this case, the dependence on image on request will cease to exist. To make this approach more valuable and applicable for e.g. entire Switzerland it is also planned to test other tree species of different geographical regions (e.g. Central and Southern Alps). Another approach will be the usage of tree texture properties and of the seasonal variability of tree species using multi-temporal data.

The third objective, the extraction of forest stands, produced visually satisfactory results but still suffers from some limitations. Structure, the third necessary parameter to define a stand, had to be ignored since it can only be derived from full-waveform LiDAR data. Another drawback is that we used tree height classes supposing a relation to the diameter at breast height. Nevertheless, we are able to extract semi-automatically stand classes that will help for a better understanding of the structure of forest.

To summarize, this study clearly shows the potential and the limits of the three extracted forest attributes: area, composition and stand using high-resolution airborne remote sensing data. These forest attributes may be helpful to support some tasks in the Swiss NFI (e.g. stereo-image interpretation, field surveys). Furthermore, this information could also be useful for updating existing forest masks, for forest management and protection tasks on a regional level and in future also on a national level.

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