SEMIAUTOMATIC CLASSIFICATION OF TREE SPECIES BY MEANS OF MULTI-TEMPORAL AIRBORNE DIGITAL SENSOR DATA ADS40

L. T. Waser [a, *], E. Baltsavias [b], C. Ginzler [a], M. Küchler [a]

[a] WSL, Landscape Inventories, Swiss Federal Research Institute WSL, 8903 Birmensdorf, Switzerland - (waser, ginzler, kuechler)@wsl.ch
[b] Institute of Geodesy and Photogrammetry, ETH Zurich, 8093 Zurich, Switzerland - manos@geod.baug.ethz.ch

Commission VII

KEY WORDS: Forestry, Ecosystem, Classification, Modelling, Aerial, High resolution, Multi-temporal

ABSTRACT:

Temporally frequent, cost-efficient and precise forest information requirements for national forest inventories, monitoring or protection tasks have grown over time and will continue to do so in the future. New perspectives are given by the airborne digital sensor ADS40, which provides entire image strips with high geometric, radiometric and temporal resolution (every three years for entire Switzerland). This study presents an approach for semi-automated tree species classification in different types of forests using multi-temporal ADS40-SH40 and ADS40-SH52 images from May and July 2007 and August 2008 to support tasks of the Swiss National Forest Inventory.
Based on image segments seven different tree species were classified by combined logistic regression models using spectral variables derived from each of the three different ADS40 images. Additional classification was established combining the May and July 2007 imagery. Explanatory variables were derived from each image data set using a step-wise variable selection.
Classifications were five-fold cross-validated for 230 trees that had been visited in field surveys and detected in the ADS40 images. The 7 tree species were therefore classified up to four times providing its spectral variability during the vegetation period. The overall accuracies vary between 0.67 and 0.8 and Cohen's kappa values between 0.6 and 0.69 whereas the classification based on the May 2007 images performed best. Independent from the sensors and acquisition date of the images lowest accuracies were obtained for *Acer sp.*This study reveals the potential and limits of the ADS40 data to classify tree species and underscores the advantage of a multi-temporal classification of deciduous tree species with spectral similarities.

1. INTRODUCTION

1.1 General Instructions

New methods for the extraction of forest attributes from airborne remote sensing data have grown over time and will continue to do so in the future since exact information on forest composition is needed for many environmental, monitoring or protection tasks. The present study focuses on the classification of tree species using multi-temporal ADS40 imagery and was carried out in the framework of the Swiss National Forest Inventory (NFI) (Brassel and Lischke, 2001; Brändli, 2010). Tree species classification is highly correlated to a large number of other forestry attributes (e.g. composition, biomass, volume, tree damage etc.) and is an essential index in forest studies, inventories, management and other forest applications.
Several studies have integrated multisensoral data to perform tree species classification which lead to better accuracies than using only a single data input (St-Onge et al., 2004; Hirschmugl et al., 2007; Waser et al., 2008b, Waser et al., 2010) or LiDAR (Heinzel et al., 2008; Holmgren et al., 2008; Chubey et al., 2009). A few studies have incorporated multi-temporal data (Key et al. 2001)
According to Guisan et al. (2004) modern regression approaches such as generalized linear models (GLMs) have proven particularly useful for modelling the spatial distribution of plant species and communities. Küchler et al. (2004) show that spatially explicit predictive modelling of vegetation using remotely sensed data can be used to construct current vegetation cover using information on the relations between current vegetation structure and various environmental attributes. Thus, logistic regression models seem also promising for modelling tree species when analyzing the relationship between categorical dependent variables (e.g. tree species) and explanatory variables derived from remotely sensed data (Waser et al., 2008a and 2008b).
The objective of this study was to classify semi-automatically three deciduous and four coniferous tree species. The contribution of three multi-temporal ADS40 images was tested and best image combination for tree species classification was assessed. Preliminary results are very promising for future monitoring, updating and management tasks of a continuous Swiss National Forest Inventory (NFI).

2. MATERIAL

2.1 Study area

The study area is characterized by open and closed mixed forests and is located in the Swiss central Plateau (approx. 47°22' N / 8°28' E) and has an extent of approx. 7.5 km^2. The altitude ranges from 450 m to 850 m a.s.l. The forest area covers approx. 5.1 km^2, and is mostly characterized by mixed forest. The dominating deciduous tree species are *Fagus sylvatica* and *Fraxinus excelsior* and less frequently *Acer sp.* The main coniferous trees are *Abies alba*, *Larix decidua*, *Picea abies* and *Pinus sylvestris.*

* Corresponding author

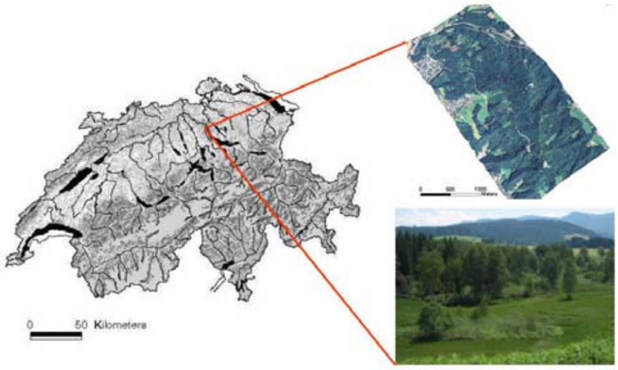

Figure 1. Study area. © SWISSTOPO.

2.2 Ground truth

The ground truth data to validate the tree species classifications was collected in the natural environment to be representative. Two ground surveys were carried out in summer 2008 and 2009 focusing on the most frequent tree species (at least 10% coverage in Switzerland) which were also visible in the aerial images. For a total of 230 sampled trees we recorded the species (table 1) and delineated in the field the crowns of all visited trees on the corresponding aerial images. This information was used as reference to digitize the corresponding tree crowns on the ADS40 RGB images.

Scientific tree species name (common tree species name)	Num. of samples	Species prop.
Acer sp. (maple)	28	< 10%
Fagus sylvatica (beech)	42	20%
Fraxinus excelsior (ash)	32	15%
Abies alba (white fir)	28	15%
Larix decidua (larch)	20	<10%
Picea abies (Norway spruce)	56	25%
Pinus sylvestris (Scots pine)	24	<10%

Table 1. Tree species sampled with number of samples. Species proportion is based on estimates by an expert during the field surveys

2.3 Remotely sensed data

2.3.1 Airborne Digital Sensor Data (ADS40): First generation ADS40-SH40 and second generation ADS40-SH52 images Level 1 (Leica Geosystems AG, Switzerland) were used in this study (for further details on the sensor see e.g. Reulke et al. (2006). The main drawback of the first-generation ADS40-SH40 is that the NIR line CCD is placed 18° forward from the nadir RGB CCDs which makes it difficult to combine all four lines. The second generation ADS40-SH52 provides the NIR band in the same nadir position as the RGB bands. Three Digital Surface Models (DSMs) were generated automatically from the above images with a spatial resolution of 0.5 m using modified strategies of NGATE of SOCET SET 5.4.1 (BAE Systems). Prior to the DSM generation, a Wallis filter was applied to enhance contrast, especially in shadow regions, and to equalize radiometrically the images for matching.

Sensor	ADS40-SH40	ADS40-SH52
Acquisition date	24/05/2007 & 13/07/2007	18/08/2008
Focal length	62.8 mm	62.8 mm
Spectral resolution (nm)	Red: 610-660 Green: 535-585 Blue: 430-490	Red: 608-662 Green: 533-587 Blue: 428-492 NIR: 833-887
Ground pixel size	~25 cm	~25 cm
Orthoimage	25 cm	25 cm
Radiometric resolution	11 bit	11 bit

Table 2. Summary of characteristics of the image data used

2.3.2 LiDAR: National LiDAR digital terrain data (DTM) produced by the Swiss Federal Office of Topography (SWISSTOPO) for the study area (acquisition date: March 2002, reflown March 2003 leaves-off) were used. The data were acquired by Swissphoto AG / TerraPoint using a TerraPoint ALTMS 2536 system with an average flying height above ground of 1200 m. The DTM has an average point density of 0.8 points / m^2 height accuracy (1 sigma) of 0.5 m (Artuso et al., 2003) and was interpolated to a regular grid with 0.25 m.

3. METHODS

3.1 Variables derived from ADS40 imagery

To extract tree area and classify tree species, several variables (geometric and spectral signatures) were derived from the remote sensing data using standard digital image processing methods as described in e.g. Gonzales and Woods (2002). Details about extraction of geometric and spectral explanatory variables derived from airborne remote sensing data are described in Waser et al. (2007, 2008a and 2008b). A good fit to the given (training) data is not a sufficient condition for good predictive models. To obtain good predictions, a small set of powerful variables has to be selected.
Therefore stepwise variable selection (AIC, both directions, Akaike, 1973) was applied using the defaults of R version 2.9.1. A separate stepwise selection was performed for each tree species. The variables were ranked according to their contribution to the model.
The input variables used in this study consist of four commonly used geometric parameters derived from the CHMs (slope, curvature, and two local neighborhood functions). For further details, see Burrough (1986) and Moore et al. (1991). Spectral variables were derived from each of the three images. This includes for each set of variables the mean and standard deviations of: 3 x 3 original bands of ADS40-SH40 RGB and ADS40-SH52 RGB and CIR images and the colour transformation from RGB and CIR (only from the 2008 images) to IHS into the 3 channels intensity (I), hue (H), and saturation (S).

3.2 Image segmentation

Homogenous image segments of individual tree crowns or tree-clusters are needed to classify tree species (see below). Both the ADS40-SH40 and /ADS40-SH52 orthoimages were therefore subdivided into patches by a multi-resolution segmentation using the Definiens 7.0 software (Baatz & Schäpe, 2000). Segmentation was iteratively optimized using several levels of detail and adapted to shape and compactness parameters. The final segmentation provided groups of trees and individual trees with similar shapes and spectral properties. Finally, the means and standard deviations of the geometric and spectral variables were calculated for each segment.

3.3 Tree cover

The extraction of the area covered by trees is required for the area-wide mapping of the classified tree species. Tree cover and non-tree area masks were generated as described in detail in Waser et al. (2008). Briefly summarized: First, digital canopy height models (CHM) were produced subtracting the LiDAR DTM from the three DSMs. In a second step, pixels with CHM values ≥ 3 m were used to extract potential tree areas according to the definition in the Swiss NFI (Brassel and Lischke, 2001). In a third step, non-tree objects, e.g. buildings, rocks, and artifacts were removed using spectral information from the ADS40-SH40 and ADS40-SH52 RGB images (low IHS pixel values) as well as information (curvature) about the image segments (e.g. segments on buildings have lower curvature values and ranges than trees or large shrubs). These four steps resulted in three canopy covers providing sunlit tree area for each study area.

3.4 Classification of tree species

3.4.1 Evaluation of modelling procedures: Image segments representing single trees were to be assigned to classes (species) by predictive modelling. The classes were given by a field sample from the 7 dominant tree species of the study area as described in section 2.2. As the response variable has more than two possible states, a multinomial model had to be applied. The logistic regression model is a special case of the generalized linear model (GLM) and described in e.g. McCullagh and Nelder (1983). Combination of logistic models was implemented by fitting a binomial logistic regression model to each class (species) separately and assigning the respective segment to the species with the highest probability. For details on the logistic regression function with quadratic terms see e.g. Hosmer and Lemeshow (2000). The explanatory variables as given in section 3.1 were used.
In a first run, a single classification was performed using each set of variables separately. Then the explanatory variables from both the 2007 May and July images were tested together within a logistic regression model since the same flight path was used and the shadows were quite similar. Due to large differences in the flight paths and shadows between 2007 and 2008 the 2008 data had to be used separately in a separate logistic regression model (see Fig. 2). In total, tree species were classified four times using different logistic regression models and input imagery (see also table 3).

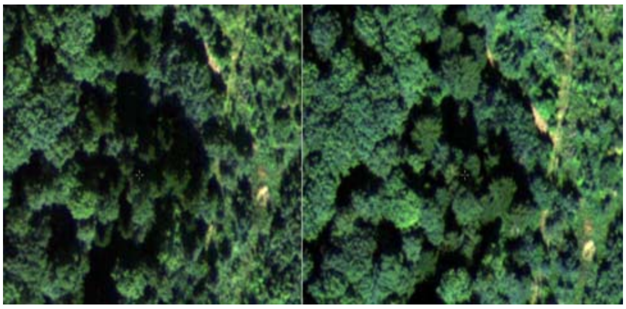

Figure 2. Example of the same area of trees acquired by different flight paths between 2008 August (left) and 2007 July (right) images.

3.4.2 Validation: In order to validate the predictions of tree species, the digitized reference tree data (see section 2.2) had to be assigned to the corresponding image segments. Since the delineations of the field samples were not always congruent with the automatically generated image segments each of the 230 digitized reference trees was assigned to an image segment using the following rule: If one segment contained more than one digitized field sample, the segment was assigned to the field sample covering the greater part of the segment. If less than 10% of the image segment was covered by the sample polygon, the segment was not assigned at all. The predictive power of the models was verified by a 5-fold cross-validation. The statistical measures used to validate the results were: producer's (*PA*)- and user's accuracy (*UA*), correct classification rate (*CCR*), and kappa coefficient (*K*).

4. RESULTS

4.1 Confusion matrices

The classification of the seven tree species was achieved semi-automatically and, depending on the image data used, quite high accuracies were obtained. The overall accuracies for tree species classification obtained by the different input imagery are summarized in table 3. The confusion matrices of the May, July and August classifications with best *CCR* and *K* are summarized in Tables 4 - 6. The classified main tree species are: *Abies alba (Aa), Picea abies (Pa), Pinus sylvestris (Ps), Larix decidua (La), Acer sp. (Ac), Fagus sylvatica (Fs), and Fraxinus excelsior (Fe).*

Input data sets	*CCR*	*K*
05-2007	0.798	0.691
07-2007	0.668	0.598
05 and 07-2007 combined	0.691	0.632
08-2008	0.757	0.667

Table 3. Overall accuracies for four different tree species classifications.

Table 4 shows that five of seven tree species are classified with accuracies > 73% when using the May 2007 images. Best agreements are obtained for *Picea abies* (92%) and *Fagus sylvatica* (86%). The most frequent failures happen in classifying the non-dominant tree species *Acer sp.* (43%), and *Larix decidua* (56%) which are often misclassified either as *Fagus sylvatica* or *Picea abies.*

May 2007 Field	Classified as							
	Aa	*Pa*	*Ps*	*La*	*Ac*	*Fs*	*Fe*	PA
Aa	**29**	2	--	--	--	--	4	0.83
Pa	--	**77**	--	2	2	2	1	0.92
Ps	--	--	**14**	--	--	--	--	0.76
La	--	12	1	**10**	--	--	--	0.43
Ac	1	2	--	--	**19**	9	3	0.56
Fs	1	3	--	--	3	**55**	2	0.86
Fe	3	4	--	--	2	2	**54**	0.83
UA	0.85	0.76	0.93	0.67	0.73	0.81	0.84	

Table 4. Confusion matrix for tree species classification using the explanatory variables from May 2007 ADS40-SH40

imagery with the producer's- and user's accuracy of the classified tree species.

Table 5 shows that best agreements for the classification based on the summer 2007 images are obtained for *Picea abies* (89%) and *Larix decidua* (78%). The confusion matrix clearly reveals that especially deciduous trees are misclassified. But also *Pinus sylvestris* is confused with *Picea abies*. *Acer sp*. and *Fraxinus excelsior* are generally overestimated.

July 2007 Field	Classified as							
	Aa	*Pa*	*Ps*	*La*	*Ac*	*Fs*	*Fe*	PA
Aa	**28**	5	0	0	1	6	4	0.64
Pa	2	**68**	2	3	1	0	0	0.89
Ps	0	5	**12**	1	2	1	0	0.57
La	0	4	0	**14**	0	0	0	0.78
Ac	1	0	0	0	**19**	10	12	0.45
Fs	6	4	0	1	11	**54**	15	0.59
Fe	4	1	0	0	5	8	**38**	0.67
UA	0.68	0.78	0.86	0.74	0.49	0.68	0.54	

Table 5. Confusion matrix for tree species classification using the explanatory variables from July 2007 ADS40-SH40 imagery with the producer's- and user's accuracy of the classified tree species.

Table 6 shows that five of seven tree species are classified with accuracies > 74% when using the Summer 2008 images including the NIR band.
The obtained accuracy for *Acer sp.* remains very low because it is often misclassified as *Fagus sylvatica* and *Fraxinus excelsior*.

August 2008 Field	Classified as							
	Aa	*Pa*	*Ps*	*La*	*Ac*	*Fs*	*Fe*	PA
Aa	**29**	3	1	0	0	1	2	0.81
Pa	2	**78**	2	5	0	2	2	0.86
Ps	0	7	**16**	0	0	1	0	0.67
La	0	4	0	**23**	0	0	2	0.79
Ac	0	1	0	0	**12**	14	8	0.34
Fs	2	1	0	1	7	**64**	11	0.74
Fe	3	0	0	0	8	8	**84**	0.82
UA	0.81	0.83	0.84	0.79	0.44	0.71	0.77	

Table 6. Confusion matrix for tree species classification using the explanatory variables from August 2008 ADS40-SH52 images with the producer's- and user's accuracy of the classified tree species.

4.2 Predictive mapping

The tree species which have been modelled with > 90 % probability in the 2007 and 2008 images are depicted in Fig. 3. At first glance, a visual image analysis suggests that the agreements in most parts of the site are good. However, a more detailed image inspection confirms the results of tables 4-6 and indicates that *Acer sp.* is often misclassified as *Fagus sylvatica* or *Fraxinus excelsior* - independently from the acquisition date of the images. Fig. 3 also shows that the predictions of the tree species slightly vary in each of the maps. The underestimation of *Larix decidua* is clearly visible in the May images whereas the overestimations of *Fraxinus excelsior* and *Fagus sylvatica* are clearly visible in the July 2007 images.

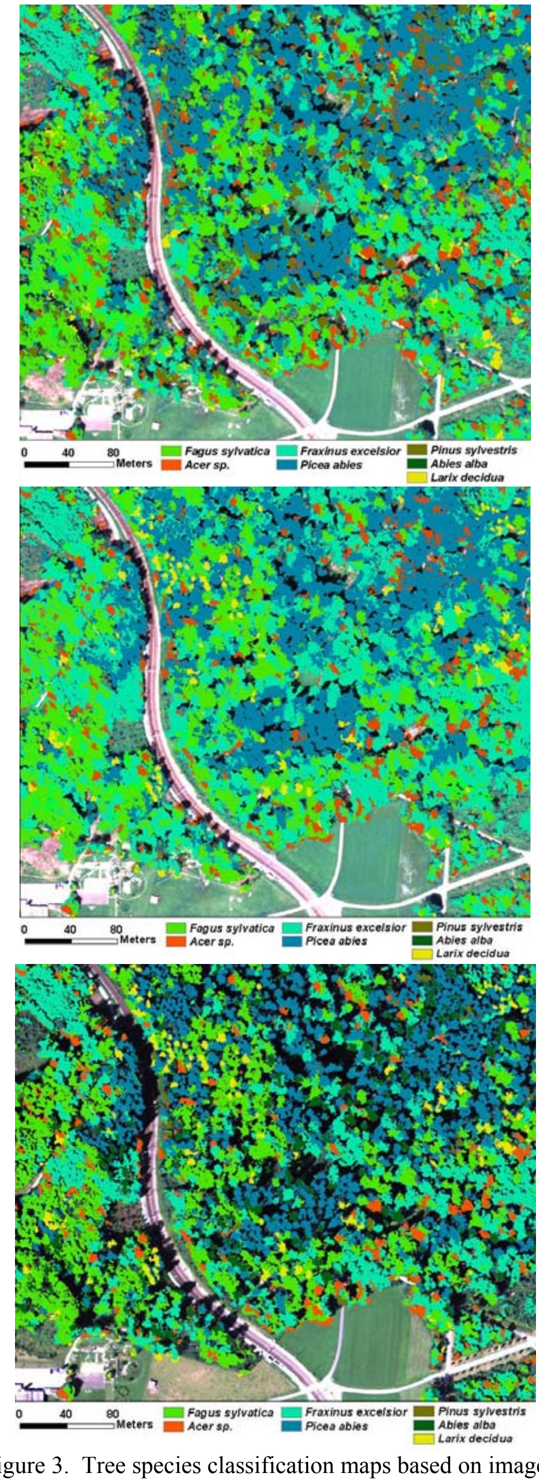

Figure 3. Tree species classification maps based on imagery from May 2007 (top), July 2007 (middle) and August 2008 (bottom) with the largest shadows.

5. DISCUSSION

The potential and the limits of classifying seven tree species has been tested using multi-temporal multispectral ADS40 imagery. The most significant achievement is the demonstration that spring ADS40 imagery as input for the classification of tree species is superior to the summer imagery – even without the additional information of the NIR band. Summer imagery from

the second generation ADS40-SH52 (including the NIR band) is superior to the summer RGB images of the first generation ADS40-SH40.
The study shows that logistic regression models proved to have a high potential to produce meaningful tree species classifications with a minimum amount of effort involved in image acquisition, data pre-processing, derivation of explanatory variables and field work. Some limitations of this approach are briefly discussed below.

5.1 Ground truth

The tree samples were delineated in the field on aerial images, which means that well visible trees may have been preferred, or only the lighted parts of trees have been delineated. Additionally, trees may be shaded or partly hidden by others so that one image segment could contain more than one species. However, when comparing correct classification rates or kappa values to other studies, we emphasize that this is a qualitative approach. For the same reasons the model results were checked for plausibility by visual examination of the aerial photographs. These uncertainties render the statistical evaluations relative.

5.2 Comparison with other studies

Overall, the species accuracies obtained in this study are in the line or higher with those in similar studies.
Our best result (spring 2007 data) with an overall accuracy of nearly 80% for seven tree species is higher to those obtained in other studies. Overall accuracies between 75% (based on CIR aerial images, Brandtberg, 2002) and 89% (based on DMC camera, Olofsson et al., 2006) are obtained in most studies to classify Norway spruce, Scots pine, birch or aspen
Obviously, classification accuracies are lower the more tree species there are and if non-dominant tree species are included as well. Chubey et al. (2009) classified 4-6 coniferous and 4-6 deciduous species in Canadian forests with an overall accuracy around 70%.

5.3 Multispectral versus multi-temporal

Although we found that our approach produces in general good results and is suitable a more detailed analysis of the misclassifications is needed. The full potential of a multi-temporal approach could not be realized in this study. Due to differences in the flight paths and different acquisition daytimes (different shadows) between the 2007 and 2008 images a classification based on all three datasets could not be established. The 2008 data was therefore used separately.
Although multi-temporal multispectral data is known as valuable (e.g. Key et al., 2001), in the present study combinations of the two images of May and July 2007 tended to give lower accuracies. For the classification of *Larix decidua* and *Picea abies*, the single usage of multispectral information obtained by the August 2008 imagery was more valuable than multi-temporal information of the May and July 2007 imagery. The reason for this might be the additional usage of the NIR information provided by the ADS40-SH52 2008 images.
Problems for classifying deciduous tree species are increasing when using summer imagery. Visual analysis of the spectral ranges of each species moreover revealed very similar spectral properties between the summer 2007 and 2008 images for *Fagus sylvatica* and *Fraxinus excelsior.* Even within species, spectral variability can be large because of illumination and view-angle conditions, openness of trees, natural variability, age of the trees, shadowing effects and differences in crown health. Fig. 4 illustrates this situation.

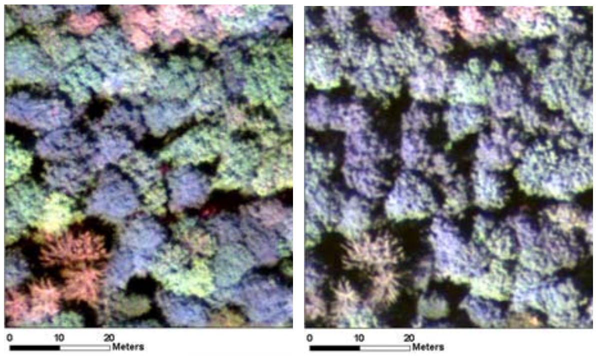

Figure 4. Examples of the deciduous tree species *Fagus sylvatica* (blue-grey), *Fraxinus excelsior* (light green) and *Acer sp.* (green-blue) as they appear in the May 2007 images (left) and July 2007 images (right).

5.4 Non-dominant tree species

Generally, a relatively small sample size of non-dominant tree species - compared to the other species in a study area – leads to underestimation of these species. Tables 4 - 6 clearly reveal that most frequent failures happen in classifying the non-dominant tree species *Acer sp*. Visual image inspection showed that *Acer sp.* are often short and therefore partly obscured by nearby large and dominant trees, or by the merging of close crowns. The two other non-dominant (coniferous) tree species *Larix decidua* and *Pinus sylvestris* in this study are classified with higher accuracies.

6. OUTLOOK

The promising results and experiences made in this study are of great practical interest for the Swiss National Forest Inventory. Actual and accurate maps of tree species and composition are needed by environmental agencies and land surveying offices to assess possible changes in species distribution or condition of other habitat.
The most obvious opportunities for follow up are: The usage of NFI field sample plots as training data to reduce field work. Further development is needed for testing larger areas, which may consist of several image strips. BRDF-related problems or influences of the BRDF in terms of classification accuracy should also be investigated.

7. REFERENCES

Akaike, H.,1973. Information theory as an extension of the maximum likelihood principle. In: Petrov, B.N., Csaki, F. (eds.), *Second International Symposium on Information Theory.* Akademiai Kiado, Budapest, Hungary, pp. 267-281.

Artuso, R., Bovet, S., and Streilein, A., 2003. Pratical Methods for the Verification of countrywide Terrain and Surface Models, In: *International Archives of Photogrammetry and Remote Sensing, vol. XXXIV-3/W13*

Baatz, M., and Schäpe, A., 2000. Multiresolution Segmentation – an optimization approach for high quality multi-scale image segmentation. In J. Strobl, T. Blaschke and G. Griesebner (eds.), *Angewandte Geographische Informationsverarbeitung Vol. XII* (pp. 12-23). Heidelberg, Germany: Wichmann

Burrough, P.A., 1986. *Principles of Geographical Information Systems for Land Resources Assessment*. New York: Oxford University Press, 50 p.

Brändli, U.-B., 2010. Schweizerisches Landesforstinventar. Ergebnisse der dritten Erhebung 2004-2006. Birmensdorf, Eidgenössische Forschungsanstalt für Wald, Schnee und Landschaft WSL. Bern, Bundesamt für Umwelt, BAFU. 312 p.

Brandtberg, T., 2002. Individual tree-based species classification in high spatial resolution aerial images of forests using fuzzy sets. *Fuzzy Sets and Systems, 132*, pp. 371-387.

Brassel, P. and Lischke, H., 2001. *Swiss National Forest Inventory: methods and models of the second assessment*. Birmensdorf, Swiss Federal Research Institute WSL, 336 p.

Chubey, M., Stehle, K., Albricht, R., Gougeon, F., Leckie, D., Gray, S., Woods, M., and Courville, P., 2009). Semi-Automated Species Classification in Ontario Great Lakes - St.Lawrence Forest Conditions. Final Report: Great Lakes - St. Lawrence ITC Project (2005/2008). Ontario Ministry of Natural Resources. January 2009. 71 p.

Gonzales, R.C., & Woods, R.E., 2002. *Digital image processing*. Second edition. New Jersey: Upper Saddle River.

Guisan, A., Weiss, S.B., and Weiss, A.D., 2004). GLM versus CCa spatial modeling of plant species distribution. *Plant Ecology* 143(1), pp. 107-122.

Heinzel, J.N., Weinacker, H., and Koch, B., 2008. Full automatic detection of tree species based on delineated single tree crowns – a data fusion approach for airborne laser scanning data and aerial photographs, *Proceedings of the SilviLaser 8th international conference on LiDAR applications in forest assessment and inventory*, (pp. 76-85)*, September 18-19, 2008, Edinburgh, UK.*

Hirschmugl, M., Ofner, M., Raggam, J., and Schardt, M., 2007. Single tree detection in very high-resolution remote sensing data. *Remote Sensing of Environment, 110*, pp. 533-544.

Holmgren, J., Persson, Å., and Söderman, U., 2008. Species identification of individual trees by combining high resolution LiDAR data with multi-spectral images. *International Journal of Remote Sensing, 29*, pp. 1537-1552.

Hosmer, D.W., and Lemeshow, S., 2000. *Applied logistic regression*, *2nd edition*, New York: Wiley, 373 p.

Key, T., McGra, J.B., and Fajvan, M.A., 2001. A comparison of multispectral and multitemporal information in high spatial resolution imagery for classification of individual tree species in a temperate hardwood forest. *Remote Sensing of Environment, 75*, pp. 100-112.

Küchler, M., Ecker, K., Feldmeyer-Christe, E., Graf, U., Küchler, H., & Waser, L.T., 2004. Combining remotely sensed spectral data and digital surface models for fine-scale modelling of mire ecosystems. *Community Ecology,* 5(1), pp. 55-68.

McCullagh, P., and Nelder, J.A., 1983. *Generalized linear models*. London: Chapman and Hall, 511 p.

Moore, I. D., Grayson, R. B., and Landson, A. R., 1991. Digital Terrain Modelling: a Review of Hydrological, Geomorphological, and Biological Applications. Hydrological Processes. Vol. 5, pp. 3-30.

Olofsson, K., Wallermann, J., Holmgren, J., and Olsson, H., 2006. Tree species discrimination using Z/I DMC imagery and template matching of single trees. *Scandinavian Journal of Forest Research, 21,* pp. 106-110.

Reulke, R., Becker, S., Haala, N., and Tempelmann, U., 2006. Determination and improvement of spatial resolution of the CCD-line-scanner system ADS40. *ISPRS Journal of Photogrammetry & Remote Sensing, 60*, pp. 81–90.

Scott, J.M., Heglund, P.J., Samson, F., Haufler, J., Morrison, M., and Wall, B., 2002. *Predicted species occurrences: issues of accuracy and scale,* Island Press, Covelo, California, 868 p.

St-Onge, B., Jumelet, J., Cobello, M., and Vega, C., 2004. Measuring individual tree height using a combination of stereophotogrammetry and lidar. *Canadian Journal of Forest Research, 34*(10), pp. 2122-2130.

Waser, L.T., Küchler, M., Ecker, K., Schwarz, M., Ivits, E., Stofer, S., and Scheidegger, C. (2007). Prediction of Lichen Diversity in an Unesco Biosphere Reserve - Correlation of high Resolution Remote Sensing Data with Field Samples. *Environmental Modeling & Assessment*, *12*(4), pp. 315-328

Waser, L.T., Baltsavias, E., Ecker, K., Eisenbeiss, H., Ginzler, C., Küchler, M., Thee, P., and Zhang, L. (2008a). High-resolution digital surface models (DSM) for modelling fractional shrub/tree cover in a mire environment. *International Journal of Remote Sensing, 29*(5), pp. 1261 – 1276

Waser, L.T., Ginzler, C., Kuechler, M., and Baltsavias, E. (2008b). Potential and limits of extraction of forest attributes by fusion of medium point density LiDAR data with ADS40 and RC30 images. *Proceedings of the SilviLaser 8th international conference on LiDAR applications in forest assessment and inventory*, *September 18-19, 2008, Edinburgh, U,* pp. 625-634.

Waser, L.T., Klonus, S., Ehlers, M., Küchler, M., and Jung, A., 2010. Potential of Digital Sensors for Land Cover and Tree Species Classifications - A Case Study in the Framework of the DGPF-Project. *Photogrammetrie, Fernerkundung und Geo-information*, Vol. 10 (2), pp. 132- 141.

8. ACKNOWLEDGEMENTS

The study was carried out within the framework of the Swiss National Forest Inventory (NFI) and funded by the Swiss Federal Office for the Environment (FOEN) and WSL. We are grateful to Patrick Thee for his valuable help in the field surveys.