USABILITY OF A SUNLIT - SHADED AREA SEPARATION IN INDIVIDUAL TREE SPECIES CLASSIFICATION

Eetu Puttonen [a, *], Paula Litkey, Juha Hyyppä [a]

- [a] Dept. Of Remote Sensing and Photogrammetry, Finnish Geodetic Institute
- Geodeetinrinne 2, 02400 Kirkkonummi, Finland
- (eetu.puttonen, paula.litkey, juha.hyyppa)@fgi.fi

Commission III, WG III/2

KEY WORDS: Aerial, Classification, Forestry, Fusion, Imagery, Multispectral

ABSTRACT:

Individual tree species classification can be done using Light Detection and Ranging (LIDAR) and aerial multichannel images simultaneously. LIDAR is typically used to derive shape features and aerial images are employed to extract colour features from a dataset. Different lighting conditions are a common problem when images are utilised: the position of the sun has a significant impact on the backscatter radiation of the trees. Methods and results that work on a set of data can be ineffective on another dataset if the method is not robust in changing lighting conditions. The current solutions to shading induced problems are spectral rationing and the use of a subset of well illuminated tree pixels. We present a method, Illumination Dependent Colour Channels (IDCC), for separating the sunlit and shadowed side of a tree sample in this paper. We test if the features derived from this separation can be used effectively in individual tree species classification. Pixel values of the digital aerial image are mapped to Canopy Height Model (CHM) derived 3D representation of the trees. The sun position together with the mapping aircraft position are then utilised to determine the sunlit and shadowed parts on the tree model surface. The classification results are computed on a separate test set and compared with a reference method. Improved overall classification accuracy of 11.0 percentage points were achieved with the used dataset, when results were compared with the ones acquired from two separate reference methods.

1. INTRODUCTION

The management of today's forests is becoming increasingly complex. New objectives of the forest management are introduced including preservation of biodiversity, sequestration of carbon, creation of recreational opportunities, and hunting considerations. From the industrial point of view, better information of the raw wood material quality and quantity are requested. In order to meet these requirements, more precise information from forest inventory is needed. Thus, airborne laser scanning (ALS) is increasingly used for operative, standwise inventory in Scandinavia. The two main approaches used to derive forest information from ALS data have been based on laser canopy height distribution e.g. (Næsset, 1997, Næsset, 2002) and individual tree detection e.g. (Hyyppä and Inkinen, 1999). In both approaches, the two main development areas are: 1) practical solution for tree species classification and 2) improvement in accuracy and quality of the reference sample plots.

Knowledge of tree species is needed in forest industry. Both the tree growth and the timber volume estimates are species dependent. The species information aids also forest management planning. Very fine level information on the forest is needed especially in wood procurement planning and in forest protection survey (Maltamo et al., 2007). Biological studies on forest habitat mapping could also benefit from species specific forest information, since for example the preferred tree species of some endangered species could be located using remote sensing (Goetz et al., 2007). In forest industry, the species information determines the usability of the wood material.

The stand-wise field reference measurements are species specific, but they require a massive amount of work. The number of assessments per stand is also low, which lowers the precision estimation of tree species specific timber sortiment (Maltamo et al., 2007).

There are two approaches to achieve species classification from aerial images: pixel-based and object based. In pixel based classification, either image pixels or integrated data raster cells are classified. This approach is closely related to the methods used in land cover classification and is mainly used in determining the forest type or the main species in large forested areas (Franklin et al., 2003). In the object based species classification, trees or a group of trees are first detected, delineated and extracted from data. Features of a single tree object are then computed for classification.

The integration of aerial images and LIDAR has been used in several studies (Persson et al., 2004, Heinzel et al., 2008, Korpela et al., 2008). Persson et al. (2004) integrated LIDAR data and aerial colour-infrared (CIR) imagery to classify tree species into three classes: spruce, pine and deciduous. LIDAR data was used to segment trees. Segments were mapped to the corresponding aerial image. The classification was done using 10% of the brightest pixels of each tree crown. Each chosen pixel was represented by two angle values, which were calculated from the green, red, and infrared components of the pixel. A sample tree was represented by the mean of the pixel angle values within the tree segment. Spectral band ratio filtering was suggested for the reduction of shadowing effects. An overall classification accuracy of 90% was reported for the training set. A spectral rationing algorithm and formation of a hybrid colour composite image has been also used to reduce shadow effects in other studies, e.g. (Bork and Su, 2007).

* Correspondence author.

Heinzel et al. (2008) used LIDAR digital elevation model (DEM) data in tree delineation. Histogram linearized CIR true orthophotos were transformed into hue (H), saturation (S), and intensity (I) channels. The detected tree polygon was fitted to the spectral data and shaded areas with very low intensity values were removed. The classification was done in two steps: first using the hue channel histogram and second using NIR band. The overall classification accuracy for tree classes of oak / hornbeam, beech, and conifer was 84%. LIDAR data were also used to delineate tree crowns, when five tree species were classified from aerial images taken with ADS40 and RS30 digital cameras (Waser et al., 2008). The training set consisted of CIR images. An overall classification accuracy of 86% was reached.

In Korpela et al. (2008), the integration of LIDAR data and aerial images was used to classify seedling trees in a raster cell setup with an approximate resolution of 0.5 m. Used reference classes were conifers, decidious broad-leaved trees, other low vegetation, and abiotic surfaces. The achieved classification accuracy varied between the study stands with minimum 61.1% and maximum 77.8%. Respective minimum and maximum accuracies changed to 61.6 and 78.9 percents, when the used tree samples were limited to those in direct sunlight.

Good tree species classification results have been also reported using only aerial images (Meyer et al., 1996). Healthy and damaged spruce, pine, fir and beech trees were classified semiautomatically using CIR images of 0.5 m resolution. The achieved average classification accuracy was 80%.

According to the recent studies reviewed above, the most typical approach to object based tree species classification is the use of LIDAR data for tree crown delineation and for selection of the corresponding image pixels. The species classification is typically done either by combining only features based on image colour channels or by combining them with LIDAR based structural features. Shadowing problems are handled using filtering and pixel selection.

A comprehensive EuroSDR tree extraction project, where different extraction methods were tested on freely available datasets, took place in 2008 (Kaartinen and Hyyppä, 2008). Twelve different groups participated into it. Only two participants classified tree species. The tree species classification results were 78% correctly classified trees using airborne photographs (57% of the trees were classified) and 54% correctly classified trees using laser data (64% of the trees were classified). The abovementioned results are of interest because of the great variation between their classification percents and the ones published in articles presenting classification methods with over 80% classification accuracy. We assume that the good previous results have been obtained by having controlled conditions. The EuroSDR test showed that the tree classification accuracies published before (e.g. in tree finding) did not match with the results obtained in the joint test. Thus, methods that work in non-optimal forest conditions are still needed. More research should be also focused into method comparison.

We assume that there could be features with measurable differences between different tree species when the sunlit and shaded parts of the tree canopies are first separated and then compared with each other. This assumption is based on the fact that foliages of different tree species scatter light differently due to their general shape and leaf properties, e.g. (Kaasalainen and Rautiainen, 2007). We anticipate that the transmittance of the tree canopy affects the image brightness on the shadowed side of the tree. Separation of lit and shaded parts of a tree canopy should also allow better utilisation of the available dataset as heavy filtering is not needed for shadow removal. Different viewing geometries are also taken into account as long as the locations of both the camera and the sun are known. The separation of an individual tree canopy into sunlit and shaded parts has been done before in Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI) and canopy radiative transfer studies (Chen and Leblanc, 2001, Hall et al., 2008, Hilker et al., 2008).

We test in this study if we are able to find classification aiding features by separating a single tree dataset into sunlit and shaded parts. The dataset and the methods used in data extraction are introduced in chapter 2. Tested features and the used classification methods are presented in chapter 3. The classification results are given in chapter 4 and the discussion on the results and possible further studies are in chapter 5.

2. DATA AQUISITION

2.1 Test area

The test area was located in Espoo city, southern Finland (N 60° 8.985', S 24 ° 39.358'). Vegetation in the test area was a mix of common city lawn, planted deciduous trees (linden, alder, for example), and mixed natural growing stock. The test area had a varying contoured topography with heights between 0 – 30 meters from the sea level.

2.2 ALS data

The ALS dataset used in this research was acquired on the 12th of July in 2005. The used sensor was Optech ALTM 3100 Optech Incorporated, Vaughan, Ontario). The main flight lines were flown 1000 metres over the test area. The average point density on these lines was 2-4 points/m2. In overlapping areas of flight lines the laser point density rose up to 10-12 points/m^2. All scanned laser points were used to form rasterized digital surface and terrain models (DSM and DTM) of the test area. Both DSM and DTM were created with TerraScan (Terrasolid, Jyväskylä, Finland). The highest point in a rasterized cell was used to determine its elevation in the DSM. In the DTM height was determined from the average of a raster cell for points classified as ground. Height value of a raster cell was interpolated, if there were no laser points in the cell area. The raster cell size was set to 30 cm and each cell was georeferenced into a national coordinate system (EUREF-FIN). A canopy height model (CHM) was calculated from the difference of DSM and DTM.

2.3 Digital aerial images

Digital aerial images were taken on the 1st of September in 2005. The used sensor was Intergraph's Digital Mapping Camera (DMC) (Intergraph Corporation, Huntsville, Alabama). Only the data from four parallel multispectral colour cameras of DMC were utilised to form composite images. Each multispectral camera had a resolution of 3072 x 2048 pixels with the pixel size of 12 µm. Focal length of the cameras was 25 mm. The multispectral colour cameras were sensitive in the following spectral bands: Blue (400-580 nm), Green (500-650 nm), Red (590-675 nm), and NIR (675-850 nm). One pixel footprint size on the ground was approximately 0.25 x 0.25 m^2.

2.4 Tree sample data

The dataset used for tree species classification consisted of 294 sample trees. Location and species of each sample tree were verified in the field. In some cases a sample consisted of more than one tree of the same species. In such a case trees in the sample were growing so closely to each other that they had a common canopy. Tree samples were chosen from the three most common tree species (birch, pine, and spruce) in Finnish forests. The total amount of tree samples was 151 birches, 98 pines, and 45 spruces. Samples were chosen so that they represented different ages and sizes of their species. The whole dataset of 294 trees was further divided into a teaching set that consisted of 230 tree samples in total. The remaining 64 tree samples (30 birch, 20 pine, and 14 spruce samples) were used as a test set in classification.

3. METHODS

3.1 Tree crown delineation

Data for each tree sample were manually extracted and registered from ALS data and a digital aerial image. The sample extraction was done using an interactive interface built with Matlab (Mathworks, Natick, Massachusetts). A dataset of a tree sample consisted of several data cells. The position coordinates, elevation, canopy height, RGBIR colour values, visibility to the sensor, and shading status of each data cell were saved. Metadata describing surroundings and the used extraction parameters were also saved for each tree sample in addition to the data stored in data cells.

Height and position values for data cells located in each selected sample canopy were extracted from both the CHM and the DSM. A 3x3 median filter was applied to all CHM and DSM raster cells within the selected canopy. Height values were smoothened to avoid cases, where the laser beam had penetrated the canopy giving a raster cell a low height value compared to its neighbours. Unit normal vectors pointing towards the sun and the camera were also calculated for each data cell after height and position extraction.

3.2 Data cell visibility and shading determination

Different viewing angle geometries were considered after height value extraction. Both DSM and CHM were created as if the viewer would be all time straight above each data cell. In an aerial image each pixel was viewed from a different angle depending on the location of the sensor and the pixel's footprint on ground. This meant that a varying number of data cells in each selected tree sample were not seen by the sensor. This situation is presented in figure **1** (*Left*).

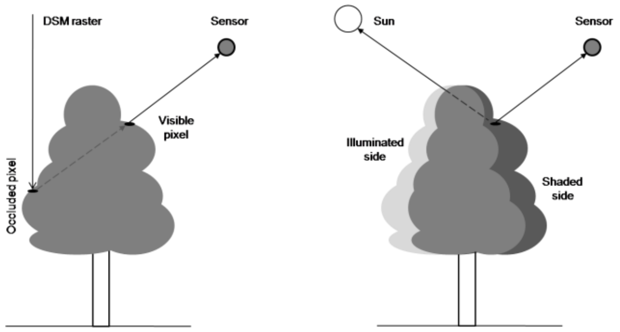

Figure 1: *Left*: Visibility inspection of a cell. *Right*: lllumination status inspection. Details of both procedures are explained in text. Individual raster cells are not shown. Their size was 30 x 30 cm.

A following procedure was done to check whether an extracted data cell was visible to the sensor or not. A vector pointing towards the sensor was drawn from the data cell location. Then the height component of the vector was compared with the height values of all data cells it crossed on xy-plane. If the vector's height component was smaller than the height value of the crossed data cell in the same location, then the original data cell was taken as occluded. The occluded data cell was then discarded after the visibility determination and it was replaced with a new one. The outermost visible cell of the occluding ones was taken as the new data cell. Data cell shifting preserved the amount of data points. The procedure explained above can be written as follows:

$$\mathbf{x} = \mathbf{x}_0 + n * \mathbf{c} \tag{1}$$

$$\begin{aligned} &\textstyle\sum_{i,j}(z(i,j) < z_{DSM}(i,j)) \\ &= \textstyle\sum_{i,j}(z_0 + n * c_z(i,j) < z_{DSM}(i,j)) \\ &= \begin{cases} <= L & \text{, if cell is visible} \\ > L & \text{, cell is occluded} \end{cases} \end{aligned} \tag{2}$$

where $\mathbf{x}$ is the vector pointing towards the camera, $\mathbf{x}_0$ is the data cell location in ground coordinates, $\mathbf{c}$ is the unit vector towards the camera, and the n is the preset amount of iteration steps taken along $\mathbf{c}$ during visibility determination. The n works thus as an effective cutoff range.

The length of a step was set to 30 cm for the test dataset. $z(i, j)$, $c(i , j)$, z_0 and $z_{dsm}(i, j)$ are the corresponding height components in the raster cell point (i, j). L is a preset number of occluding pixels that are blocking the line of sight between the sun and the data cell. It serves as an estimate for transmittance of direct sunlight through canopy. It is used because the rasterized elevation model cannot make a difference between full and partial occlusion. Completely opaque materials would be described with $L = 0$. This means, in terms of L, that even a one blocking data cell in (3) would cause complete occlusion of the original data cell. Same type of visibility determination is also used in true orthophoto generation from several aerial images (Bang et al., 2007).

Individual data cell shading was inspected after the data cell visibility verification. The data cell shading inspection was analogous to that done in visibility verification, but this time the vector drawn from the inspected data cell was pointing towards the sun. If any of the other data cells along the vector's line were higher than the vector's height component in any point, the data cell was marked as shaded. Otherwise the data cell was marked as illuminated. This situation is shown in figure **1** (*Right*). The location of the sun was calculated using the flight time records and a Matlab routine written by (Roy, 2004). The routine uses algorithms presented in (Reda and Andreas, 2003). Shadowing inspection was done only for the direct shading. Transmittance properties of different species and possible diffuse effects were not considered.

In this study, trees were approximated as opaque objects in both visibility and shadow detection. Thus the value of $L = 0$ in both visibility and shading calculations.

3.3 Colour value shading

Colour values were linked to each data cell by registering and extracting them from an original digital aerial image. All colour values for one tree sample were taken from a single aerial image. Registration and extraction were done by calculating the projected location of each data cell on the original image using collinearity equations (Kraus, 1993). These equations are given in (3).

$$\begin{aligned} x &= x_0 - f\frac{r_{11}(X-X_0)+r_{12}(Y-Y_0)+r_{13}(Z-Z_0)}{r_{31}(X-X_0)+r_{32}(Y-Y_0)+r_{33}(Z-Z_0)}, \\ y &= y_0 - f\frac{r_{21}(X-X_0)+r_{22}(Y-Y_0)+r_{23}(Z-Z_0)}{r_{31}(X-X_0)+r_{32}(Y-Y_0)+r_{33}(Z-Z_0)}, \end{aligned} \tag{3}$$

where *(x,y)* is the coordinate of a pixel on the aerial image corresponding the projected cell, *(X,Y,Z)*is the cell location on the DSM, and (X_0,Y_0,Z_0) is the sensor location. f is the focal length of the sensor, and r_{ij} are the elements of the (ω,φ,κ) rotation matrix.

3.4 Feature set selection

Illumination dependent colour channels (IDCC): A new feature set, Illumination Dependent Colour Channels (IDCC), was formed using previously mentioned tree crown delineation, data cell visibility, and shading inspection procedures. These procedures were utilised to divide a tree sample into an illuminated and a shaded part using height information derived from the surface and canopy models. Information from this division was then used for tree species classification.

The IDCC feature set consisted of different combinations of colour channel values and their illumination status, which was either illuminated or shaded. An average of each colour channel was calculated separately for both the lit and the shaded sections of every tree sample. The intensity ratio between the shaded and the illuminated part of the canopy was also calculated for every colour channel. These separations provided a total of 12 features (4 values for illuminated parts, 4 for shaded parts, and 4 intensity ratios) to be used in tree species classification. Different combinations of these features were then tested for the best possible classification result.

A tree sample was removed from its dataset, if it was seen completely illuminated (or shaded). The removal was done, because it was not possible to calculate ratio between illuminated and shaded parts. All trees used in feature set comparisons had both shaded and illuminated sides.

Reference feature set: Another classification procedure presented by Persson et al. (2004) was used as a reference. In this method, tree sample data is filtered so that the brightest 10% of the pixels are used in classification in this method. A normalized unit vector in colour space is formed for every tree sample from the averaged intensities of the green, red and near-IR colour channels. Two angles, azimuth and elevation, are calculated between the colour vector components after the normalization. These two angles are then used as classification features. Classification is done with a quadratic discrimination function. We used this method as a reference as its implementation was straightforward, but we did not use pan-sharpened images which were utilised in the reference article. The colour channel analysis was done with the original multispectral aerial images to preserve extracted colour values as well as possible. The suggested feature extraction procedure was followed otherwise.

Classification methods: The used classification algorithms were quadratic, linear, and Mahalanobis distance based discrimination functions. The classification was done using Matlab Statistics Toolbox.

4. RESULTS AND DISCUSSION

4.1 Classification results

The error matrices for the tree species classification with the proposed and the reference feature sets are in table 1. Only the best cases are shown for each feature set. The best colour channel combination was RGIR in all cases.

The proposed feature set, IDCC, gave the best classification result when a combination of illuminated colour channel values and the ratios between shadowed and illuminated parts of a tree sample was used. Colour information of the shaded data cells were not used on their own. The overall classification percentage with this feature set was 76.6%. Coniferous and deciduous trees were separated from each other with the percentage of 82.8%. These results were achieved with the quadratic discrimination function.

Species wise classification resulted in an overall recognition of 65.6% for the reference method. Separation percentage between conifers and deciduous trees was 71.9%. Best results were achieved using linear discriminant analysis. Both quadratic and Mahalanobis distance using discrimination functions gave notably lower classification results.

We also tested the validity of the proposed method by classifying extracted tree samples using only colour values of original aerial images. The DSM and CHM data were used to delineate tree crowns, but the height information was not used otherwise in classification. The overall classification result was relatively high: 65.6%. The separation result for deciduous and coniferous trees was 76.6%. These results were obtained with linear classification.

4.2 Factors affecting the quality of results

Aerial image data was taken during an afternoon hour in late summer. This means that the sun was already relatively close to the horizon, which leads to lower overall illumination. The low position of the sun caused also more shadowing, both between the trees and their surroundings. The sun position was also changing most rapidly at this time of the year. The solar zenith angle changed 4.6^{o} during flight in the test area. Aerial images were not radiometrically corrected so the sun movement had an effect on colour channel values between different images.

	IDCC (quadratic)			Reference (Persson, 2004) (linear)			Aerial images, no filtering (linear)		
	Birch	**Pine**	**Spruce**	**Birch**	**Pine**	**Spruce**	**Birch**	**Pine**	**Spruce**
Birch	**20**	1	0	**24**	8	4	**22**	3	4
Pine	9	**18**	3	6	**11**	3	8	**17**	7
Spruce	1	1	**11**	0	1	**7**	0	0	**3**
Correct	20	18	11	24	11	7	22	17	3
Total	30	20	14	30	20	14	30	20	14
Ratio	0.667	0.900	0.786	0.867	0.550	0.500	0.733	0.850	0.214
Overall	0.766			0.656			0.656		
Coniferous vs Deciduous	0.828			0.719			0.766		

Table 1: Error matrices of the best results obtained with used methods. Classification type with the best results is given in parenthesis below the name of the method.

The flight time was not optimal from the spectral point of view. Colour of deciduous leaves gets dark green as the leaves grow old during summer as their chlorophyll concentration increases, e.g. (Rautiainen et al., 2009). This darkening makes them to resemble the needles of coniferous trees in used channels. In well illuminated conditions this may not be such a notable issue, but a shadowed dark leaf might get mixed with illuminated needles within the used scale.

Data synchronization between aerial images and elevation models was not exact as there was a month and a half between flights. Tree shapes had changed as the canopies had grown. Canopy shapes could have been affected by the local weather conditions, mainly by the wind. Different wind directions during flights cause notable changes in the canopy shape. Both aerial images and the laser scanning for elevation models need to be taken at the same time for optimal results.

The used classification algorithms may not have performed optimally. The size of the sample tree data was relatively small, only 294 trees in total, and heterogeneous. Variation within the data of all tree species was large with used feature sets and the further separation of data into training and teaching datasets lowered dataset sizes even more.

The spatial resolution of each data cell was quite coarse. This means that the data in each cell represents a general average of the area it is covering. The coarse resolution could also explain why the results of the reference method were similar with those gained from non-filtered, original aerial image data. Heavy colour channel filtering seems to suit better for aerial images with high resolution, like the pan-sharpened images used in the reference article of Persson et al. (2004).

Extracted height values in data cells were mainly interpolated. Within the normally covered DSM region (2−4 laser hits/m^2) approximately 70% of rasterized height values were interpolated, when sides of a raster cell were 30 cm long. In more densely covered areas (10−12 laser hits/ m^2) most of the extracted data cells contained a measured value. However, these point densities seemed to be sufficient for the height resolution, that was needed in shading detection. The classification results showed a clear improvement compared to the cases, where height data were not used. It would be justifiable to study how ALS derived point density scales with the general classification accuracy in this type of measurement.

4.3 Further development

The ALS derived surface models were only utilised to determine shadowing of each tree sample in this study. It could be possible, however, to derive other canopy describing features out of them. Such a new feature could be the general inclination of canopy structure.

The calculation of DSM (and DTM/CHM) has an effect on the shadowed area determination. The extent of the shadowed area depends on the original point density, the process which removes the penetrated hits, and the filtering method applied to the DSM. In practice, the laser always sees the trees smaller in size and height than what they are in reality due to the penetration of the laser hits inside the crown. These effects should be studied further in the future.

5. CONCLUSIONS

A data extraction method (IDCC) for tree species classification was presented and tested in this study. The proposed method gave an improved classification accuracy of 11.0 percentage points, when it was compared with another reference method, namely Persson et al. (2004), and with non-filtered original aerial images. The proposed method was based on using features from the illuminated part and the ratio of the illuminated and shaded parts of each tree sample in classification. A laser derived DSM and colour channel values from aerial images were used to separate the illuminated and shaded parts of each tree. Applied colour channels from aerial images were RGIR. The results are acceptable compared to the reference methods. Feature variations were large for all tree species within the test dataset. The tree samples of each species were of different ages and sizes, and they were located in different growing places with varying surroundings. Even though earlier studies have shown high classification accuracy for boreal forest tree species classification, the practical obtainable accuracy has been from 50 to 70% at individual tree level.

The proposed method can be easily generalized for other types of cameras and hyperspectral sensors. Usage of hyperspectra, especially in the NIR region, should yield more species dependent spectral features to improve a classification procedure. The effects caused by shadow movements during different times of day are accounted as the sun location is known all the time. Radiometric changes due to the sun movement as well as the atmospheric changes need to be noted separately and improvements in radiometry of images are expected to improve the classification results.

ACKNOWLEDGEMENTS

The authors would like to thank Academy of Finland and Tekes for financial support of the projects "Towards improved characterization of map objects", "Improving forest supply chain by means of advanced laser measurements" and "Development of Automatic, Detailed 3D Model Algorithms for Forests and Built Environment".

The authors would also like to thank Leena Matikainen for her help and comments with the surface model generation and writing process.

REFERENCES

Bang, K., Habib, A., Shin, S. and Kim, K., 2007. Comparative Analysis of Alternative Methodologies for True Ortho-Photo Generation from High Resolution Satellite Imagery. American Society of Photogrammetry and Remote Sensing (ASPRS) Annual Conference: Identifying Geo-Spatial Solution, May 7-11, 2007, Tampa, Florida, USA

Bork, E. W. and Su, J. G., 2007. Integrating lidar data and multispectral imagery for enhanced classification of rangeland vegetation: A meta analysis. Remote Sensing of Environment 111, pp. 11 – 24.

Chen, J. M. and Leblanc, S. G., 2001. Multiple-Scattering Scheme Useful for Geometric Optical Modeling. IEEE Transactions on Geoscience and Remote Sensing 39(5), pp. 1061 – 1071.

Franklin, J., Phinn, S. R., Woodcock, C. E. and Rogan, J., 2003. Rationale and Conceptual Framework for Classification Approaches to Assess Forest Resources and Properties. Kluwer Academic Publishers, Boston.

Goetz, S., Steinberg, D. and R. Dubayah, B. B., 2007. Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, USA. Remote Sensing of Environment 108, pp. 254 – 263.

Hall, F. G., Hilker, T., Coops, N., Lyapustin, A., Huemmrich, K. F., Middleton, E., Margolis, H., Drolet, G. and Black, T. A., 2008. Multi-angle remote sensing of forest light use efficiently by observing PRI variation with canopy shadow fraction. Remote Sensing of Environment 112, pp. 3201 – 3211.

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. In: Silvilaser 2008, Sept 17 – 19 Edinburgh, U.K.

Hilker, T., Coops, N., Hall, F. G., Black, T. A., Wulder, M. A. and Krishnan, Z. N. P., 2008. Separating physiologically and directionallyinduced changes in PRI using BRDF models. Remote Sensing of Environment 112, pp. 2777 – 2788.

Hyyppä, J. and Inkinen, M., 1999. Detecting and Estimating Attributes for Single Trees Using Laser Scanner. Photogrammetric Journal of Finland 16(2), pp. 27 – 42.

Kaartinen, H. and Hyyppä, J., 2008. Tree extraction – report of EuroSDR project. In: EuroSDR Official Publication No. 53, Frankfurt a.M., p. 60.

Kaasalainen, S. and Rautiainen, M., 2007. Backscattering measurements from individual scots pine needles. Applied Optics 46(22), pp. 4916 – 4922.

Korpela, I., Tuomola, T., Tokola, T. and Dahlin, B., 2008. Appraisal of seedling stand vegetation with airborne imagery and discrete-return lidar – an exploratory analysis. Silva Fennica 42(5), pp. 753 – 772.

Kraus, K., 1993. Photogrammetry, Volume 1: Fundamentals and standard processes. 4th edn, Dümmler, Bonn.

Maltamo, M., Packalèn, P., Peuhkurinen, J., Suvanto, A., Pesonen, A. and Hyyppä, J., 2007. Experiences and possibilities of ALS based forest inventory in Finland. In: Proceedings of the ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007, Vol. XXXVI, part 3 / W52.

Meyer, P., Staenz, K. and Itten, K. I., 1996. Semi-automated procedures for tree species identification in high spatial resolution data from digitized colour infrared – aerial photography. ISPRS Journal of Photogrammetry and Remote Sensing 51, pp. 5 – 16.

Næsset, E., 1997. Determination of mean tree height of forest stands using airborne laser scanner data. ISPRS Journal of Photogrammetry and Remote Sensing 52(2), pp. 49 – 56.

Næsset, E., 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sensing of Environment 80(1), pp. 88 – 99.

Persson, Å., Holmgren, J., Söderman, U. and Olsson, H., 2004. Tree species classification of individual trees in sweden by combining high resolution laser data with high resolution nearinfrared digital images. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XXXVI - 8/W2.

Rautiainen, M., Nilson, T. and Lükk, T., 2009. Seasonal reflectance trends of hemiboreal birch forests. Remote Sensing of Environment 113(4), pp. 805 – 815.

Reda, I. and Andreas, A., 2003. Solar position algorithm for solar radiation application. Technical Report NREL/TP-560-34302, National Renewable Energy Laboratory (NREL). Revised in Jan 2008, http://www.nrel.gov/docs/fy08osti/-34302.pdf.

Roy, V., 2004. Sun position calculator for Matlab. Available in http://www.mathworks.com/matlabcentral/fileexchange/4605.

Waser,L. T., Ginzler, C., Kuechler, M. and Baltsavias, E., 2008. Potential and limits of extraction of forest attributes by fusion of medium point density lidar data with ADS40 and RC30 images. In: Silvilaser 2008, Sept 17 – 19 Edinburgh, U.K.