Predicting the Plot Volume by Tree Species Using Airborne Laser Scanning and Aerial Photographs

Petteri Packalén and Matti Maltamo

Abstract: Several studies have indicated that forest characteristics can be accurately predicted using airborne laser scanner (ALS) data, but there are very few studies in which species-specific forest characteristics have been estimated. This article compares two approaches for determining species-specific volumes at plot level by combining ALS data with aerial photographs. The first approach consists of two stages: (1) prediction of total volume using ALS data, and (2) assignment of this total volume to tree species by fuzzy classification and aerial photographs, in which three fuzzy classification methods were tested. In the second approach, volumes by tree species and the total volume are predicted simultaneously using a nonparametric k-most similar neighbor (k-MSN) method based on both ALS data and aerial photographs in one phase. The test area, located in Finland, consists of 463 sample plots. Species-specific volumes were estimated for pine, spruce, and the deciduous trees as a species group, total volume being the sum of the species-specific volumes. The k-MSN method produced considerably more accurate estimates for the species-specific volumes than any fuzzy classification method, the relative RMSEs for the volumes of pine, spruce, and deciduous trees being 45.50%, 61.98%, and 92.30%, respectively, and that for the total volume 23.86%. FOR. SCI. 52(6):611–622.

Key Words: Airborne laser scanning, aerial photographs, species-specific volume.

AIRBORNE LASER SCANNER (ALS)-based forest inventory applications have emerged as an interesting and realistic alternative for operative forestry in recent years (see Næsset 2004b), as several studies have indicated that essential forest characteristics, e.g., mean height, basal area, and stand volume, can be accurately predicted using ALS data (e.g., Magnussen and Boudewyn 1998, Lim et al. 2003, Næsset et al. 2004). The costs of ALS data have also decreased considerably (Eid et al. 2004). The two main approaches for predicting forest characteristics using ALS are the laser canopy height distribution approach, usually with low-resolution data (e.g., Næsset 1997, 2002, Lim et al. 2003, Holmgren 2004), and the individual tree delineation (ITD) approach for high-resolution data (Brandtberg 1999, Hyyppä and Inkinen 1999, Persson et al. 2002, Leckie et al. 2003, Popescu et al. 2003, Maltamo et al. 2004). Both approaches have proven to provide competent results in many cases, but most actual forestry applications have so far been based on the former.

The major difference between the laser canopy height distribution and ITD approaches is that the latter relies on the quality of the segmentation of individual trees, whereas the former uses height hits directly at the plot (or stand) level to estimate forest characteristics by means of regression analysis. It should be noted, however, that regression is not the only modeling technique available for predicting forest characteristics directly using laser height hits.

Tree Species Classification

Most laser studies have focused on predicting total forest characteristics, e.g., the total volume or mean height of all tree species, but there are also studies that take tree species into account in the analysis (Törmä 2000, Persson et al. 2003, Holmgren and Persson 2004, Collins et al. 2004, Næsset 2004b). These have not produced final species-specific estimates, however, but only estimates of the tree species proportions or definitions of the main tree species. In addition, as laser data sets alone are not very well suited for tree species identification, they are often combined with aerial images or other optical image material when species-specific information is required. The majority of species classification studies have been made using the ITD approach, in which the unit of classification is quite obvious, a single tree.

Holmgren and Persson (2004) used only ALS data to classify two coniferous tree species, Scots pine and Norway spruce, at the individual tree level, using the structure and shape of the tree crowns to discriminate between the species. The classification turned out to be very reliable in separating pine and spruce, its overall accuracy being 95%. Holmgren and Persson also proposed that the method could be combined with near-infrared aerial photos, which are used to discriminate between coniferous and deciduous tree species. In the first Nordic operational stand-based forest

Petteri Packalén, Faculty of Forestry, University of Joensuu, PO Box 111, FIN-80101 Joensuu, Finland—Fax: 358-13-251-3634; Petteri.Packalen@joensuu.fi. Matti Maltamo, Faculty of Forestry, University of Joensuu, PO Box 111, FIN-80101 Joensuu, Finland—Matti.Maltamo@joensuu.fi.

Acknowledgments: The authors acknowledge Prof Jyrki Kangas and Kauko Kärkkäinen of UPM-Kymmene Ltd. for their support and sponsorship of this research, and Aki Suvanto, Henri Maijala, and Risto Juntunen for collecting the field data. They also thank Dr Perttu Anttila for valuable comments.

Manuscript received January 30, 2006, accepted May 23, 2006

inventory using ALS data, tree species was taken into account as a separate step by prestratification (Næsset 2004b). Visual interpretation of aerial photographs was used to define the main tree species for each stand at the same time as stand delineation was performed.

Calibration of Aerial Photographs

The radiance observed by aerial photographs is affected by several forms of spectral distortion, such as light fall-off effects and bi-directional effects (King 1991, Pellikka 1998, Lillesand et al. 2004). The light fall-off effect is a camera-related spectral distortion that causes the edges and corners to be darker than the center areas of images. It is caused by varying exposure in different parts of the image, and an anti-vignetting filter is used to compensate for it (Lillesand et al. 2004). The bi-directional reflectance effect can be perceived in aerial photographs as a variation in brightness, caused by the fact that the tree crowns in the direction of incoming radiation expose their shady sides to the camera and those in the opposite direction their illuminated sides (Holopainen and Wang 1998).

Two approaches have been adopted to correcting illumination effects: physical or empirical modeling. The purpose of physical modeling is to find a bi-directional reflectance function (BRDF) that describes the underlying mechanism of the effect (see Suits 1972, Li and Strahler 1986, Nilson and Kuusk 1989, Leblanc et al. 1999). BRDF modeling is more often applied to satellite data than to airborne images (Leckie et al. 1995), and is rarely used in forestry applications because of its complexity (Tuominen and Pekkarinen 2004) and because the radiative transfer models used to define the physical correction function require knowledge of a set of parameters that are not immediately accessible to the user (Beisl and Woodhouse 2004). Several empirical and semi-empirical methods have been developed and tested in aerial photo-based forest inventories, however (see Holopainen and Wang 1998, Pellikka et al. 2000, Tuominen and Pekkarinen 2004). One advantage of empirical models is their simplicity and suitability for operational use, whereas one disadvantage is that they often, but not always, require a priori knowledge of the surface types in the inventory area (Tuominen and Pekkarinen 2004). Despite difficulties in correcting illumination effects in aerial photographs, it is essential to reduce these anomalies for the purposes of computer-aided interpretation of image mosaics.

Nonparametric Regression

One alternative for generalize information would be to use nonparametric methods (Altman 1992), the most frequently applied being the k-nearest neighbor method (Kilkki and Päivinen 1987). This requires that the form of the similarity (or distance) measure be specified to define the neighborhood of a given point. Similarity measures based on absolute differences or Euclidean or Mahalanobis distance functions have typically been used. One important special case is the most similar neighbor (MSN) method, in which similarity is based on canonical correlations and Mahalanobis distance (Moeur and Stage 1995). The benefit of the MSN method is that the similarity measure can be solved analytically. The k-MSN method is the same as MSN except that it takes the *k* nearest observations into account.

Nonparametric methods have been used for a number of purposes in forestry, including generalization of sample tree information, diameter distribution models, different growth and yield models, forest area estimation, and applications of multisource and multivariate forest inventories (Kilkki and Päivinen 1987, Moeur and Stage 1995, Maltamo and Kangas 1998, Franco-Lopez et al. 2001, Malinen et al. 2001, Sironen et al. 2001, McRoberts et al. 2002, Tomppo and Halme 2004, LeMay and Temesgen 2005).

Fuzzy Classification

In the context of pattern recognition, a pattern is a vector of features describing an object. In remote sensing, these features are usually spectral reflectance values at different wavelengths and certain other image-derived features such as texture metrics. The aim of pattern recognition is to create a relationship between a pattern and a class of objects. The relationship between an object and its class may be of a one-to-one kind, producing a hard classification, or of a one-to-many kind, producing a fuzzy classification. The conventional classification of remote sensing data is regarded as hard classification because the final outcome is a class (e.g., forest type) for each object (normally a pixel) (Tso and Mather 2001).

A fuzzy classification does not force each object to belong to a single class. Instead, it allows multiple and partial class memberships among the candidate classes (Wang 1990, Foody et al. 2003). Thus, a membership value between 0.0 and 1.0 is assigned for every class with respect to each object, so that these values generally sum to 1.0 across all the candidate classes. From a probabilistic viewpoint the membership value can be looked on as the probability of the object belonging to a particular class (Foody et al. 2003). There are a number of classification techniques that may be used to derive fuzzy membership values, the most frequently used being probabilistic classifiers, artificial neural networks, and methods based on fuzzy set theory (Foody 1992, 1996, Tso and Mather 2001). Note that the term fuzzy classification (also known as soft classification) is used here as a generic term and does not refer exclusively to fuzzy sets.

Objectives

ALS produces a point cloud for which the *x*, *y*, and *z* coordinates are known. Although these height hits can be related very accurately to many forest stand and tree level attributes, ALS data as such do not provide sufficient information about tree species. As aerial photos provide information about tree species, it makes sense to combine aerial photos and ALS data to predict species-specific characteristics. The objective of this research was therefore to test different approaches and their accuracies in predicting species-specific volumes at the plot level using a combination of ALS data and aerial photos. Two modeling principles were explored, the first consisting of two steps, (1) prediction of total volume using ALS data, and (2) assignment of this total volume to tree species using fuzzy classification and aerial photos, and the second of simultaneous prediction of volumes by tree species and total volume by the nonparametric k-MSN method, using both ALS data and aerial photographs in one phase.

Materials

Test Area

The Matalansalo test area is a typical managed boreal forest area in Finland. It is located near the city of Varkaus in eastern Finland and is owned by forest industry company UPM-Kymmene, Ltd. The area is dominated by coniferous tree species, with Scots pine (*Pinus sylvestris* L.) the main tree species on 59% of the plots and Norway spruce (*Picea abies* [L.] Karst.) on 34%. Deciduous trees, mainly downy birch (*Betula pubescens* Ehrh.) and silver birch (*Betula pendula* Roth.), are usually in the minority. The development classes consist of young (27%), middle-aged (42%), and matured (31%) stands, while the proportions of the site fertility classes are grass-herb sites (Oxalis-type) 2%, moist sites (Myrtillus-type) 48%, dry sites (Vaccinium-type) 42% and poor sites (Calluna-type) 8%.

Field Measurements

A network of 463 circular sample plots of radius 9 meters distributed over 67 forest stands was established in the test area in summer 2004. The stand level as such was not used in this particular study, however. Differential global positioning systems (GPS) (Trimble Pro XRS) were used to determine the position of the center of each plot. The accuracy of the positioning in the *xy* direction was approximately 1 m. The dbh, tree and story class, and tree species were measured for each tree with dbh greater than 5 cm, and height for one sample tree of each species and story class on each sample plot, whereupon the height models of Veltheim (1987) were used to calculate the heights of the rest of the trees. Height measurements were used to calibrate the height model. The species-specific volume models of Laasasenaho (1982), based on dbh and tree height, were used to calculate tree volumes. Finally, species-specific volumes per hectare were determined.

The sample plots were divided into two parts, for use as modeling data (265 plots) and test data (198 plots). This division was carried out by selecting approximately 60% of the plots in each stand for the modeling data set and the rest for the test data set, without any particular order. Separate data sets were used because cross-validation was not applicable to fuzzy classification. The tree species recognized here are pine, spruce, and deciduous trees. All the deciduous species were lumped together because it was known beforehand that it is almost impossible to distinguish between them in remote sensing under Finnish conditions, where the forests are dominated by coniferous tree species and birch accounts for the bulk of the deciduous trees. Plot volumes for the modeling and test data sets and proportions of the dominant tree species are presented in Table 1. Since 247 of the 265 plots in the modeling data set and 181 of the 198 in the test data set contained at least two tree species, over 92% of the plots can be considered to represent mixed forest.

ALS Data

The ALS data for the Matalansalo test area were collected at night on Aug. 4, 2004 using an Optech ALTM 2033 laser scanning system operating at an altitude of 1,500 m above ground level (agl) with a flight speed of 75 ms^{-1} and using a half-angle of 15° (i.e., the field of view was 30°). This resulted in a swath width of 800 m and a nominal sampling density of about 0.7 measurements per square meter. The divergence of the laser beam (1,064 nm) was 0.3 mrad, which produced a footprint of 45 cm at ground level. Altogether, seven laser strips were measured with an overlap of 35%, and both the first and last pulse data were recorded. The area covered by the ALS data was approximately 20 km^2.

The ALS data were further used to generate a digital terrain model (DTM). The first step required to interpolate this is to classify the laser points as ground and nonground hits. This was done using the TerraScan software (method explained in Axelsson 2000). A raster DTM with a pixel size of one meter was then created from the ground points

Table 1. Means and standard deviations of stem volumes and proportions of dominant tree species on the sample plots

V, m^3 ha^{-1}	Pine	Spruce	Deciduous	Total
Modeling data				
Mean	95.85	92.54	22.06	210.45
Standard deviation	90.05	119.27	36.34	105.21
Dominant tree species (%)	55.85	37.36	6.79	
Test data				
Mean	99.51	76.14	21.53	197.19
Standard deviation	82.94	105.36	36.55	100.39
Dominant tree species (%)	60.10	32.32	7.58	

Figures are presented separately for pine, spruce, deciduous, and all tree species as a whole. Modeling data consist of 265 sample plots and test data 198 sample plots.

by taking the mean height of the ground hits within each cell. Missing values in the DTM were interpolated afterward using Delaunay triangulation and bilinear interpolation.

Optical Image Material

The aerial photographs were captured on a color-infrared film to a scale of 1:30,000. As the film was sensitive to visible and near-infrared light, it recorded the green, red, and near-infrared portions of the spectrum. The photographs were taken with a Leica RC30 camera using a UAGA-F 13158 objective with a 163.18 mm focal length and anti-vignetting filter (AV525 nm). The films were digitized at a resolution of 14 μm with a Leica DSW600 film scanner and then ortho-rectified and resampled to a pixel size of 0.5 m. The DTM generated from the ALS data was used in the ortho-rectification. The test area was covered with three aerial photographs, acquired on July 22, 2004. The Landsat 7 ETM scene used for radiometric correction of the aerial photographs had been captured on June 16, 2002. Since it was known beforehand that there had been no logging in the test area in 2002–2004, the 2-year time difference between the acquisition dates of the aerial photographs and the Landsat scene is insignificant.

Methods

Processing of Aerial Photographs

The digitized aerial photographs were corrected radiometrically by the method presented by Tuominen and Pekkarinen (2004), in which the idea is to correct anomalies caused by the bi-directional reflectance effect using a local adjustment method and image material that is less affected by the bi-directional effect. The bi-directional reflectance-affected intensities of the aerial photographs were adjusted to the local intensities of a reference image, in this case the Landsat 7 ETM, as its BRDF effect is insignificant relative to that of aerial photos. The correction was made band-by-band using the approximately equivalent Landsat ETM channel to correct the corresponding aerial photograph channel (ETM2 for green, ETM3 for red, and ETM4 for NIR). The correction formula is defined as (Tuominen and Pekkarinen 2004)

$$\hat{f}_{\mathrm{AP}_i}(x, y) = \frac{\bar{f}_{\mathrm{ETM40}i}}{\bar{f}_{\mathrm{AP40}i}} f_{\mathrm{AP}i}(x, y), \quad (x, y) \in I, i = 1, \ldots, n, \tag{1}$$

where $\hat{f}_{\mathrm{AP}_i}(x, y)$ is the adjusted value of the pixel (x, y) of channel i on aerial photograph I, $\bar{f}_{\mathrm{AP40}_i}$ is the mean value of aerial photograph within a moving circle centered around a pixel (x, y) with a radius of 40 m on channel i, $\bar{f}_{\mathrm{EMT40}_i}(x, y)$ is the mean Landsat 7 ETM value within a moving circle centered around a pixel (x, y) with a radius of 40 m on channel i, $f_{\mathrm{AP}_i}(x, y)$ is the value of the pixel of channel i in the original aerial photo, and n is the number of channels. Equation 1 does not change the shape of the histogram within a moving circle, it only transfers the location of the histogram. The benefit of this method is that it does not require any a priori information on the surface of the study area (Tuominen and Pekkarinen 2004).

The spectral values and textural features calculated from the calibrated aerial photographs were used as predictor variables in the subsequent analysis. The textural features were calculated from the gray-tone spatial-dependence matrix on the principle presented by Haralick et al. (1973). These textural features have been widely used in remote sensing during recent decades (see Haralick et al. 1973, Weszka et al. 1976, Franklin and Peddle 1990, Marceau et al. 1990, Muinonen et al. 2001, Coburn and Roberts 2004, Tuominen and Pekkarinen 2005). There are a large number of parameters to consider when selecting how to calculate textural features, among which at least the following need to be considered (Franklin et al. 2000, Tuominen and Pekkarinen 2005):

- Number of requantification classes
- Pixel size
- Window size
- Direction
- Lag (distance)
- Channel and channel transformations
- The texture measure itself.

Textural features were calculated for each channel and for NDVI transformation with different numbers of requantification classes and lag distances using a pixel size of 0.5 m. All the texture measures were calculated as average of all directions (0°, 45°, 90°, and 135°). As it would have been impossible to test all potential parameter combinations, the set of combinations had to be reduced somehow. Unfortunately, there is no unambiguous way of resolving which of these combinations should be used. Thus the reduced set of textural features to be used here was selected based on previous studies (e.g., Tuominen and Pekkarinen 2005), correlation analysis (Pearson product moment correlations and Spearman rank correlations) and discriminant analysis. Correlation analysis was used to evaluate the parameter combinations in relation to species-specific volumes, and a stepwise discriminant analysis was performed to determine which combinations of texture measures were best able to discriminate between spruce and pine. The final textural features were calculated using 16 requantification classes and a lag distance of 2.5 m, although these parameters had a minor influence on the result. The features of the aerial photographs selected for use in the subsequent analysis are listed in Table 2. Instead of using the often-used moving window technique to calculate textures around the local neighborhood of each pixel, all the textural features were extracted directly from the circular sample plot with a radius of 9 meters, i.e., the window size was equal to the size of the sample plot.

Processing of ALS Data

The orthometric laser scanning heights were converted to above ground heights (i.e., canopy heights) by subtracting

Table 2. Spectral and textural features of the aerial photographs used in the analysis

Channel	Feature
Green	Mean value
Red	Mean value
NIR	Mean value
NDVI	Entropy
NDVI	Sum of squares: Variance
NIR	Contrast
NIR	Inverse difference moment
NIR	Difference entropy
NDVI	Sum average
NIR	Sum average
NDVI	Difference variance

The textural features are described in detail in Haralick et al. (1973).

the DTM at the corresponding location. The ground hits were excluded by assuming that any point whose canopy height is less than 2 meters is a ground hit and the remaining points are canopy hits. After that the first and last pulse height distributions for each sample plot were created from the canopy height hits. Numerous height and density metrics have been derived from these distributions in previous studies (see Næsset 2002). Percentiles for the canopy height were computed for 5, 10, 20, . . . , 90, 95, and 100% (h_5, . . . , h_{100}) (see Næsset 2004a), proportional canopy densities (p_{05}, . . . , p_{100}) were calculated for these quantiles. In addition, the proportions of canopy hits versus ground hits were determined (0–100%). All metrics were calculated separately for the first and last pulse data and used as predictor variables in the subsequent modeling of species-specific volumes.

Fuzzy Classification-Based Volume Estimation

The estimation of species-specific tree volumes based on fuzzy classification consisted of two separate phases. First the total volume of all tree species was predicted using solely the ALS data, and after that the total volume was divided into tree species using features from the aerial photographs and fuzzy classification. Thus the species-specific volume estimates were obtained by multiplying the total volume by the proportion of each tree species. Note that the methods used to derive the proportion of tree species guarantee that the proportions for a single observation always sum to 1.0, and therefore the species-specific volumes sum to the total volume.

Linear mixed-effect modeling was used to estimate the total volume because there a hierarchical structure (forest stands, sample plots) existed in the study design (Searle 1971, Venables and Ripley 2002). A stepwise selection procedure based on the Akaike information criterion (AIC) was used to identify an appropriate set of predictors among the ALS-based variables. The plot volume was modeled as

$$V_{ij} = X\beta + s_i + e_{ij}, \quad (2)$$

where V_{ij} is the volume (m^3 ha^{-1}) of plot j in stand i, X is a matrix of ALS-based explanatory variables, β is the fixed-effects parameter vector, s_i is the random stand variable ($s_i \sim N(0, \sigma_s^2)$) and e_{ij} is the random error term ($e_{ij} \sim N(0, \sigma_e^2)$). The parameters of the models were estimated using the restricted maximum likelihood (REML) method in an *R* environment (Venables and Ripley 2002).

The proportions of the tree species in the sample plots were calculated as ratios of the species-specific volumes and used as signatures to train classifiers. The signatures are not pure examples of each class, e.g., pine plot or spruce plot, however, because there are usually many tree species on one sample plot. Hence the training data consisted of different grades of membership of each class in each sample plot, where degree of membership is equivalent to the proportion of the given tree species in the plot. To overcome the problem of noncategorical signatures, an approach presented by Wang (1990) was used that takes into account the fuzziness of signatures and enables the use of partial class memberships. Each training observation (modeling plot) is given a weight proportional to its degree of membership in the estimation of the mean, variance and covariances for each class (tree species). The final signatures then contain exactly the same information as traditional pure signatures (for more details, see Wang 1990).

Numerous feature sets were tested in the fuzzy classification to find the best combination (see Table 2), the number of features varying from three to six and also including combinations in which only textural or spectral features were present. Three fuzzy classification approaches were studied: a posteriori probabilities of maximum likelihood (ML) classification, fuzzy classification based on the underlying logic of fuzzy sets (FZ) and linear mixture modeling (LMM). ML classification is based on an estimated conditional probability for each class and relies on Bayesian probability theory and an assumption of normality (i.e., the probability of occurrence is the same for all object features). Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the co-variance matrix (Zhang and Foody 1998, Lillesand et al. 2004). Still assuming normality, the conditional probability of observation x_i belonging to class w_j is given by

$$P(x_i|w_j) = \frac{1}{\sqrt{2\pi^{\rho}}\sqrt{|C_j|}} \exp\left(-\frac{1}{2}(x_i - \mu_j)^T C_j^{-1}(x_i - \mu_j)\right), \quad (3)$$

where C_j is the covariance matrix of class w_j with the dimension ρ, μ_j is the mean vector of class w_j, and $|x|$ denotes the determinant (Tso and Mather 2001). ML classification also enables the use of prior probabilities of belonging to a class, but uniform probabilities were assumed here.

A fuzzy set classifier (FZ) allows partial membership, in that one data element (observation) may simultaneously attain several nonzero degrees of membership for different classes (Tso and Mather 2001). FZ classification thus provides a good basis for tree species decomposition. It can be characterized by a membership function μ_G:*s*, which assigns a degree of membership within the interval [0, 1] to each element s. Fuzzy set membership was calculated here using the standardized Euclidean distance from the mean of the signature by means of a sigmoidal membership function (Eastman 2001). The underlying logic is that the degree of membership at the same location as the mean of the signature must be 1.0. As distance increases, fuzzy set membership decreases, until it reaches the user-defined Z-score distance at which it is 0.0. After preliminary testing, a Z-score value of 1.96 was selected, corresponding to a distance of one SD from the class mean.

LMM is the most commonly used technique for spectral mixture analysis (Settle and Drake 1993). Its principle is close to that of the fuzzy methodology, i.e., it provides an alternative way of determining the proportions of ground cover components. LMM uses a set of end members that represent pure information classes, e.g., a pure pine or pure spruce plot. All mixtures present in the image can be formed by mixing these end members (Tso and Mather 2001). Moreover, LMM assumes that the mixture of ground cover components will lead to a signature that is an aggregate of the constituent components. On the above assumptions it is possible to estimate the proportions of each end member, and as the end members represent pure information classes, the proportion of an end member is same as the proportion of its information class, e.g., the proportion of pine (Eastman 2001). A detailed description of spectral unmixing techniques is given in Tso and Mather (2001).

k-MSN-Based Volume Estimation

The k-MSN method uses canonical correlation analysis to produce the weighting matrix used to select of the k most similar neighbors from the reference data, i.e., observations, which are similar to the target of prediction in terms of the predictor variables. By using canonical correlations it is possible to find the linear transformations U_k and V_k for the set of dependent variables (Y) and independent variables (X), which maximizes the correlation between them:

$$U_k = \alpha_k Y, \quad \text{and} \quad V_k = \gamma_k X, \tag{4}$$

where α_k represents the canonical coefficients of the dependent variables and γ_k the canonical coefficients of the independent variables. U_k and V_k are ordered in such a manner that the canonical correlation is largest for $k = 1$, second largest for $k = 2$, etc. The predictive power is thus concentrated in the first few canonical components.

The MSN distance metric derived from canonical correlation analysis is

$$D_{uj}^2 = \underset{1\times p}{(\mathrm{X}_u - X_j)}\, \underset{p\times p}{\Gamma\Lambda^2\Gamma'}\, \underset{p\times 1}{(X_u - X_j)'}, \tag{5}$$

where X_u is the vector of the known search variables from the target observation, X_j is the vector of the search variables from the reference observation, Γ is the matrix of canonical coefficients of the predictor variables, and Λ is the diagonal matrix of squared canonical correlations. The original MSN article by Moeur and Stage (1995) gives an excellent in-depth discussion of the MSN procedure.

The k-MSN method is the same as MSN except that an estimate for the target observation is calculated as a weighted average of the k nearest observations instead of from the nearest observation alone. The weighting was based on the inverse of the MSN distance. The weight W_{uj} of a reference plot u for the target plot j was calculated as

$$W_{uj} = \frac{1/D_{uj}^2}{\sum_{1}^{k} \frac{1}{D_{uj}^2}}, \tag{6}$$

where k is the number of nearest observations. Theoretically, a division by zero may occur in Equation 6 if the MSN distance between the reference and target observations is exactly zero. In such a case a very small factor is added to the distance. No zero distance occurred in the present material, however. A pseudo-optimal value for k was searched for heuristically by means of iterations. As plots within the same stand will be closely correlated, the nearest neighbors were never taken from the same stand as the target plot to avoid excessively optimistic results.

One advantage of the k-MSN method is that it enables the simultaneous modeling of multiple dependent variables, a feature used in this study. The volumes of pine, spruce, and deciduous trees are modeled simultaneously and the total volume is calculated as the sum of the species-specific volumes. All the predictor variables, both those based on the ALS data and those from the aerial photographs, are used in the estimation.

Reliability Characteristics

The reliability of the volume estimates was tested on a separate test data set, and reliability characteristics were calculated for the estimates for each tree species and for the total volume. The accuracy of the estimates at the sample plot level was expressed in terms of the RMSE:

$$\mathrm{RMSE} = \frac{\sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}}{n}, \tag{7}$$

where n is the number of sample plots, y_i is the observed volume for plot i, and $\hat{y}_i$ is the predicted volume for plot i. The biases were calculated as

$$\mathrm{bias} = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)}{n}. \tag{8}$$

Moreover, the relative RMSE values and biases were computed by dividing the absolute values (7, 8) by the true mean of the volume concerned.

Results

Volume Models and Feature Selection

Various combinations of features derived from the aerial photographs, ranging in number from three to six and including combinations representing only textural or spectral features, were tested in the fuzzy classification. The sets that had only textural or spectral features did not produce results as good as those with both types. There seems to be a clear dependence of the NIR band on the abundance of deciduous trees, and a similar relationship was observed concerning the red band, so that the best estimate for the deciduous volume is obtained when both the NIR and red bands are included in the analysis (Table 3). It was also perceived that textural features are useful for discriminating between the coniferous tree species. The texture metrics used in the final models were most often calculated using the NIR band. Stepwise selection of the ALS variables used in the fuzzy classification-based total volume model resulted in three variables: the proportion of first pulse vegetation hits, the canopy density corresponding to the proportion of last pulse laser hits above the 30% quantile, and the quantile corresponding to the 60th percentile of the first pulse laser canopy heights (Table 3). Due to the logarithmic transformation a bias correction is required, while to obtain an unbiased prediction, a half of the estimate for the error variance must be added to the prediction before back-transformation.

The same observations as were made above regarding the predictive power for discriminating tree species also apply to the k-MSN analysis, but due to the modeling technique, the input-output relationship is not as evident as it is in fuzzy classification. Predictor variables for the k-MSN model were selected manually using insertions and deletions iteratively, i.e., a variable or group of variables was inserted into the model or removed from it and the best combination of variables was selected on the basis of the RMSE. Since it was not difficult to select a combination of variables in which the accuracy of the pine and spruce estimates was sufficient, the selection focused mainly on minimizing the RMSE of the volume of deciduous tree species. Bias was also considered in the selection of variables, although it was not a serious problem at any point in the k-MSN method. The final model contained the mean values for the NIR and red bands, two texture variables and numerous laser variables (Table 3).

Accuracy of Volume Estimates

The k-MSN method produced considerably more accurate estimates of species-specific volumes than any fuzzy classification method (Table 4), the relative RMSE values for the volume of pine, spruce, and deciduous trees being 45.50%, 61.98%, and 92.30%, respectively, where the corresponding figures for the best fuzzy classification-based method, ML, were 62.87%, 81.41%, and 148.75%. The other fuzzy classification methods, FZ and LMM, yielded highly imprecise estimates.

The relative RMSE of the total volume was 18.88% for the methods based on fuzzy classification and 23.86% for the k-MSN method. Thus the precision of the fuzzy classification approach, in which the total volume is predicted beforehand using mixed model regression, is slightly better than that of the k-MSN method, in which the total volume is obtained by summing the species-specific volumes. Note that in both approaches the sum of the species-specific volumes logically gives the total volume.

The biases were also considerably higher in the fuzzy classification approaches than in the k-MSN method (Table 4). ML was the only fuzzy classification method that produced fairly unbiased estimates, except for deciduous trees. The FZ method resulted in a vast underestimate for pine and a corresponding overestimate for deciduous trees with all the Z-score parameters tested, while the biases of the species-specific estimates in the k-MSN method were minor for pine (1.91%) and deciduous trees (3.51%); only the volume of spruce (−9.92%) was moderately overestimated. The bias of the total volume was lower in the fuzzy classification approach (−1.48% versus −2.48%) than in the k-MSN method, although the level of bias was acceptable.

Due to the obvious bias and impreciseness, the residuals of the fuzzy classification-based estimates were not evenly distributed, except in the case of regression-modeled total volume. Instead, the residuals of the k-MSN based estimates were well distributed. Measured versus predicted volumes for the k-MSN method are depicted in Figure 1. There is a great deal of scatter in the species-specific estimates, but the

Table 3. Volume models and predictor variables

Fuzzy classification-based volume model	
Total volume model	$\ln(V) = 2.100 - 0.0116f\_pgh - 0.00995l\_p30 + 1.452 \ln(f\_h60) + \delta^2/2$
	The prefix *f* or *l* denotes the laser pulse type: first or last pulse, *pgh* refers to the proportion of ground hits, *p*30 refers to canopy density corresponding to the proportion of laser hits above the 30% quantile, *h*60 denotes the height at which 60% of the height distribution has accumulated. The variance estimate (δ_s^2) for a random stand variable is 0.0067 and that (δ_e^2) for the random error is 0.0248. The bias correction δ^2 ($\delta_s^2 + \delta_e^2$) is 0.0315.
Classification variables	mean_{NIR}, mean_{RED}, var_{NDVI}, idm_{NIR}, cont_{NIR}
	The subscript denotes the band, mean = mean intensity, var = sum of squares: variance, idm = inverse difference moment, cont = contrast.
k-MSN-based volume model	
Predictor variables	$\ln(\text{mean}_{NIR})$, $\ln(\text{mean}_{RED})$, $\ln(\text{cont}_{NIR})$, $\ln(\text{savg}_{NIR})$, $\ln(f\_h20)$, $\ln(f\_h60)$, $\ln(f\_h95)$, $\ln(l\_h10)$, $\ln(l\_p30)$, $\ln(l\_p70)$, $\ln(f\_pgh)$
	The subscript denotes the band, mean = mean intensity, cont = contrast, savg = sum average, *f* or *l* denotes the laser pulse type: first or last pulse, *p*30 refers to the canopy density corresponding to the proportion of first or last pulse laser hits above the 30% quantile, *h*20 denotes the height at which 20% of the height distribution has accumulated, *pgh* = proportion of ground hits.

Table 4. Accuracy of the volume estimates by tree species and the total volume estimate

	RMSE (m^3)				RMSE (%)			
	Pine	Spruce	Decid.	Total	Pine	Spruce	Decid.	Total
ML	62.57	61.99	32.03	37.22	62.87	81.41	148.75	18.88
FZ	83.32	61.18	62.26	37.22	83.73	80.35	289.19	18.88
LMM	79.44	86.68	57.13	37.22	79.83	113.83	265.36	18.88
k-MSN	45.28	47.20	19.87	47.05	45.50	61.98	92.30	23.86
	Bias (m^3)				Bias (%)			
ML	1.39	8.15	−12.46	−2.92	1.40	10.70	−57.87	−1.48
FZ	51.74	−2.17	−52.50	−2.92	52.00	−2.85	−243.85	−1.48
LMM	24.53	−16.18	−11.28	−2.92	24.65	−21.25	−52.39	−1.48
k-MSN	1.90	−7.55	0.76	−4.90	1.91	−9.92	3.51	−2.48

ML = maximum likelihood classification, FZ = fuzzy classification, LMM = linear mixture modeling, and k-MSN = k-most similar neighbor.

trend is predicted very well. In addition, summing of the species-specific estimates produces an accurate estimate for the total volume.

Discussion

The aim of this study was to test two approaches to predicting volume by tree species from ALS data and aerial photographs, the first consisting of two steps, prediction of the total volume using ALS data and its assignment to tree species using aerial photographs and fuzzy classification, in the context of which three fuzzy classification methods were tested, and the second predicting volumes by tree species simultaneously using the nonparametric k-MSN method and obtaining the total volume as a sum of species-specific estimates. Hence, the species-specific volumes add up logically to the total volume in both approaches.

The primary conclusion to be drawn here is that the k-MSN method produced much more precise estimates of species-specific volumes than any fuzzy classification method. Although there is still a great deal of imprecision in the k-MSN estimates, a very favorable characteristic is that the species-specific estimates sum up to the accurate total volume without notable bias. It must also be taken into account that the results are presented at the plot level, and would be considerably better at the stand level (e.g., Næsset 2004a), i.e., calculated using a grid-based approach (Næsset et al. 2004).

It is obvious that the manner in which the FZ and LMM methods were used here is not suitable for estimating species-specific volumes, as both produced imprecise and highly biased estimates. ML was the best fuzzy classification method studied, but it still produced biased and imprecise estimates compared with the k-MSN method. The principle in which the total volume is predicted in advance in a separate step and later divided into species classes may nevertheless be valid. More advanced classification methods, e.g., certain nonlinear fuzzy classifiers, should be tested, and the use of fuzzy signatures also requires further investigation.

One obvious reason why the volume of deciduous trees was more difficult to estimate than that of spruce and pine is that deciduous trees do not usually occur in the dominant canopy layer in the test area, as site fertility conditions and the favoring of coniferous tree species in past silvicultural operations in Finland act against them. It is almost impossible to estimate the characteristics of nondominant tree layers using remote sensing techniques. Other reasons for the lack of accuracy of the volume of deciduous trees are the sparse modeling data, which did not contain a representative set of plots in which deciduous trees were dominant, and the difficulty of estimating a characteristic that is abundant only in a minority of the plots. Because a realistic description of the tree species composition was desired, the tree species composition of the sample plots should be approximately the same as the actual tree species composition of the area. Specifically choosing plots where deciduous tress species dominated would potentially distort the results, e.g., if the data were to contain considerably more deciduous trees than are present in the actual species composition of this particular area.

The selecting of predictor variables is an essential part of the solution, and there are also numerous parameters to consider during the modeling chain. It was assumed here that texture measures discriminate between spruce and pine, and therefore the texture metrics and parameters used to derive these metrics were selected in such a manner that the maximum discrimination between these species could be achieved. Correspondingly, it was assumed that spectral values, especially the NIR channel, are effective in differentiating between deciduous and coniferous tree species, and the aerial photographs were calibrated with this in mind. Furthermore, the ALS height and density metrics were assumed to be good predictors of the volume itself, and this required certain parameter decisions as well. Thus there are many stages at which selections must be made with regard to a parameter value or a metric itself. For instance, there are numerous possibilities for calculating texture metrics, and not all the combinations can be tested in the final model. The set of predictors must be reduced somehow beforehand, i.e., to select valid metrics and the best parameters for this particular model. How the selection is done is a key component of the accuracy of the final model.

The ALS sampling density of about 0.7 measurements

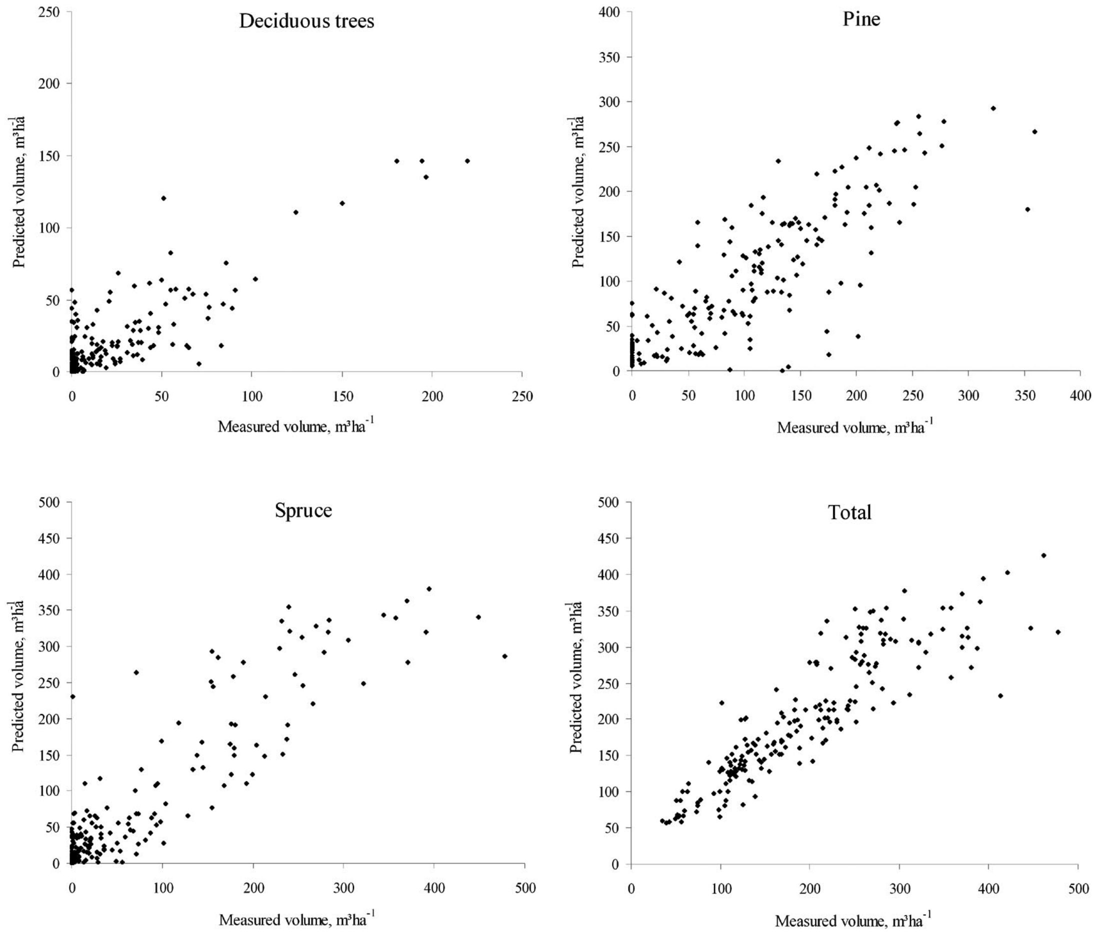

Figure 1. Measured versus predicted volumes by tree species and total volume, using the k-MSN method.

per square meter used here can be considered rather low, but it has the obvious advantage of being cost-effective to acquire. It has been shown, however, that a point density of one measurement per square meter or even lower can produce an accurate volume prediction (Holmgren 2004, Maltamo et al. 2006), and it is this level that is used in operational ALS-based forest inventories (Næsset 2004b).

In the present case the total volume was estimated accurately and it is unlikely that a higher point density would have improved the results to any substantial extent. A higher point density may be useful to discriminate between tree species, but this probably requires an individual tree delineation approach. The aerial photographs used here are similar to those regularly used in stand delineation, and as these images are needed anyway, they do not introduce any additional costs into the inventory system. Nevertheless, a higher spatial resolution than the 50 cm used here could improve the results, as the texture metrics, for instance, are sensitive to pixel size. Furthermore, digital aerial cameras are becoming more common all the time, which will presumably improve the radiometric characteristics of future aerial images, and thereby the discrimination of tree species as well.

Choice of the proper nearest neighbor estimator requires comprehensive modeling data. It is also important that the modeling data should cover the whole range of variability: otherwise, as nearest neighbor methods cannot be extrapolated, extremely high values are underestimated and extremely small values overestimated. The number of observations required in the modeling data is always a problem-specific issue. In the authors' experience a few hundred observations are a minimum for predicting forest characteristics. Therefore, the 265 sample plots used here as a modeling data set cannot be considered optimal. In addition, the necessary number of observations is higher in the case of multiple dependent variables than in a modeling scheme in which only one variable is to be predicted. When species-specific volumes are to be predicted, for example, accurate prediction requires that comparable observations should exist in the modeling data in terms of all the tree species. In this research the modeling data did not contain many plots on which deciduous trees were dominant, and this restricted the accuracy.

The k-MSN method proved to be a promising approach for estimating species-specific volumes using ALS data and aerial photographs, although the selection of predictor variables requires further development. As species-specific volumes and total volume are estimated simultaneously, there cannot be just one goal or criterion for selecting the best predictor variables. It is always up to the user as to how much importance is given to different target variables. Here the volume of deciduous trees was given more weight than the other target variables because this was clearly the most difficult variable to estimate. Thus preference was given to insertions or deletions of predictor variable that improved the accuracy of deciduous trees and other target variables, or at least did not reduce the accuracy of other target variables to any appreciable degree. Different combinations of variables were tested manually in this work, which was fairly time-consuming due to the large number of candidate predictors and their transformations. The outcome is still more or less subjective, however, due to the lack of strict decision rules as to how to accept the insertion or deletion of a candidate predictor. However, because the k-MSN method enables rapid iteration with alterations in the subset of predictors, it would be possible to implement a heuristic algorithm for stepwise optimization of the RMSE. This should take into account the multiple criteria nature of the problem and the ability of the k-MSN method to predict other stand characteristics as well should be verified.

The role of species-specific results is very important in Finnish forestry. In the current inventory system by compartments, stand characteristics are assessed by species in the field. Furthermore, stand volume and future development are predicted using tree-level species-specific models. Finally, information concerning the end products obtainable from tree stock is usually required at the species level, but the accuracy of the current field inventory data is not very good at this level. According to the results of a study by Haara and Korhonen (2004) in which typical Finnish stands were used, the stand level standard errors in stem volume for pine, spruce, and deciduous tree species were 29.3%, 43.0%, and 65.0%, respectively. Unfortunately, due to the comparatively small number of test plots within a stand (approximately 3 test plots per stand), stand level standard errors in stem volume could not be adequately estimated. However, we expect that the error should substantially decrease as the plot volumes are averaged to the stand level, for example using the grid-based approach adopted by Næsset et al. (2004), and make the combined laser scanning, aerial photography, and k-MSN approach presented here comparable in accuracy to that possible from the standard ground-based inventory system that is currently in use.

Literature Cited

ALTMAN, N.S. 1992. An introduction to kernel and nearest-neighbor nonparametric regression. *Amer. Statist.* 46:175–185.

AXELSSON, P. 2000. DEM generation from laser scanner data using adaptive TIN models. P. 110–117 in *Proc. of XIXth ISPRS Conference*, Vol. XXXIII, IAPRS, Amsterdam, The Netherlands.

BEISL, U., AND N. WOODHOUSE. 2004. Correction of atmospheric and bidirectional effects in multispectral ADS40 images for mapping purposes. In *Proc. of conf. Geo-Imagery Bridging Continents*, XXth ISPRS Congress, IAPRS, Vol. XXXV, part B7, ISSN 1682-1750.

BRANDTBERG, T. 1999. *Automatic individual tree-based analysis of high spatial resolution remotely sensed data*. PhD thesis, Acta Universitatis Agriculturae Sueciae, Silvestria 118, Swedish University of Agricultural Sciences, Uppsala, Sweden. 155 p.

COBURN, C.A., AND A.C.B. ROBERTS. 2004. A multiscale texture analysis procedure for improved forest stand classification. *Int. J. Remote Sensing* 25(20):4287–4308.

COLLINS, C.A., R.C. PARKER, AND D.L. EVANS. 2004. Using multispectral imagery and multi-return LIDAR to estimate trees and stand attributes in a southern bottomland Hardwood forest. In *ASPRS Annual Conference Proceedings*, Denver, Colorado, May 2004 (on CD-ROM).

EASTMAN, J.R. 2001. *Idrisi32 release 2*, *guide to GIS and image processing*, vol. 2. Clark University, Worcester, MA.

EID, T., T. GOBAKKEN, AND E. NÆSSET. 2004. Comparing stand inventories for large areas based on photo interpretation and laser scanning by means of cost-plus-loss analyses. *Scand. J. For. Res.* 19:512–523.

FOODY, G.M. 1992. A fuzzy sets approach to the representation of vegetation continua from remotely sensed data: An example from lowland heath. *Photogram. Eng. Remote Sensing* 58:221–225.

FOODY, G.M. 1996. Fuzzy modelling of vegetation from remotely sensed imagery. *Ecol. Modell.* 85:3–12.

FOODY, G.M., R.G. JACKSON, AND C.P. QUINE. 2003. Potential improvements in the characterization of forest canopy gaps caused by windthrow using fine spatial resolution multispectral data: Comparing hard and soft classification techniques. *For. Sci.* 49(3):444–445.

FRANCO-LOPEZ, H., A.R. EK, AND M.E. BAUER. 2001. Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbors method. *Remote Sensing Environ.* 77:251–274.

FRANKLIN, S.E., R.J. HALL, L.M. MOSKAL, A.J. MAUDIE, AND M.B. LAVIGNE. 2000. Incorporating texture into classification of forest species composition from airborne multispectral images. *Int. J. Remote Sensing* 21(1):61–79.

FRANKLIN, S.E., AND D.R. PEDDLE. 1990. Classification of SPOT HRV imagery and texture features. *Int. J. Remote Sensing* 11(3):551–556.

HAARA, A., AND K.T. KORHONEN. 2004. *Kuvioittaisen arvioinnin luotettavuus*. Metsätieteen aikakauskirja 4/2004:489–508. The Finnish Society of For. Sci. & Finnish For. Res. Inst., Finland. (In Finnish).

HARALICK, R.M., K. SHANMUGAM, AND J. DINSTEEIN. 1973. Textural features for image classification. *IEEE Trans. Syst. Man. Cybern.* 3:610–621.

HOLMGREN, J. 2004. Prediction of tree height, basal area and stem volume in forest stands using airborne laser scanning. *Scand. J. For. Res.* 19:543–553.

HOLMGREN, J., AND Å. PERSSON. 2004. Identifying species of individual trees using airborne laser scanner. *Remote Sensing Environ.* 90:415–423.

HOLOPAINEN, M., AND G. WANG. 1998. The calibration of digitized aerial photographs for forest stratification. *Int. J. Remote Sensing* 19:677–696.

HYYPPÄ, J., AND M. INKINEN. 1999. Detecting and estimating attributes for single trees using laser scanner. *Photogram. J. Finland* 16:27–42.

KILKKI, P., AND R. PÄIVINEN. 1987. Reference sample plots to compare field measurements and satellite data in forest inventory. P. 209–215 in *Proc. of Conf. on Remote Sensing-aided Forest Inventory*, organized by SNS, Hyytiälä, Finland, 10–12 December 1986. University of Helsinki, Department of Forest Mensuration and Management, Research Notes 19. Helsinki University Press, Helsinki, Finland.

KING, D. 1991. Determination and reduction of cover type brightness variations with view angle in airbornemultispectral video imagery. *Photogram. Eng. Remote Sensing* 57:1571–1577.

LAASASENAHO, J. 1982. Taper curve and volume function for pine, spruce and birch. *Comm. Inst. Forestalis Fenniae* 108:1–74.

LEBLANC, S.G., P. BICHERON, J.M. CHEN, M. LEROY, AND J. CIHLAR. 1999. Investigation of directional reflectance in boreal forests with an improved four-scale model and airborne POLDER data. *IEEE Trans. Geosci. Remote Sensing* 37(3):1396–1414.

LECKIE, G.D., J. BEAUBIEN, J.R. GIBSON, N.T. O'NEILL, T. PIEKUTOWSKI, AND S.P. JOYCE. 1995. Data processing and analysis for mifucam: A trial of MEIS imagery for forest inventory mapping. *Can. J. Remote Sensing* 21:337–356.

LECKIE, D.G., F.A. GOUGEON, D. HILL, R. QUINN, L. ARMSTRONG, AND R. SHREENAN. 2003. Combined high density lidar and multispectral imagery for individual tree crown analysis. *Can. J. Remote Sensing* 29(5):1–17.

LEMAY, V., AND H. TEMESGEN. 2005. Comparison of nearest neighbor methods for estimating basal area and stems per hectare using aerial auxiliary variables. *For. Sci.* 51:109–119.

LI, X., AND A.H. STRAHLER. 1986. Geometric-optical bidirectional reflectance modeling of a conifer forest canopy. *IEEE Trans. Geosci. Remote Sensing* 30:276–292.

LILLESAND, T., R. KIEFER, AND J. CHIPMAN. 2004. *Remote sensing and image interpretation*, 5th ed. Wiley, New York. 763 p.

LIM, K., P. TREITZ, K. BALDWIN, I. MORRISON, AND J. GREEN. 2003. Lidar remote sensing of biophysical properties of tolerant northern hardwood forests. *Can. J. Remote Sensing* 29:648–678.

MAGNUSSEN, S., AND P. BOUDEWYN. 1998. Derivation of stand heights from airborne laser scanner data with canopy-based quantile estimators. *Can. J. For. Res.* 28:1016–1031.

MALINEN, J., M. MALTAMO, AND P. HARSTELA. 2001. Application of most similar neighbor inference for estimating characteristics of a marked stand characteristics using harvester and inventory generated stem databases. *Int. J. For. Eng.* 12:33–41.

MALTAMO, M., K. EERIKÄINEN, P. PACKALÉN, AND J. HYYPPÄ. 2006. Estimation of stem volume using laser scanning based canopy height metrics. *Forestry* 79(2):217–229.

MALTAMO, M., AND A. KANGAS. 1998. Methods based on k-nearest neighbor regression in estimation of basal area diameter distribution. *Can. J. For. Res.* 28:1107–1115.

MALTAMO, M., K. MUSTONEN, J. HYYPPÄ, J. PITKÄNEN, AND X. YU. 2004. The accuracy of estimating individual tree variables with airborne laser scanning in a boreal nature reserve. *Can. J. For. Res.* 34(9):1791–1801.

MARCEAU, D.J., P.J. HOWARTH, J.M.M. DUBOIS, AND D.J. GRATTON. 1990. Evaluation of the grey-level co-occurrence matrix (GLCM) method for land-cover classification using SPOT imagery. *IEEE Trans. Geosci. Remote Sensing* 28(4):513–519.

MCROBERTS, R.E., M.D. NELSON, AND D.G. WENDT. 2002. Stratified estimation of forest area using satellite imagery, inventory data, and the k-nearest neighbors technique. *Remote Sensing Environ.* 82:457–468.

MOEUR, M., AND A.R. STAGE. 1995. Most similar neighbor: An improved sampling inference procedure for natural resource planning. *For. Sci.* 41:337–359.

MUINONEN, E., M. MALTAMO, H. HYPPÄNEN, AND V. VAINIKAINEN. 2001. Forest stand characteristics estimation using a most similar neighbor approach and image spatial structure. *Remote Sensing Environ.* 78:223–228.

NÆSSET, E. 1997. Estimating timber volume of forest stands using airborne laser scanner data. *Remote Sensing Environ.* 51:246–253.

NÆSSET, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing Environ.* 80:88–99.

NÆSSET, E. 2004a. Practical large-scale forest stand inventory using a small airborne scanning laser. *Scand. J. For. Res.* 19:164–179.

NÆSSET, E. 2004b. Accuracy of forest inventory using airborne laser-scanning: Evaluating the first Nordic full-scale operational project. *Scand. J. For. Res.* 19:554–557.

NÆSSET, E., T. GOBAKKEN, J. HOLMGREN, H. HYYPPÄ, J. HYYPPÄ, M. MALTAMO, M. NILSSON, H. OLSSON, Å. PERSSON, AND U. SÖDERMAN. 2004. Laser scanning of forest resources: The Nordic experience. *Scand. J. For. Res.* 19:482–499.

NILSON, T., AND A. KUUSK. 1989. A reflectance model for the homogeneous plant canopy and its inversion. *Remote Sensing Environ.* 27:157–167.

PELLIKKA, P. 1998. Development of correction chain for multispectral airborne video camera data for natural resource assessment. *Fennia* 176:1–110.

PELLIKKA, P., D.J. KING, AND S.G. LEBLANC. 2000. Quantification and reduction of bidirectional effects in aerial CIR imagery of deciduous forest using two reference land surface types. *Remote Sensing Rev.* 19:259–291.

PERSSON, Å., J. HOLMGREN, AND U. SÖDERMAN. 2002. Detecting and measuring individual trees using an airborne laser scanner. *Photogram. Eng. Remote Sensing* 68:925–932.

PERSSON, Å., J. HOLMGREN, AND U. SÖDERMAN. 2003. Detection, measurements, and species classification of individual trees for forest inventory and visualization. P. 222–233 in *Proc. of Scandlaser scientific workshop on airborne laser scanning of forests*, Hyyppä, J., E. Næsset, H. Olsson, T. Granqvist Pahlen, and H. Reese (eds.). Working paper 112 2003, Swedish University of Agricultural Sciences, Department of Forest Resource Management and Geomatics, Umeå, Sweden.

POPESCU, S.C., R.H. WYNNE, AND R.F. NELSON. 2003. Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Can. J. Remote Sensing* 29(5):564–577.

SEARLE, S.R. 1971. *Linear models*. John Wiley & Sons, New York.

SETTLE, J.J., AND N.A. DRAKE. 1993. Linear mixing and the estimation of ground cover proportions. *Int. J. Remote Sensing.* 14(6):1159–1177.

SIRONEN, S., A. KANGAS, M. MALTAMO, AND J. KANGAS. 2001. Estimating individual tree growth with k-nearest neighbour and Most Similar Neighbour methods. *Silva Fennica* 35:453–467.

SUITS, G.H. 1972. The calculation of the directional reflectance of a vegetative canopy. *Remote Sensing Environ.* 2:117–125.

TOMPPO, E., AND M. HALME. 2004. Using coarse scale forest variables as ancillary information and weighting of variables in k-NN estimation: A genetic algorithm approach. *Remote Sensing Environ.* 92(1):1–20.

TÖRMÄ, M. 2000. Estimation of tree species proportions of forest stands using laser scanning. P. 1524–1531 in *Proc. of XIXth ISPRS Conference*, IAPRS, Vol. XXXIII, Amsterdam, The Netherlands.

TSO, B., AND P.M. MATHER. 2001. *Classification methods for remotely sensed data*. Taylor & Francis Ltd., London, United Kingdom.

TUOMINEN, S., AND A. PEKKARINEN. 2004. Local radiometric correction of digital aerial photographs for multi source forest inventory. *Remote Sensing Environ.* 89:72–82.

TUOMINEN, S., AND A. PEKKARINEN. 2005. Performance of different spectral and textural aerial photograph features in multisource forest inventory. *Remote Sensing Environ.* 94(2):256–268.

VELTHEIM, T. 1987. *Pituusmallit männylle, kuuselle ja koivulle*. MSc thesis, University of Helsinki, Department of Forest Mensuration and Management, Helsinki, Finland. 59 p. (In Finnish).

VENABLES, W.N., AND B.D. RIPLEY. 2002. *Modern applied statistics with S-plus*, 4th ed. Springer-Verlag, New York.

WANG, F. 1990. Fuzzy supervised classification of remote sensing images. IEEE Trans. Geosci. *Remote Sensing* 28(2):194–201.

WESZKA, J., C.R. DYER, AND A. ROSENFELD. 1976. A comparative study of texture measures for terrain classification. *IEEE Trans. Syst. Man. Cybern.* 6:269–285.

ZHANG, F., AND G.M. FOODY. 1998. A fuzzy classification of sub-urban land cover from remotely sensed imagery. *Int. J. Remote Sensing* 19:2721–2738.