CLASSIFYING TREE SPECIES USING STRUCTURE AND SPECTRAL DATA FROM LiDAR

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ABSTRACT

Two airborne laser scanning datasets with leaf-on and leaf-off conditions were used to compare parameters derived from crown structure metrics and intensity data. Five deciduous species and six coniferous species were collected at the Washington Park Arboretum, Seattle, Washington, USA. Linear (LDA) and quadratic (QDA) discriminate functions were used to classify these selected species groups. Overall, classification accuracy was highest when using intensity variables with the leaf-off data in both LDA (98.9%) and QDA (99.0%). In terms of structure variables, leaf-on variables showed higher accuracy (74.9 %) than leaf-off variables (50.2 %) while in terms of intensity variables, leaf-off variables showed higher accuracy (97.1 %) than leaf-on variables (63.0 %) in LDA. QDA showed higher classification accuracy than LDA for all cases. The overall result indicates that parameters computed from LiDAR-based crown structures and intensity data can be used to differentiate species groups and also implies that tree species classification depends on the collected LiDAR datasets and the derived parameters.

Key words: LiDAR, Classification, Leaf-on and leaf-off conditions, Deciduous and coniferous species.

INTRODUCTION

Light Detection and Ranging (LiDAR) offers an advantage over most other remote sensing technologies in its ability to capture 3-dimensional measurements over large areas. The ability to measure 3-dimensional structures by penetrating beneath the top layer of the canopy makes airborne laser systems useful for directly assessing vegetation characteristics.

One variable included with most LiDAR data is a relative measure of the strength of the return signal associated with each return. This value, called the intensity, provides a measure of the amount of energy reflected from a target. Intensity values vary depending on the flight height, atmospheric conditions, directional reflectance properties, the reflectivity of the target, and the laser settings (Baltsavias, 1999). Most commercial LiDAR systems used for topographic mapping use lasers that emit energy in the near infrared range of the electromagnetic spectrum (often 1064nm). Because green vegetation reflects this wavelength well (Swain and Davis, 1978), LiDAR intensity data should contain information relating to forest type and condition. However, because LiDAR intensity data are not calibrated it has not been used as extensively as the three dimensional structure data represented by laser returns. As the importance of laser scanner data increases, the influences of scanning angle or flight height on the biophysical vegetation products (Ahokas et al., 2005) or on the DSM (Morsdorf et al., 2006) have been studied.

LiDAR intensity data were used for land cover classification (Song et al., 2002; Brennan and Webster, 2006; Hasegawa, 2006) and for differentiating tree species; between deciduous species (Brandtberg et al., 2003 and 2007; Moffiet et al., 2005), between coniferous species (Holmgren and Persson, 2004; Donoghue et al., 2007; Ørka et al., 2009) and between various deciduous and coniferous species (Kim et al., 2009). According to all of these study results, LiDAR intensity data are a promising tool for species classification albeit calibration of LiDAR intensity should be studied more.

Historically, LiDAR technology has been used to capture and detect the 3-dimensional structure of objects. Nelson (1998) described the effect of different canopy shapes on simulated laser measurements of height and estimates of basal area, volume and biomass derived via simulation. Although his study focused on modeling forest canopy heights, he assumed a particular tree's canopy, in profile, was one of four geometric shapes: cone, paraboloid, ellipsoid, or spheroid. He recommended that tree canopy shapes should be noted when field data were collected for purposes of height simulation but he did not attempt to derive tree canopy shapes directly from laser points. Popescu and Wynne (2004) assumed that deciduous trees and evergreen pines had different relationships between tree height and crown width when they estimated plot-level tree height by measuring individual trees identifiable on the three-dimensional LiDAR surface. They tried to find the best fitting model for each group and found that the two groups required different models. They found that filtering for local maximum with a circular window produced better results for pines and filtering with a square window provided slightly better results for deciduous trees. Their study implies that simple measurements such as crown length to width ratio can be used to separate deciduous trees and evergreen pines.

Several authors report efforts to distinguish tree species using positions of laser points within individual tree crowns as well as intensity data (Brandtberg et al., 2003 and 2007; Holmgren and Persson, 2004; Brennan and Webster, 2006; Ørka et al., 2009). Ørka et al. (2009) identified candidate features related to structure and intensity derived from laser scanner data to discriminate between evergreen coniferous (Norway spruce) and deciduous angiosperm species (birch). They concluded that promising classification results for spruce and birch were obtained using identified candidate features.

Kim et al. (2009) normalized intensity data from the two LiDAR datasets based on numerous features collected from leaf-on and leaf-off datasets. However, they found that two intensity data variables could be used for the tree species classification. In the present study, crown structure metrics were added to the analysis and classification of selected several deciduous and coniferous species and compared with the already developed intensity parameters used in Kim et al. (2009)'s study. Finally, two parameters of intensity and crown structure metrics derived from two LiDAR datasets will be compared and ability of the candidate parameters to classify two species group will be investigated.

STUDY AREA AND DATA COLLECTION

The study area is the Washington Park Arboretum located in Seattle, Washington (see Figure 1). The area covers 93 hectares and a topographic range is 15 to 55 m above sea level with less than 30% of slope for the majority of the site.

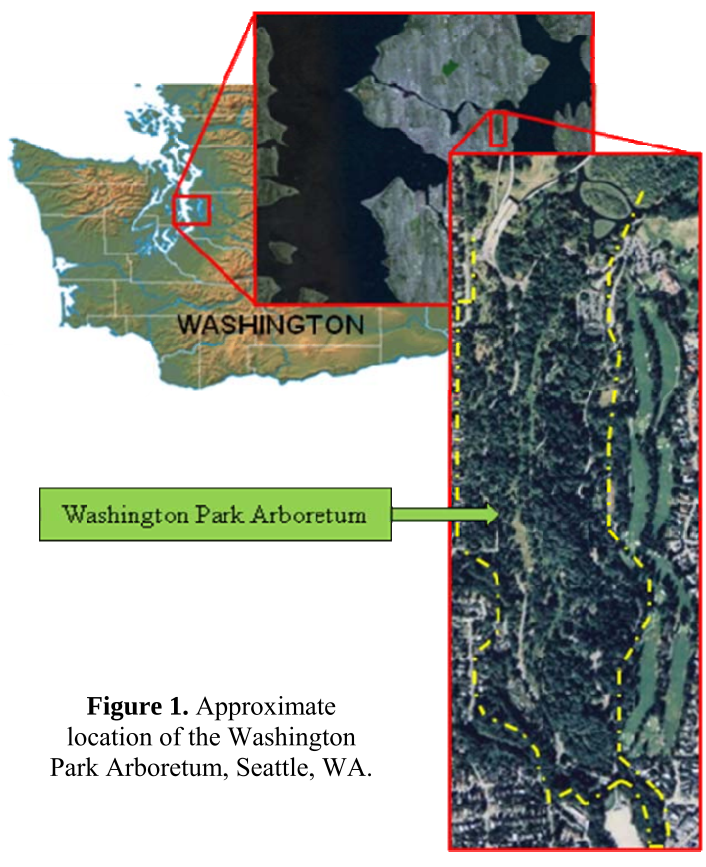


Figure 1. Approximate location of the Washington Park Arboretum, Seattle, WA.

LiDAR Data

System specifications for both acquisitions are shown in Table 1. Because the topographic range for this study site is not significant and scan angles are narrow (<11 ^{o} off-nadir) for both datasets, raw intensity data were used without additional radiometric calibration (Coren and Sterzai, 2006; Donoghue et al. 2007; Hasegawa, 2006). For this study, leaf-on LiDAR intensity data were multiplied by a scaling factor (16.43949) to directly compare with leaf-off intensity data by testing intensity values using numerous objects between two LIDAR datasets (Kim et al., 2009). The digital terrain model (DTM) described by Kim et al.(2009) was used with 1- by 1- m resolution using FUSION/LDV software (McGaughey and Carson, 2003; McGaughey et al., 2004).

Table 1. Laser scanner system specifications.

Specifications	Leaf-on data	Leaf-off data
Acquisition date	August 30, 2004	March 17, 2005
Laser wavelength	1,064 nm	1,064 nm
Laser scanner	Optech ALTM 30/70	Optech ALTM 3100
Scan angle (from nadir)	11 ^{o}	10^{o}
Flying height above ground	1200 m	900 m
Scan pulse repetition frequency	71 kHz	100 kHz
Maximum number of returns per pulse	3	4
Footprint size	0.372 m	0.279 m
Scan width (approximate)	554 m	310 m
Flight line overlap	0 percent (single flight line)	50 percent
Point density	2 to 5 points/m^2	3 to 20 points/m^2

Species Selection

Two groups of species were selected from the fifteen species used in Kim et al. (2009)'s study considering that leaf-off LIDAR data did not capture all trees under leaf-off conditions due to widely varying phenology across the wide range of species within the arboretum and unusually early bud break for 2005. The groups were five deciduous species which had no foliage at the time of leaf-off LiDAR data acquisition and six evergreen coniferous species were selected. The five deciduous species were big leaf maple (*Acer macrophyllum*), birch (*Betula spp.)*, elm (*Ulmus spp.*), oak (*Quercus spp.)* and ash (*Sorbus spp*.). The six coniferous species were western red cedar (*Thuja plicata*), Douglas-fir (*Pseudotsuga mensiesii*), pine (*Pinus spp.*), western hemlock (*Tsuga heterophylla*) and coastal redwood (*Sequoia sempervirens*).

Field Measurements

Field data were collected from April through July 2005. Individual specimens of the selected species were identified by determining the tree locations before selecting plot locations. If over ten tree specimens were grouped together, this study site was regarded as a plot and then three reference points were located using a Trimble Pro XR/XRS GPS system. Individual tree locations were recorded from at least two of the triangle points to confirm accurate tree locations. For the most part, isolated individual trees in relatively open areas were selected. Total heights and crown base heights were measured using a clinometer and an Impulse LR laser. In this study, crown diameter was measured to assist in detecting individual tree locations in the LiDAR point clouds by averaging two perpendicular measurements, one in the north-south direction through the center of the stem and the other in the east-west direction crossing the mid- point of the north-south length. In the office, all GPS data were post processed to obtain differentially corrected coordinates. The details about field measurements and post processing are described in Kim et al. (2009).

METHODOLOGY

Isolation of Individual Tree Crowns

A method of isolating individual tree crowns was developed to obtain a more precise, "pure" set of laser points belonging to each individual tree crown. The idea is based on naturally grown physical shapes of tree crowns, especially for conifers. For example, coniferous trees generally have their apexes at the center point of the crown (i.e., aligned with the stem) and the crown surface drops from this point to the crown edge. After analyzing the distributions of LiDAR point clouds and excluding points belonging to neighborhood trees, the final subset of laser points for each tree crown was used to compute crown structure parameters. This technique of isolating individual tree crowns is described in Kim et al. (2009).

Computation of Parameters

Four variables describing the vertical distribution of the crown were derived for the leaf-on and leaf-off datasets; relative 10th height percentile, relative 90th height percentile, relative median height percentile, and relative standard deviation of height. These variables were obtained by finding the total height and height to the crown base of each tree, dividing the difference (crown length) into the 10^{th}, median, and 90^{th} percentiles, adding the height to the crown base to get the height to each of these crown locations, and dividing by total height to convert them to relative percentiles. IDL (Interactive Data Language) was used to compute these variables.

When lower tree crowns overlap, x, y, and z coordinates of laser returns are difficult to assign to a particular tree and measurements of the lower crown become less reliable than those for the upper crown where overlap does not occur. To avoid issues with loss of accuracy where lower crowns overlap to varying degrees, this study focused on three upper crown locations: 10 (1/10) %, 25 (1/4) %, and 33.3 (1/3) % of the crown length. For each of these three locations crown length and crown width were computed for each individual tree. For each 45 degree sector of the crown, radius at 10%, 25% and 33.3% of the crown length was computed as the maximum horizontal distance using x and y coordinates of laser returns from the tree center to the farthest laser returns. If the isolation method found overlap in the upper crown of any of these sectors, those sectors were dropped and crown width was computed by averaging the radii. Of the remaining sectors, crown length to 10%, 25% and 33.3% was computed by measuring the distance from the z-value of the lowest positioned laser return and the z-value of the highest positioned laser return. Finally, the length to width ratio at the 10%, 25% and 33.3% locations were computed from the corresponding length and width data.

For the leaf-on and leaf-off LiDAR datasets, the following intensity parameters were calculated: mean intensity for the entire crown using first returns (entire_1), coefficient of variation using first return intensity for the whole crown (cv_1), and proportion of first returns (prop_1). The method of computing these intensity variables and selecting this subset of variables are described in Kim et al. (2009).

Statistical Analysis

For the variables associated with crown structure, mean values were computed for each species with the leaf-on and leaf-off LiDAR datasets. Student's *t*-test was used to evaluate significant differences between deciduous and coniferous species for each variable.

A simple tree species classification test for two species groups, deciduous and coniferous species, was performed on the selected subset of the original variables using a linear discriminate function (LDA). To perform LDA more efficiently, principal component analysis (PCA) was conducted to determine a subset that contains, in some sense, virtually all the information available in the complete set of variables (Everitt and Dunn, 2001). The size of the subset of original variables to be retained was determined by the number of components (Jolliffe, 1972). Jolliffe (1972) suggested using eigen values greater than 0.7 to select which components to be retained from a correlation matrix. Each variable is selected, one associated with each component, as the one not already chosen which has the greatest absolute coefficient value on the component. In this study, all the original variables in both leaf-on and leaf-off datasets were used for the PCA to select a subset of variables using the R statistical package. For both leaf-on and leaf-off data, the same two variables were selected according to these criteria; length to width ratio at the upper 25 % and length to width ratio at the upper 33 %.

In forestry research, distinguishing individual deciduous and coniferous species is important. The validity of classifying these two groups can be tested using discriminate functions. Venables and Ripley (1994) described the functions using sample covariance matrices:

$$W = \frac{(X - GM)^T (X - GM)}{n - g} \text{ and } B = \frac{(GM - 1\overline{X})^T (GM - 1\overline{X})}{g - 1},$$

where W is the within-class covariance matrix, that is the covariance matrix of the variables centered on the class means, and B is the between-classes covariance matrix, that is of the predictions by the class means. M is g x p matrix of class means, and G is the n x g matrix of class indicator variables (so $g_{ij} = 1$ if and only if case i is assigned to class j). Consequently the predictions are the product of matrices G and M. $\overline{X}$ is the vector of means of the variables over the whole sample. Fisher (1936) introduced a linear discriminate analysis seeking a linear combination, xa, of the variables which has a maximal ratio of the separation of the class means to the within-class variance, that is maximizing the ratio a^TBa / a^TWa.

To evaluate the performance of a linear discriminate function, the function was applied to the data from which it had been derived. A discriminate function is derived from just n-1 members of the sample and then used to classify the member not included. The process is carried out *n* times, leaving out each sample member in turn (Everitt and Dunn, 2001).

In this study, discriminate analysis was conducted using *discrim* function in S plus. All discriminate functions fit by *discrim* assume that the feature vectors are normally distributed. A linear function is computed if the feature data covariances are assumed to be equal among the groups, otherwise a quadratic function is computed. Much of *discrim* and its methods are based on the *lda* and *qda* functions and methods of the MASS library developed by Venables and Ripley (1994). In this research, the two species groups, deciduous and coniferous species, are tested for the classification using *lda* and *qda*. The priori probability was set to 0.5, which is suggested by Huberty and Olejnik (2006).

This classification method was performed on different LiDAR datasets and different parameters. For the structure analysis, the two selected variables (ratio 25%, ratio 33%) were used respectively with the leaf-on and leaf-off datasets, and then the combining four variables were used for the combined structure analysis. For the intensity analysis, three selected variables (entire_1, cv_1 and prop_1) were used initially with the leaf-on and leaf-off datasets and then the combining six variables were used. By combining crown structure and intensity parameters, the overall classification rate was computed and compared between different LiDAR datasets and between parameters regarding crown structure and intensity data. Also, for each variable associated with upper crown shapes, a linear discriminate function was developed to compare classification rate between deciduous and coniferous species.

RESULTS

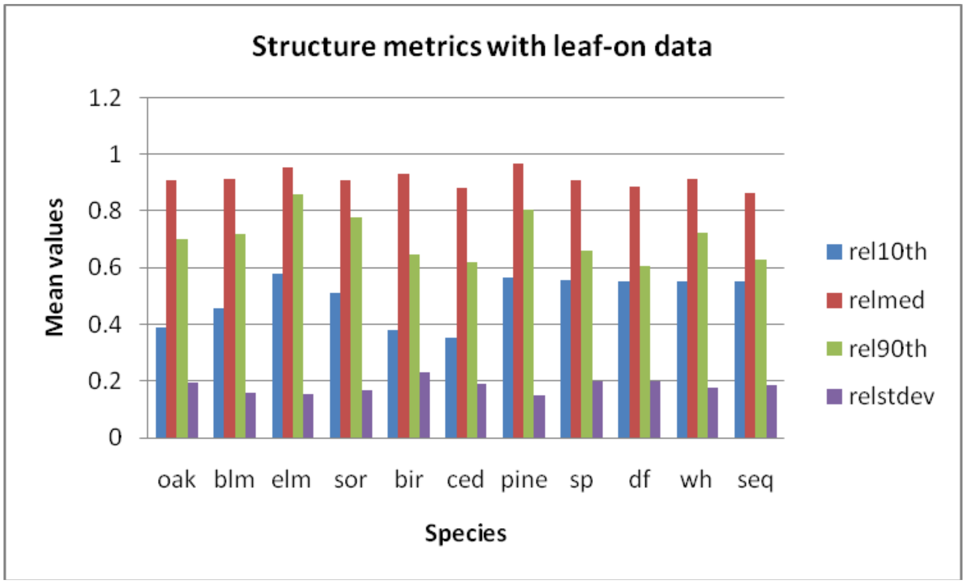
Analysis of Structure Metrics: Vertical Distributions of Laser Returns

Mean values of the four variables associated with vertical distributions of laser returns for each species are shown in Figure 2 for (a) leaf-on and (b) leaf-off data. Generally, the higher the 10^{th} height percentiles (rel10th), the lower the standard deviations of heights (relstdev) in both datasets. Pine showed the highest values for the three relative height percentiles among the coniferous species.

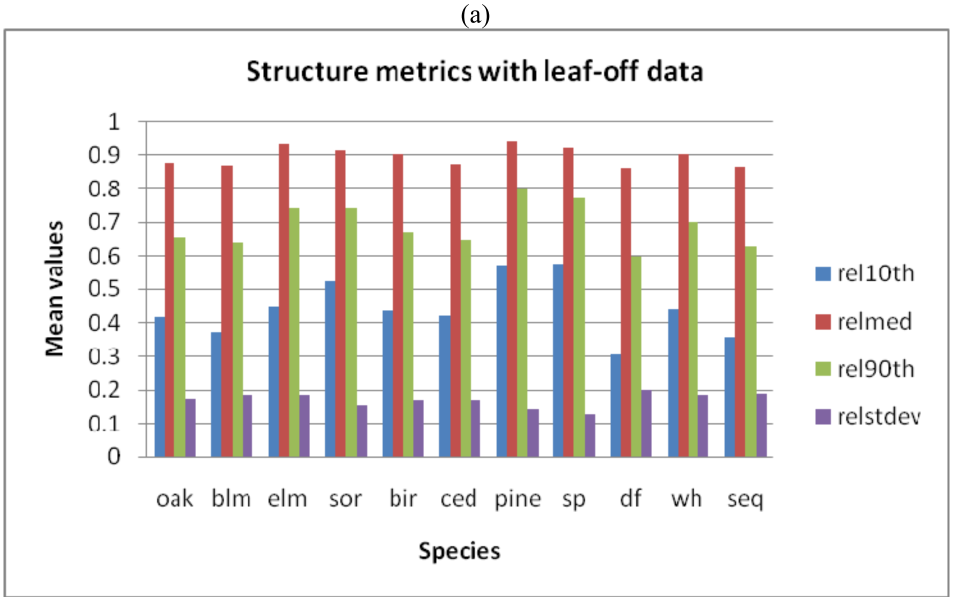
The results of the two-sample *t*-tests for deciduous and coniferous species for each variable are shown in Table 2. The *p*-value is given for group means for each variable. In leaf-off data, the two species groups did not show significant differences for any variables ($p>>0.05$) while in leaf-on data, they showed significant differences for the three height percentiles ($p<0.01$) with higher mean values for deciduous species.

Analysis of Structure Metrics: Length to Width Ratio Within Upper Portions of a Crown

The result for length to width ratio within the upper crown is shown in Figure 3 with (a) leaf-on data and (b) leaf-off data. Coniferous species showed higher ratio than deciduous species in both datasets except birch. Birch's length to width ratio was higher than other deciduous species and it was even higher than pine, a coniferous species. Among coniferous species, pine showed very low ratios in both datasets. The ratio was highest at 10% of crown length and lowest at 33% of crown length for the all species except redwood in both datasets. Redwood had the highest ratio at 25% of crown length.



(a)



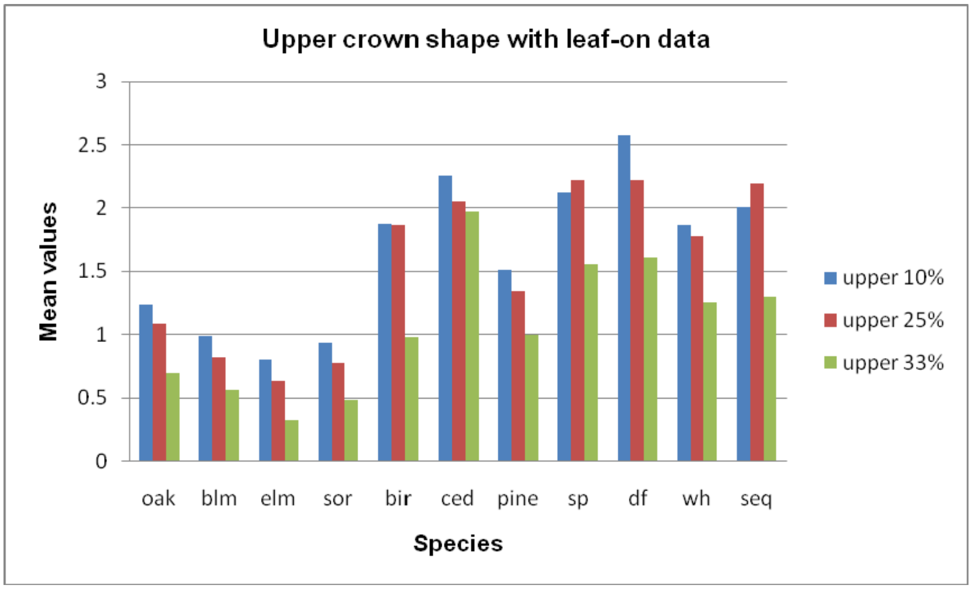
(b)

Figure 2. Mean values for four height dependent parameters for each species with (a) leaf-on and (b) leaf-off data (rel10th, relmed and rel90th—relative 10th, 50th, and 90th height percentile; relstdev—relative standard deviations of heights; blm-big leaf maple; sor-ash; bir-birch; ced-western red cedar; sp-spruce; df-Douglas-fir; wh-western hemlock; seq-coastal redwood).

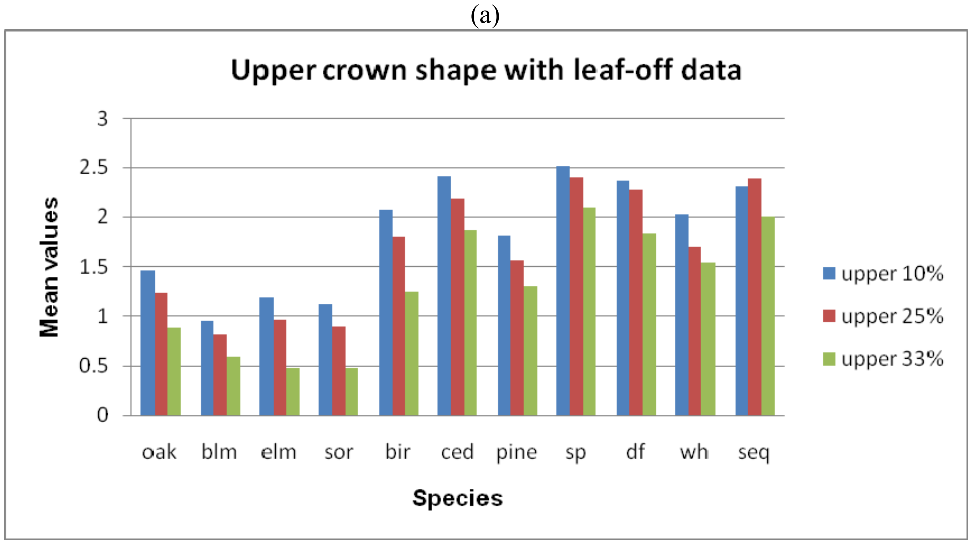
Table 2. Mean values for four height-related variables for deciduous and coniferous species and the *p*- value for *Student*'s *t*-test with the leaf-on data. Leaf-off data is indicated within the parenthesis next to the leaf-on data.

Variable	Group means: Broadleaved	Group means: Coniferous	*p*
Relative 10th height percentile	0.458 (0.470)	0.403 (0.444)	0.006 (0.337)
Relative median height percentile	0.720 (0.698)	0.670 (0.682)	0.001 (0.159)
Relative 90th height percentile	0.929 (0.901)	0.907 (0.891)	0.001 (0.285)
Relative standard deviations	0.182 (0.163)	0.187 (0.169)	0.483 (0.373)

The result of Student's *t*-test for deciduous and coniferous species for each upper crown variable is shown in Table 3 with mean and *p*-values. In addition, linear discriminate function was conducted and compared between variables (see Table 3). In both datasets, deciduous and coniferous species showed significant differences using *t*-statistics ($p < 0.001$) with higher mean values for coniferous species. In leaf-on data, the ratio at 33% of crown length showed the highest classification accuracy (61.3%) and the ratio at 10% of crown length showed the lowest accuracy (55.3%). However, with leaf-off data, the ratio at 10% of crown length showed the highest classification accuracy (58.2%) and the ratio at 33% of crown length showed the lowest accuracy (46.5%).



(a)



(b)

Figure 3. The result for length to width ratio at the upper 10 %, 25 % and 33 % of a crown length with the (a) leaf-on and (b) leaf-off data (upper 10%, 25% and 33%—length to width ratio within an upper 10%, 25% and 33% of a crown length; blm-big leaf maple; sor-ash; bir-birch; ced-western red cedar; sp-spruce; df-Douglas-fir; wh-western hemlock; seq-coastal redwood).

Table 3. Mean values for length to width ratios within three different portions of an upper crown for deciduous and coniferous species, the *p*- value for *Student*'s *t*-test and the classification accuracy using linear discriminate analysis for the leaf-on data. Leaf-off data is indicated within a parenthesis next to the leaf-on data.

Variables	Group means		*P*	Classification accuracy (%)
	Deciduous	Coniferous		
Ratio at upper 10 %	1.13 (1.35)	2.01 (2.18)	<0.001 (<0.001)	55.3 (58.2)
Ratio at upper 25 %	1.02 (1.15)	1.92 (2.02)	<0.001 (<0.001)	58.7 (54.4)
Ratio at upper 33 %	0.60 (0.76)	1.41 (1.70)	<0.001 (<0.001)	61.3 (46.5)

Intensity Analysis

Mean intensity values for the whole crown using the first returns were compared using a boxplot (see Figure 4). Discriminate functions were developed for deciduous and coniferous species using linear discriminate analysis (LDA) and quadratic discriminate analysis (QDA) for the different combinations of variables: one set of variables is associated with structure and intensity data and the other set of variables is associated with leaf-on and leaf-off datasets (see Table 4). Overall, classification accuracy was highest when using intensity variables with the leaf-off data in both LDA (98.9%) and QDA (99.0%). Among the four sets of variables, structure variables using leaf-off data showed the lowest classification accuracy in LDA while in QDA, intensity variables using leaf-on data showed the lowest accuracy. In terms of structure variables, leaf-on variables showed higher accuracy (74.9 %) than leaf-off variables (50.2 %) while in terms of intensity variables, leaf-off variables showed higher accuracy (97.1 %) than leaf-on variables (63.0 %) in LDA. QDA showed higher classification accuracy than LDA for all cases.

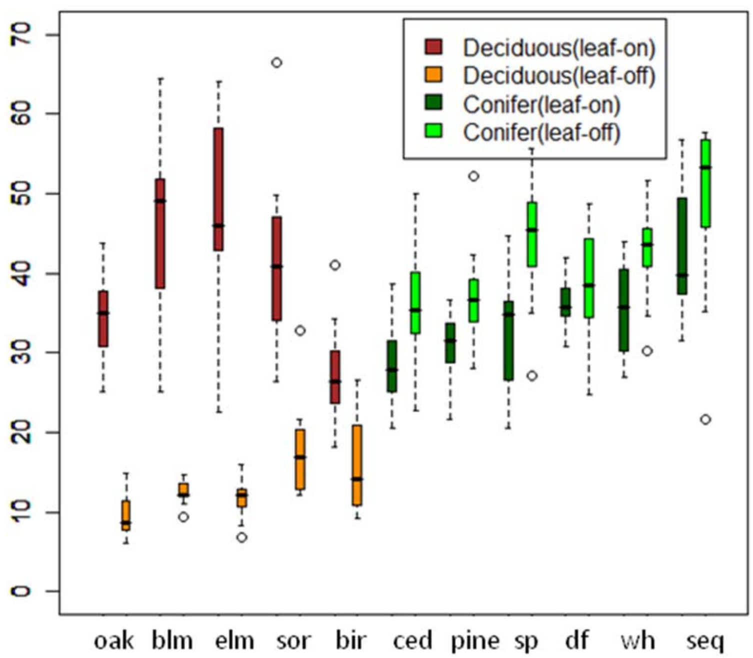


Figure 4. Box plots of entire crown mean intensity values using first returns among species with leaf-off data and scaled leaf-on data (blm-big leaf maple; sor-ash; bir-birch; ced-western red cedar; sp-spruce; df-Douglas-fir; wh-western hemlock; seq-coastal redwood).

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Table 4. The result of linear discriminate analysis (LDA) and quadratic discriminate analysis (QDA) conducted for the different combinations of variables: one set of variables is associated with structure and intensity data and the other set of variables is associated with leaf-on and leaf-off datasets.

Variables	Structure	Intensity	All
Leaf-on	74.9 (75.8)	63.0 (68.1)	75.3 (79.8)
Leaf-off	50.2 (72.2)	97.1 (97.5)	80.7 (84.3)
All	74.0 (78.5)	98.9 (99.0)	85.2 (86.1)

*Note: for each cell, QDA (%) is indicated within a parenthesis next to the LDA (%).

DISCUSSION

This study supplemented Kim et al. (2009)'s study by adding structure analysis and by selecting more appropriate species groups to improve the ability to classify trees by species. Therefore, instead of analyzing intensity data thoroughly, intensity parameters were used for the purpose of comparing with the crown structure parameters, parameters newly introduced in this study.

In terms of intensity results, separation between deciduous and coniferous species was improved over Kim et al. (2009). With leaf-off data, the selected deciduous species showed lower mean intensity values than the selected coniferous species. For the leaf-off data, coniferous species had leaves while the selected deciduous species had no leaves. It is known that green foliage has higher spectral reflectivity than woody materials (Roberts et al., 2004). Under leaf-off conditions, most of the laser energy would be that reflected from woody materials such as stems, branches and bark resulting in lowering the overall reflectance of the deciduous species.

With leaf-on data, deciduous species had higher intensity values than conifers but the separation between two species groups was not as clear as using leaf-off data. Birch showed the lowest intensity values among all species probably because this species has relatively sparse foliage distributions consisting of small leaves increasing the amount of laser energy that reflects from branches. Big leaf maple and elm had the highest mean intensity values among all species probably because they have big broad leaves and dense foliage distributions within the crowns. Dense foliage distributions will increase the amount of laser energy that reflects from leaves rather than branches. Therefore, mean intensity values of tree crowns seem to be related to the density of foliage distributions of the laser point clouds.

For isolated individual tree crowns, relative height percentiles using laser returns did not separate deciduous and coniferous species but simple shape metrics in the upper 1/3 of crowns separated these two species groups in this study. However, more rigorous methods for describing tree crowns are suggested for the further study.

Holmgren and Persson (2004) suggested that QDA would produce higher classification accuracy if more training data is available because a higher number of parameters (two covariance matrices) can be estimated. This study found that adding more variables did not necessarily improve the classification and that it is important to select the most appropriate variables to classify species groups. In terms of intensity variables, using leaf-off data showed better classification accuracy than using leaf-on data and even better than using combined datasets while in terms of structure variables, leaf-on data showed better classification accuracy than leaf-off data. This result implies that crown structures of deciduous species could be better distinguished from those of coniferous species using leaf-on conditions than leaf-off conditions.

For deciduous species, intensity values were significantly different between two LiDAR datasets. However, structure metrics were not significantly different between the leaf-on and leaf-off datasets , as expected. Therefore, it is obvious that intensity values would be more promising parameter than structure metrics to identify deciduous and conifers when using different seasonal LiDAR datasets.

The results presented in this study can be expanded to the classification of different forest types at the stand scale. As Moffiet et al. (2005) reported, the classification results could be better at the stand scale than at the individual tree scale. The approach to analyze intensity data for the upper portions of a crown can be applied to densely overlapped forests. In many cases, upper canopies are more open than lower canopies in dense forests and it is known that upper canopies make an important role in biophysical functions of trees such as photosynthesis.

Each parameter was computed from laser point clouds after applying crown isolation method introduced in Kim et al. (2009) which was rather conservative by deleting all point cloud data within a 45 degree radial sector if tree crowns overlapped over a certain degree. Depending on how many radial sectors were deleted within individual tree crowns, the whole crown shapes might be transformed. To reduce the bias between real crown shapes and the transformed crown shapes, a limited method was used in this study to compute structure-related variables by using height percentiles and length to width ratios within upper 1/3 of a crown with the remaining sectors. This may be one of the reasons why this study found that intensity variables resulted in better classification accuracy than structure variables. Therefore, if other methodology could be developed to isolate individual tree crowns considering crown structures, the overall classification results, especially for the structure variables might be improved.

CONCLUSIONS

This study contributes to the understanding of how LiDAR data can be used to describe and identify individual tree species using intensity data and structure metrics. In this study, different sets of parameters using leaf-on and leaf-off datasets were compared and combined for tree species classification with promising results. Although this study found higher classification accuracy using intensity variables with the leaf-off LiDAR data, it should be noted that the utility of LiDAR intensity data depends on a reliable calibration of raw intensity data.

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REFERENCES

Ahokas, E., X. Yu, J. Oksanen, J. Hyyppäe, H. Kaartinen, and H. Hyyppäe, 2005. Optimisation of the scanning angle for countrywide laser scanning, *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *36* Part 3/W19.

Brandtberg, T., T. Warner, R.E. Landenberger, and J.B. McGraw, 2003. Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density LiDAR data from the eastern deciduous forest in North America, *Remote Sensing of Environment*, *85*(3), 290-303.

Brantberg, T., 2007. Classifying individual tree species under leaf-off and leaf-on conditions using airborne LiDAR, *ISPRS Journal of Photogrammetry and Remote Sensing*, *61*(5), 325-340.

Brennan, R., and T.L. Webster, 2006. Object-oriented land cover classification of LiDAR-derived surfaces, *Canadian Journal of Remote Sensing, 32*(2), 162-172.

Coren, F., and P. Sterzai, 2006. Radiometric correction in laser scanning, *International Journal of Remote Sensing*, *27*(15–16), 3097−3104.

Donoghue, D.N.M., P.J. Watt, N.J. Cox, and J. Wilson, 2007. Remote sensing of species mixtures in conifer plantations using LiDAR height and intensity data, *Remote Sensing of Environmen*t, 110(4), 509-522.

Everitt, B.S., and G. Dunn, 2001. *Applied Multivariate Data Analysis*: Second edition, Oxford University Press Inc., New York.

Fisher, R.A., 1936. The use of multiple measurements in taxonomic problems, *Annals of Eugenics* 7, pp. 179-188.

Hasegawa, H., 2006. Evaluations of LiDAR reflectance amplitude sensitivity towards land cover conditions, *Bulletin of the Geographical Survey Institute*, 53.

Holmgren, J., and Å. Persson, 2004. Identifying species of individual trees using airborne laser scanner, *Remote Sensing of Environment*, 90(4), 415-423.

Huberty, Carl J., and S. Olejnik, 2006. *Applied MANOVA and Discriminant Analysis*: Second Edition, Wiley Series in Probability and Statistics.

Jolliffe, I.T., 2002. *Principal Component Analysis*, Springer-Verlag, New York.

Kim, Sooyoung, R. McGaughey, H.-E. Andersen, and G. Schreuder, 2009. Tree species differentiation using intensity data derived from leaf-on and leaf-off airborne laser scanner data, *Remote Sensing of Environment*, 113(8):1575-1586.

McGaughey, R.J., and W.W. Carson, 2003. Fusing LiDAR data, photographs, and other data using 2D and 3D visualization techniques, in *Proceedings from the Terrain Data: Applications and Visualization –Making the Connection*, pp. 16-24.

McGaughey, R.J., W.W. Carson, S.E. Reutebuch, and H.-E. Andersen, 2004. Direct measurement of individual tree characteristics from LiDAR data, in *Proceedings from the 2004 Annual ASPRS Conference*.

Moffiet, T., K. Mengersen, C. Witte, R. King, and R. Denham, 2005. Airborne laser scanning: exploratory data analysis indicates potential variables for classification of individual trees or forest stands according to species, *ISPRS Journal of Photogrammetry and Remote Sensing*, 59(5), 289–309.

Morsdorf, F., O. Frey, E. Meier, K. Itten, and B. Allgower, 2006. Assessment of the influence of flying height and scan angle on biophysical vegetation products derived from airborne laser scanning, in *Proceedings of Workshop on 3D Remote Sensing in Forestry*, Vienna, Austria, pp. 145−150.

Ørka, H.O., E. Næsset, and O.M. Bollandsås, 2009. Classifying species of individual trees by intensity and structure features derived from airborne laser scanner data, *Remote Sensing of Environment*, 113(6): 1163-1174.

Popescu, S.C., and R.H. Wynne, 2004. Seeing the trees in the forest: using LiDAR and multispectral data fusion with local filtering and variable window size for estimating tree height, *Photogrammetric Engineering & Remote Sensing*, 70(5): 589-604.

Roberts, D.A., S.L. Ustin, S. Ogunjemiyo, J. Greenberg, S.Z. Dobrowski, J. Chen, and T.M. Hinckley, 2004. Spectral and structural measures of northwest forest vegetation at leaf to landscape scales, *Ecosystems*, 7, 545-562.

Song, J-H., S.H. Han, K. Yu, and Y.L. Kim, 2002. Assessing the possibility of land-cover classification using LiDAR intensity data, *ISPRS Commission III*, "Photogrammetric Computer Vision", Graz, Austria, 2002, 34(3B), 259-262.

Swain, P.H., and S.M. Davis (eds.), 1978. *Remote Sensing: The Quantitative Approach*. McGraw Hill, New York, 1978, pp. 396.

Venables, W.N., and B.D. Ripley, 1994. *Modern Applied Statistics with S-PLUS*, Springer-Verlag, New York.