Predicting Forest Stand Characteristics with Airborne Scanning Lidar

Joseph E. Means, Steven A. Acker, Brandon J. Fitt, Michael Renslow, Lisa Emerson, and Chad J. Hendrix

Abstract

Currently, commercial forestry applications of airborne scanning lidar are limited to geo-technical applications such as creation of digital terrain models for layout of roads or logging systems. We investigated the feasibility of predicting characteristics of forest stands with lidar data in a university-industry partnership. Lidar lends itself well to such applications because it allows direct measurement of important structural characteristics of height and canopy closure. We found that lidar data can be used to predict the stand characteristics of height, basal area, and volume quite well. The potential for commercial applications appears bright. Lidar data can be used to estimate stand characteristics over large areas or entire forests. After the process is streamlined, it should be possible to provide maps of height, basal area, and volume in such areas within a few weeks of the lidar collection flight.

Introduction

Currently, forest inventories are done almost completely on the ground by field crews. Data on stand structure (size, stocking level) and types (Douglas-fir, hardwoods, mixed) can come from geographic information system (GIS) coverages of treatment history and classified imagery and are used to identify the different stands to be sampled. Inventories are conducted with fixed-area plots or variable-radius plots. Depending on company policy, plots can cover from 10 percent to over 50 percent of the ground. This clearly takes considerable personnel time for each measurement period. With over ten million acres of Douglas-fir-dominated forest land in western Oregon and Washington, much field work is conducted each year. We believe that, with lidar-based (LIght Detection And Ranging) estimates of important stand parameters integrated into the inventory, significantly less field work would be needed.

We report here on the results of a university-industry partnership in the NASA-sponsored Affiliated Research Center (ARC) program that explored this potential. The commercial partner in this study was Pacific Meridian Resources, Portland, Oregon, and the ARC is at Oregon State University (OSU). Spencer B. Gross, Inc., Portland, Oregon, provided the lidar data and will receive all results of the project as per a mutual agreement of all parties. The goal of the partnership was to assess the potential for predicting important characteristics of Douglas-fir stands with small-footprint lidar data. Our steps were to collect lidar data over existing ground plots, develop software for analyzing the lidar data for vegetation characteristics, analyze the data for predictive relationships, and consider the potential market for these new capabilities.

Airborne Laser Scanning

Airborne scanning lidar is currently enjoying rapidly increasing use for several purposes, especially terrain mapping and powerline assessment. A recent paper gives an overview of terrain mapping applications of lidar (Flood and Gutelius, 1997). Many companies fly lidar instruments throughout the world, and they are best located through the Airborne Laser Mapping web site (**http://www.airbornelasermapping.com/**). This site also provides background information and explanations of lidar and up-to-date industry news. Issue 2–3, Volume 54 of the *ISPRS Journal of Photogrammetry and Remote Sensing* contains a wealth of technical information on laser scanning and applications by several authors.

We chose to use small-footprint lidar data because they are readily available commercially and they provide information about forest structure. Small-footprint lidar instruments, which are flown in aircraft 200 to 1000 m above the ground (Baltsavias, 1999), send many short, narrow pulses of laser light towards the landscape each second. The light pulses have footprints at ground level of approximately 0.2 to 0.9 m in diameter and collect one to five reflections or returns from each pulse. Millions of returns can "image" trees and stands in three dimensions, and characteristics of stands important to forest industry, such as volume and height, are three-dimensional features.

Attempts to assess forest stand characteristics with small-footprint lidar have met with improving success. Early work was moderately successful at predicting stand height (Aldred and Bonnor, 1985). Recent studies in conifer stands in Norway (Næsset, 1997a) and British Columbia (Magnussen and Boudewyn, 2000) have shown stand height can be predicted with r^2 values of over 0.9 and volume with r^2 values of 0.45 to 0.89 (Næsset, 1997b).

Several studies in the last 20 years have shown that large-footprint lidar, which collects a full waveform of reflected light, can provide good estimates of stand features (MacLean

J. Means is with the Department of Forest Science, Oregon State University (OSU), Corvallis, OR 97331-5752 (joe.means@orst.edu).

S. Acker was with the Department of Forest Science, OSU, at the time this work was done. He is now with the National Park Service, 909 Firt Ave., Seattle, WA 98104.

B. Fitt is with the Department of Geosciences, OSU, Corvallis, OR 97331-5752.

M. Renslow is with Spencer B. Gross, Inc., 331 West 13th Ave., #E, Eugene, OR 97401.

L. Emerson is with Spencer B. Gross, Inc., 13545 N.W. Science Park Drive, Portland, OR 97229.

Chad J. Hendrix is with Pacific Meridian Resources, 5915 Hollis Street, Building B, Emoryville, CA 94608.

Photogrammetric Engineering & Remote Sensing
Vol. 66, No. 11, November 2000, pp. 1367–1371.

0099-1112/00/6611–1367$3.00/0

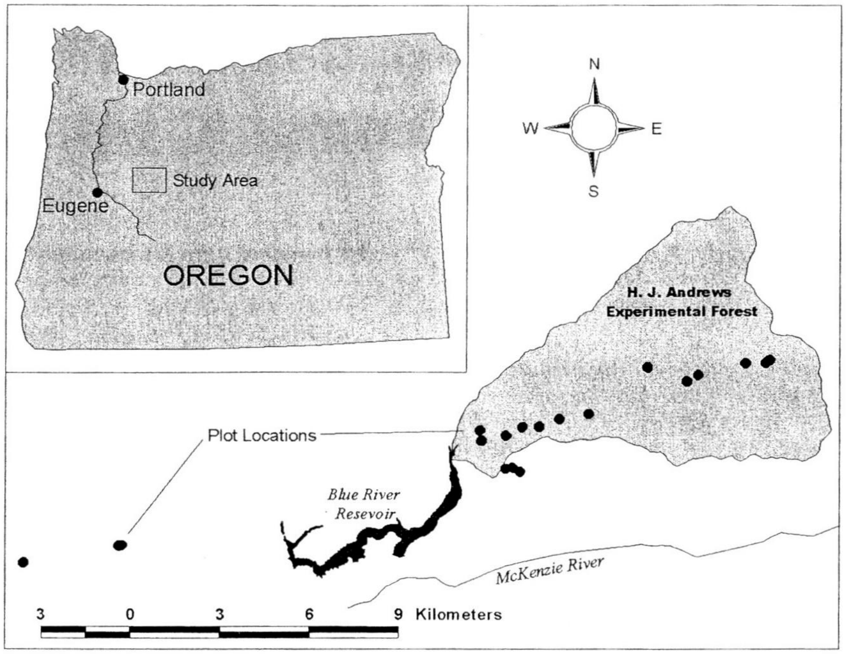

Figure 1. Location in Oregon of H.J. Andrews Experimental Forest study area and study plots.

and Krabill, 1986; Nelson, 1997; Lefsky *et al.*, 1999; Means *et al.*, 1999). However, most large-footprint lidar instruments are operated by NASA, and such data are not commercially available at present.

Study Area and Ground Data

The study area, in the western Cascades of Oregon (Figure 1), was chosen because stands are typically dominated by Douglas-fir and because geolocated ground plots, suitable for our project, are available from a previous study (Means *et al.*, 1999). These plots, in and near the H.J. Andrews Experimental Forest, are 50 by 50 m in area and were installed in the fall of 1996 in stands spanning the full range of developmental stages found in the western Cascades: shrub-dominated, young (20 to 80 years old), mature (120 to 200 years old), and old-growth (200 to 500 years old). Diameters of all trees and heights on a subsample of trees were measured, allowing computation of average stand height, stand basal area, and stand volume. Stand volume was accumulated from individual tree volumes, most of which were calculated using equations based on tree volumes measured with a Barr and Stroud optical dendrometer (Means *et al.*, 1994). More information on field methods and calculation of heights and basal areas for these stands is available elsewhere (Means *et al.*, 1999).

For all but old-growth stands, the calculated heights, basal areas, and volumes were projected from Fall 1996 to Fall 1999 as follows: (1) heights of shrub and young stands (King, 1966) and mature stands (McArdle *et al.*, 1961) were projected using appropriate height growth equations and tables; and (2) basal areas and volumes of shrub and young (Curtis *et al.*, 1982) and mature (McArdle *et al.*, 1961) were projected by deriving increments from appropriate tables and adding the three-year increment to the 1996 field values. The data used in this study are summarized in Table 1.

Lidar Data Acquisition

The AeroScan lidar instrument is owned and operated by EarthData Technologies, a wholly owned subsidiary of EarthData International of Hagerstown, Maryland. Spencer B. Gross, Inc. is their Northwest business affiliate for AeroScan lidar services and data. The whole system includes a kinematic Global Positioning System (GPS) receiver, a high-accuracy inertial measurement unit, and a high-precision clock. It is flown in a fixed wing aircraft and collects 15,000 lidar reflections per second. More information on the AeroScan lidar is available on the web (**http://www.sbgmaps.com/lidar_technologies.htm**). Lidar footprints were about 60 cm in diameter and spaced 0.6 to 3.0 m apart in a zig-zag pattern. In this way, they are different from pixels in an image which are contiguous in a square grid. AeroScan collected up to four reflections per lidar shot in this study, and we used only the first and last of these returns. Figure 2 is a lidar-based image of vegetation height in which the larger identifiable tree crowns are old-growth Douglas-fir and the patch of shorter vegetation is 35-year-old Douglas-fir.

Initially the lidar flight was planned for mid-summer 1999. This was timed to be after melting of the thick snow packs at some of the high elevation sites and after completion of branch and needle elongation on Douglas-fir. The flight occurred 15 October 1999.

Processing Lidar Data

Data collected in flight from the lidar instrument, GPS, and inertial measurement unit were processed with proprietary software by Spencer B. Gross, Inc. to yield *X*, *Y*, *Z* coordinates in the

Table 1. Ranges in Characteristics of Field Plots Used in the Stand Study.

Seral Stage	Number of plots	Height [m]	Basal area [m^2/ha]	Volume [m^3/ha]
Shrub	1	7	6	18
Young	7	17–28	26–49	283–556
Mature	3	30–42	47–70	544–944
Old-growth	8	35–52	71–132	1313–2051

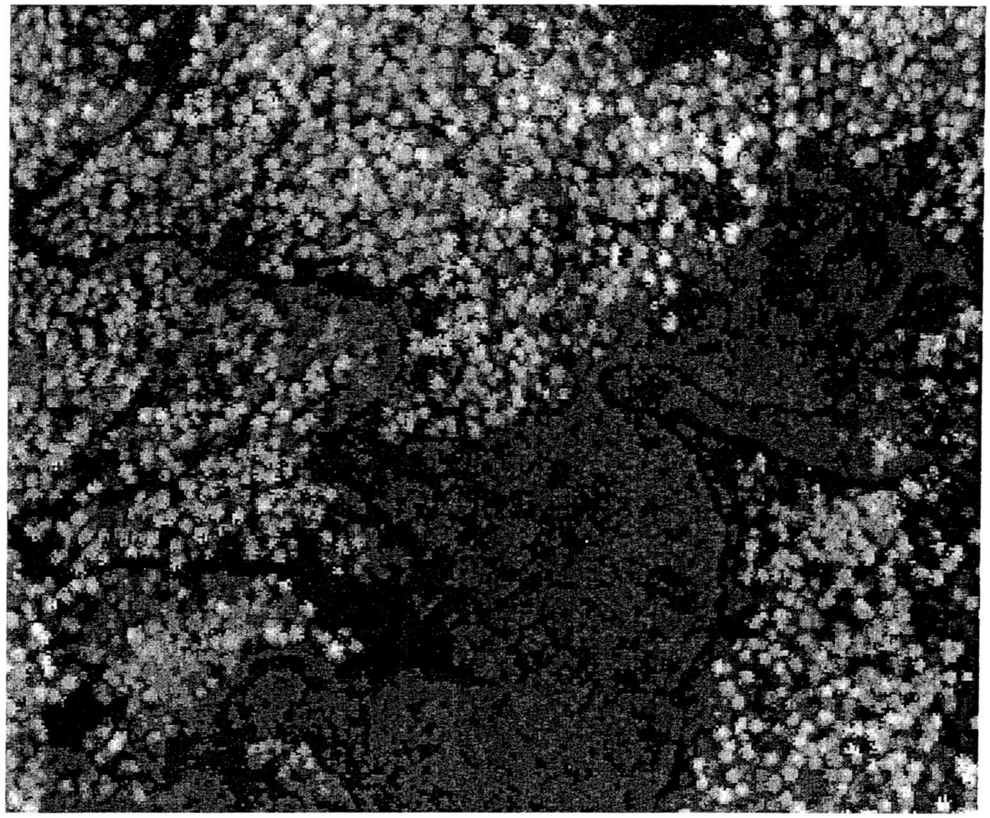

Figure 2. Image of vegetation height derived from AeroScan lidar data, 790 m by 670 m with 2-m pixels. The individual tree crowns are old-growth Douglas-fir. The dark gray vegetation is vegetation in a clearcut planted with Douglas-fir 35 years ago and is mostly 10 to 20 m tall. Image brightness scales from black for zero vegetation height to white for vegetation 70 to 80 m tall, in 10-meter classes.

UTM projection in NAD83 and NAVD88 datums above the surface of the Earth.

An approximate digital terrain model (DTM) was produced by selecting the lowest lidar last return in each 10- by 10-m grid cell to be the ground elevation for that cell. Within each 50- by 50-m plot, for each lidar first return, the ground elevation directly beneath it was calculated from the DTM by bilinear interpolation. Its height was calculated as the difference between the interpolated ground and its elevation. Height percentiles from 0 percentile to the 100th percentile were calculated. A given height percentile was calculated as the height greater than a given percentage of lidar first returns. Canopy cover percentiles were calculated as the proportion of first returns below a given percentage of total height. Maximum height on the plot was also determined. All lidar returns were assigned to a 10- by 10-m cell in a grid oriented parallel with the plot sides. Average of the mean heights (AveMeanHt) in each cell and the average of the maximum heights (AveMaxHt) in each cell were calculated because the latter was found to be a good predictor of stand height by others (Magnussen and Boudewyn, 2000; Næsset, 1997a).

Regression Analysis

We explored relationships between ground data and lidar measures using scatter plots and stepwise regression analysis in the Statistical Analysis System software (SAS Institute, 1999). In order to enter the model, a candidate predictor variable had to have an entering F statistic with a significance level of 0.05 or less, and no predictor was left in the model with a partial F statistic with a significance level greater than 0.05.

Dependent variables derived from ground data and predicted in regressions were stand height, basal area (BA), and stand volume. Candidate predictor variables derived from lidar data were average maximum height, maximum height, average mean height, height percentiles from 0 to 100 by tens, and canopy cover percentiles from 0 to 100 by tens. Good fits were obtained to each stand characteristic using the 19 plots. The regressions and r^2 values are shown in Table 2.

Height is predicted fairly accurately (Equation 1, $r^2 = 0.93$, Table 2 and Figure 3). AveHtMax (defined above) serves to reduce the height predicted by Ht90ile alone.

Basal area showed heteroscedasticity and an exponentially increasing curve when plotted against the best single predictor variables, so regressions were fit to the natural logarithm of basal area (Equation 2, Table 2). It is not surprising that a cover measure and a height measure are both in this equation and that the cover measure has the largest coefficient. The relationship between predicted and measured basal areas is shown in Figure 4.

Stem wood volume showed heteroscedasticity and an exponentially increasing curve when plotted against the best single predictor variables, so regressions were fit to the natural logarithm of volume (Equation 3, Table 2). Height percentiles and cover percentiles are both important here. The Ht0ile comes in with a negative coefficient for predicting volume. It is zero for most plots and has the effect of reducing the estimated

TABLE 2. REGRESSIONS OF FIELD-MEASURED STAND ATTRIBUTES ON LIDAR MEASURES. HT0ILE, HT80ILE, and HT90ILE ARE THE 0-, 80-, AND 90-PERCENTILES OF HEIGHT, RESPECTIVELY. COV20ILE IS THE 20-PERCENTILE OF COVER. THE ROOT-MEAN-SQUARE ERROR (RMSE) IS ONLY GIVEN FOR REGRESSIONS USING UNTRANSFORMED DATA.

Equation Number	Figure	Regression Equation	Units	r^2	RMSE
Equations Using All Plots (n = 19)					
1	2	Ht = 7.69 + 1.90*Ht90ile − 1.23*AveMaxHt	m	0.93	3.4
2	3	Ln(BA) = 1.464 + 0.03629*Ht80ile + 1.4744*Cov20ile − 0.1103*Ht0ile	m^2/ha	0.95	
3	4	Ln(Volume) = 2.532 + 0.05651*Ht80ile + 2.355*Cov20ile − 0.1581*Ht0ile	m^3/ha	0.97	
Equations not using old-growth plots (n = 11)					
4		Ht = 1.75 + 0.84*Ht90ile − 1.59*Ht0ile	m	0.98	1.7
5		BA = 31.8 − 6.13*AveMaxHt + 7.11*Ht80ile + 574.6*Cov90ile	m^2/ha	0.94	5.4
6		Volume = −83.4 + 16.29*Ht80ile + 9327.*Cov90ile	m^3/ha	0.95	73.

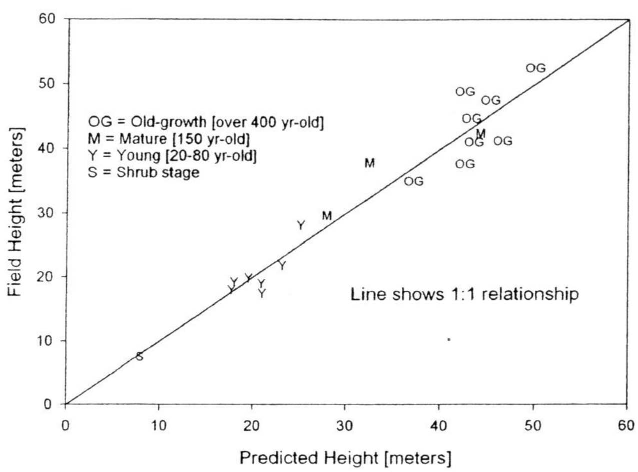

Figure 3. Field-measured over predicted stand height.

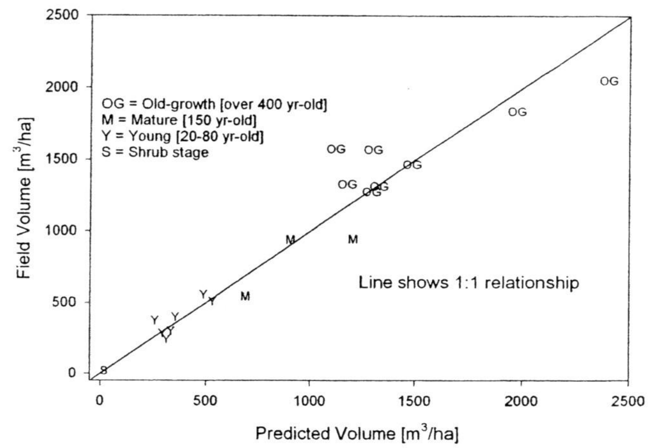

Figure 5. Field-measured over predicted stand volume.

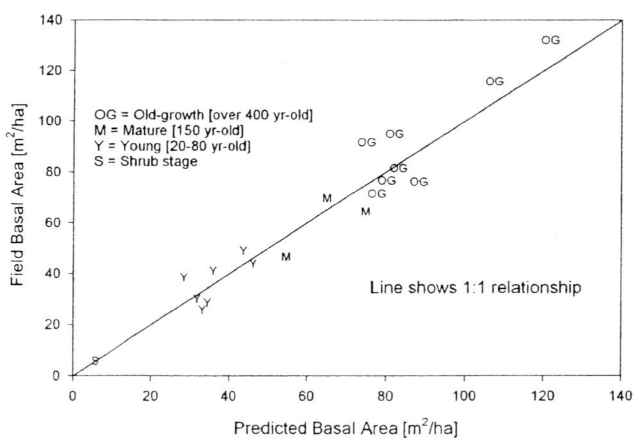

Figure 4. Field-measured over predicted stand basal area.

values on four stands. The relationship between predicted and measured volumes is shown in Figure 5.

Regressions were also fit to just the shrub and to young and mature stands because old-growth is becoming rare on industrial forest land. The same regression modeling approach was used, and logarithmic transformations were not needed. The resulting models had better or comparable fits to this younger data subset (Table 2). The root-mean-squared error for height was reduced by half.

Discussion

The models of stand characteristics are good predictors and offer encouragement that commercial applications of small-footprint lidar for forest inventory may be feasible. Some caution is merited however. Note that the highest r^2 values are for the log-transformed values. This caused the low values for shrub-stand basal area and volume to weigh heavily in the regression fit and artificially inflate the r^2 somewhat. Also, the wide range of the response variables for stands (Table 1) made it more likely that the r^2 would be high.

Though our method of building the ground DTM for the stand models was simple and not as accurate as those used by lidar companies, regression results are encouraging. This approach could save time when greater accuracy is not needed, or a more accurate approach would almost certainly improve estimates.

We have shown that, given lidar and ground data, empirical relationships can be developed that have significant potential for predicting important stand characteristics. The next step should be a test with full stands of commercial forestland. Commercial use of this approach will require both lidar and ground data for each application. Lidar has many opportunities for commercial applications but only a few are discussed below.

Commercial Metrics

The forest variables estimated from lidar data in this study (height, basal area, and volume) are of key interest to the timber

TABLE 3. AN EXAMPLE COST COMPARISON BETWEEN CURRENT, TRADITIONAL FIELD METHODS OF FOREST INVENTORY AND A POTENTIAL LIDAR-BASED METHOD.

	Time Estimate	Cost Estimate
Traditional methods (field work and analyses)	14 weeks	$32,000
Lidar methods		
Lidar data collection (200 acres @ $7 per acre + $5,000 staging fee) and delivery	1 week	$6,400
Field sampling (10% of lidar coverage = 20 acres)	1 week	$3,200
Lidar analysis	2 weeks	$7,000
Total for lidar methods	4 weeks	$16,000
Savings per year with lidar methodology	10 weeks	$15,000

industry and represent information that is expensive to collect in the field. Typical forestry field sampling includes tree height, basal area, and tree form in some subsample of the forest lands being considered.

The tools developed here would allow an entire forest to be mapped from lidar data using a small field sample. Or, as a more cost-effective alternative, a multi-stage sampling design could be used. Lidar data would be collected over a sample of the forest. Within the lidar coverage area, an appropriate number of field samples could be collected to build the relationships between lidar-derived variables and stand attributes that could be extended to the entire lidar sample and, in turn, to the forest area in question.

Following this approach, a cost comparison example is considered (Table 3) for a typical even-aged, managed forest of 500,000 acres. Each year, two percent of 10,000 acres (200 acres) are sampled to determine what management steps are needed. This cost comparison is favorable; however, actual costs will be different for different proportions of area sampled on the ground and other components of the traditional and lidar-supplemented sampling designs. The partnership with Pacific Meridian Resources and Spencer B. Gross, Inc. positions them to move into this field which will be new for them.

The commercial applications of lidar in forestry look very promising. Based on the market potential among the "early-adopters" of advanced technologies, the industry should be positioned to support 6 million dollars of work during the next two years (based on 20 percent of the market potential).

Riparian habitat is a key component of stream habitat for fish. The Oregon Department of Environmental Quality, the U.S. Army Corps of Engineers, and the Federal Emergency Management Agency are seeking to map riparian vegetation in the entire Willamette Valley of Oregon. Key components of this mapping are vegetation height (tree size) and location relative to the stream, because they influence shading of streams from solar radiation and eventual input of logs to streams; woody debris in streams provides important habitat and structure. We estimate traditional air photo techniques would require about 10 years to complete the job and may not meet the needed accuracy. Lidar technologies, including the tools developed here, offer two improvements. They will allow this work to be done in three years, and the maps of vegetation height and basal area will meet or exceed the needed accuracy. New business for companies that fly lidar instruments would be about ten million dollars.

Acknowledgments

These partnerships were supported by the Commercial Remote Sensing Program of NASA, an NSF grant to the H.J. Andrews Forest LTER, and Oregon State University. The authors gratefully acknowledge field data collection by Scott Miller, Crystal Dickard, Becky Fasth, Matthew Goslin and Kerry Halligan, sometimes in very inclement weather. We appreciate helpful reviews by Al Peters, Jennifer Swenson and Jon Kimerling.

References

Aldred, A.H., and G.M. Bonnor, 1985. *Application of Airborne Lasers to Forest Surveys*, Information Report PI-X-51. Petawawa National Forestry Institute, Chalk River, Ontario, Canada, 62 p.

Baltsavias, E.P., 1999. Airborne laser scanning: existing systems and firms and other resources, *Remote Sensing of Environment*, 54(2–3):164–198.

Curtis, R.O., G.W. Clendenen, D.L. Reukema, and D.J. DeMars, 1982. *Yield Tables for Managed Stands of Coast Douglas-Fir*, General Technical Report PNW-135, Pacific Northwest Research Station, USDA Forest Service, Portland, Oregon, 182 p.

Flood, M., and B. Gutelius, 1997. Commercial implications of topographic terrain mapping using scanning airborne laser radar, *Photogrammetric Engineering & Remote Sensing*, 63(4):327–366.

King, J.E., 1966. *Site Curves for Douglas-Fir in the Pacific Northwest*, Weyerhaeuser Forestry Paper 8, Forestry Research Center, Weyerhaeuser Company, Centralia, Washington, 49 p.

Lefsky, M.A., W.B. Cohen, S.A. Acker, G.G. Parker, T.A. Spies, and D. Harding, 1999. Lidar remote sensing of the canopy structure and biophysical properities of Douglas-fir western hemlock forests, *Remote Sensing of Environment*, 70:339–361.

MacLean, G.A., and W.B. Krabill, 1986. Gross-merchantable timber volume estimation using an airborne LIDAR system, *Canadian Journal of Remote Sensing*, 12(1):7–18.

Magnussen, S., and P. Boudewyn, 2000. Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators, *Canadian Journal of Forest Research*, 28:1016–1031.

McArdle, R.E., W.H. Meyer, and D. Bruce, 1961. *The Yield of Douglas-Fir in the Pacific Northwest*, Technical Bulletin 201, United States Department of Agriculture, Washington, D.C., 74 p.

Means, J.E., H.A. Hansen, G.J. Koerper, P.B. Alaback, and M.W. Klopsch, 1994. *Software for Computing Plant Biomass—BIOPAK Users Guide*, General Technical Report PNW-GTR-340, Pacific Northwest Research Station, USDA Forest Service, Portland, Oregon, 184 p.

Means, J.E., S.A. Acker, D.J. Harding, J.B. Blair, M.A. Lefsky, W.B. Cohen, M.E. Harmon, and W.A. McKee, 1999. Use of large-footprint scanning airborne lidar to estimate forest stand characteristics in the western Cascades of Oregon, *Remote Sensing of Environment*, 67(3):298–308.

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

———, 1997b. Estimating timber volume of forest stands using airborne laser scanner data, *Remote Sensing of Environment*, 61(2):246–253.

Nelson, R., 1997. Modeling forest canopy heights: The effects of canopy shape, *Remote Sensing of Environment*, 60(3):327–334.

SAS Institute, 1999. *The SAS System for Windows Version 8*, The SAS Institute, Cary, North Carolina (on-line HTML Help Files).