
Use of LIDAR for Forest Inventory and Forest Management Application

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Abstract.—A significant impediment to forest managers has been the difficulty in obtaining large-area forest structure and fuel characteristics at useful resolutions and accuracies. This paper demonstrates how LIDAR data were used to predict canopy bulk density (CBD) and canopy base height (CBH) for an area in the Sierra National Forest. The LIDAR data were used to generate maps of canopy fuels for input into a fire behavior model (FARSITE). The results indicate that LIDAR metrics are significant predictors of both CBD ($r^2 = 0.71$) and CBH ($r^2 = 0.59$). In summary, LIDAR is no longer an experimental technique and has become accepted as a source of accurate and dependable data that are suitable for forest inventory and assessment.

Introduction

In this article we present an overview of the use of LIDAR for forest inventory and canopy structure mapping and explore the efficacy of a large-footprint, waveform-digitizing LIDAR for the estimation of canopy fuels for utilization in fire behavior simulation models. Because of its ability to measure the vertical structure of forest canopies, LIDAR is uniquely suited among remote sensing instruments to observe canopy structure characteristics, including those relevant to fuels characterization, and may help address the relative lack of spatially explicit fuels data. Two canopy structure

characteristics have been identified that help quantify these fuel loads: canopy bulk density (CBD) and canopy base height (CBH). These have been adopted for fire behavior modeling (Sando and Wick 1972, Scott and Reinhardt 2001). CBD is defined as the mass of available canopy fuel per unit canopy volume and CBH is the lowest height in the canopy where there is sufficient fuel to propagate fire vertically into the canopy (Scott and Reinhardt 2001).

This article provides a brief, simple description of the different types of LIDAR systems and how they work and summarizes previous research utilizing LIDAR for landsurface characterization. It also examines the use of large-footprint, waveform-digitizing LIDAR data to predict and create maps of CBD and CBH as well as the use of LIDAR-derived products to run a fire behavior model. LIDAR metrics are compared to field-based estimates of CBD and CBH and, based on the regression models resulting from these comparisons, maps of CBD and CBH are generated that are then tested as inputs into a fire behavior model.

LIDAR

LIDAR (frequently used synonymously with the term *laser altimetry*) provides a direct and elegant means to measure the structure of vegetation canopies (Dubayah and Drake 2000). LIDAR is an active remote sensing technique in which a pulse of light is sent to the Earth's surface from an airborne or spaceborne laser. The pulse reflects off of canopy materials such as leaves and branches. The returned energy is collected back at the instrument by a telescope. The time taken for the pulse

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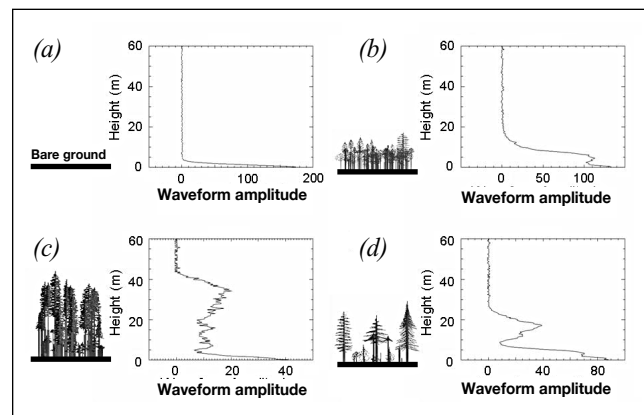
to travel from the instrument, reflect off of the surface, and be collected at the telescope is recorded. From this ranging information various structure metrics can be calculated, inferred, or modeled (Dubayah and Drake 2000). A variety of LIDAR systems have been used to measure vegetation characteristics. Most of these are small-footprint, high pulse rate, first- or last-return-only airborne systems that fly at low altitudes. Other, experimental LIDAR systems are large footprint and full waveform digitizing and provide greater vertical detail about the vegetation canopy. Dubayah *et al.* (2000) and Lefsky *et al.* (2002) provide thorough overviews of use of LIDAR for landsurface characterization and forest studies.

Canopy height, basal area, timber volume and biomass have all been successfully derived from LIDAR data (Drake *et al.* 2002a, Drake *et al.* 2002b, Hyde *et al.* 2005, Lefsky *et al.* 1999, Maclean and Krabill 1986, Magnussen and Boudewyn 1998, Means *et al.* 1999, Naesset 1997, Nelson *et al.* 1984, Nelson *et al.* 1988, Nelson 1997, Nilsson 1996, Peterson 2000). Many of these studies rely on small-footprint systems. Small-footprint LIDARs have the advantage of providing very detailed measurements of the canopy top topography. Most small-footprint (5-cm to 1-m diameters) systems are low flying and have a high sampling frequency (1,000 to 10,000 Hz). Although small-footprint systems typically do not digitize the return waveforms, the high frequency sampling produces a dense coverage of the overflown area. This can provide a very detailed view of the vegetation canopy topography; however, the internal structure of the canopy is difficult to reconstruct because data from the canopy interior are sparse (Dubayah *et al.* 2000).

Recently, LIDARs have been developed that are optimized for the measurement of vegetation (Blair *et al.* 1994, Blair *et al.* 1999). These systems have larger footprints (5- to 25-m diameters) and are fully waveform digitizing, meaning that the complete reflected laser pulse return is collected by the system. LIDAR remote sensing using waveform digitization records the vertical distribution of surface areas between the canopy top and the ground. For any particular height in the canopy, the waveform denotes the amount of energy (i.e., the amplitude of the waveform) returned for that layer (Dubayah *et al.* 2000). The amplitude is related to the volume and density of canopy material located at that height (fig. 1).

Subcanopy topography, canopy height, basal area, canopy cover, and biomass have all been successfully derived from large-footprint LIDAR waveform data in a variety of forest types (Drake *et al.* 2002a, Dubayah and Drake 2000, Hofton *et al.* 2002, Hyde *et al.* 2005, Lefsky *et al.* 1999, Means *et al.* 1999, Peterson 2000). For example, results from Hofton *et al.* (2002) show that large-footprint LIDAR measured subcanopy topography in a dense, wet tropical rainforest with an accuracy better than that of the best operational digital elevation models (such as U.S. Geological Survey 30-m DEM products). Means *et al.* (1999) used large-footprint LIDAR to recover mean stand height ($r^2 = 0.95$) for conifer stands of various ages in the Western Cascades of Oregon. Drake *et al.* (2002a) found that metrics from a large-footprint LIDAR system were able to model plot-level biomass ($r^2 = 0.93$) for a wet tropical rainforest. Dubayah *et al.* (2000), Dubayah and Drake (2000), and Lefsky (2002) provide a thorough overview of forest structure derived using large-footprint LIDAR. In sum, LIDAR is a proven method for deriving many characteristics relevant to forest management. LIDAR data have also been used to measure canopy structure relevant to fire behavior modeling

Figure 1.—Illustrations showing sample waveforms for different cover types in the Sierra Nevada. (a) Waveform return from bare ground—no canopy return. (b) Waveform return for a short, dense forest stand. The canopy return blends in with the ground return. (c) Waveform return for a tall, dense forest stand. The waveform shows layering in the canopy and the ground return is clearly defined. (d) Waveform return for a tall, sparse forest stand. The waveform shows a distinct upper canopy layer and a layer of low-lying vegetation that mixes in with the ground return. The stand diagrams were created with the Stand Visualization System based on field measurements.



(Andersen *et al.* 2005, Morsdorf *et al.* 2004, Riaño *et al.* 2003, Riaño *et al.* 2004, Seielstad and Queen 2003) and this specific application is explored in the remainder of this paper.

Study Site and Data Collection

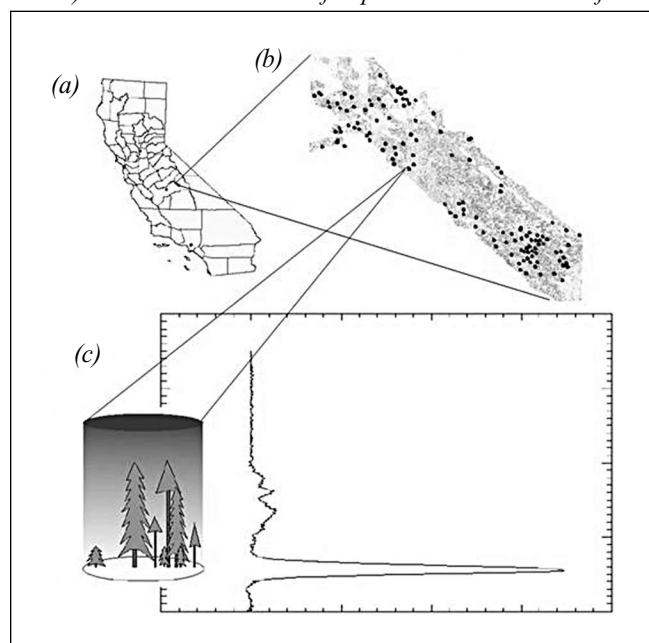
The study area is located in the Sierra National Forest in the Sierra Nevada mountains of California near Fresno (fig. 2) and covers a wide range of vegetation types (e.g., fir, pine, mixed conifer, mixed hardwood/conifer, meadow), canopy cover, and elevation. Common species of the region include red fir (*Abies magnifica* A. Murr.), white fir (*Abies concolor* (God. & Glend.) Hildebr.), ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.), Jeffrey pine (*Pinus jeffreyi* Grev. & Balf.), and incense cedar (*Libocedrus decurrens* Torr.), among others. Canopy cover can range from completely open in meadows or ridge tops to very dense, especially in fir stands. The study area extends over nearly 18,000 ha of U.S. Department of Agriculture Forest

Service and privately owned lands. The topography varies considerably with some areas characterized by very steep slopes and an elevation range between approximately 850 and 2,700 m.

The LIDAR data used in this study were collected by the Laser Vegetation Imaging Sensor (LVIS) (Blair *et al.* 1999). LVIS is a large-footprint LIDAR system optimized to measure canopy structure characteristics. LVIS mapped a 25- by 6-km area of the Sierra National Forest in October of 1999 in a series of flight tracks (fig. 2). Flying onboard a NASA C-130 at 8 km above ground level and operating at 320 Hz, LVIS produced thousands of 25-m diameter footprints at the surface.

Field data were collected in the summers of 2000–02 in the Sierra National Forest. Circular plots were centered on LIDAR footprints and measured 15 m in radius. The 15-m radius was chosen to ensure complete overlap with the LVIS footprint and to account for trees located beyond the 12.5-m radius of the footprint with crowns overhanging the footprint. Within these plots all trees over 10-cm diameter at breast height (d.b.h.) (diameter at breast height) were sampled. Measurements included tree height, height to partial crown, partial crown wedge angle, height to full crown, four crown radius measurements, and distance and azimuth relative to the plot center. Tree crown shape and species were also recorded.

Figure 2.— Schematic showing the location of the study site, plot distribution, and footprint-centered plot design. (a) Locator map of the study area in the Sierra Nevada, northeast of Fresno. (b) The study area was delimited by swaths of LVIS data covering the region. The combined area of the swaths is approximately 25 by 6 km. (c) The individual plots were colocated with the LVIS footprints. Each circular plot (15-m radius) is centered on an LVIS footprint with its own waveform.



LVIS = Laser Vegetation Imaging Sensor.

Derivation of CBD and CBH

The data from the 135 plots were used to calculate field-based CBD according to an inventory-based method. The original methodology was presented in Sando and Wick (1972) and relied on conventional field-sampled data (e.g., height, d.b.h., stem count density) to derive quantitative observations of canopy fuels. This method was subsequently modified for inclusion in Fire and Fuels Extension to the Forest Vegetation Simulator (Beukema *et al.* 1997). As described by Scott and Reinhardt (2001) a vertical profile of bulk density is derived by first calculating the foliage and fine branch biomass for each tree in the plot, then dividing that fuel equally into 1-foot (0.3048-m) horizontal layers from the base of the tree's crown through to the maximum tree height and finally summing the

fuel loads contributed by each tree in the plot for all 1-foot segments. CBD is estimated by finding the maximum of a 4.5-m deep running average for the horizontal layers of CBD. CBH is typically defined as the height in the profile at which the CBD reaches a predetermined threshold value. In this study, CBH is defined as the height in the profile at which the bulk density equals or exceeds 0.011 kg/m^3 (Scott and Reinhardt 2001).

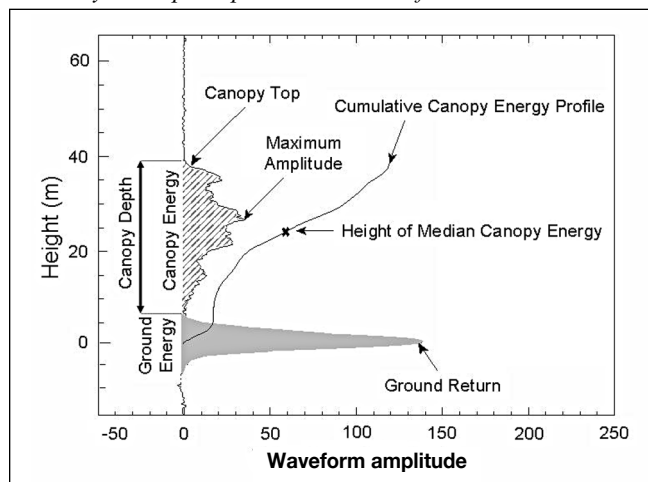
CBD and CBH were derived from LIDAR data for waveforms that were coincident with the study's field plots. This process involved several steps. First, LIDAR metrics were identified as potential predictors based on previous work deriving other biophysical characteristics from waveform data such as canopy cover, basal area, and biomass. The LIDAR metrics selected were canopy height (HT), canopy height squared (HT^2), canopy energy (CE), canopy energy/ground energy ratio (CE/GE), lowest canopy return (L), canopy depth (D), peak amplitude (MAX), and the height of median cumulative canopy energy (HMCE) (fig. 3).

Second, individual waveforms were normalized by dividing the energy present in each waveform bin (representing the energy returned for each vertical resolution unit, in this

case approximately 30-cm deep) by the total energy in the waveform. The normalization process accounts for flight-to-flight as well as footprint-to-footprint variations in energy in the waveform, caused, for example, by flying at day versus night or by the incident angle of the laser beam. Normalization allows for easier comparison of waveform-derived metrics.

Third, the waveform metrics listed above were calculated for each of the normalized waveforms. HT was determined by subtracting the range to the ground (defined as the midpoint of the last peak) from that of the first detectable canopy return above noise. HT^2 is the squared value of HT. CE and GE are derived by separating the waveform into a canopy portion and a ground portion and then summing the bin values for those portions of the waveform. L is the height of the bottom of the canopy portion of the waveform. D is the vertical extent of the canopy portion of the waveform. MAX is the peak amplitude value in the canopy portion of the waveform. HMCE is the height at which the cumulative energy in the canopy portion of the waveform reaches the 50th percentile. Several additional metrics were derived to predict CBH from the cumulative canopy energy profile. The additional LIDAR-derived CBH metrics include the 0.5th-, 1st-, 5th-, and 10th-percentile heights of the cumulative canopy energy.

Figure 3.—Schematic of an individual LIDAR waveform showing LIDAR metrics. A pulse of laser energy reflects off canopy (e.g., leaves and branches) and the ground beneath, resulting in a waveform. The amplitudes of individual peaks in the waveform are a function of the number of reflecting surfaces at that height. The different LIDAR metrics used in this study are superimposed on the waveform.



A transformation was also applied to the LVIS waveforms. Some previous studies (Lefsky *et al.* 1999, Means *et al.* 1999) have maintained that LIDAR waveform data need to be adjusted to correct for shading of lower foliage and branches by higher foliage and branches. This adjustment consists of applying an exponential transform to the waveform (modified MacArthur-Horn [1969] method) and is described in detail in Lefsky *et al.* (1999). The transform has the effect of increasing the amplitude of the waveform return from the lower part of the canopy.

Once the LIDAR metrics were calculated, they were used as explanatory variables in multiple linear regression analyses to determine which set of metrics best predicted CBD and CBH. Separate regression equations were derived for different vegetation types. The vegetation type categories used in this study were red fir, white fir, ponderosa pine, miscellaneous pine (comprised of Jeffrey pine, sugar pine, and lodgepole

pine), Sierra mixed conifer, mixed hardwood conifer/mixed hardwood, and meadow/bare ground. Because the number of plots in two of the vegetation classes (white fir and ponderosa pine) was small, some explanatory variables were dropped out of the regression equations for these classes. Stepwise regression techniques were used to determine which variables should be dropped because they had relatively low explanatory power. The same suite of LIDAR metrics were recalculated from the waveforms once the modified MacArthur-Horn transformation was applied. The metrics derived from the transformed waveforms were then used as variables in the same series of regression analyses for the different vegetation types as described above.

The LIDAR-predicted and field-derived CBD compared rather well. The r^2 value of 0.71 ($p < 0.0001$, root square error (RSE) = 0.036) is based on the correlation between the collective observed and predicted estimates of CBD. The regression analyses were then repeated using the transformed LIDAR data. This dropped the r^2 value to 0.67. The comparison between the LIDAR-based and field-based estimates of CBH is also rather good. For CBH, the regression model was improved when using the LIDAR metrics derived from the transformed waveform. The r^2 using the transformed data was 0.59 ($p < 0.0001$, RSE = 0.573) as compared to an r^2 of 0.48 using the metrics from the original waveform. Again, the reported r^2 for the CBH derivation is based on the correlation between the collective observed and predicted estimates.

The differences between the various vegetation-type specific regression models most likely reflect structural differences among the various forest stands included in the study. For most of the vegetation types the relationship between the LIDAR-metrics and field-derived CBD is fairly strong (i.e., $r^2 > 0.6$), the exception being the mixed conifer class ($r^2 = 0.3811$), where, in the higher range of values, the predicted CBD was lower than the observed CBD. The greatest error in predicting CBD occurred in stands characterized by a dense canopy layer of mid and understory trees with a few dominant tree crowns interspersed. The equations used to calculate CBD

from the field data could be overestimating the canopy loads of the codominant and subdominant trees. The trees in denser stands have crowns that are often irregular in shape, meaning that actual fuel load for these trees is likely much lower than predicted when a regular shape is assumed in an algorithm. In addition, there is considerable variation in crown shape among species. White fir, for example, tends to be rather cone shaped while sugar or ponderosa pine crowns are more parabolic. Furthermore, the field-based estimates of CBD only consider the fraction of fuels made up of fine (e.g., foliar) material rather than the total biomass in the plot, which is recorded by the LIDAR waveform.

We believe that at least part of the error in the CBH derivation can be attributed to the fact that trees less than 10 cm d.b.h. were not sampled in the field. For certain plots (especially mixed conifer) this excludes a significant number of smaller stems and could lead to an erroneously high derivation of CBH from the field data. The omission of smaller trees could cause the amount of material assigned to the lower part of the density profile to be less than it should be.

Other factors such as slope and varying footprint size (due to changes in surface elevation) were explored to determine if they might be a source of error for both the CBD and CBH LIDAR derivations. No relationship between the residuals of the regression and these factors could be discerned, however.

Interestingly, the results of the CBH regression analyses show that LVIS metrics that were derived from waveforms transformed using the modified MacArthur-Horn method were better able to predict CBH ($r^2 = 0.59$) than the untransformed metrics ($r^2 = 0.48$). The transform increases the amplitude of the return in the lower portion of the waveform and therefore it has a greater impact on the metrics derived from that part of the waveform. The overall effect of the transform was to lower the height of several metrics. This caused the correlation between predicted and observed CBH at the shorter end of the range (0–2 m) to improve, thereby also improving the overall r^2 . The poorest results were again for the mixed conifer class.

FARSITE Simulations

The fire behavior model used in this study is the Fire Area Simulator (FARSITE, Finney 1998). FARSITE is a Geographic Information System-based fire behavior model in common use with agencies throughout the United States. In all, FARSITE has eight input layers (Finney 1998). The first five (elevation, slope, aspect, fuel model, and canopy cover) are all that are needed to simulate surface fires. The last three (canopy height, CBD, and CBH) are needed to model crown fire behavior.

Once the regression models for CBD and CBH were developed they were used to derive CBD and CBH from all of the LVIS waveforms in the study area. First, the required LIDAR metrics were calculated from the waveforms. Then the LVIS data were classified by land cover type and the vegetation-type specific regression models were applied. This created point data of CBD and CBH for the entire study area. These point data were then gridded into 25-m raster layers using ArcInfo. These grids are hereafter referred to as LVIS grids. An inverse difference weighting (IDW) technique was used for gridding and to compensate for gaps in the data caused by irregularities in the flight lines. To complete the set of canopy structure data needed to run FARSITE, an LVIS-derived canopy height grid was also created. Hyde *et al.* (2005) validated the LVIS canopy height measurement for the Sierra Nevada study site. For this study, the height data were also gridded to 25 m using the IDW technique.

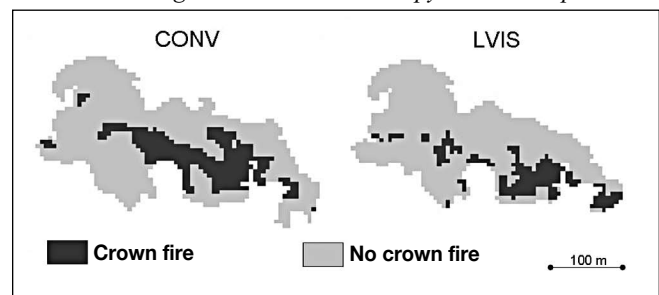
Once the LVIS grids were created they were first compared to canopy height, CBD, and CBH data layers that were generated using conventional methods, referred to hereafter as CONV grids. The CONV grids were only available for a smaller part of the study area—at the far southeastern end of the flight lines. Therefore, the LVIS grids were clipped to match the extent of the CONV grids. There are obvious differences between the two sets of data. Of particular note is the increased spatial heterogeneity contained in the LVIS grids relative to the CONV grids.

FARSITE was then run twice: once using the LVIS canopy structure grids and once using the CONV input grids. All other spatial inputs were kept constant as was the point of ignition.

The wind and weather input data used for the two model runs were representative of a dry, warm day and the simulated duration was set to 40 hours.

Figure 4 shows the output (crown fire/no crown fire status) for the two model runs. The extent of the fire spread is very similar for both of the model runs. Though occurring in similar locations, the occurrence of crown fire as discrete clusters in the LVIS output is very different from the larger, continuous areas of crown fire shown in the CONV output grid. In the LVIS output grid the crown fire clusters appear to be associated with the presence of higher CBD values and lower CBH values, which are assumed to promote the spread of fire to the canopy. Future research will explore not only the effect of increasing or decreasing the canopy structure values on model outputs but also the effect of increased spatial heterogeneity in the input layers.

Figure 4.—FARSITE crown-fire/no-crown-fire outputs for two model runs using LVIS and CONV canopy structure inputs.



CONV = conventional; LVIS = Laser Vegetation Imaging Sensor.

Conclusions

LIDAR systems of different types have had success in recovering forest structure characteristics for a variety of vegetation types in a comparatively simple and direct manner. In recent years LIDAR has become recognized as a valuable remote sensing tool for forest inventory and structure mapping and is gaining in use for informing forest management decisionmaking. Because of its ability to measure canopy structure both horizontally and vertically, LIDAR has potential for providing the type of forest structure required for fuels estimation and fire behavior modeling. The results of this paper demonstrate that waveform data from a large-footprint system may provide

the spatially explicit forest structure needed for fire behavior modeling. We will continue to explore and improve on methods for deriving CBD and CBH from LIDAR. One option to be considered is to incorporate various remote sensing data from other sensor types into a fusion-based approach for deriving the canopy structure variables. These results also have implications for remote-sensing-based inventory at larger scales. ICESAT and other near-future space-based LIDAR systems are or will likely be large footprint and waveform digitizing. Though these are not imaging systems, the global samples of three-dimensional structure that they will provide can be incorporated into forest inventory.

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Literature Cited

- Andersen, H.E.; McGaughey, R.J.; Reutebuch, S.E. 2005. Estimating forest canopy fuel parameters using LIDAR data. *Remote Sensing of Environment*. 94: 441-449.
- Beukema, S.J.; Greenough, D.C.; Robinson, C.E.; Kurtz, W.A.; Reinhardt, E.D.; Crookston, N.L.; Brown, J.K.; Hardy, C.C.; Sage, A.R. 1997. An introduction to the fire and fuels extension to FVS. In: Teck, R.; Mouer, M.; Adams, J., eds. *Proceedings, forest vegetation simulator conference*. Gen. Tech. Rep. INT-GTR-373. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Research Station: 191-195.
- Blair, J.B.; Coyle, D.B.; Bufton, J.; Harding, D. 1994. Optimization of an airborne laser altimeter for remote sensing of vegetation and tree canopies. In: *Proceedings, IEEE international geoscience and remote sensing symposium*. Los Alamitos, CA. 2: 939-941.
- Blair, J.B.; Rabine, D.L.; Hofton, M.A. 1999. The Laser Vegetation Imaging Sensor (LVIS): a medium-altitude, digitization-only, airborne laser altimeter for mapping vegetation and topography. *ISPRS Journal of Photogrammetry and Remote Sensing*. 54: 115-122.
- Drake, J.B.; Dubayah, R.O.; Clark, D.; Knox, R.; Blair, J.B.; Hofton, M.; Chazdon, R.L.; Weishampel, J.F.; Prince, S. 2002a. Estimation of tropical forest structural characteristics using large-footprint LIDAR. *Remote Sensing of Environment*. 79: 305-319.
- Drake, J.B.; Dubayah, R.O.; Knox, R.G.; Clark, D.B.; Blair, J.B. 2002b. Sensitivity of large-footprint LIDAR to canopy structure and biomass in a neotropical rainforest. *Remote Sensing of Environment*. 81: 378-392.
- Dubayah, R.; Drake, J. 2000. LIDAR remote sensing for forestry. *Journal of Forestry*. 98: 44-46.
- Dubayah, R.; Knox, R.; Hofton, M.; Blair, B.; Drake, J. 2000. Land surface characterization using LIDAR remote sensing. In: Hill, M.; Aspinall, R., eds. *Spatial information for land use management*. Singapore: Gordon and Breach: 25-38.
- Finney, M.A. 1998. FARSITE: Fire Area Simulator—model development and evaluation. Res. Pap. RMRS-RP-4. Ft. Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 47 p.
- Hofton, M.; Rocchio, L.; Blair, J.B.; Dubayah, R. 2002. Validation of vegetation canopy LIDAR sub-canopy topography measurements for dense tropical forest. *Journal of Geodynamics*. 34: 491-502.

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- Hyde, P.; Dubayah, R.; Peterson, B.; Blair, J.B.; Hofton, M.; Hunsaker, C.; Knox, R.; Walker, W. 2005. Mapping forest structure for wildlife analysis using waveform LIDAR: validation of montane ecosystems. *Remote Sensing of Environment*. 96: 427-437.
- Lefsky, M.A.; Cohen, W.B.; Parker, G.G.; Harding, D.J. 2002. LIDAR remote sensing for ecosystem studies. *BioScience*. 52: 19-30.
- Lefsky, M.A.; Harding, D.; Cohen, W.B.; Parker, G.; Shugart, H.H. 1999. Surface LIDAR remote sensing of basal areas and biomass in deciduous forests of eastern Maryland, USA. *Remote Sensing of Environment*. 67: 83-98.
- MacArthur, R.; Horn, H. 1969. Foliage profile by vertical measurements. *Ecology*. 5: 802-804.
- Maclean, G.; Krabill, W.B. 1986. Gross-merchantable timber volume estimation using an airborne LIDAR system. *Canadian Journal of Remote Sensing*. 12: 7-18.
- Magnussen, S.; Boudewyn, P. 1998. Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators. *Canadian Journal of Forest Research*. 28: 1016-1031.
- Means, J.E.; Acker, S.A.; Harding, D.J.; Blair, J.B.; Lefsky, M.A.; Cohen, W.B.; Harmon, M.E.; McKee, W.A. 1999. Use of large-footprint scanning airborne LIDAR to estimate forest stand characteristics in the western Cascades of Oregon. *Remote Sensing of Environment*. 67: 298-308.
- Morsdorf, F.; Meier, E.; Kötz, B.; Itten, K.I.; Dobbertin, M.; Allgöwer, B. 2004. LIDAR-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management. *Remote Sensing of Environment*. 92: 353-362.
- Naesset, E. 1997. Determination of mean tree height of forest stands using airborne laser scanner data. *Remote Sensing of Environment*. 61: 246-253.
- Nelson, R. 1997. Modeling forest canopy heights: the effects of canopy shape. *Remote Sensing of Environment*. 60: 327-334.
- Nelson, R.; Krabill, W.; Maclean, G. 1984. Determining forest canopy characteristics using airborne laser data. *Remote Sensing of Environment*. 15: 201-212.
- Nelson, R.; Swift, R.; Krabill, W. 1988. Using airborne lasers to estimate forest canopy and stand characteristics. *Journal of Forestry*. 86: 31-38.
- Nilsson, M. 1996. Estimation of tree heights and stand volume using an airborne LIDAR system. *Remote Sensing of Environment*. 56: 1-7.
- Peterson, B. 2000. Recovery of forest canopy heights using large-footprint LIDAR. College Park, MD: University of Maryland. 59 p. M.A. thesis.
- Riaño, D.; Chuvieco, E.; Condés, S.; González-Matesanz, J.; Ustin, S. 2004. Generation of crown bulk density for *Pinus sylvestris* L. from LIDAR. *Remote Sensing of Environment*. 92: 345-352.
- Riaño, D.; Meier, E.; Allgöwer, B.; Chuvieco, E.; Ustin, S. 2003. Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. *Remote Sensing of Environment*. 86: 177-186.
- Sando, R.W.; Wick, C.H. 1972. A method of evaluating crown fuels in forest stands. Res. Pap. NC-84. St. Paul, MN: U.S. Department of Agriculture, Forest Service, North Central Forest Experiment Station. 10 p.
- Scott, J.H.; Reinhardt, E.D. 2001. Assessing crown fire potential by linking models of surface and crown fire behavior. Res. Pap. RMRS-RP-29. Ft. Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 59 p.
- Seielstad, C.A.; Queen, L.P. 2000. Using airborne laser altimetry to determine fuel models for estimating fire behavior. *Journal of Forestry*. 101: 10-15.

Area-Independent Sampling for Basal Area

James W. Flewelling¹

Abstract.—An unbiased direct estimator of total basal area for a stand (Flewelling and Iles 2004) is reviewed. Stand area need not be known. The estimator's primary application is in conjunction with a randomly positioned grid of sample points. The points may be centers for horizontal point samples or fixed-area plots. The sample space extends beyond a stand's boundary, though only trees within the boundary are tallied. Measured distances from sample trees to stand boundaries are not required.

Introduction

Most methods of estimating basal area for a stand are area dependent in that they are the product of an estimated basal area per hectare and a known or estimated area. A major concern in applying these methods is the avoidance of edge bias. Such bias can arise when the distance from a tree to the stand's edge affects its sampling probability and the estimator is not able to fully account for the varying probabilities. Unbiased estimators do exist, but are difficult or impossible to apply with complex stand boundaries. Methods which adjust for edge bias are reviewed by Schreuder *et al.* (1993). The "walkthrough" solution (Ducey *et al.* 2004) offers an operationally simpler alternative to the mirage method of Schmid-Haas (1969, 1982). The foregoing methods confine sample points to being within the stand boundaries. Schmid-Haas (1982: 264) also suggested a substantively different approach to the edge bias problem: "One possibility is obvious; sample plots whose centre lies outside the area under investigation are also included in the sample, care being taken to ensure that the probability density for such plot centers is the same as for those within the (stand) area." That concept is embodied in the toss-back method by Iles (2001) and in the area-independent method reviewed here.

Sample Protocol and Estimators

The sampling protocol addressed here is that of a regular grid of sample points. The orientation of the grid is predetermined. A starting point is randomly located within an area corresponding to a grid cell, and the sample points extend indefinitely to areas inside and outside the stand. Other protocols are addressed by Flewelling and Iles (2004). Each sample point may be the center of a fixed-area plot or a horizontal point sample. No distinction is made between sample points that fall inside the stand, and those that fall outside the stand. At each point, only the sample trees within the stand are considered.

For fixed-area plots, the estimator of total basal area is

$$\hat{G} = A_g \times \sum g_i \quad (1)$$

where A_g is the area per grid point as established by the grid spacing, g_i is the basal area per hectare on the i^{th} sample plot, and the summation is over all sample plots. For horizontal point samples, the estimator is

$$\hat{G} = T \times F \times A_g \quad (2)$$

where F is the basal area factor and T is the total tree count, summed over all sample points. Modified versions of horizontal point sample may use several different basal area factors depending on tree size, and may invoke fixed-area plots for certain ranges of tree sizes. The generalized estimator for these modified samples is

$$\hat{G} = A_g \times \sum_{\text{points}} \sum_{\text{trees}} F_v \quad (3)$$

where F_v is a variable basal area factor, the first summation is over all sample points, and the second summation is over all the trees at a particular sample point. For tree sizes being sampled with an angle gauge, F_v is the basal area factor of the gauge. For

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tree sizes being sampled with fixed area plots, F_v is the ratio of the tree's basal area to the plot area.

Discussion

The most likely application of the area-independent estimator is for stands where the area is unknown. An example is in the determination of the basal area of that portion of a stand which excludes riparian corridors whose extent and area are unknown.

The appeal of the area-independent estimator is not limited to stands with unknown areas. This estimator and the toss-back method both are unbiased for any stand geometry and are relatively easy to use. The exact delineation of the stand boundary in the vicinity of the sample points is not required. Independent random errors in the location of sample points would seem not to introduce bias. This lack of sensitivity to location error is not shared by methods that limit sample points to a stand's interior; this feature could be used to advantage by using hand-held Geographic Positioning System units to navigate to sample points. An operational difficulty of the method is that some of the sample points outside of the stand may be inaccessible; for those sample points, the selection of sample trees will be much more difficult than making a prism sweep.

The Forest Inventory and Analysis (FIA) program is generally not concerned with individual stands. Instead, forest attributes are sought within populations such as States or counties, and by various condition classes such as forest cover type. The FIA's grid of ground plots have a constant sampling density and could be analyzed with the area-independent estimator to make unbiased estimates of basal area by cover type. The FIA sampling program, however, is multiphase; the first phase measures or estimates forest area (Reams *et al.* 2005), and could potentially subdivide the forested area into condition classes. Hence, area-dependent estimators for basal area and other attributes are being used; these should be presumed to have lower variance than would the area-independent estimators.

Literature Cited

- Ducey, M.G.; Gove, J.H.; Valentine, H.T. 2004. A walkthrough solution to the boundary overlap problem. *Forest Science*. 50: 427-435.
- Flewelling, J.W.; Iles, K. 2004. Area-independent sampling for total basal area. *Forest Science*. 50: 512-517.
- Iles, K. 2001. Edge effect in forest sampling, part II. *Inventory and Cruising Newsletter*. 53: 1-3. <http://www.proaxis.com/~johnbell/>. (7 January 2006).
- Reams, G.A.; Smith, W.D.; Hansen, M.H.; Bechtold, W.A.; Roesch, F.A.; Moisen, G.G. 2005. The forest inventory and analysis sampling frame. In: Bechtold, W.A.; Patterson, P.L., eds. *The enhanced Forest Inventory and Analysis program—national sampling design and estimation procedures*. Gen. Tech. Rep. SRS-80. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station: 11-26.
- Schmid-Haas, P. 1969. Stichproben am Walrand. Sample plots at forest stand margins. *Mitteilungen der Schweizerischen Anstalt für das forstliche Versuchswesen*. 45: 234-303. English summary.
- Schmid-Haas, P. 1982. Sampling at the forest edge. In: Ranney, B., ed. *Statistics in theory and practice: essays in honour of Bertil Matern*. Umea, Sweden: Swedish University of Agricultural Science: 263-276.
- Schreuder, H.T.; Gregoire, T.G.; Wood, G.B. 1993. *Sampling methods for multi-resource inventories*. New York: John Wiley. 446 p.