Article

Regional Forest Inventory using an Airborne Profiling LiDAR

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ABSTRACT

A 5,159km profiling airborne LiDAR data set consisting of 56 parallel flight lines (fls) systematically spaced one kilometer apart acquired over the State of Delaware (USA) in y2000 are used to test the accuracy and precision of LiDAR-based forest inventory estimates. Nonparametric techniques is employed to develop simple linear regressions (SLRs) relating ground-measured biomass to laser height and crown closure. The ground-laser models are used to estimate total aboveground dry biomass at the county (3 counties in Delaware - 1,124km², 1,542km² and 2,539km²) and State (5,205km²) levels. The laser estimates are compared to U.S. Forest Service-Forest Inventory and Analysis (FIA) estimates from a 1999 ground-based survey of 215 FIA plots. In addition, the 56-fl data set is treated as a population and subsampled to test three variance estimators. The three variance estimators include weighted versions of the simple random sampling (SRS) estimator, a successive differences (SD) estimator, and a Newton's Method (NM) estimator. Results, constrained to this particular 56 fl data set and post-stratification, indicate the following: (1) Using all 56 fls in conjunction with the nonparametrically derived SLRs, LiDAR-based estimates of biomass are within 4%-24% at the county level and 14%-18% at the state level. (2) Across the 3 counties and State, considering the full range of flight line sampling intensities (from 2 to 28km between fls), the SRS estimator most closely tracks systematic sampling variability. The SD estimator is most conservative, consistently overestimating biomass variability by ~15%. (3) When a limited, more realistic range of inter-flight line distances from 2-6km between parallel fls is considered, the behavior of the SRS estimator changes markedly. The SD and NM estimators overestimate systematic standard errors (SEs) by ~18%, whereas the SRS estimator becomes the most conservative, overestimating systematic SEs by ~30%. This SRS role reversal from least to most conservative as the distance between fls decreases suggests that the fls spaced 2-6km apart are, in Delaware, spatially autocorrelated. We suggest that analysts employ the SD or NM estimators when fls are closely spaced, e.g., 2-6km apart. (4) Inclusion of prediction error, i.e., the residual noise around regression lines used to predict, for instance, biomass as a function of profiling LiDAR height measurements, adds approximately 0.7-1.2 t/ha (an 8-15% increase) to the biomass standard error, averaged across strata and sampling intensities. (5) The positive relationship between the distance between flight lines and the systematic standard error appears to be generally linear (albeit noisy) for a given cover type and study area. Figures are provided illustrating the empirical relationship between flight line distance and systematic SE, by stratum within study area. These may be used to guide the design of airborne LiDAR-based forest surveys on areas from 1,000-5,000km².

Keywords: profiling LiDAR, laser, systematic sampling

INTRODUCTION

Airborne lasers, both scanning and profiling, have been and are being used for regional forest inventory. Scandinavian researchers employ small footprint scanning LiDARs to conduct wall-to-wall forest inventories on 50 - 900km² parcels in Norway (NÆSSET, 2004a; b; NÆSSET *et al.*, 2004). The level of acceptance concerning the accuracy and reliability of the science, in fact, has risen to the point where private companies have commercialized their LiDAR-based forest inventory

products (E. NÆSSET, T. AASLAND, pers. comm.). In the state of Delaware, profiling data have been used to estimate forest volume and biomass, impervious surface area, open water area (NELSON *et al.*, 2003a), carbon (NELSON *et al.*, 2004), and wildlife habitat area (NELSON *et al.*, 2005). In this study, that same Delaware profiling data set is used to look at additional questions regarding large-area sampling using airborne LiDARs.

The objectives of this study are threefold: (1) to report the accuracy and precision of regional airborne LiDAR-based forest inventory, (2) to investigate three different variance

estimators to see which best characterizes systematic sampling variability, and (3) to provide some level of guidance with respect to flight line (fl) spacing in those situations where airborne laser profilers are used as sampling tools for large-area (1,000-5,000km²) forest inventory.

A small, portable airborne LiDAR profiler (NELSON *et al.*, 2003b) was used to systematically sample the State of Delaware, on the mid-Atlantic coast of the eastern United States, during the summer of y2000. Delaware is a small, relatively flat state encompassing 5,205km². According to a 1997 airphoto-based GIS (University of Delaware Spatial Analysis Laboratory - <http://www.udel.edu/FREC/spatlab/>, LA=April 23, 2007), approximately 34% of the state is forested, 44% supports agriculture, 18% is residential-urban, and 4% is inland water. Delaware is divided into three counties, urbanized Newcastle County to the north (1,124km²), and the more agrarian Kent County (1,542km²) and Sussex County (2,539km²) as one moves south. Profiling measurements were collected along 56 N-S fls spaced one kilometer apart. The shortest fl was 17km, the longest 153km; 5159km of profiling data were collected and analyzed. Post spacing was nominally 25cm., and at a flying altitude of 150m AGL, the spot size was ~37cm.

METHODS AND MATERIALS

Statistical procedures outlined in Nelson *et al.* (2004, see erratum) were used to develop county and state-level estimates of forest biomass, specifically total aboveground dry biomass. Nonparametric regression procedures were used to fit simple linear models to relate ground-measured dry biomass to laser height and crown closure. One hundred forty

two - 40m Line Intercept Samples (LIS, see DEVRIES, 1986) were collected on the ground throughout the state in seven of eight strata, four forest strata-hardwood/deciduous, mixed-wood, conifer, wetlands, and three nonforest strata-agriculture, residential, and urban/barren. An eighth stratum, open water, was not sampled on the ground. One generic equation was developed across the strata to produce a non-stratified predictive equation. In addition, five stratum-level simple linear regressions were calculated, one for each of the four forested strata, and one collectively for the three nonforest strata. The wetlands equation was used to predict biomass in the open water strata. Stratified and non-stratified results were compared to see if stratification improved accuracy and/or increased precision. The single generic and five stratum-level equations used in this study are reported in Table 1.

Regional estimates of biomass depend on the use of predictive equations that relate biomass to laser measurements. In this study, the equations reported in Table 1 are used to calculate biomass on fl segments ≤40m long. Laser-based predictions are summed within fls, and fl estimates are averaged across the region to calculate county and state estimates. Variance calculations at the regional level reflect fl, not segment-level, variation. But the segment-level, laser-based predictions, i.e., the $\hat{b}$ or $\hat{b}_j$ in Table 1, upon which the entire laser inventory is based, are themselves average responses. There is scatter around a given prediction for a segment ≤40m that we implicitly ignore in our variance calculations, and that scatter is characterized by the root mean square error of the SLR.

In this study, we look at the effects of including this residual noise in the form of prediction error in our variance calculations. We account for scatter about a given predictive

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Table 1. Non-stratified and stratified simple linear models used to predict biomass, $\hat{b}$, in tons/hectare, based on laser-measured heights, in meters, and crown closure, in percent.

		R ²	RMSE (t/ha)	n
<u>Non-stratified model:</u>				
	$\hat{b}=[(8788.5)(\bar{h}_{qc})+0.00]/1000.0$	0.66	63.59	142
<u>Stratified models:</u>				
hardwood	$\hat{b}_j=[(106.80)(\bar{h}_a)(g)-31959.9]/1000.0$	0.30	115.51	24
mixedwood	$\hat{b}_j=[(7259.2)(\bar{h}_a)-36636.0]/1000.0$	0.28	49.17	22
conifer	$\hat{b}_j=[(9342.0)(\bar{h}_{qa})-7412.9]/1000.0$	0.44	68.05	23
wetlands	$\hat{b}_j=[(506.1)(\bar{h}_{qc}^2)+0.00]/1000.0$	0.95	24.16	22
ag/res/urb	$\hat{b}_j=[(6903.6)(\bar{h}_{qc})+0.00]/1000.0$	0.76	41.60	51

where $\bar{h}_a$ =average height, all pulses in a segment ≤ 40 m long; $\bar{h}_{qa}$ =quadratic mean height, all pulses; $\bar{h}_{qc}$ =quadratic mean height, canopy hits, and g =crown closure, 0-100%.

equation by adding a random normal component to each segment-level, laser-based prediction, e.g., for hardwoods:

$$\hat{b} = [(106.80)(\bar{h}_a)(g) + 31959.9]/1000.0 + (m)(s)\sqrt{1 + \mathbf{x}'_0(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_0},$$

where m is a normally distributed random variable, $m \sim N(0,1)$, s is the RMSE of the predictive regression reported in Table 1 (for hardwoods, $s=115.51$), $\mathbf{x}_0$ and $\mathbf{x}'_0$ is the current laser measurement and its transpose, and $(\mathbf{X}'\mathbf{X})^{-1}$ is the inverse of the sum of squares and cross-products matrix of the independent variables used to fit the linear equation. This prediction noise, assumed to be homoskedastic and normally distributed, is added at the segment level.

RESULTS

Accuracy and Precision of the County and State Biomass Estimates

Accuracy figures were generated for systematic samples of 14 fls, 28 fls, and all 56 fls, for stratified and non-stratified models, with and without regression error included. The y2000 laser estimates are compared with y1999 US Forest Service-Forest Inventory and Analysis (FIA) estimates based on 215 ground plots. Fig. 1 illustrates the accuracy of the 14 and 56 fl samples for the stratified models; the figures for the other test cases are available upon request.

A number of observations are immediate. First, at this scale, there appears to be no perceptible difference between laser estimates or standard errors with or without regression error included. This is to be expected since the random variation about the predictive regression has an expected zero mean. Second, the laser-based estimates are more precise than FIA estimates, even when only 14 parallel fls spaced 4km apart are considered, though this observation is tentative due to additional considerations discussed below. Third, if we use the

FIA estimates as the standard and assume unbiasedness, then the airborne LiDAR profiler underestimates FIA total biomass in Newcastle/Kent Counties, Sussex County, and Delaware by 4.5%, 21.9%, and 14.1%, respectively. These differences may be due to (1) biased laser prediction equations and/or (2) the fact that the estimates are not directly comparable. With respect to (1), there is preliminary evidence that suggests that these laser equations under-report biomass (G. PARKER, pers. comm.). With respect to (2), the FIA estimates reflect standing stocks on "timberland", i.e., "forest land producing or capable of producing crops of industrial wood (more than 20 ft³ per acre per year) and not withdrawn from timber utilization" (GRIFFITH and WIDMANN, 2001). Twenty cubic feet/acre/year is equivalent to 1.4m³/ha/yr. The laser estimates are based on biomass found in the four forest classes defined by photointerpreters working with 1992 color-infrared and 1997 B&W airphotos, a 1m spatial resolution, and a 1.6ha (4acre) minimum mapping unit. Though the FIA and laser estimates are not directly comparable, discussions with FIA personnel suggested that this particular comparison was the best possible given the inherent differences in sampling methodology and forest class definitions.

It must be noted that the laser-based confidence limits illustrated in Fig. 1 are probably not correct. There are at least two reasons to question the veracity of these laser confidence limits. First, recent evidence from a laser study in Quebec indicates that covariance terms can markedly increase the variance of county and state biomass estimates. County-level estimates of biomass are calculated as an area-weighted sum of stratum estimates within the county. The county-level estimate is, then, a linear sum, i.e., $b_{county} = w_1(b_1) + w_2(b_2) + \dots + w_s(b_s)$, where the b 's are biomass in tons/ha of strata 1 to 8 and w_1 to w_s are area weights that sum to 1.0 (NELSON *et al.*, 2004; see Erratum, 2005). The variance of a linear sum is the sum of the weighted variances + all possible covariance terms, i.e., $\text{var}(b_{county}) = w_1^2(\text{var}(b_1)) + w_2^2(\text{var}(b_2)) + \dots + w_s^2(\text{var}(b_s)) +$

Fig. 1 Comparison of county and state USFS-FIA biomass estimates to stratified laser estimates based on (A) 14 fls-4km fl separation, and (B) 56 fls-1km fl separation. Laser estimates without and with regression error (Lnr and Lrg, resp.) included in calculations are shown. The black bars depict 95% confidence intervals calculated using a simple random sampling estimator.

$$2w_1w_2(\text{cov}(b_1, b_2)) + 2w_1w_3(\text{cov}(b_1, b_3)) + \dots + 2w_7w_8(\text{cov}(b_7, b_8))$$

The cover type covariance terms were not taken into account in the calculation of the county-level confidence limits because we assumed that biomass estimates along flight lines are independent (hence the covariances = 0). In hindsight, this is probably a poor assumption. Likewise, the county-level covariance terms were not taken into account at the State level for the same reason. So those laser confidence limits in Fig. 1 may be biased downward. The second reason to question the veracity of the confidence intervals has to do with an offsetting inflationary effect that may occur when we treat a systematic sample of flight lines as a random sample. This problem is discussed directly below. The net effect of these two offsetting trends is unknown; research is underway to address the problems.

Variance Estimators for Laser Surveys

Fig. 1 depicts error bars calculated assuming that the

systematically acquired fls were actually a random sample. Previous research has shown that the application of such an SRS estimator in a situation where data were actually systematically acquired may lead to an overestimation of the sampling variability (OSBORNE, 1942; NYSSONEN *et al.*, 1967; 1971) if the study area is spatially ordered with respect to the dependent variable, e.g., biomass. Two alternative estimators might mitigate this SRS overestimation tendency (if it exists at all) - a successive differences (SD) estimator and the Newton's Method (NM) estimator (COCHRAN 1977). The SD estimator calculates fl variation based on weighted, squared differences between adjacent fls; the NM estimator works similarly but looks at three adjacent fls instead of two. The 3 candidate variance estimators, SRS, SD, and NM, were compared to empirical systematic sample variances by treating the 56 fl data set as a population. Formulas for the SRS, SD, and NM estimators, and the systematic standard error formula are provided below.

Simple random sample (SRS) variance of the stratum estimates:

For a given repetition or collection of sampled flight lines,

$$\hat{\text{var}}(\hat{b}_j) = \frac{\sum_{k=1}^{n_j} w_{jk} (\hat{b}_{jk} - \hat{b}_j)^2}{n_j - 1} \quad (1),$$

$$w_{jk} = \frac{l_{jk}}{\sum_{k=1}^{n_j} l_{jk}}, \text{ and } \sum_{k=1}^{n_j} w_{jk} = 1.0,$$

where

$\hat{b}_j$ = an estimate of biomass/ha in the j th stratum across all n_j flight lines,

$\hat{b}_{jk}$ = an estimate of biomass/ha for the j th stratum, k th flight line,

l_{jk} = the length of interception of the j th stratum, k th flight line, and

n_j = the number of flight lines that intercept stratum j .

Note that n_j does not necessarily equal the total number of flight lines, n , flown over a study area because some flight lines may not intercept stratum j .

We condition on the particular post-stratified sample that we've selected, allowing us to treat n_j and l_{jk} as fixed quantities when, in fact, they're random variables. As a result of this condition, however, all inferences and conclusions drawn from study results are limited to the specific set of flight lines and to the particular post-stratification used in this study.

Successive differences (SD) variance of the stratum estimates:

For a given repetition where the sample size is n_j flight lines,

$$\hat{\text{var}}_{sd}(\hat{b}_j) = \frac{(n_j) \sum_{k=2}^{n_j} (w_{jk} + w_{j, k-1})^2 (\hat{b}_{jk} - \hat{b}_{j, k-1})^2}{8(n_j - 1)} \quad (2, \text{LINDBERG 1926, eq. 4}).$$

Newton's method (NM) variance of the stratum estimates:

For a given repetition where the sample size is n_j flight lines,

$$\hat{\text{var}}_{nm}(\hat{b}_j) = \frac{(n_j) \sum_{k=2}^{n_j-1} (w_{j, k-1} + 2(w_{jk}) + w_{j, k+1})^2 (\hat{b}_{j, k-1} - 2(\hat{b}_{jk}) + \hat{b}_{j, k+1})^2}{96(n_j - 2)} \quad (3)$$

Equation 3 is derived from a nonweighted equivalent (COCHRAN 1977, pg. 225, eq. 8.45) and weights reported by LINDBERG (1926, eq. 6).

In the simulation that we report below, equations 1, 2, and 3 were computed for each systematic sample. The average value of each was compared to the variance of $\hat{b}_j$ observed in the simulation. The latter is called the systematic variance.

Systematic variance:

Flight lines are systematically subsampled to calculate systematic variability at a particular sampling intensity. Sampling intensity is specified as a distance between adjacent, parallel airborne LiDAR flight lines.

$$\hat{\text{var}}_{sys}(\hat{b}_j) = \frac{\sum_{r=1}^{n_{sys}} (\hat{b}_{jr} - \hat{b}_j)^2}{n_{sys} - 1} \quad (4), \text{ where } \hat{b}_j = \frac{\sum_{r=1}^{n_{sys}} \hat{b}_{jr}}{n_{sys}} \quad (5)$$

and

$\hat{b}_{jr}$ = an estimate of biomass per hectare for the r th systematic sample in the j th stratum for a given sampling intensity, and

n_{sys} = the number systematic sample observations for a given sampling intensity.

It turns out that the distance, in kilometers, between adjacent, systematically subsampled flight lines equals n_{sys} . This identity exists because we acquired flight lines 1km apart. This systematic variance is the standard against which the three variances estimators are compared.

The 56 parallel fls, acquired 1km apart, were divided into systematic samples 2km apart, 3km apart, 4km,... up to half the number of fls in the particular county or State. Newcastle County was transected by 31 fls, Kent by 36 fls, and Sussex County and Delaware by 56 fls. So systematic samples of fls spaced from 2 to 15km apart were considered in Newcastle, 2 to 18km apart in Kent, and 2 to 28km apart in Sussex and Delaware. For a given fl spacing and county/state, the "true" systematic variance was computed as a function of the squared difference between each systematic estimate of biomass and the average of the systematic estimates. The SRS, SD, and NM standard errors were compared with the systematic standard error to see which estimator most closely tracked systematic variability.

When we consider results based on the nonparametrically-derived, non-stratified and stratified SLR models across the full range of distances between flight lines and across all strata, the SRS estimator does the best job of tracking systematic sampling variability. The SRS estimator ranged from 93-105% of the systematic SEs. The comparable range for the SD estimator is 109-119%, and 97-118% for the NM estimator. A percentage less than 100% indicates that the estimator is underestimating the true systematic error; numbers greater than 100% indicate conservative estimates.

The relationships among the three estimators change when more realistic inter-flight line distances are considered. If we consider more closely spaced flight lines, i.e., from 2-6km between adjacent, parallel lines, then the SRS estimator becomes the most conservative, ranging from 111-151% of the systematic SEs. The SD and NM estimators are also conservative, but the estimator/systematic ratios collectively range from 109-133%.

These results, and the role reversal manifested by the

SRS estimator from least to most conservative, indicate that closely spaced flight lines, in Delaware, are spatially autocorrelated. This spatial autocorrelation inflates the SRS estimator. These results suggest that researchers should employ the SD or NM estimator if (1) they space their flight lines from 2-6km apart, (2) their study areas are on the order of 1000-5000km² in size, and (3) they believe that biomass is spatially ordered across the landscape. We would argue that many study areas show this spatial ordering. Delaware, for instance, supports more biomass on the western side of the State than on the wetter, sandier east side, and the N-S flight lines capture this biomass gradient.

Laser Sampling Error, by Stratum and Study Area

Fig. 2 depicts systematic standard errors for the non-stratified, nonparametrically fit SLR (the first equation in Table 1), with prediction error included, for the three counties and

for the entire State. The areal extent of each stratum is reported as a percentage, in parentheses, next to the stratum name. In some cases, the stratum name (percentage) could not be noted directly on the plotted line. In these situations, an abbreviation is used (e.g., "res" for residential), and complete information listed to the left, in square brackets. Though the systematic errors reported in Fig. 2 are specific to the y2000 Delaware profiling lines and to our particular post-stratification, it is our hope that researchers might find this information useful when they design their own airborne laser-based forest inventory on areas encompassing 1,000-5,000km².

We should note that systematic errors depicted Fig. 2 do not suffer from the vagaries associated with missing covariance terms and estimator differences discussed at the end of Results Section A and the beginning of Section B (above). These systematic errors are our ground reference information; they are, in fact, true systematic sampling errors. We continue to search for estimators that more closely track

Fig. 2 Distance between flight lines versus systematic standard errors of estimate (t/ha) for eight strata in 4 study areas: (A) Newcastle County, (B) Kent County, (C) Sussex County, and (D) Delaware. Bold lines are forested strata; light lines are nonforest strata. Numbers in parentheses following the stratum name report the percentage, by area, of that particular stratum in the County or State.

these systematic errors.

Although the relationships are noisy due to the relatively limited population and small sample sizes, trends are apparent. Arguably, systematic SEs appear to increase linearly as the distance between flight lines increases. Larger study areas support smaller SEs due to the fact that a laser will measure strata more frequently given a fixed distance between flight lines. Note that the upper limits of the Y-axes increase as the size of the study areas decrease. With respect to laser sampling, the best-case scenario would be a requirement to sample a low biomass, ubiquitous stratum on a large study area, e.g., the agriculture stratum in Delaware. The worst-case scenario is the opposite, i.e., the requirement to measure a relatively rare cover type on a small study area that supports high and/or inherently variable biomass loads, e.g., the conifer or mixedwood strata in Newcastle County.

Stratification

In this study, stratification did not consistently improve the strength of the predictive models (Table 1) or consistently decrease standard errors. Looking at differences between non-stratified and stratified SEs for forested strata, we found that use of the stratified equations increased SEs, i.e., decreased precision, by 2.5 ± 4.3 t/ha, averaged across all sampling intensities and study areas. The precision of the nonforest strata, conversely, increased on average, with SEs decreasing by 1.0 ± 1.4 t/ha. The net effect across all 8 strata was an overall reduction in precision, or an average systematic SE increase of 0.8 ± 3.7 t/ha if stratified predictive models were employed to estimate biomass.

SUMMARY

The laser-based estimates of total aboveground dry biomass underestimated FIA totals by 4-24% at the county level and 14-18% at the state level. Though the two inventories are not directly comparable, the level of disagreement suggests that better methods need to be developed to relate airborne LiDAR profiling measurements to ground-measured biomass. In particular, we note the weak linear relationships between LiDAR height measurements and ground-based estimates of hardwood and mixedwood biomass. POPESCU et al. (2003) made similar observations concerning mid-Atlantic hardwood versus pine cover types on a study area in central Virginia, approximately 500km SW of our Delaware study area. K. ZHAO (2007, pers. comm.) demonstrated that hardwoods put more woody biomass into lateral growth, weakening the height-dbh and therefore the height-biomass relationship on which LiDAR researchers depend. He asserts, and we concur, that better, more effective hardwood models are needed.

Fig. 2 provides guidance to airborne LiDAR researchers designing flight plans for large-area forest inventory. The figure reports standard errors that might be expected in eight

different strata on four different study areas ranging in size from 1,100 to 5,200km².

Of the three variance estimators considered, the SD and NM estimators, though conservative, mitigate the overestimation tendencies of all three estimators when flight lines are spaced 2-6km apart. Based on these results, we suggest that analysts employ the SD or NM variance estimators in situations where the flight lines are closely spaced and/or where a regional biomass gradient exists roughly perpendicular to the direction of the systematic, parallel flight lines. The use of the SD or NM estimators should be considered a stopgap while work continues to identify a variance estimator that more closely tracks systematic sampling variability.

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