USING AIRBORNE & SPACE LiDARS FOR LARGE-AREA INVENTORY

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Boudreau et al (2008) reports on a three-phase statistical framework for estimating forest biomass and carbon using a space LiDAR – ICESat/GLAS – as a large-area sampling tool to inventory the Province of Quebec. An airborne profiling LiDAR was used to tie ground plot observations to GLAS pulses by overflying both plots and pulses to facilitate development of two sets of regression equations. The first equation (or set of equations if the area is stratified) related ground-measured dry biomass to airborne LiDAR measurements. This first equation was then used to predict biomass on individual GLAS pulses overflown by the profiler in order to develop a GLAS-based equation to predict biomass regionally. Results indicated that, in the southern half of the 1.27 million km^2 study area, GLAS-based estimates were within 10% of the ground estimates. But the associated variance estimates, a sum of between-flight line sampling error and a covariance term that accounted for correlations between land cover strata, were unstable. This instability was manifest in variances which were occasionally negative due to a negative covariance term that overwhelmed the sampling error.

A study to estimate forest basal area, volume, and biomass in Hedmark County, Norway (27,000 km^2) was undertaken to develop statistical techniques whereby airborne laser profilers and scanners could be used as sampling tools to inventory large areas. A central objective of this study was to derive variance estimators that could logically be applied to a two-phase or two-stage (air, ground) sampling scenario, a more tractable problem than the three-level situation faced in Quebec. Two potentially useful sampling frameworks were formulated, the first a model-based, two-phase design (the GS estimator, Ståhl et al. 2010) and the second a model-assisted two-stage design (the TG estimator, Gregoire et al. 2010).

The same linear models were used to predict total aboveground dry biomass in both sampling frameworks. The GS estimator assumes that the laser model(s) used to predict biomass in particular strata are correctly specified, and a unique model must be specified for each stratum reported. Attempts were made to develop models for each of the four productive forest strata, but the best models in two of the four classes were unacceptably weak, exhibiting $R^2 < 0.4$. The four productive forest classes, then, were concatenated into one productive forest class. The design-based TG estimator does not rest on an assumption of a correctly specified model, but rather corrects the profiling LiDAR biomass estimates based on ground plots intercepted by the profiling LiDAR. On 105 flight lines, the profiling LiDAR intercepted 763 of 1300 ground plots measured in the County between 2005 and 2007. Using the TG estimator, the single productive forest biomass equation was used to predict biomass in each of the 4 productive forest classes. Results for all of Hedmark County are presented in Table 1.

Table 1. LiDAR estimates of total aboveground dry biomass (t/ha) based on (1) plot crossings within 17.9 m of plot center (763 plots crossed out of 1300 overflown), (2) 105 parallel flight lines spaced 3 km apart, (3) 8308.8 km total flight line length, in Hedmark County, Norway. The ground reference estimates are based on Provincial ground plots.

	GS estimator			TG Estimator		Ground Reference		
	Mean (t/ha)	SE (t/ha)	model error (%)	Mean (t/ha)	SE (t/ha)	Mean (t/ha)	SE (t/ha)	n
Productive Forest								
High Prod.For.				116.49	24.19	123.41	8.17	90
Medium Prod.F.				95.18	14.57	94.20	3.67	238
Low Prod.For.				43.10	9.32	47.27	2.32	296
Young Forest				42.43	4.08	40.55	2.82	324
All Productive For.	57.58	2.21	56.54	63.29	5.61	64.33	1.72	948
Nonproductive Forest/Nonforest								
Nonproductive F	29.69	2.03	86.81	26.38	4.56	26.99	2.10	185
Land > 850 m	6.46	3.07	97.94	6.01	1.91	21.49	2.04	126
Developed	10.88	3.00	97.67	8.08	0.79	23.95	4.91	41
Water	3.12	4.78	99.77	2.62	0.00	0.00	0.00	0
All Nonprod/Nonfor				10.39	1.55	23.01	1.51	352
All Strata	35.61	1.49	71.35	37.95	3.00	45.62	1.16	1300

A number of observations can be made based on the results presented in Table 1.

1. The TG estimates are within 8.7% of the ground reference value for each of the productive forest class, and across all four productive forest classes, the TG estimate is within 1.6% of the reference value. The GS estimator of productive forest differs from the comparable ground reference value by 10.5%.
2. The GS estimator allows one to calculate the percentage of variance due to model error. With the relatively weak and noisy profiling models, model error accounts for 50 to almost 100% of the overall variance.
3. Despite the more extensive coverage provided by the profiling LiDAR, almost all of the LiDAR standard errors are larger than the ground reference values, calling into question the utility of the first stage LiDAR coverage.

Literature Cited:

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