Model Effects on GLAS-based regional estimates of forest biomass and carbon

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Abstract

ICESat/GLAS waveform data are used to estimate biomass and carbon on a 1.27 million km^2 study area, the Province of Québec, Canada, below treeline. The same input data sets and sampling design are used in conjunction with four different predictive models to estimate total aboveground dry forest biomass and forest carbon. The four models include nonstratified and stratified versions of a multiple linear model where either biomass or $\sqrt{biomass}$ serves as the dependent variable. The use of different models in Québec introduces differences in Provincial biomass estimates of up to 0.35 Gt (range 4.94±0.28 Gt to 5.29±0.36 Gt). The results suggest that if different predictive models are used to estimate regional carbon stocks in different epochs, e.g., y2005, y2015, one might mistakenly infer an apparent aboveground carbon "change" of, in this case, 0.18 Gt, or approximately 7% of the aboveground carbon in Québec, due solely to the use of different predictive models. These findings argue for model consistency in future, LiDAR-based carbon monitoring programs. Regional biomass estimates from the four GLAS models are compared to ground estimates derived from an extensive network of 16,814 ground plots located in southern Québec. Stratified models proved to be more accurate and precise than either of the two nonstratified models tested.

1. Introduction

The forestry LiDAR community, having demonstrated and continuing to improve the utility of airborne LiDAR systems for forest measurement and monitoring, now must consider doing so from space. One civilian space LiDAR, the ICESat satellite (Ice, Cloud, and land Elevation Satellite) carrying the GLAS (Geosciences Laser Altimeter System) LiDAR, is currently in orbit. The U.S. may launch three additional space LiDAR systems over the next decade. This report briefly describes these proposed space LiDARs, the configurations of which are all under discussion and subject to change. We also introduce two concerns associated with space and airborne LiDAR instruments that must be addressed by our community if we hope to effectively monitor global forest resources with lasers. In order to monitor forest change at the regional, national, continental, or global scale, our estimates at time 1 (t1) and time 2 (t2) must be consistent. Spurious changes may be noted or actual changes may be missed if our t1, t2 estimates are not comparable. Assuming the use of the same sampling design, inconsistencies may be introduced by the use of different predictive models at t1, t2, and/or they may be introduced by sensor changes over time which might result in systematic measurement differences. The objective of this paper is to address the former, i.e., model consistency, providing one example of the degree to which the use of different predictive models impacts regional estimates of biomass and carbon.

1.1. U.S. Space LiDARs – Current Thoughts

The U.S. National Research Council (NRC), in a document known as the Decadal Survey (NRC 2007), has identified seventeen space missions of paramount importance to the U.S. scientific community for monitoring the status and function of the biosphere. The NRC suggests that these seventeen missions be launched in the 2010 – 2020 timeframe. Three of these Earth remote sensing missions incorporate space LiDARs capable of measuring forest structure. These missions include (1) ICESat II, a follow-on to the current ICESat satellite (Abshire et al. 2005), designed to monitor ice sheet elevation changes; (2) DESDynI (Deformation, Ecosystem Structure, and Dynamics of Ice), primarily a solid Earth mission which couples an L-band RaDAR and LiDAR to map surface deformation; and (3) LIST (Laser Imaging for Surface Topography), a swath mapping LiDAR for global topography and hydrology. All will be in near-polar orbits.

The specific design of ICESat II and DESDynI is currently a topic of much discussion, so the descriptions below may not resemble the configurations that may ultimately reach orbit. In addition, the launch of these three satellites is by no means assured given the prerequisite that the U.S. Congress must find the funds needed to build and operate this hardware. However the Decadal Survey carries much weight at NASA, and the current expectation is that ICESat II will be launched somewhere in the 2015 timeframe in a flight configuration similar to the first ICESat, e.g., a single beam, waveform profiler with 50 m – 70 m footprints and an along-track post spacing of 140 m. The 2015 launch date is notable in that the ICESat I/GLAS LiDAR, currently collecting data during ~33 day, spring and fall campaigns, is expected to last an additional 1½ to 3 years, with the 3rd and final laser due to fail sometime between the spring of 2010 and the autumn of 2012. This leaves an ICESat I – ICESat II observational hole of 3-5 years if ICESat II launches in 2015.

The DESDynI and LIST missions will fly later. Expectations are that DESDynI will most likely be some sort of multi-beam LiDAR with ~25 m footprints and 25 m – 30 m post spacing, i.e., near-contiguous profiles along-track. Across-track, parallel profiles will be kilometers apart, perhaps on the order of 2 – 5 km separating each of the 3 – 5 beams on the satellite. DESDynI is currently configured as a joint L-band RaDAR and multibeam LiDAR satellite, but many aspects of this mission are under consideration and are actively being investigated, including the need to physically tie the RaDAR to the LiDAR on the same platform, orbital repeat times, baseline issues regarding the RaDAR acquisitions, the RaDAR acquisition capabilities, e.g., SAR vs. InSAR, LiDAR beam spacing, number of beams, off-nadir pointing capabilities, and pulse width. LIST is currently configured as a swath mapper, collecting global wall-to-wall coverage over it's 5 year design life. The footprint of the contiguous pulses will be on the order of 5 m. Given LIST's late launch, most effort is going into research to address the ICESat II and DESDynI flight configurations.

1.2. Using ICESat/GLAS to Measure Forests

In the context of the current ICESat profiler and the possibility of an ICESat II follow-on, the forestry LiDAR community has entered a period where space-based LiDAR measurements are routinely collected globally and systematically, albeit with extended periods without space LiDAR measurements. With this capability comes questions concerning how we might best use these satellite ranging observations to measure, and more importantly, monitor forest biomass and carbon resources at regional, national, continental, and global scales.

Although the ICESat/GLAS LiDAR is not optimally configured for or operated as a vegetation assessment tool, these data have proved useful for biomass and carbon assessments across areas spanning hundreds of thousands of square kilometers. Kimes et al (2008) and Boudreau et al. (2008) report results of studies that employ the ICESat/GLAS LiDAR to estimate forest volume, biomass, and carbon in south central Siberia (just north of Mongolia) and in Québec, Canada, respectively. Kimes et al. (2008) uses 101,831 GLAS waveforms acquired along 55 orbits over a 10º x 12º, 811,414, km^2 area just northwest of Lake Baikal to attribute 16 forest cover type – canopy density classes derived from MODIS (Moderate Resolution Imaging

Spectrometer) data. Using field observations acquired on 51 GLAS pulses, they developed a sparse neural network relating GLAS waveform metrics to ground estimates of merchantable volume (Ranson et al. 2007). If they constrain their data and use only those pulses acquired on slopes of 10º or less as characterized using SRTM topographic information, their regional estimate of merchantable volume, 73.85 x 10^6 ± 5.33 x 10^6 m^3 (one standard error), is within 1.1% of comparable ground estimates, 74.63 x 10^6 m^3 (Shepashenko et al. 1998 per hectare estimate in conjunction with a percent forest cover estimate for the study area of 63% from an 1990 Russian forest map, V.I. Kharuk, pers. comm.). If GLAS pulses on all slopes are considered, the regional GLAS-based per hectare estimate of volume increases from 163.4 ± 11.8 m^3/ha to 171.9 ± 12.4 m^3/ha, a 5.2% increase. This apparent increase in area-based volume estimates suggests that steeper slopes broaden the waveform response, increasing apparent canopy height and inflating the volume estimates. Slopes, as noted by Lefsky et al. (2005, 2007) and Rosette et al. (2008), negatively affect the height accuracy of the large-footprint GLAS waveform data, convolving forest canopy architecture with topography and increasing the vertical extent of the waveform.

Boudreau et al. (2008) uses a multiphase sampling approach to relate GLAS waveform and SRTM topographic measurements to field estimates of total aboveground dry biomass in Québec, Canada. They flew an airborne profiling LiDAR over existing ground plots and along GLAS orbital transects and developed two sets of equations. The first set relates field biomass estimates to airborne LiDAR metrics; the second set relates airborne LiDAR estimates of biomass to GLAS waveform metrics. They estimate that, on average, the forested areas of Québec south of treeline support 39.0 ± 2.2 t/ha of dry biomass. Botkin and Simpson (1990) report an average value of 41.8 ± 10.1 t/ha for all of the North American boreal forest based on stratified ground measurements.

These studies report the accuracy and precision of statistical approaches that may be used to conduct regional inventories using a space LiDAR. Of interest in this paper, however is an assessment of the need for consistency in model selection when estimating regional biomass repeatedly over time. The objective of this study is to quantify the degree to which model differences may affect regional estimates of biomass and carbon. Four different models are used to estimate standing dry biomass and carbon for all of Québec below treeline, a area encompassing 1.27 million square kilometers. In addition, results from the four models are compared to ground reference data to determine which of the models most closely estimates biomass in the southern half of the Province

2. Methods

The data sets and analysis procedures employed in this study are the same as those described in detail in Boudreau et al. (2008). This study incorporates the following data sets:
(1) ICESat/GLAS LiDAR waveform data: 104,044 GLAS waveforms acquired along 97 orbits across all of Québec, acquisition L2a, autumn 2003. Spacing between adjacent near-N-S orbits are very variable but average 15.6 km.
(2) Digital vegetation zone map of Québec: tessellates Québec into seven vegetation zones; from south to north: (2.1) Northern Temperate forest, (2.2) Mixedwood forest, (2.3) southern Boreal forest (commercial forest), (2.4) northern Boreal forest (noncommercial forest), (2.5) Taiga, (2.6) Treed Tundra, (2.7) Southern Arctic. The Southern Arctic, that vegetation zone whose southern border is identified as the Provincial tree line, was assumed to contain no forest biomass.
(3) Landsat ETM+ land cover map: up to 24 land cover classes identified in each vegetation zone. Forests are identified as being conifer, hardwood, or mixedwood; 3 canopy density classes in each forest cover type. Data resampled to a 25 m grid.
(4) SRTM digital elevation data: available up to 60º N latitude (the Provincial treeline tracks

around 58º - 59ºN). 90 m pixels. 3x3 window around each GLAS pulse used to characterize local topography.
(5) Ministry of Natural Resources Québec (MNRQ) ground plots: 16,814 fixed area, 11.3 m radius, 400 m^2, temporary sample plots located in the southern 3 vegetation zones south of the commercial forest line that bisects the Boreal vegetation zone. Total aboveground dry biomass calculated on each plot.
(6) Profiling airborne LiDAR data (Nelson et al. 2003): flown over 295 MNRQ ground plots and over ~5000 km of GLAS orbits, summer 2005. The NIR profiler acquired sequential first/last returns on 0.40 m footprints at 0.12 m post spacing across ground plots and GLAS pulses. The profiling data are used to tie ground plot information to GLAS measurements.

These six data sets are utilized within a multiphase sampling framework. The airborne profiler was flown over 295 ground plots. Ground estimates of biomass were regressed against the airborne profiler measurements in order to develop predictive regressions based on the airborne measurements. One nonstratified equation (R^2 = 0.65) and a set of seven stratified ground-air equations (R^2 range from 0.51 – 0.73, Boudreau et al. 2008) are developed based on the Landsat land cover strata. The ground-air equation(s) is(are) then used to calculate airborne laser-based estimates of biomass on 1325 GLAS pulses measured by the airborne profiler.

Four different models are constructed (n=1325) to predict dry biomass as a function of GLAS waveform and SRTM topographic measurements. The four models follow:

· linear, nonstratified:

$$b_{air,\,ns} = -4.52 + 3.85^*\, w_{GLAS} - 6.59^*\, f_{GLAS} - 0.75^*\, r_{SRTM} \qquad (1)$$

R^2 = 0.60, RMSE = 32.0 t/ha;

· linear, stratified:

$$b_{air,st} = \mathit{2.37 + 3.63^*}\, w_{GLAS} \mathit{- 5.92^*}\, f_{GLAS} \mathit{- 0.73^*}\, r_{SRTM} \qquad (2)$$

R^2 = 0.58, RMSE = 31.7 t/ha;

· square root, nonstratified:

$$\sqrt{b_{air,\,ns}} = 2.67 + 0.27^*\, w_{GLAS} - 0.83^*\, f_{GLAS} - 0.06^*\, r_{SRTM} \qquad (3)$$

R^2 = 0.59, RMSE = 2.40 $\sqrt{t/ha}$;

· square root, stratified:

$$\sqrt{b_{air,\,ns}} = 2.98 + 0.26^*\, w_{GLAS} - 0.65^*\, f_{GLAS} - 0.06^*\, r_{SRTM} \qquad (4)$$

R^2 = 0.53, RMSE = 2.55 $\sqrt{t/ha}$;

where $b_{air,\,ns}$ = an airborne profiling estimate of biomass calculated using the nonstratified ground-air equation,
$b_{air,st}$ = an airborne profiling estimate of biomass calculated using the stratified ground-air equations,
w_{GLAS} = vertical extent of the GLAS waveform, signal start to signal end,
f_{GLAS} = the slope of the leading edge of the GLAS waveform; and
r_{SRTM} = the range, in meters of the topographic difference found in a 3x3 pixel SRTM window centered on an GLAS pulse.

The variance inflation factors for all 4 models are less than 1.61; multicollinearity is not an issue (Myers 1989). The square-root transform is used in an attempt to control marked heteroskedasticity; the transform only marginally improved residual patterns. The square-root biomass values are back-transformed using the unbiased backtransformation technique reported by Gregoire et al. (2008).

In the context of this report, stratification refers to the development of equations, by cover type and vegetation zone, in the ground – air phase, not in the air – satellite phase. In other words, the b_{air} dependent variables in equations 2 and 4 above were calculated using stratified ground-air equations; the b_{air} in equations 1 and 3 were calculated using a generic or nonstratified ground-air equation (Boudreau et al. 2008, his Table 2). Attempts were made to develop stratified GLAS equations for the linear and square root models, but R^2 decreased and RMSEs increased as the latitude of the vegetation zones increased and as the average height of the trees decreased. Stratified GLAS equations in the Taiga and the Treed Tundra had R^2 values in the 0.1 – 0.2 range and were deemed unusable. This finding is not unexpected given the ground height – GLAS height comparisons reported in the literature. Sun et al. (2008) compares various GLAS height metrics to comparable airborne LiDAR estimates and reports RMSEs of 3 m – 5.5 m (his Table 2) in the temperate forests of the eastern U.S. Rosette et al. (2008) report ground-GLAS height RMSEs of 2.86 m after correcting for topography. Lefsky et al. (2005) report RMSEs associated with ground-GLAS maximum canopy height comparisons of ~4.5 m, and Lefsky et al. (2007), after correcting for local topography using trailing edge measures, illustrates an RMSE of 5m across diverse study sites in his Figure 3. Given this height scatter and the open, sparse, stunted coniferous nature of Québec's northern forests near treeline, one might conclude that GLAS does not have the measurement sensitivity to accurately measure high-latitude forests. As a result, stratified GLAS equations were not employed in this study due to the lack of predictive power of some of the northern equations. This lack of sensitivity in short-stature forests also calls into question the accuracy of the GLAS-based biomass and carbon estimates near treeline.

The stratified models, i.e., equations 2 and 4 above, were processed differently from the nonstratified models 1 and 3. Every GLAS shot was assigned to one of the Landsat land cover classes based on the plurality of the land cover types in a 3 x 3 Landsat ETM window that surrounded a given GLAS pulse. The nonstratified models were applied to all 104,044 GLAS shots collected over Québec regardless of the land cover identity of that GLAS pulse. So GLAS pulses judged (by the Landsat classification) to have illuminated barren areas, rock, moss, herb, etc, could still contribute to Provincial biomass if nonzero heights were measured by GLAS. In effect, in the nonstratified models, GLAS measurements trumped Landsat land cover identities, and a GLAS pulse could contribute to the biomass estimate even if the Landsat classification suggested that no forest biomass should exist on that spot illuminated by the GLAS pulse. Just the opposite was true with respect to the stratified models. Models 2 and 4 were utilized only on those GLAS shots judged to be capable of supporting forest biomass. In the case of the stratified models, then, specific cover types could never contain forest biomass regardless of what the GLAS pulses intercepting that cover type may have measured. The net result of this processing rule is that the nonstratified models have higher biomass totals for the Province because they accumulate estimates across larger areas.

The Ministry of Natural Resources Québec made available 16,814 temporary sample plots measured between 1998 and 2004. The intensity and location of the MNRQ TSP multiyear measurement campaign is illustrated in Boudewyn et al. (2007), his Figure 1. All plots are located south of the commercial forest line. A small portion of these plots, ones more recently measured, are used to develop the models discussed above. All 16,814 are used to validate the models.

3. Results

Table 1 reports per hectare and total biomass estimates for the entire 1.27 million km^2 Province of Québec south of treeline. The models are ranked, largest to smallest in terms of total Provincial biomass, and, as one would expect due to processing rules, the nonstratified models report the largest Provincial biomass totals.

The exact same data are input into each model to calculate model coefficients. Based on model differences alone, Provincial biomass and carbon estimates vary approximately 7% even under the ideal circumstance that all of the data input into the various models are identical. No such ideal circumstance would exist if one were monitoring regional biomass over time since the input data would certainly change between t1 and t2. The 7% difference amounts to, in Québec, a model-induced difference of 0.35 Gt of biomass, or 0.18 Gt of carbon assuming a conversion factor of 0.5 t C/1 t biomass (Gower et al. 1997; Houghton et al. 2000). Given a current carbon credit price of ~15 euros per ton carbon, this scenario might result in an undeserved carbon penalty or an unearned carbon credit of up to 2.64 billion euros for Québec, depending on which model was used at t1 and which at t2.

The results in Table 1 indicate that LiDAR-based biomass and carbon monitoring will require model consistency between measurement epochs or, alternatively, a post-processing statistical methodology that would equate current estimates with ones previously made using a different model or LiDAR sensor.

Table 1. Provincial estimates of total above ground dry biomass on 1.27 million km^2 south of tree line in Québec. Model estimates are ranked largest to smallest, top to bottom. All standard errors calculated assuming simple random sampling, covariances are included, prediction error is not.

	dry biomass estimates			**Prov. biomass totals**	
model	**mean (t/ha)**	**stan. err. (t/ha)**	**coef.var. (%)**	**total (Gt)**	**stan. err. (Gt)**
nonstratified, square root (3)	41.72	2.82	6.8	5.29	0.36
nonstratified, linear (1)	40.63	5.21	12.8	5.15	0.66
stratified, linear (2)	39.73	3.32	8.4	5.04	0.42
stratified, square root (4)	38.94	2.17	5.6	4.94	0.28

The accuracy and precision of the four models can be assessed, at least in the three southern vegetation zones, by comparing GLAS-based estimates to biomass estimates on the 16,814 ground plots, accumulated across Landsat vegetation classes (Table 2). All four models underestimated ground-based southern provincial estimates by amounts ranging from –7.3 to –12.4%. Models (2) and (4), the stratified linear and stratified square route models, were, respectively, the most accurate and most precise at the regional level. The ground reference information and the stratified GLAS model results are reported in Table 2, by forest cover type within vegetation zone, and for the entire southern portion of the Province.

Table 2. A comparison of ground reference estimates of biomass with the stratified linear and stratified square-root GLAS model results for the three southern vegetation zones (VZ), by Landsat forest cover type. Northern Temperate vegetation zone – 109,769 km^2, Mixedwood vegetation zone – 98,101 km^2, Southern Boreal vegetation zone – 374,665 km^2. All standard errors are calculated assuming simple random sampling, covariances are included, prediction error is not.

	MNRQ Ground Reference			**GLAS – stratified, linear**			**GLAS–stratified,square root**		
	biomass (t/ha)	stan. err. (t/ha)	no. plots	biomass (t/ha)	stan. err. (t/ha)	difference (%)	biomass (t/ha)	stan.err. (t/ha)	difference (%)
Northern Temperate V.Z.									
conifer	76.60	5.82	49	65.47	2.02	-14.5	62.76	2.55	-18.1
deciduous	77.85	4.95	176	89.70	4.47	+15.2	91.74	4.85	+17.8
mixedwood	65.91	2.79	313	82.66	0.85	+25.4	82.74	1.78	+25.5
Mixedwood V.Z.									
conifer	85.90	1.57	583	72.68	3.02	-15.4	70.55	2.27	-17.9
deciduous	75.00	2.98	290	83.27	2.63	+11.0	83.39	2.61	+11.2
mixedwood	87.15	1.43	1177	80.82	2.51	- 7.3	79.69	2.17	- 8.6
Southern Boreal V.Z									
conifer	86.36	0.37	10007	63.85	5.13	-26.1	61.75	4.07	-28.5
deciduous	56.71	1.77	617	60.54	1.52	+ 6.8	59.22	1.26	+ 4.4
mixedwood	82.16	0.73	3602	69.13	1.44	-15.9	67.44	1.24	-17.9
Prov. Commercial Forest	81.90	0.50	16814	75.93	3.03	- 7.3	75.04	2.25	- 8.4

4. Discussion

Within the next decade, the forestry LiDAR community can expect to have access to extensive data sets that will enable us to conduct regional and national assessments from space. Researchers have already demonstrated that, even with GLAS optimized for ice rather than vegetation measurements, analysts can develop comprehensive, extensive, timely estimates of forest biomass and carbon on areas encompassing hundreds of thousands to well over a million square kilometers. The use of space-based laser altimetry, specifically GLAS waveform data, currently presents numerous challenges, e.g., large footprints that convolve forest canopy structure with topography in the presence of slope, an apparent insensitivity to small, sparse woodland heights, significant laser power changes over time, data collection epochs - late fall, early spring- tailored to ice studies but non-optimal from a vegetation measurement/monitoring standpoint, changing footprint shapes and orientations, and noncontiguous profiles. But space LiDARs currently under design will mitigate many of these problems, though the slope issue is still outstanding as are questions concerning height sensitivity in low biomass situations near treeline.

Monitoring changes to aboveground biomass and carbon stocks over time using air-borne or space LiDARs raises it's own set of issues, issues that will come to the forefront and call into question the validity of those laser-based estimates if we do not address them ahead of time. If LiDAR surveys at time1 and time 2 are to be compared to assess, for instance, compliance with carbon agreements or to provide the quantitative estimates needed to purchase or sell carbon credits, then those t1 and t2 surveys must be consistent. Consistency in this context involves the use of:

- the same ground-based allometry at t1 and t2 (if new plots are measured),
- the same statistical framework, e.g, design, sample size, number of phases,
- the same predictive models,
- the same sensor, or a different sensor with the same flight configuration with respect to laser power, repetition rate, footprint size, pulse width.

The good news is that many of these factors are in our control – the allometry, the statistical framework, model selection. And if an analyst wants to update the allometry or improve/change her/his predictive models, she/he can do so and reprocess the old t1 data with the improved versions to insure comparability. What is most likely not in our control is the sensor, i.e., the operational characteristics of the airborne or space LiDAR. Airborne LiDAR technology is changing so rapidly that data providers commonly swap out their one or two year old scanners for newer, faster, improved versions. And the satellite LiDARs discussed in this paper typically have design lives of ~5 years. We can be fairly certain that most regional surveys done every five to ten years will be done with different sensors.

The results presented in this paper provide one example of the effects of allowing one item on this consistency checklist to stray. Provincial estimates changed ~7% due only to changes in model form and due to changes to the rules used to process the GLAS data. The forestry LiDAR community should begin to address questions concerning consistency and calibration in order to develop procedural or statistical techniques to ensure comparability of LiDAR-based surveys done years apart. These results provide an impetus to develop statistical procedures that can effectively draw equivalence between multitemporal, regional LiDAR-based biomass or carbon estimates that might not be directly comparable due, perhaps, to the use of different predictive models, different allometry, or changing LiDAR sensors in different measurement periods.

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