Physically based vertical vegetation structure retrieval from ICESat data: Validation using LVIS in White Mountain National Forest, New Hampshire, USA

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1. Introduction

Remote estimation of vegetation structure characteristics and forest biomass has become essential to ecosystem modeling studies and advancement in understanding of many ecosystem processes. Unlike many other remote sensing measurements, vegetation lidars provide direct and indirect measurements of vegetation structure (Dubayah & Drake, 2000). Recently vegetation lidar data have become more widely available to study the link between vegetation lidar signals and vegetation structure characteristics. The spaceborne Geoscience Laser Altimeter System (GLAS), part of the ICESat mission, provides global lidar data with a variable diameter ~70 m footprint spaced at ~170 m (Zwally et al., 2002; Harding & Carabajal, 2005; Lefsky et al., 2005). Airborne data have also been collected using a Scanning Lidar Imager of Canopies by Echo Recovery (SLICER) with a 15 m footprint and the Laser Vegetation Imaging Sensor (LVIS) with a footprint of 20 m.

Vegetation structure retrieval accuracies from spaceborne Geoscience Laser Altimeter System (GLAS) on the Ice, Cloud and land Elevation Satellite (ICESat) data are affected by surface topography, background noise and sensor saturation. This study uses a physical approach to remove surface topography effect from lidar returns to retrieve vegetation height from ICESat/GLAS data over slope terrains. Slope-corrected vegetation heights from ICESat/GLAS data were compared to airborne Laser Vegetation Imaging Sensor (LVIS) (20 m footprint size) and small-footprint lidar data collected in White Mountain National Forest, NH. Impact of slope on LVIS vegetation height estimates was assessed by comparing LVIS height before and after slope correction with small-footprint discrete-return lidar and field data. Slope-corrected GLAS vegetation heights match well with 98 percentile heights from small-footprint lidar (R² = 0.77, RMSE = 2.2 m) and top three LVIS mean (slope-corrected) heights (R² = 0.64, RMSE = 3.7 m). Impact of slope on LVIS heights is small, however, comparison of LVIS heights (without slope correction) with either small footprint lidar or field data indicates that our scheme improves the overall LVIS height accuracy by 0.4–0.7 m in this region. Vegetation height can be overestimated by 3 m over a 15° slope without slope correction. More importantly, both slope-corrected GLAS and LVIS height differences are independent of slope. Our results demonstrate the effectiveness of the physical approach to remove surface topography from large footprint lidar data to improve accuracy of maximum vegetation height estimates.

GLAS waveforms were compared to aggregated LVIS waveforms in Bartlett Experimental Forest, NH, to evaluate the impact of background noise and sensor saturation on vegetation structure retrievals from ICESat/GLAS. We found that GLAS waveforms with sensor saturation and low background noise match well with aggregated LVIS waveforms, indicating these waveforms capture vertical vegetation structure well. However, waveforms with large noise often lead to mismatched waveforms with LVIS and underestimation of waveform extent and vegetation height. These results demonstrate the quality of ICESat/GLAS vegetation structure estimates.
Our recent modeling work used the vegetation canopy Geometric Optical and Radiative Transfer (GORT) model to quantify the impacts of surface topography, footprint size, off-nadir pointing, surface roughness and laser pulse distribution on lidar vegetation height and lidar waveforms (Yang et al., in press). We developed an analytical approach to quantify the impact of surface topography and footprint size on vegetation height with the assumption that vegetation canopy is uniformly distributed within each footprint. Vegetation height can be estimated from either GLAS full waveform extent or LVIS height metrics using this approach. The main objective of this study is to apply this approach to retrieve vegetation height from ICESat/GLAS and to evaluate our approach by comparing retrieved ICESat/GLAS vegetation heights with LVIS, small-footprint discrete-return lidar and field data collected in southern White Mountains, NH. National Elevation Data (NED) was used to estimate slope. However, with the availability of global elevation productions from Shuttle Radar Topography Mission (STRM) and Advanced Spaceborne Thermal Emission and Reflection (ASTER) data, our approach may have the potential to derive global elevation productions from Shuttle Radar Topography Mission collected in southern White Mountains, NH.

We then obtained GLAS waveforms can be saturated at canopy layer for dense vegetation or at ground for sparse vegetation. ICESat samplings are sparse, therefore, it would be valuable to assess if these noisy and saturated waveforms have any valuable vegetation structure information. We compared GLAS with aggregated LVIS waveforms and assessed impact of background noise and saturation on GLAS vegetation structure measurements.

The paper is organized as follows: Section 2 describes the site and datasets. Section 3 presents LVIS waveform aggregation and height estimate algorithms. Section 4 first discusses the evaluation results of our slope correction method by inter-comparing heights from GLAS, LVIS, small-footprint discrete-return lidar and field data; then assesses GLAS waveform data quality under different conditions by comparing GLAS and aggregated LVIS waveforms. Section 5 discusses the uncertainties of our algorithm and differences from other methods. Section 6 is the conclusion.

2. Data and site description

2.1. Study site

The study site is the southern portion of White Mountain National Forest in New Hampshire, USA. The region is featured with old-growth northern hardwoods. The dominant species include beech, yellow birch, sugar maple and eastern hemlock. In lower elevations, most of the forest is covered by tall canopies where sugar maple/beech/yellow birch dominates the upper canopy layer with maximum height around 30 m. At higher elevation before reaching the forest line, spruce, fir, and hemlock are commonly mixed with hardwoods, and can be dominant on cool steep slopes (Filip & Little, 1971). The regional terrain varies from flat in the lower valley to slopes of over 30° on higher mountain passes. Higher slopes usually occur at higher elevation (Fig. 1).

2.2. Data sets

2.2.1. ICESat/GLAS data

Global ICESat/GLAS data is available from 2003 to 2008. ICESat/GLAS is the first spaceborne lidar system designed to observe surface structures, including ice sheet mass balance and vegetation characteristics in three dimensions at a global scale. Three onboard lasers were designed to sample Earth's surface at a 172 m interval along the track with a maximum cross track separation of 15 km at the equator (Zwally et al., 2002). Due to the unexpectedly short lifetime of the laser system, the GLAS mission started to operate with a 91-day repeat orbit (with a 33 day sub-cycle) (Sun et al., 2008). In each of the operating years, GLAS acquired data in winter (Feb–March), summer (May–June) and fall (October–November) periods. The three sub-cycles were designed to capture seasonal and interannual change on land surface, e.g. ice and forest canopy. Studies had shown the typical geolocation accuracy of GLAS altimetry data is between 2.4 and 5.8 m (Abshire et al., 2005; Carabajal & Harding, 2005; Neuenschwander et al., 2008), although it can be as high as 60 m (Sun et al., 2008).

To measure the vertical structure of land and ice surfaces, GLAS uses the 1064-nm laser pulses and records the returned laser energy from an ellipsoidal footprint. The original GLAS footprint size was designed to be ~65 m; however, actual footprint diameter was about 110 m, 90 m and 55 m for Lasers 1, 2 and 3, respectively (Zwally et al., 2002; Abshire et al., 2005; Schutz et al., 2005). GLAS footprint size, orientation and ellipticity can vary by shot and precise measurements can only be obtained from laser far field patterns, or Laser Profile Array (LPA) images (Bae and Schutz, 2002). In general, GLAS footprint ellipticity is the smallest for Laser 3 and largest for Laser 1, and only Laser 3 footprint is close to a circle (http://www.nsdc.org/). Since most LPA images are not available in our study region, we chose to use only Laser 3 data, collected in June of 2005 (L3C) and 2006 (L3F), to reduce GLAS footprint coverage uncertainty due to lack of precise ellipticity information.
footprint sizes and ellipticities from the laser operation average, and assumed the footprint is a circle and the diameter equals the mean of major and minor axes.

The background noise level of GLAS data can increase under cloudy condition due to the backscattering from clouds (Abshire et al., 2005). Two rules were used to select good quality GLAS data: 1) the minimum signal-to-noise ratio was set to 15, and 2) the elevation differences from the built-in SRTM and GLAS were used to detect potential low cloud data. Because SRTM penetrates through clouds and GLAS does not, elevation difference from these two datasets indicates the lidar returns are from the cloud or ground. The threshold of the elevation difference was set slightly larger than the maximum vegetation height in the region (50 m) to remove potential low cloud data.

2.2.2. LVIS data
LVIS data in southern White Mountain region of NH were acquired during July 18–20, 2003 with 20 m footprint size (Fig. 1). The LVIS is an airborne lidar system designed to collect data on surface topography and vegetation structure (Blair et al., 1999). LVIS standard data products include the fully digitized waveforms and the height metrics (relative to surface) where 25%, 50%, 75% and 100% of the waveform energy occur, named as $RH_{25}$, $RH_{50}$, $RH_{75}$ and $RH_{100}$, respectively (Blair et al., 2006). Often all LVIS height metrics are released for public access, but the fully digitized waveforms are only publicly available for some intensive study sites.

For this study, we used relative heights at 100% waveform energy, or $RH_{100}$, to estimate forest canopy heights in the whole region and the available full waveform data within the 2 km radius area of the main flux tower in Bartlett Experimental Forest, NH for waveform comparisons with the GLAS data.

2.2.3. NED data
National Elevation Dataset (NED) is a seamless and nationally consistent set maintained by the U.S. Geological Survey (USGS) (http://egsc.usgs.gov). The standard 1 arc-second (~20×30 m resolution in our study region) NED digital elevation model was used to derive slope. The slope for each NED grid cell was determined as the maximum rate of change between each cell and its immediate neighbors. At 1 arc-second scale, previous research had shown NED’s slope accuracy is 3° or less (Holmes et al., 2000).

The slope for each ICESat or LVIS footprint was calculated as the mean of slopes for all grid cells within the footprint. Since LVIS footprint is similar in size to NED’s 1 arc-second grid, we expect the slope within each LVIS footprint has similar accuracy to the NED grid scale i.e. 3° or less. For GLAS, better slope accuracy might be achieved due to the larger footprint size.

2.2.4. Small-footprint discrete-return lidar data
First- and last-return discrete lidar data were collected at Bartlett Experimental Forest (see Fig. 1) using an Optech ALTM 2025/2050 sensor in August of 2005. The reported accuracies of lidar data were 15 cm vertically and 50 cm horizontally. To derive canopy height, a “bare earth” digital elevation model was first constructed at 1 m spatial resolution using the Toolbox for Lidar Data Filtering and Forest Studies (TIFFS) program (Chen, 2007). TIFFS uses morphological approaches with variable window sizes to resolve pixels without any lidar shot penetrating canopy to construct the best “bare earth” digital elevation model (Chen et al., 2007). Any lidar points above the bare earth surface are considered to be vegetation canopy returns. In this study, a 1 m lidar canopy height model was created using the highest lidar canopy returns within each 1 m grid cell.

2.2.5. Field data
Field data were collected during the summer 2009 Deformation, Ecosystem Structure and Dynamics of Ice (DESDnyI) field campaign in NH, within the LVIS sampling range. Field data collection consists of eight 1-ha plots (50×200 m grid size), each plot was divided into 16 subplots (25×25 m). The heights of the tallest trees (varying from one to three) were measured and their average was used to compare with LVIS and small-footprint maximum height. Field plot geolocation uncertainties range from 4–8 m and 12–14 m for two subplots. 4 or 6 years differences between LVIS/small foot print and field data was

Fig. 1. Slope map derived from National Elevation Data (NED) overlaid with GLAS footprints (thick black dots), field sample sites (triangulars), small-footprint discrete-return lidar sampling area (blue rectangle) and LVIS data extent (parallelograms) in southern White Mountain National Forests, NH. Circle indicates the location of Bartlett Experimental Forest where full LVIS waveform data are available.
taken into account in our analysis. No field data is available within GLAS footprints. Fig. 1 shows the spatial coverage of GLAS, LVIS, small-footprint discrete-return lidar and field sites.

3. Method

3.1. Vegetation height retrieval from lidar over slope terrains

The two most commonly used height metrics to infer vegetation height from lidar are waveform extent for GLAS and RH100 for LVIS (Fig. 2). Waveform extent is defined as the height difference between the first and last elevations at which the waveform energy exceeds a threshold. The threshold was set as 4.5 times of background noise in GLAS (Lefsky et al., 2005, 2007) and three times of background noise in LVIS (Blair et al., 2006). RH100 is defined as the distance from the top of vegetation returns to the peak of last Gaussian pulse or ground returns (Blair et al., 1999).

Both waveform extent and RH100 are influenced by surface topography, footprint size and laser pulse energy distribution/surface roughness. Yang et al. (in press) extended the Geometric and Radiative Transfer (GORT) vegetation lidar model to take into account the impacts of surface topography and off-nadir pointing on vegetation lidar waveforms and vegetation height retrieval. This study presented an analytical formula to quantify the first-order influence of surface topography, footprint size, laser pulse energy distribution/surface roughness and off-nadir pointing effect on lidar vegetation height. For nadir-viewing lidar application, the relationship between vegetation height (H) (i.e. lidar vegetation height at a flat terrain), RH100, waveform extent (L_{ext}) and surface topography (with slope \( \theta \)), footprint size (d) and the pulse width/surface roughness can be described by the following equations (see Fig. 3):

\[
L_{\text{ext}} = H + d \tan \theta + c \cdot \text{FWHM} / 2
\]

\[
RH100 = H - d \tan \theta / 2
\]

(1)

where \( c \) is the speed of light and FWHM (Full Width at Half Maximum) describes the laser pulse width, which is 6 ns (equivalent to 1.8 m) for GLAS and 10 ns (equivalent to 3 m) for LVIS. Surface roughness also plays the similar role of broadening waveforms as the Gaussian laser pulse energy distribution, and \( c \cdot \text{FWHM} \) is the combined effect of laser pulse width, energy distribution and surface roughness.

Eq. (1) suggest that vegetation height (H) can be retrieved from RH100 or waveform extent (\( L_{\text{ext}} \)), knowing footprint size, d, slope (\( \theta \)), and \( c \cdot \text{FWHM} \), and are described as follow:

\[
H = L_{\text{ext}} - d \tan \theta - c \cdot \text{FWHM} / 2
\]

\[
H = RH100 - d \tan \theta / 2
\]

(2)

However, this relationship was derived based on very smooth waveforms, whose extent and canopy top is defined with zero threshold. In reality, waveforms have background noise and their extents or RH100 values are defined using a non-zero threshold, e.g. 4.5 times of background noise in GLAS, three times in LVIS. Therefore, in Eq. (2) waveform extent/RH100 needs to be corrected (extended).

We applied a simple correction scheme to extend waveforms with a zero-threshold: waveforms were smoothed first to reduce uncertainty caused by noises; then extended linearly with a zero-threshold using locations of the original zero and 10 percentile of waveforms as two reference points. The same procedure was applied to the lower end of waveforms. Then waveform extents were recalculated using the extended waveforms. In this study we were not able to correct RH100 due to unavailability of LVIS full waveforms within most GLAS footprints. We expect that the impact on RH100 would be much smaller (\(-1/3\)) comparing to GLAS waveform extent due to its smaller threshold (see discussion before) and for one side of waveform correction only.

To evaluate our approach, we compared LVIS RH100 with and without slope correction with small-footprint discrete-return lidar and field measured vegetation height. We also compared slope-corrected GLAS with slope-corrected LVIS and small-footprint discrete-return lidar heights (see Section 4).

3.2. GLAS and LVIS waveform comparison

To evaluate GLAS waveforms, GLAS waveforms were compared to aggregated LVIS waveforms, which were calculated as a summation of all LVIS waveforms within each GLAS footprint weighted by GLAS laser energy Gaussian distribution (see Fig. 4):

\[
F(z) = \sum_i f_i(z) \cdot w_i
\]

\[
w_i = \frac{g_i}{\sum_i g_i}
\]

\[
g_i = e^{-2z_i/d_{\text{GLAS}}}
\]

where \( F(z) \) is the aggregated LVIS waveform intensity at height \( z \), \( f_i(z) \) is the \( i \)th LVIS waveform intensity at height \( z \), \( z \) is the relative height to the mean LVIS ground elevation, this indicates that during the aggregation, heights for each LVIS waveform on a slope were shifted vertically relative to mean ground elevation in the GLAS footprint. \( w_i \) is the normalized weight for \( i \)th LVIS waveform, \( g_i \) is the weight for \( i \)th LVIS waveform, \( r_i \) is the distance from GLAS centroid to \( i \)th LVIS footprint center, and \( d_{\text{GLAS}} \) is the GLAS footprint diameter.

For comparison, LVIS waveforms were aggregated vertically from its original resolution, 0.3 m, to GLAS resolution, 0.6 m. GLAS and the aggregated LVIS waveforms are not directly comparable because the total waveform energy is different. We also compared normalized waveforms, instead of empirically re-scaling them by peak energy returns (Neuenschwander et al., 2008).
The elevations reported in GLAS and LVIS or other airborne data do not have exact agreement (Sun et al., 2008; Neuenschwander et al., 2008). To overlay GLAS and LVIS aggregated waveforms, this study used an automatic approach by first adjusting the height of GLAS and LVIS waveforms relative to their corresponding ground elevation; then the waveforms are aligned by assuming the same ground elevation. This approach allows us to overlay LVIS and GLAS waveforms automatically for comparison as opposite to manual shifting waveforms used in Neuenschwander et al. (2008).

Ground elevation is a standard LVIS product, and LVIS mean ground elevation at the GLAS footprint was calculated as the mean of all LVIS data within each GLAS footprint. We chose not to use ground elevation estimated from the Gaussian peaks in the GLAS product to avoid ground peak identification uncertainties, which could be significant under dense canopy conditions and on slope terrains due to its large footprint size (Lefsky et al., 2007; Yang et al., in press; Chen, 2010a). Original heights in GLAS waveforms were relative to the elevation estimated from the Gaussian peaks in the GLAS product (Fig. 4). In this study, heights in each GLAS waveform were shifted relative to GLAS ground elevation (\(H_g\)) using the elevation difference between \(H_g\) and \(H_{w\text{-end}}\), and the GLAS ground elevation was treated as the same as the LVIS mean elevation. The height shift is described as,

\[
H_{g} - H_{w\text{-end}} = (d_{GLAS} \tan \theta + c \cdot FWHM_{GLAS}) / 2
\]

where FWHM_{GLAS} is FWHM for GLAS. Since we don't have surface roughness information, the impact of \(c \cdot FWHM_{GLAS}\) was ignored in Eq. (4).

4. Results

4.1. Vegetation height comparisons

4.1.1. LVIS, field and small-footprint discrete-return lidar data comparison

Although LVIS footprint size (20 m) is much smaller than GLAS', LVIS height could also be affected by slope as discussed before. To evaluate the quality of LVIS height data and the impact of slope on LVIS heights, we first compared LVIS height before and after slope correction with field measured maximum heights and small-footprint discrete-return lidar data. Fig. 5 compares LVIS height, \(H_{LVIS}\) (with slope correction), \(RH100\) (without slope correction) with field measured maximum tree height (\(H_{\text{field}}\)) and the dependences of their differences, \((RH100 - H_{\text{field}})\) and \((H_{LVIS} - H_{\text{field}})\) on slope. The slope-corrected LVIS heights match better to field measurements than

\[
\text{RH100 (RMSE 4.8 m and } R^2 0.29 \text{ vs. RMSE 5.2 m and } R^2 0.19) \text{. Overall, field measured heights tend to be taller than LVIS', which is likely due to the tree growth between 2003 (LVIS data collected) and 2009 (field data collected). RH100 and measured maximum tree height difference, } (RH100 - H_{\text{field}}) \text{, increases with slope indicating the impact of slope on RH100 (Fig. 5c). However after removing slope from RH100 using our scheme, LVIS and field measured height difference, } (H_{LVIS} - H_{\text{field}}), \text{ indicates no relationship with slope (Fig. 5d). RH100 without slope correction could overestimate height by 3 m over a terrain with a 20° slope. The result indicates our slope correction successfully removes slope-effect in RH100. The relative large RMSE could be caused by large geolocation uncertainties of field data (approximately 4–8 m).}

Fig. 6 shows the same comparison as in Fig. 5 except with small-footprint discrete-return lidar height (\(H_{SF}\)), calculated as 98 percentile of canopy height to reduce canopy top height uncertainty. This
Fig. 7. The relationship of height differences between the 98 percentile of small-footprint lidar height ($H_{SF}$) and field measured maximum height ($H_{field}$) with slope.

comparison shows similar results as shown in Fig. 5. Our scheme improves the overall height retrieval accuracy by 0.7 m (RMSE 3.7 m in Fig. 6a vs 3.0 m in Fig. 6b). Similar slope dependency of ($RH100 − H_{SF}$) as in Fig. 5c was shown in Fig. 6c. However after removing slope impact, ($HLVIS − H_{SF}$) is independent on slope (Fig. 6d) indicating the slope effect was removed from $RH100$. The height retrieval bias can reach 4–5 m at 15° slope terrain (Fig. 6c). The overall uncertainty is smaller in Fig. 6 (RMSE=3.0 m) than the one in LVIS and field-measured height comparison as shown in Fig. 5 (RMSE=4.8 m) implying LVIS is better geolocated with small-footprint discrete-return lidar data than with the field data. Opposite to what is shown in Fig. 5, LVIS slightly overestimates small-footprint lidar height. This is somewhat expected because LVIS height is very close to top of the canopy height, but small-footprint lidar sometimes misses the tallest tree tops.

We also compared the small-footprint discrete-return lidar and field measured height differences, ($H_{field}−H_{SF}$), which tend to show a slightly decreasing trend with slope (Fig. 7). The trend might be caused by the mismatched geolocation problem or by some other random factors.

4.1.2. GLAS and small-footprint discrete-return lidar height comparison

We compared slope-corrected GLAS height ($H_{GLAS}$) with small-footprint discrete-return lidar (Fig. 8). GLAS heights match well with 98 percentile of small-footprint lidar heights ($H_{SF}$) (RMSE = 2.2 m and $R^2 = 0.77$) (Fig. 8a). Comparing to the LVIS and small-footprint discrete-returns lidar height comparison with a larger RMSE = 3.0 m, it might indicate that our scheme works better for a larger footprint lidar. However we cannot rule out the possibility that the larger uncertainty in LVIS height estimates comes from the uncertainty of $RH100$ estimates, particularly at large slopes and for dense vegetation. $RH100$ was estimated using the Gaussian decomposition approach and particularly at steep slopes, the ground return is well mixed with vegetation returns and identifying ground peaks might not be possible for dense canopies.

We also evaluated the waveform extent correction scheme (see Section 3.1) (Fig. 8b). Comparison of small-footprint ($H_{SF}$) and slope-corrected GLAS heights with (Fig. 8a) and without (Fig. 8b) waveform extent correction indicates that correction of waveform extent improves height accuracy ($R^2 = 0.77$ and RMSE = 2.2 m in Fig. 8a vs. $R^2 = 0.74$ and RMSE = 2.9 m in Fig. 8b).

We further investigated the effectiveness of slope correction scheme by comparing GLAS and small-footprint lidar height differences ($H_{GLAS} − H_{SF}$) with slope (Fig. 8c). To examine the impact of correction of waveform extent on height retrieval, we overlay ($H_{GLAS} − H_{SF}$) with/without correction of waveform extent (Fig. 8c). Retrieved heights can increase from 0 to 5 m using our correction scheme. Height differences, ($H_{GLAS}−H_{SF}$), show slightly decreasing trends with slope for both schemes. The trend is roughly the same as the slope dependency of small-footprint lidar and field measured height differences (Fig. 7c). In summary, extending original GLAS waveform extent to a zero-threshold is necessary for our slope correction scheme. However, a more systematic study is required in the future. $H_{GLAS}$ with the correction of waveform extent is used for the rest of the paper.

4.1.3. GLAS and LVIS height comparison

To further evaluate GLAS height at a large scale with an increased slope range, we compared GLAS with LVIS heights (Fig. 9). LVIS height was calculated as the mean of three tallest LVIS heights (slope-corrected) within each GLAS footprint. Direct comparison of GLAS and LVIS height (Fig. 9a) shows RMSE = 3.7 m and $R^2 = 0.64$. The RMSE here is larger than the value in GLAS and small-footprint lidar comparison (RMSE = 2.2 m). Two possible factors contribute to this: a) larger height range in LVIS data (13.6–35.5 m with standard deviation, std = 4.6 m) than in small-footprint lidar (19.6–29.9 m, std = 3.1 m), the possible uncertainty in $RH100$ estimate (see the discussion before).

Fig. 9b and c compare the slope dependencies of the uncorrected lidar height differences ($L_{ext}−RH100$) and slope-corrected lidar heights ($H_{GLAS}−H_{LVIS}$). The slope dependency is strong between uncorrected lidar height differences (Fig. 9b) but minimal after slope correction (Fig. 9c). The dependence of these differences on slope can be derived from Eq. (1) and described as follows:

$$L_{ext}−RH100 = \left(\frac{d_{GLAS}−d_{LVIS}}{2}\tan\theta\right) + c\cdot FWHM_{GLAS}/2$$

$$H_{GLAS}−H_{LVIS} = c\cdot FWHM_{GLAS}/2$$

(5)

where $d_{GLAS}$ and $d_{LVIS}$ are GLAS and LVIS footprint diameters, $FWHM_{GLAS}$ is FWHM for GLAS. The positive correlation between ($L_{ext}−RH100$) and slope in Fig. 9b is consistent with Eq. (5). Once slope effect is removed from GLAS waveform extent and LVIS RH100, the difference between GLAS and LVIS heights shows very little dependence on slope (Fig. 9c). This result demonstrates the effectiveness of the slope correction used in this study.

Fig. 8. Comparison of slope-corrected GLAS heights ($H_{GLAS}$) with 98 percentile of small-footprint lidar height ($H_{SF}$) a) with the correction of waveform extension and b) without the correction) and c) the dependence of residuals of slope-corrected GLAS heights, ($H_{GLAS}−H_{SF}$) on slope with trend. Two GLAS heights in c): circles with the correction of waveform extent and stars without the correction.
4.2. GLAS and LVIS waveform comparison in BEF

GLAS and aggregated LVIS waveforms were analyzed under three different categories: typical, noisy and saturated waveforms. Noisy waveforms refer to those with background noise greater than 2 Digital Number (DN). Background noise is calculated as the standard deviation of DN values from non-vegetation and non-ground returns. 2DN was selected as the threshold to separate lower and higher noise groups shown in the GLAS data. Saturated waveforms refer to those with sensor saturation, occurring in either vegetation returns for very dense canopies or ground returns for very sparse canopy partly due to a wrong sensor gain mode. Saturation index in GLAS products was used to determine if each GLAS waveform is saturated or not. We call the rest of the waveforms, which are acquired under more common atmospheric conditions with a proper sensor gain mode, typical waveforms. By our definition, for 31 leaf-on GLAS waveforms collected in BEF, 12 are noisy, 8 saturated and 13 typical.

4.2.1. Typical waveforms

9 out of 13 GLAS waveforms matched well with aggregated LVIS waveforms over various slopes (0.2 to 14.4°). Fig. 10 shows comparison for four typical waveforms with two good matches and two mismatches. The matched waveforms occur in both relatively dense (Fig. 10a) and multilayered (Fig. 10b) vegetation canopies. Two types of mismatches were found in four mismatched waveforms: One type (Fig. 10c) has two similar waveform shapes but with mismatched height, probably due to either GLAS or LVIS ground elevation error. The other type (Fig. 10d) has two similar canopy or ground peaks but with mismatches in magnitudes. Several factors could contribute to this mismatch, such as geolocation uncertainty between datasets, LVIS’ and GLAS’ small off-nadir pointing effects and LVIS non-uniform sampling effects within each GLAS footprint. In forest stands with non-random spatial distribution of tree heights, the small LVIS off-nadir pointing angle can cause some waveform change, compared to the near-nadir viewing GLAS data (Neuenschwander et al., 2008). We found that the mismatches caused by the above sources are usually not significant, and overall most typical GLAS waveforms match well with the aggregated LVIS waveforms.

4.2.2. Saturated waveforms

Fig. 11 shows the same comparison as Fig. 10 except for saturated GLAS waveforms at ground (Fig. 11a and b) and at canopy (Fig. 11c and d). For canopy-saturated waveforms, GLAS and LVIS waveform shapes are generally in good agreement, except for slight differences in peak return magnitudes. This indicates that saturation in canopy might not be strong and these canopy-saturated waveforms are still good for extracting vegetation structure.

Ground-saturated waveforms (Fig. 11a and b) show very strong ground returns and weak canopy returns from both GLAS and LVIS data, indicating these sites are sparsely vegetated regions. Ground-saturated GLAS waveforms are consistently located several meters above LVIS data, which could be caused by underestimation in GLAS ground elevation or ignoring surface roughness effects in our analytical estimation of ground peak in GLAS waveforms. Comparisons for canopy-saturated waveforms (Fig. 11c and d) show little height differences between GLAS and LVIS waveforms. Ground-saturated waveforms show weaker ground peak returns in GLAS and some mismatch in canopy returns (Fig. 11a and b). Saturation in GLAS
4.2.3. Noisy Waveforms

Fig. 12 shows the same kind of comparison as in Fig. 10 except for noisy GLAS waveforms. In general, GLAS and LVIS waveform shapes match well; however, GLAS waveform extent can be reduced due to larger threshold value used to determine top and bottom of the waveform extent. By examining the relationship between GLAS waveforms and their extent (shaded area) shown in Fig. 12, we found that the waveform extent is usually a few meters shorter than what the visually interpreted waveform range should be.

The degree of waveform extent underestimation is depending on waveform shape, or vegetation structure, slope and sensor view angle. When both canopy and ground returns are strong (Fig. 12a), waveform extent underestimation is very small. However, significant underestimation can occur in ground (Fig. 12b and d) or canopy (Fig. 12c) when ground or canopy returns are weak. This indicates that waveform extent determined by the simple threshold method can be problematic in noisy waveforms especially when either canopy or ground returns are weak; therefore, our vegetation height method should be used with caution for noisy waveforms.

4.2.4. Evaluation of GLAS vegetation height

Fig. 13 compares GLAS and mean of top three LVIS vegetation heights for all BEF data. The comparison was categorized into two groups: typical and saturated waveforms and noisy waveforms. Fig. 13 shows that LVIS mean-top-three-heights match well with GLAS heights for typical and saturated waveforms ($R^2 = 0.8$ and RMSE $= 2.4$ m). The result is similar to the earlier GLAS and small-footprint lidar height comparison (Fig. 8a), which covers a similar area. However, noisy waveforms often result in underestimating waveform extent and vegetation height. Height underestimation is usually about a few meters, but can be up to 15 m for very sparse and dense forests, in which identifying first and last return is particularly sensitive to the threshold.

![Fig. 12. Comparison of LVIS and noisy GLAS waveforms.](image)

![Fig. 13. GLAS and LVIS height comparison in Bartlett, NH for typical and saturated (circle) and noisy (X) GLAS waveforms. $R^2$ and RMSE for typical and saturated waveforms and RMSE, for noisy waveforms.](image)

5. Discussion

The most unique part of our height retrieval scheme is that slope is corrected using an analytical formula with auxiliary slope data. The same correction will be applied for the same slopes no matter what the vegetation condition is. Other GLAS height estimation schemes, for example statistical approaches, have their own advantages as results are estimated from waveform shape parameters and calibration coefficients and could be more accurate for specific sites. Nonetheless, recalibration is likely a necessary process as topography effects on waveform shape are affected by local vegetation conditions and sensor view angle (Chen, 2010b; Neuenschwander et al., 2008; Yang et al., in press). Our physical approach provides a systematic analysis to quantify the specific error sources. Such a physical approach to retrieve vegetation height from lidar over slope terrains offers an important compliment to current retrieval methods and a significant step to map global vegetation structure from future lidar missions.

The slope-corrected vegetation height scheme presented in this study is different from other height retrieval schemes such as Lorey's height (Lefsky et al., 2007) or crown-weighted height (Pang et al., 2008), which consider the canopy distribution on height estimate. Our slope-based scheme is to retrieve maximum vegetation height, which is similar to RH100 in LVIS data. Maximum canopy height might be less related to biomass than other height metrics such as Lorey's height, crown-weighted height or RH75, RH50 derived from LVIS data. However, maximum canopy height is a critical structure input for surface roughness estimate in land surface biophysical models. Retrieving other vegetation height metrics is more complicated and will be further investigated in our future work.

Our results have demonstrated that first-order topography effects on lidar heights can be removed analytically using the slope-correction scheme. However, its height retrieval accuracy is affected by several factors. One of the largest uncertainties might come from unevenly distributed vegetation. Our scheme was developed with the assumption that similar vegetation structure is evenly distributed within each footprint. This assumption may not be valid on vegetation distribution has a large variation in height and unevenly distributed over a slope.

GLAS, LVIS and small-footprint lidar height comparison results presented in this study show that slope-corrected LVIS height has larger RMSE (3.0 m) than slope-corrected GLAS height (with RMSE = 2.2 m) when compared to small-footprint lidar height. This result might indicate that our algorithm works better for large footprint lidar (ICESat/GLAS) than medium-footprint lidar (LVIS). However, uncertainty in RH100 estimates over sloped terrains might cause larger uncertainty in LVIS height retrieval presented in this study (see discussion before). Further work is necessary to use both the full waveform extents from LVIS and GLAS data for our slope correction scheme in order to fully validate our conclusion.
Non-uniform spatial vegetation distribution might also contribute to the larger uncertainty in the two large footprint lidar height comparison (GLAS and LVIS, RMSE = 3.0 m) than in the GLAS and small-footprint lidar height comparison (RMSE = 2.2 m), particularly when large variation of tree heights are on slopes. For example, lidar return from top canopy near the edge of GLAS footprint might not be detectable because laser energy is much lower than it is in the center. But the same canopy can be detected by small-footprint lidar or LVIS footprint. We expect the sampling bias to be larger, thus larger RMSE when GLAS is compared with LVIS than with small-footprint lidar because small-footprint lidar has higher spatial samplings density.

In addition, accurately quantifying surface roughness effects on waveforms can also reduce uncertainties on lidar heights retrieval when ground peaks are questionable. It is not trivial to quantify surface roughness effects because of the lack of knowledge of detailed surface elevation characteristics.

To fully quantify lidar height distortion on slope, both topography information (slope and aspect) and sensor zenith and azimuth angle are needed (Yang et al., in press). We chose to use the simpler nadir correction scheme because the off-nadir angles are small and lack of accurate sensor zenith and azimuth angles and slope orientation. In our study region, the estimated off-nadir pointing angles are about 3–5° for LVIS and 0–2° for GLAS, resulting in height error ranging from 0.1 to 1 m for 2-degree off-nadir angle in GLAS and from 0.2 to 1.5 m for 5-degree off-nadir pointing angle in LVIS (estimated using equations in Yang et al., in press). Furthermore, the uncertainty caused by the 3° accuracy of NED slope dataset is about 0.55 m for LVIS RH100 and 2.7 m for GLAS waveform extent (at typical GLAS footprint size (50 m) in our study) at 10 degree slope. For a global application, SRTM or ASTER DEM will be used to derive slope. Our future work will assess the overall slope-corrected height accuracy when SRTM or ASTER instead of NED slope datasets are used.

6. Conclusions

Large uncertainties in vegetation structure retrieved from spaceborne ICESat/GLAS laser altimetry data are caused by surface topography, background noise, and sensor saturation. In this study we used an analytical approach to retrieve vegetation height by removing slope effect from lidar returns. We evaluated slope-corrected GLAS and LVIS heights using small-footprint lidar data and field measurements in southern White Mountain National Forest, NH. We also evaluated GLAS vertical vegetation structure content by comparing GLAS and corresponding LVIS waveforms and investigated the impact of sensor noise and saturation on vegetation structure retrieval in Bartlett Experimental Forest, NH.

Yang et al. (in press) presents an analytical scheme to quantify the impacts of surface topography, footprint size, laser pulse width and surface roughness on lidar vegetation height metrics over a forest stand. The scheme was used to remove surface topography from GLAS waveform extents and LVIS RH100 using slopes derived from the National Elevation Dataset (NED). The difference between original lidar height metrics, GLAS waveform extent and LVIS RH100 indicates a strong dependence on slope. However, after slope correction using our method, GLAS and LVIS heights match reasonably well with small-footprint data and field data with RMSE = 2.2 m for GLAS and 3 m for LVIS. Our analysis shows that the combined effect of surface topography and footprint size can be accurately removed from GLAS waveform extent and LVIS RH100. Slope-corrected GLAS heights match well with slope-corrected LVIS heights with RMSE = 3.7 m. The corrected GLAS and LVIS vegetation height differences are independent of slope, indicating the topography correction is effective.

GLAS and aggregated LVIS waveforms and vegetation height comparisons in Bartlett Experimental Forest, NH show that GLAS waveforms and heights matched well with LVIS for most waveforms without sensor saturation and with low background noise. Saturated waveforms show reasonably good match between GLAS and LVIS waveforms, indicating GLAS saturated waveforms should still capture vertical vegetation structure well. GLAS waveforms with large noise often mismatch LVIS waveforms resulting in underestimation of waveform extent and vegetation height.

Applying our slope correction scheme outside of U.S. or at global scale requires surface slope information from alternative sources. It is possible to characterize large-scale slope information from the global canopy-adjusted surface elevation data generated from SRTM, owing the elevation bias is systematic and statistically insignificant. Our initial study in New England region shows that SRTM does not provide good quality elevation data, however the slope from SRTM matches reasonably well with NED slope (Mean error ~0.9°, RMSE ~3°). With the acceptable slopes from SRTM, application of our correction scheme can be applied to global scale after further evaluation in other regions and biomes.

Nomenclature

- \( H \): Maximum vegetation Height
- \( H_{\text{GLAS}} \): slope corrected GLAS vegetation height
- \( H_{\text{LVIS}} \): slope-corrected LVIS vegetation height
- \( H_{\text{LVIS}}^{\text{ref}} \): mean height of top 3 LVIS within each GLAS footprint
- \( H_{\text{SF}} \): 98 percentile of small-footprint discrete-return lidar height
- \( H_{\text{field}} \): field measured maximum vegetation height
- \( H_{\text{v,end}} \): waveform ending height (last detectable return)
- \( L_{\text{GLAS}} \): GLAS waveform extent
- \( R_{\text{Hx}} \): LVIS height relative to ground at \( x \)% of waveform energy
- \( d \): lidar laser footprint diameter
- \( \theta \): slope
- \( d_{\text{LVIS}} \): LVIS footprint diameter
- \( d_{\text{GLAS}} \): GLAS footprint diameter
- \( \text{FWHM}_{\text{GLAS}} \): FWHM (Full Width at Half Maximum) for GLAS
- \( \text{FWHM}_{\text{LVIS}} \): FWHM for LVIS

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References
