

# Influence of Vegetation Structure on Lidar-derived Canopy Height and Fractional Cover in Forested Riparian Buffers During Leaf-Off and Leaf-On Conditions

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## Abstract

Estimates of canopy height (H) and fractional canopy cover (FC) derived from lidar data collected during leaf-on and leaf-off conditions are compared with field measurements from 80 forested riparian buffer plots. The purpose is to determine if existing lidar data flown in leaf-off conditions for applications such as terrain mapping can effectively estimate forested riparian buffer H and FC within a range of riparian vegetation types. Results illustrate that: 1) leaf-off and leaf-on lidar percentile estimates are similar to measured heights in all plots except those dominated by deciduous compound-leaved trees where lidar underestimates H during leaf off periods; 2) canopy height models (CHMs) underestimate H by a larger margin compared to percentile methods and are influenced by vegetation type (conifer needle, deciduous simple leaf or deciduous compound leaf) and canopy height variability, 3) lidar estimates of FC are within 10% of plot measurements during leaf-on periods, but are underestimated during leaf-off periods except in mixed and conifer plots; and 4) depth of laser pulse penetration lower in the canopy is more variable compared to top of the canopy penetration which may influence within canopy vegetation structure estimates. This study demonstrates that leaf-off lidar data can be used to estimate forested riparian buffer canopy height within diverse vegetation conditions and fractional canopy cover within mixed and conifer forests when leaf-on lidar data are not available.

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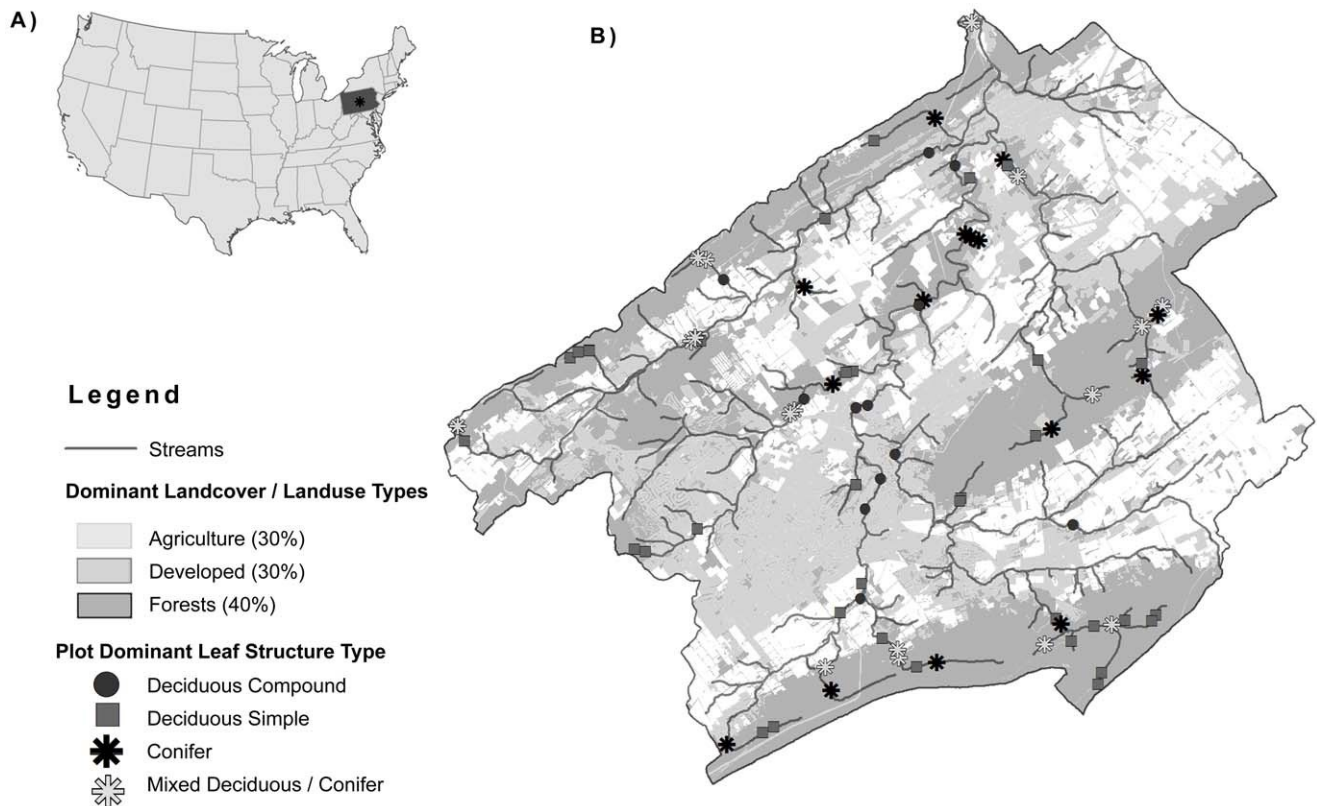
## Introduction

Forested riparian buffers provide numerous ecosystem services including pollutant filtration, wildlife habitat, stream flow mitigation and temperature mediation and thus maintain the ecological integrity of aquatic and terrestrial ecosystems [1–4]. However, their often narrow and fragmented spatial configuration make them vulnerable to disturbance which can impede buffer ecological function and yield broadscale ecological degradation [5–8]. Riparian vegetation canopy height and fractional canopy cover are two frequently measured indicators of buffer and associated stream integrity that are incorporated into monitoring initiatives (e.g. EMAP) around the world [9–11]. These metrics can be used to predict key biophysical stream and terrestrial attributes including stream temperature, detritus availability, available wildlife habitat and biomass [12–18].

Identifying and monitoring change in riparian buffer structure over broad geographic extents is important for understanding disturbance impacts on riparian forest dynamics, associated ecological consequences and the efficacy of restoration efforts. Yet detection and quantification of riparian forest change over

time is difficult [19]. Detection methods, including *in situ* plot sampling [17,20] and classification of multi-spectral satellite imagery or aerial photography [4,21–23], introduce a compromise between spatial resolution (grain) and area extent [19,24,25]. Frequent plot sampling, while necessary, is time and cost intensive limiting inventory geographic extent and riparian corridor widths are often more narrow than the grain of a multi-spectral, multi-temporal remote sensing pixel (e.g. Landsat) limiting detection [26,27]. While some spectral remote sensing methods can be used to effectively assess vegetation condition over broad geographic areas for relatively low costs [23], these techniques are unable to accurately characterize important within canopy structural attributes.

Discrete return airborne Light Detection and Ranging (lidar) provides a link between *in situ* field and spectral remote sensing techniques used to detect and quantify riparian buffer characteristics, especially in areas where buffers are narrow and fragmented. Lidar systems measure the three-dimensional characteristics of vegetation structure by sampling the canopy, understory and ground surface using reflected light from a rapidly emitted laser pulse. Within canopy reflections or ‘returns’ allow for estimation of



**Figure 1. Spring Creek Watershed: A) Context map of the United States identifying the location of the study area, Spring Creek Watershed, located in the center of Pennsylvania; B) Landuse/landcover map of Spring Creek illustrating streams, landuse and mensuration plot locations examined in the study (Landuse Data Source: Centre County Planning Commission, 2006).**  
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forest structure and composition including canopy and understory height, stand basal area and fractional cover [28–36]. Interpolation of discrete return lidar can be used to create seamless datasets that can in turn, be used to continuously map three-dimensional forested riparian vegetation conditions at high spatial resolutions. Lidar thus offers the unique opportunity to bridge the gap between horizontal resolution, sampling geographic extent and three-dimensional vertical structure that exists between spectral RS detection methods and plot data [9,14,37,38]. Despite these benefits, lidar surveys flown during maximum leaf-flush conditions, commissioned for vegetation detection are not always available for large geographic regions, whereas leaf-off lidar surveys, often commissioned for terrain generation, have expanded significantly (e.g. PAMAP, USGS National Map) with many parts of North America, Australia, and Europe being recently surveyed.

Increased lidar survey coverage provides an opportunity for land managers, ecologists and others to use lidar data that were previously collected for other purposes to monitor vegetation structure [39]. Yet, the accuracy of canopy height and fractional cover estimates using data flown during periods when vegetation is not in maximum leaf-flush conditions may be compromised. Further, the degree to which estimates accurately represent canopy height and fractional cover will vary with species type and lidar survey timing within the phenologic cycle. However, the utility of lidar flown during leaf-off conditions has been demonstrated in some forest types. For example, Naesset [40] and Orka et al. [41] demonstrated that leaf-off lidar data can estimate some biophysical properties within Scandinavian forests

(stem density, basal area and average canopy height), while Brandtberg et al. [42]; Brandtberg [43]; Kim et al. [44] and others have found that leaf-off lidar data can be used to classify vegetation in North American forests. There is a need to assess the accuracy of existing lidar data in estimating vegetation structure within a variety of ecosystems if researchers wish to utilize it in support of broad-scale vegetation inventory and assessment.

Thus, the objectives of this study are to: 1) compare leaf-on and leaf-off lidar estimates of canopy height and fractional canopy cover with plot measurements within riparian buffers of varying vegetation types to assess whether leaf-off lidar data are adequate for characterizing forested riparian buffer structure and 2) determine if the vegetation types (and associated leaf and branch structure) typical of northeastern (USA) riparian forests influence leaf-off and leaf-on lidar estimate accuracy.

## Materials and Methods

### Study Area

The study area, Spring Creek Watershed, is located within the Ridge and Valley province of Central Pennsylvania, and is part of the Chesapeake Bay watershed (Lat. 40.818°N, Long. 77.841°W). Landcover in Spring Creek is dominated by forest (40%), agriculture (30%) and urban/suburban development (30%) within an elevation range of 200 m–730 m (Fig. 1). Riparian buffers within lowland watershed valleys are narrow, surrounded by agricultural or developed landuse types. Vegetation within these lowland riparian forests is dominated by a host of species including black walnut (*Juglans nigra*) and maple (*Acer spp.*) with multi-flora

rose (*Rosa multiflora*) common in the understory. Riparian buffers within upland ridges are largely undisturbed, surrounded by large tracts of open forest. Ridge top riparian buffers are ephemerally wet and are dominated by upland vegetation including Oaks (*Quercus spp.*), Maples (*Acer spp.*) and Mountain Laurel (*Kalmia latifolia*) understory. Forested buffers within lower ridge elevations have regularly saturated floodplains dominated by Eastern Hemlock (*Tsuga canadensis*), Black Birch (*Betula nigra*) and Maple (*Acer spp.*) with Rhododendron (*Rhododendron spp.*) understory.

### Lidar Data Collection and Processing

Leaf-off lidar data, part of a larger operational acquisition for the state of Pennsylvania, known as Pennsylvania Map (PAMAP), were acquired for the study area between April 26–29<sup>th</sup>, 2006. Although leaf-off lidar data were collected at the end of April, leaf flush had not yet occurred as determined by coincident photos taken at varying elevations throughout the watershed. Leaf-on lidar data, were collected between June 15–18<sup>th</sup>, 2007 (Table 1). Lidar data were acquired using different flight parameters. These differences in flight parameterization were accounted for by comparing leaf-on and leaf-off lidar vegetation structure estimates within conifer plots where needles are retained year round.

Lidar data were classified into ground and non-ground returns using TerraScan (TerraSolid, Helsinki, Finland). Leaf-on lidar data were thinned to be comparable to the lower resolution, leaf-off lidar dataset (1.4 m point spacing, 2 returns). Data thinning utilized a gridded approach with random removal of laser pulse returns. For both lidar datasets, ground only, vegetation (>1.3 m, to coincide with digital hemispherical photography, DHP, height) and all (ground+vegetation) point clouds were extracted for the entire watershed and individual plots. A 1.8 m resolution digital surface model (DSM) of the maximum (canopy plus ground) elevation and a leaf-off lidar derived digital elevation model (vertical accuracy = 0.38 cm, DEM) were used to generate a canopy height model (CHM) representing the difference between the DSM and the DEM. To compare gridding methods, the CHM was created using both interpolation and non interpolation methods. Inverse distance weighted interpolation was used for DSM generation as a commonly used interpolation procedure for lidar data [45,46]. Lidar data were also gridded without interpolation using the max point cloud height value for each 1.8 m cell. Lidar CHMs were used to derive the mean height value within each 11.3 m radius plot for comparison with measured plot average canopy height ( $H$ ). Lidar decile and quartile percentile height values were extracted from the frequency distributions of

laser pulse returns greater than 2 m above ground level [40,47]. Lidar percentile height values were compared with  $H$  to identify lidar best estimates. Finally, fractional canopy cover was estimated by the ratio of the total number of canopy returns (>1.3 m) to all returns [31].

### Mensuration Plots

Permission was obtained from the appropriate landowners, for access to all forest plots that occurred on private lands. Vegetation canopy and understory structure including canopy height, canopy base height, diameter at breast height (DBH), fractional canopy cover and species type were measured and recorded during leaf-on conditions in eighty 400 m<sup>2</sup> ( $r = 11.3$  m) circular plots during July–August, 2010 (Table 2). A total of 80 plots were selected according to vegetation type (deciduous, conifer and mixed) and height (8–30 m) within a 100 m buffer of either side of watershed streams using a random stratified sampling design (Fig. 1). Plot centers were geographically located using a Trimble GeoXH differential GPS unit (Trimble Inc, GeoExplorer, California, USA) with horizontal accuracy better than 0.3 m. GPS points were collected for 30 minutes or more for each plot using a one second logging rate. The average horizontal accuracy of final plot location points was 0.2 m with a range of less than 0.1 m to 0.3 m. Diameter at breast height (DBH) was recorded for all stems with a height greater than 2 m and DBH greater than 0.07 m. Stem apex height and canopy base height were measured using a LaserAce Hypsometer (MDL, Aberdeen, Scotland) with a vertical accuracy of 0.05 cm or better [48]. All saplings (stems greater than 2 m in height and less than 0.07 m DBH) were recorded by species for each 1 m height class. For each plot, mean canopy height and canopy base height were calculated using dominant and intermediate stems (stems which contribute to the top of the canopy). To account for vegetation growth that occurred between the 2006/2007 lidar surveys and 2010 field mensuration, measured canopy stem heights were reduced in Forest Vegetation Simulator (FVS, US Forest Service, Fort Collins, CO, USA). FVS uses plot specific data including stem density, species, height, and DBH to predict annual growth; data were calibrated for vegetation located within the North East United States. The mean height adjustment per plot was 0.24 m per year ( $\sigma = 0.05$  m, Table 3). Growth adjustments did not significantly influence regression  $R^2$ , RMSE values or between group differences detected in canopy height estimates.

Riparian vegetation within the watershed is diverse with 59 species representing three dominant leaf-structure types (deciduous simple, deciduous compound broadleaf and conifer needle) recorded during field mensuration. Conifer species, (e.g. *T. canadensis*), have dense needles that are retained year round compared to deciduous vegetation which has a less dense leaf structure. Conversely, deciduous compound species (e.g. *J. nigra*) tradeoff woody lateral branches for leafy biomass yielding a more open leafless branch structure compared to deciduous simple leaved canopies with increased lateral branch structure [49–52]. It is known that species specific structural characteristics including leaf structure and orientation can influence laser reflections [53] however, dense vegetation did not allow for the isolation of species specific groups in plot classification. Therefore, final plot classification represented fundamental, dominant leaf-structure types (determined by basal area) for a total of four groups: 1) deciduous simple, 2) deciduous compound, 3) mixed deciduous/needle, and 4) conifer needle.

**Table 1.** Leaf-off and leaf-on lidar survey specifications.

	Leaf-off Lidar	Leaf-on Lidar
Flight Dates	April 26–29, 2006	June 15–18, 2007
Sensor	Optech ALTM 3100	Leica ALS50
Scan Angle	+/-21.5 degrees	+/-20 degrees
Average Flying Height	1,900 m	900 m
Pulse Repetition Frequency	40.6 kHz	100 kHz
Returns Collected	First, only, last	First, intermediate, last, only
Average Footprint	0.57 m	0.18 m
Point Spacing	1.4 m	0.8 m

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**Table 2.** Summary of average plot characteristics within deciduous, conifer and mixed vegetation types.

Plot Vegetation Type	N	Mean Canopy Height (m)		Basal Area (m <sup>2</sup> )		Mean # Stems	Conifer (%)	Canopy FC	Elevation Range (m)	Dominant species
		Range	Mean	Range	Mean					
All Plots	80	9.3–30.3	21.2	0.1–2.6	1.4	8–38	0–96%	0.60–0.92	220–545	59 species recorded.
<b>Dominant Leaf Structure Type</b>										
Deciduous Simple	35	9.3–27.4	20.5	0.1–1.9	1.0	9–30	<15%	0.60–0.92	280–545	<i>A. rubrum</i> , <i>P. serotina</i> , <i>Q. rubra</i>
Deciduous Compound	12	12.9–21.4	17.5	0.3–1.4	0.9	11–23	<10%	0.69–0.92	230–340	<i>J. nigra</i> , <i>F. pennsylvanica</i> , <i>G. tricanthos</i>
Conifer	9	16.5–29.9	24.8	1.7–2.6	2.1	10–38	>90%	0.75–0.89	254–507	<i>T. canadensis</i> , <i>Pinus spp</i>
Mixed Conifer/Deciduous	24	13.7–30.3	22.8	0.8–2.6	1.8	8–34	30–90%	0.80–0.91	223–532	<i>T. canadensis</i> , <i>A. rubrum</i> , <i>A. saccharum</i>

N = number of plot samples.  
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**Table 3.** Adjusted height values per year in meters for all plots and by plot vegetation leaf structure type.

Plot	Adjusted Height Values	
	Leaf-off vs. Measured	Mean
All Plots	0.25	0.05
Decid. Simple	0.24	0.06
Decid. Compound	0.24	0.03
Mixed Decid/Conifer	0.22	0.06
Conifer Needle	0.26	0.06

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**Digital Hemispherical Photography**

Fractional canopy cover (FC) per plot was estimated from gap fraction (1-gap fraction) using digital hemispherical photography (DHP) taken with a Canon EOS Rebel XS digital SLR (Canon, NY, USA) with a Sigma Circular Fisheye Lens (Sigma, NY, USA). Photographs were taken during diffuse sky conditions at a height of 1.3 m, 11.3 m from the plot centre, along four cardinal directions (N, S, E, and W) and at the plot center [38,54]. Images were processed using DHP software (Version 4.6, S. Leblanc, Canada Centre for Remote Sensing) [54]. Plot FC was estimated using annulus rings 1–3, 1–4, 1–5 and 1–6 (mean zenith angles 13.5°, 18°, 22.5° and 27° respectively). DHP has an estimated average gap fraction accuracy of +/-10–20% when compared to other methods (e.g. TRAC, LAI-2000) [55].

**Statistical Analysis**

Leaf-off and leaf-on lidar estimates of average canopy height (H) and fractional canopy cover (FC) were compared to plot measurements using linear regression. Best fit relationships were those where lidar estimates most closely represented plot measurements as determined by regression slope and intercept closest to a one to one relationship (near unity). To assess affects of vegetation type on lidar estimates, mean differences (D) were calculated between lidar estimates and *in situ* measurements for each plot and compared using analysis of variance (ANOVA). The influence of vegetation condition (leaf-off vs. leaf-on) on the distribution of laser returns throughout the canopy was measured in two ways. The coefficient of variation (Cv) was calculated for all non-ground leaf-off and leaf-on lidar points within each plot to estimate the vertical spread of within canopy laser response heights. Mean differences were also calculated between leaf-on and leaf-off lidar data for all decile and quartile percentile height values to estimate variation in penetration at the top, within and towards the bottom of the canopy. Leaf-on vs. leaf-off Cv and percentile mean difference values were compared both for all plots and between plots stratified by vegetation type using ANOVA. Histograms illustrating the frequency distribution of laser pulse returns throughout the canopy were also compared. To account for the influence of lidar flight parameterization, leaf-off and leaf-on lidar derived metrics were compared using ANOVA within conifer dominated plots (>90% conifer) where year-round needle retention removes the influence of vegetation condition. It was assumed that differences, attributed to lidar flight configuration, detected within these plots will propagate to all other forest plots [40].

## Results

### Differences in Leaf-on vs. Leaf-off Lidar Canopy Height Estimates Compared with Measured

Canopy heights estimated using: a) the percentile distribution of laser pulse returns within the canopy (Fig. 2A, 2B), b) IDW interpolation gridded canopy height model (CHM, Fig. 2C, 2D), and c) the max height gridded CHM (Fig. 2E, 2F) were compared to plot measurements. The 70<sup>th</sup> percentile height value ( $h_{70}$ ) most closely related to measured canopy heights ( $H$ ) with strong correspondence between  $h_{70}$  and  $H$  observed in leaf-on conditions ( $R^2 = 0.90$ ); leaf-off  $h_{70}$  relationships with  $H$  were similarly strong ( $R^2 = 0.86$ ). Mean differences between  $h_{70}$  and  $H$  were small on average in all plots in both leaf-on ( $D = 0.29$  m) and leaf-off (0.48 m) conditions. CHM values also correlated well with  $H$ .  $H$  derived from the non-interpolated CHMs (using the max height) were most similar to field measured values ( $D_{Lon} = -0.65$  m,  $D_{Loff} = -1.01$  m). CHMs using interpolation methods underestimated measured canopy heights by a larger margin compared to  $h_{70}$  values in both leaf-off ( $D = -2.94$  m) and leaf-on ( $D = -2.01$  m) conditions. For all plots, statistically significant differences were not detected when comparing leaf-off with leaf-on lidar CHM ( $D = 1.16$  m–2.19 m) or percentile height values ( $D = 0.4$ , Table 4).

### Influence of Vegetation Type on Lidar Canopy Height Estimates

Riparian vegetation type influenced the accuracy of lidar percentile ( $h_{70}$ ) and CHM derived estimates of canopy height. Leaf-off and leaf-on lidar CHM and percentile estimates were most similar to  $H$  within conifer plots ( $D = -0.9$ –1.4 m, Table 4). The interpolated lidar CHM underestimated  $H$  by a larger margin (compared to the non-interpolated CHM) within all plots. However, the non-interpolated leaf-on lidar CHM ( $CHM_{max}$ ) and lidar  $h_{70}$  both overestimated  $H$  by a small margin (0.9 m–1.3 m) in deciduous simple, conifer and mixed plots (excluding deciduous compound plots). In deciduous compound plots, lidar underestimated  $H$  by the largest margin using CHM ( $D = 3.3$  m–5.1 m),  $CHM_{max}$  ( $D = 1.1$  m–3.0 m) and percentile ( $h_{70}$ ,  $D = 0.7$  m–1.8 m) methods. Regression relationships were also weaker within deciduous compound plots, particularly in leaf-off conditions using both CHM ( $R^2 = 0.71$ –0.74, Table 5) and percentile methods ( $R^2 = 0.59$ , Table 4). Interestingly, vegetation condition did not have a significant impact on top of the canopy height estimates within plots containing deciduous simple leaved and mixed (deciduous simple/conifer) vegetation. In these plots, close correspondence was found between leaf-off and leaf-on datasets although  $h_{70}$  overestimated (0.4–0.7 m) whereas CHM values underestimated  $H$  (1.8–3.4 m).  $CHM_{max}$  values were within  $\pm 0.9$  m of field measurements. The influence of sensor and flight altitude on canopy height estimates as evidenced by differences between leaf-off vs. leaf-on CHM ( $D = 0.03$  m) and  $h_{70}$  ( $D = -0.25$  m) values within conifer plots was small. Slightly larger differences were observed between leaf-off and leaf-on lidar  $H$  estimates when using  $CHM_{max}$  ( $D = 1.41$ ).

### Differences in Leaf-on vs. Leaf-off Lidar Fractional Cover Estimates Compared with Measured

Within all plots, fractional cover estimated using digital hemispherical photography ( $FC_{DHP}$ ) related well with leaf-on lidar estimates ( $FC_{LOn}$ ) using annulus rings 1–6 ( $R^2 = 0.59$ ,  $RMSE = 0.02$ ) and was within 8% of measured values (Figure 3B). As expected, within all plots, leaf-off lidar FC values

( $FC_{LOff}$ ) underestimated measured fractional cover ( $FC_{DHP}$ ) and thus no relationship was found (Fig. 3A). In leaf-off conditions, it was evident that: 1) pulses most often yielded two returns given dense riparian vegetation, 2) first returns almost always represented canopy vegetation, and 3) first and only returns and last returns almost always represented the ground.

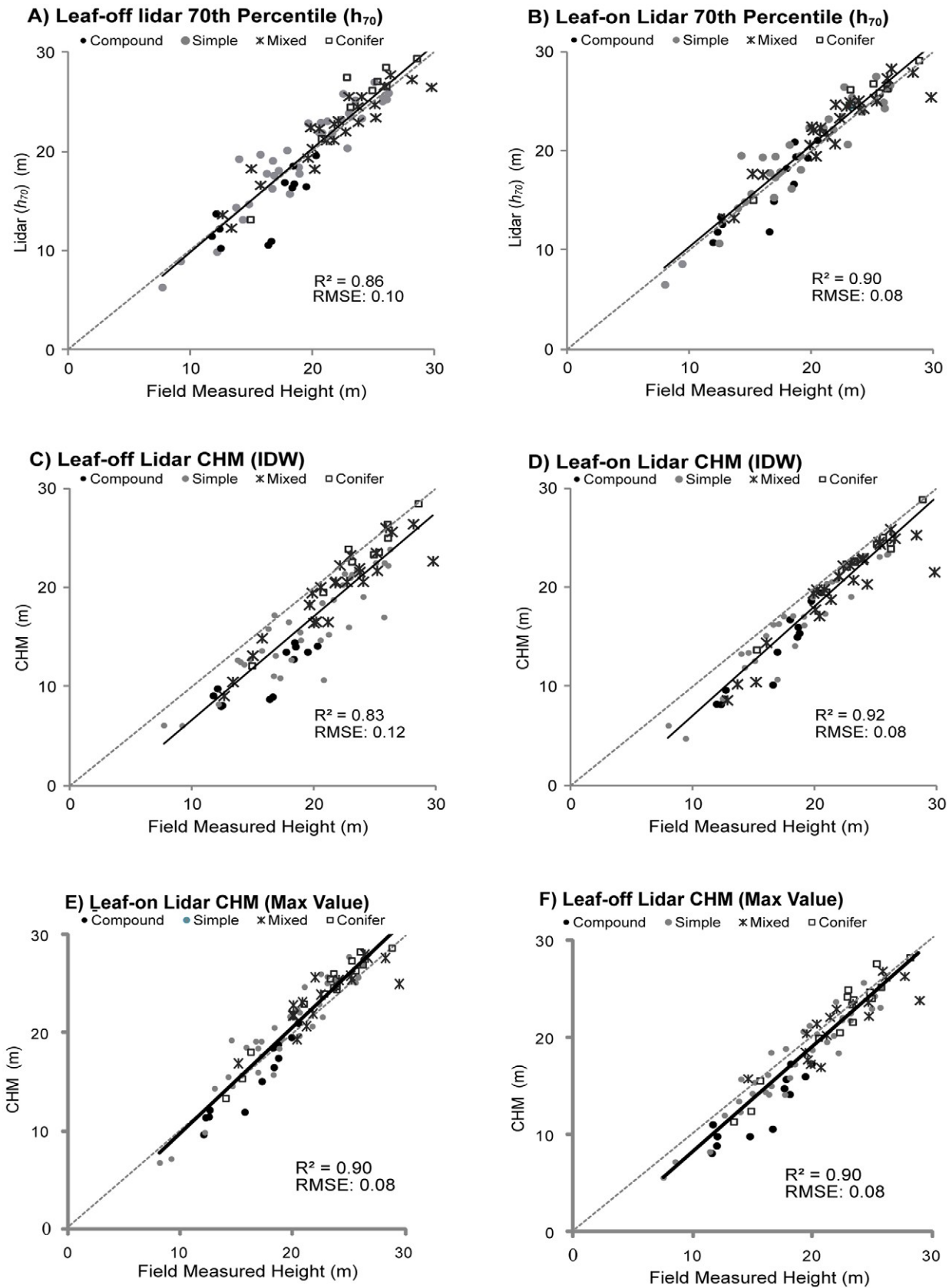
### Influence of Vegetation Type on Lidar Fractional Cover Estimates

Relationships between  $FC_{LOn}$  and  $FC_{DHP}$  were influenced by vegetation type, however, between plot differences were ranged from 4% to 11% (Range  $FC_{diff} = 0.04$ –0.11) of measured values (Table 6).  $FC_{LOn}$  estimates were most similar to  $FC_{DHP}$  within plots dominated by deciduous compound leaved vegetation whereby  $FC_{LOn}$  underestimated  $FC_{DHP}$  by 4% ( $\sigma = 4\%$ ) on average. In comparison, larger differences were observed between  $FC_{LOn}$  and  $FC_{DHP}$  in conifer, deciduous simple and mixed plots where differences ranged from 7 to 11%. While leaf-on lidar overestimated  $FC_{DHP}$  within plots of varying vegetation types, leaf-off lidar underestimated  $FC_{DHP}$ . As expected, the largest differences between  $FC_{LOff}$  and  $FC_{DHP}$  were observed in plots dominated by deciduous simple ( $D = -19\%$ ) and compound ( $D = -24\%$ ) plots while smallest differences were observed within conifer ( $D = 6\%$ ,  $\sigma = 8\%$ ) and mixed plots ( $D = 8\%$ ,  $\sigma = 10\%$ ). The influence of sensor configuration and flight altitude on FC estimates as evidenced by differences in  $FC_{LOn}$  and  $FC_{LOff}$  within conifer plots was 17% ( $\sigma = 7\%$ ). Largest differences between leaf-on vs. leaf-off lidar FC estimates occurred within deciduous simple plots ( $D = 32\%$ ,  $\sigma = 9\%$ ).

### Laser Pulse Penetration Throughout the Canopy - Influences of Vegetation Condition and Type

Differences in laser pulse penetration depth, demonstrated by both the spread and allocation of lidar point clouds throughout the canopy influenced the accuracy of lidar estimates of canopy height and fractional cover. The overall spread of lidar point clouds, as expressed by the coefficient of variation ( $Cv$ ), varied according to both vegetation condition and type.  $Cv$  describes the dispersion of returns throughout the canopy with increased dispersion represented by a greater %  $Cv$  (Table 7). In leafless canopies, the average spread of laser pulse returns ( $Cv_{mean}$ ) was 6.9% ( $\sigma = 7.3\%$ ) greater than the spread of returns in leaf-on canopies. Differences were more pronounced when compared within plots of different leaf structure types. In leafless canopies, laser pulse returns were most spread out within deciduous compound plots ( $Cv_{mean} = 49.4\%$ ), compared to a smaller spread in plots dominated by deciduous simple leaved species ( $Cv_{mean} = 39.0\%$ ) and conifers ( $Cv_{mean} = 28.4\%$ ). A similar pattern (with a lower average  $Cv$  value) was also observed during leaf-on conditions where increased spread of returns occurs within plots dominated by deciduous compound leaved species ( $Cv_{mean} = 38.0\%$ ) compared to plots dominated by deciduous simple leaved species ( $Cv_{mean} = 31.8\%$ ) and conifers ( $Cv_{mean} = 27.3\%$ ). Observed differences between leaf-on and leaf-off  $Cv$  values in conifer plots were small ( $D = 1.1\%$ ) whereas largest differences between leaf-off and leaf-on  $Cv$  values were observed in deciduous compound plots ( $D = 11.4\%$ ).

While  $Cv$  values demonstrate differences in overall spread of reflections throughout the canopy, mean differences between leaf-on and leaf-off decile and quartile percentile values and example plot histograms of laser pulse frequency distributions demonstrate differences in reflection allocation at the top, within and at the base of the canopy (Figure 4, Table 8). At the top of the canopy



**Figure 2. Regression relationships between measured average canopy height (H) and lidar values using: a) Leaf-off lidar 70<sup>th</sup> percentile; b) Leaf-on lidar 70<sup>th</sup> percentile; c) Leaf-off lidar IDW Interpolated CHM; d) Leaf-on lidar IDW Interpolated CHM; e) Leaf-off lidar Max Height CHM; f) Leaf-on lidar Max Height CHM.**  
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**Table 4.** Mean differences in meters (Lidar - measured plot average height) for all plots and plots stratified by vegetation type using both percentile and CHM lidar height estimates.

CHM Values Interpolation		Leaf-off Lidar - Measured		Leaf-on Lidar - Measured		Leaf-on - Leaf-off	
Plot		<i>D</i>	$\sigma$ ( <i>D</i> )	<i>D</i>	$\sigma$ ( <i>D</i> )	<i>D</i>	$\sigma$ ( <i>D</i> )
All Plots		-2.9	2.3	-2.0	1.6	1.2	2.2
Decid. Simple		-3.4 <sup>A</sup>	1.5	-1.8 <sup>B</sup>	1.5	1.8 <sup>A</sup>	2.3
Decid. Compound		-5.1 <sup>B</sup>	1.7	-3.3 <sup>A</sup>	1.5	2.1 <sup>A</sup>	2.2
Mixed Decid./Conifer		-2.1 <sup>BC</sup>	1.9	-2.1 <sup>AB</sup>	1.9	0.2 <sup>B</sup>	1.5
Conifer Needle		-0.9 <sup>C</sup>	1.2	-1.1 <sup>B</sup>	0.7	0.0 <sup>B</sup>	1.2
CHM Values Max Height Grid		Leaf-off Lidar - Measured		Leaf-on Lidar - Measured		Leaf-on - Leaf-off	
Plot		<i>D</i>	$\sigma$ ( <i>D</i> )	<i>D</i>	$\sigma$ ( <i>D</i> )	<i>D</i>	$\sigma$ ( <i>D</i> )
All Plots		-1.0	1.8	0.7	1.7	2.2	1.0
Decid. Simple		-0.9 <sup>A</sup>	1.5	0.8 <sup>A</sup>	1.7	2.3 <sup>A</sup>	1.0
Decid. Compound		-3.0 <sup>B</sup>	1.5	-1.1 <sup>B</sup>	1.3	2.4 <sup>A</sup>	1.2
Mixed Decid./Conifer		-0.7 <sup>A</sup>	1.9	1.0 <sup>A</sup>	1.8	2.2 <sup>A</sup>	1.0
Conifer Needle		-0.1 <sup>A</sup>	1.4	1.3 <sup>A</sup>	1.0	1.4 <sup>A</sup>	1.0
70 <sup>th</sup> Percentile Values		Leaf-off Lidar - Measured		Leaf-on Lidar - Measured		Leaf-on - Leaf-off	
Plot		<i>D</i>	$\sigma$ ( <i>D</i> )	<i>D</i>	$\sigma$ ( <i>D</i> )	<i>D</i>	$\sigma$ ( <i>D</i> )
All Plots		0.3	2.0	0.5	1.7	0.4	1.1
Decid. Simple		0.7 <sup>A</sup>	1.8	0.7 <sup>A</sup>	1.8	0.2 <sup>B</sup>	0.7
Decid. Compound		-1.8 <sup>B</sup>	2.2	-0.7 <sup>A</sup>	1.8	1.4 <sup>A</sup>	1.6
Mixed Decid./Conifer		0.4 <sup>A</sup>	1.6	0.6 <sup>A</sup>	1.5	0.5 <sup>AB</sup>	1.0
Conifer Needle		1.4 <sup>A</sup>	1.7	0.9 <sup>A</sup>	1.0	-0.3 <sup>B</sup>	1.2

Superscripts (A,B,C) identify post-hoc Tukey test results. Means with the same superscripted letter are not statistically different ( $P=0.05$ ).  
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(represented by the top 25% of the lidar distribution), within conifer, simple leaved and mixed plots, pulse returns were triggered close to stem apexes in both leaf-on and leaf-off conditions, yielding small differences in pulse penetration between datasets (-0.2–0.6 m on average, Table 3). However, within deciduous compound plots, laser pulses were triggered 1.0–1.4 m further in leafless compared to leaf-on conditions before eliciting a response. This difference was statistically significant compared to top of the canopy pulse penetration within other vegetation types, including conifer plots, and thus can be attributed to differences in vegetation structure. In all plots, at the bottom of the canopy (represented by the bottom 25% of the distribution), differences in pulse penetration depth within leafless compared to leaf-on canopies were larger compared to the top of the canopy, where in leafless canopies laser pulses were triggered further towards the ground by 1.4–2.6 m on average. Bottom of the canopy penetration depth was also more variable compared to the top, as evidenced by larger standard deviation of mean difference values, which ranged from 3.3–3.5 m on average. Bottom of the canopy differences in pulse penetration were likely caused by a combination of sensor and vegetation effects, as no statistical differences between vegetation types were detected.

Histograms of laser pulse return frequency within varying height bins illustrate reflection allocation throughout the canopy (Fig. 4). In conifer and mixed plots, a larger number of returns are reflected within the top of the canopy (>20 m) compared to the bottom of the canopy (<10 m, Fig. 4C, 4D). In these plots, returns towards the bottom of the canopy represented less than 10% of all returns in the distribution in both leaf-on and leaf-off conditions.

In contrast, in deciduous simple plots, the number of returns at the top of the canopy was similar to the number of returns towards the bottom of the canopy. In these plots, a larger proportion of returns were located within the upper middle of the canopy in leaf-on conditions. Whereas, in leaf-off conditions more returns were allocated towards the bottom of the canopy yet the top of the canopy was still well-represented by the lidar point cloud distribution (Fig. 4B). Interestingly, in both leaf-on and leaf-off conditions pulse returns were more evenly distributed throughout deciduous compound canopies compared to other plots as represented by a smaller and more uniform frequency of reflections within each height bin within the distribution (Fig. 4A).

## Discussion

Within forested riparian buffers of diverse vegetation structure and composition, lidar flown in leaf-off conditions is sufficient for estimating average canopy height and can be considered for estimating fractional canopy cover within mixed and conifer forests. Furthermore, differences in pulse penetration throughout the canopy as influenced by both vegetation condition (leaf-on vs. leaf-off) and vegetation type (leaf and branch structure) can account for variable relationship strength between lidar estimates and plot measurements.

### Average Canopy Height Estimates

Lidar percentile ( $h_{70}$ ) values best approximate measured plot average canopy height ( $H$ ) during both leaf-on and leaf-off conditions and within plots of varying vegetation types compared

**Table 5.** Regression relationships interpolated lidar CHM ( $CHM_{interp}$ ) vs. H, non-interpolated lidar CHM ( $CHM_{Max}$ ) vs. H and  $h70$  vs. H for all plots and for plots stratified by leaf structure type.

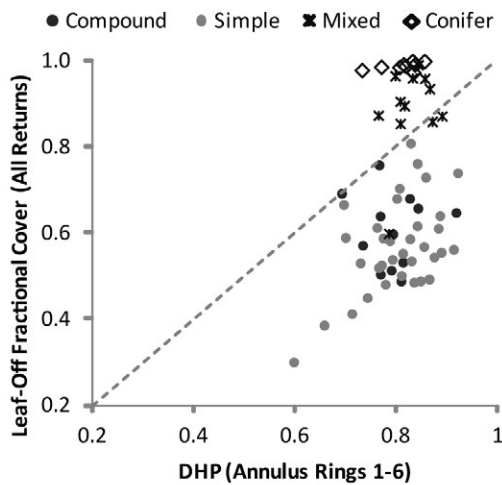
CHM Interp Values		Leaf-off vs. Measured		Leaf-on vs. Measured	
Plot		R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE
All Plots		0.83	0.12	0.92	0.08
Decid. Simple		0.77	0.12	0.93	0.07
Decid. Compound		0.71	0.09	0.90	0.08
Mixed Decid./Conifer		0.86	0.08	0.84	0.09
Conifer Needle		0.96	0.04	0.97	0.03
CHM Max Values		Leaf-off vs. Measured		Leaf-on vs. Measured	
Plot		R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE
All Plots		0.90	0.08	0.90	0.08
Decid. Simple		0.91	0.11	0.90	0.07
Decid. Compound		0.80	0.09	0.91	0.08
Mixed Decid./Conifer		0.74	0.08	0.74	0.09
Conifer Needle		0.94	0.06	0.96	0.04
70 <sup>th</sup> Percentile Values		Leaf-off vs. Measured		Leaf-on vs. Measured	
Plot		R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE
All Plots		0.86	0.10	0.90	0.08
Decid. Simple		0.89	0.09	0.88	0.09
Decid. Compound		0.59	0.14	0.78	0.11
Mixed Decid./Conifer		0.87	0.07	0.87	0.07
Conifer Needle		0.91	0.07	0.94	0.04

RMSE values are standardized relative to the mean for each vegetation type.  
doi:10.1371/journal.pone.0054776.t005

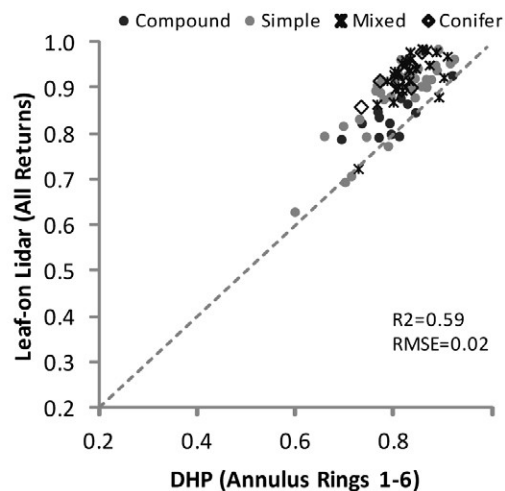
to CHM methods. These results are similar to those of Hawbaker et al. [39] who found that upper height percentile lidar estimates most closely approximated *in situ* H measurements. Interpolated CHM values underestimate top of the canopy heights by a

comparatively larger margin (Fig. 2). CHM underestimation of canopy height has been observed in other studies [e.g. 56]. For example, Hopkinson et al. [56] found that interpolated lidar CHM's underestimated tree and shrub height by 0.3 m–1.1 m on

**A) Leaf-off Lidar vs Measured (All Returns)**



**B) Leaf-On Lidar vs Measured (All Returns)**



**Figure 3. Relationships between leaf-off and leaf-on lidar FC estimates and measured FC using digital hemispherical photography.** Axes are scaled differently to allow for best representation of the data. Regression relationships not shown for leaf-off lidar plot as data were not normally distributed precluding a statistically significant relationship.  
doi:10.1371/journal.pone.0054776.g003

**Table 6.** Fractional cover results stratified by vegetation type.

Dominate Vegetation Type	Mean Measured FC	Range Measured FC	Leaf-Off vs. Measured		Leaf-On vs. Measured		Leaf-On vs. Leaf-Off	
			<i>D</i>	$\sigma(D)$	<i>D</i>	$\sigma(D)$	<i>D</i>	$\sigma(D)$
			Deciduous Compound	0.79	0.69–0.92	−0.19	0.10	0.04 <sup>A</sup>
Deciduous Simple	0.81	0.60–0.92	−0.24	0.10	0.07 <sup>B</sup>	0.05	0.32 <sup>B</sup>	0.09
Mixed	0.84	0.80–0.91	−0.08	0.10	0.10 <sup>AB</sup>	0.04	0.18 <sup>A</sup>	0.08
Conifer	0.81	0.73–0.89	−0.06	0.08	0.11 <sup>B</sup>	0.02	0.17 <sup>A</sup>	0.07

Differences between measured fractional cover (FC) and lidar FC estimates (lidar – measured). ANOVA was not run on leaf-off FC estimates as distributions deviated significantly from normal.

Superscripts (A,B,C) identify post-hoc Tukey test results. Means with the same superscripted letter are not statistically different (P=0.05).

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average representing 3 to 30% of average vegetation heights in the areas studies. Similarly, Gaveau and Hill [57] found lidar CHMs to underestimate shrub and tree height by 1–2 m respectively. This underestimation of H by lidar CHMs can be attributed to both raster creation methods and resolution. For example, IDW interpolation methods that maintain near-point integrity can be more sensitive to canopy gaps, which contain tall saplings, and suppressed canopy vegetation which can in turn negatively bias height values. Biased CHM estimates of canopy height has also been attributed to laser pulse returns missing tree crown apexes in conjunction with interpolation method smoothing effects which propagate bias throughout the CHM [57]. In this study, a 1.8 m resolution grid was produced to maintain lidar data (1.4 m point spacing) near-point integrity. However, a higher resolution grid generated from higher resolution lidar data will likely improve CHM estimates. Non-interpolated CHM methods (using the max height value) produced H values that were closer to  $h_{70}$  yet still under and overestimated H by a larger margin compared to  $h_{70}$  values. However, if raster methods are required, non-interpolated CHM max height values provide a better representation of top of the canopy conditions compared to interpolated raster methods.

Lidar percentile values estimate plot measurements well in both leaf-off and leaf-on conditions however are influenced by vegetation type. Differences are largest in deciduous compound plots (compared to plots dominated by other vegetation types)

where laser pulse returns sink further in leafless compared to leaf-on canopies before triggering a response (Fig. 4, Table 8). Thus, in deciduous compound plots, the overall distribution of returns is lower relative to the actual top of the canopy, and a value higher within the lidar point cloud distribution more closely represents measured values. For example, the 70<sup>th</sup> percentile underestimates measured plot height in deciduous compound plots, whereas it overestimates average height in other plots (Table 4).

The similarity of lidar top of the canopy percentile estimates in leaf-off compared to leaf-on conditions within deciduous plots contradicts the expectation that laser pulses will reflect lower down within leafless canopies due to decreased leaf biomass. It is possible that in some plots top of the canopy responses may have reflected from a small proportion of conifer stems found in some deciduous plots (composing 10% or less of all stems on average). However, other studies demonstrate that for some deciduous species, laser pulse returns reflect from the top of the canopy, even in leaf-off conditions [40]. For example, Brandtberg et al. [42] found no significant underestimation of canopy heights during leaf-off conditions within Eastern North American deciduous forests. Orka et al. [41] found birch species in Scandinavian forests elicited returns that are, on average, higher in leafless compared to leaf-on conditions. Thus, it is reasonable to conclude that in leaf-off conditions, dense riparian branch structure yields top of the canopy returns that are sufficient to estimate measured average canopy height.

**Table 7.** Average coefficient of variation (Cv) values and associated standard deviation of mean Cv for non-ground leaf-off and leaf-on lidar data within all plots and plots stratified by vegetation type.

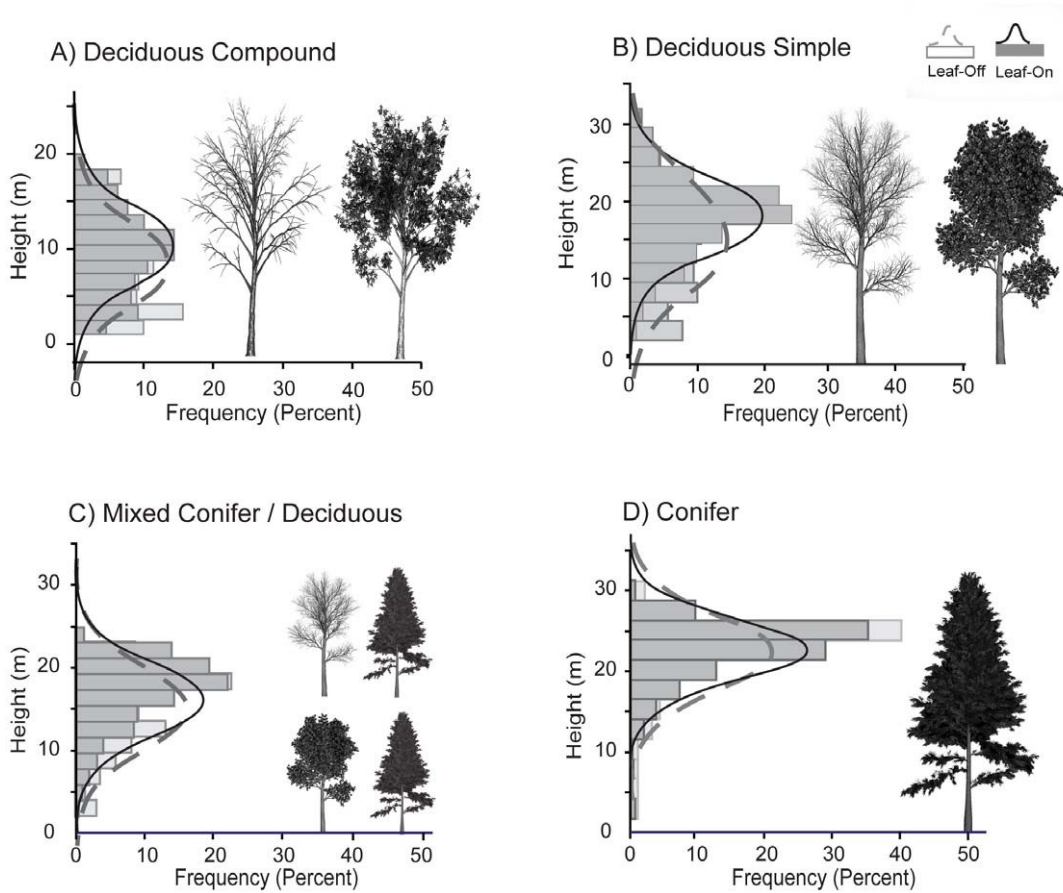
	Leaf- Off		Leaf-On	
	<i>D Cv (%)</i>	$\sigma Cv (%)$	<i>D Cv (%)</i>	$\sigma Cv (%)$
<b>All Plots</b>	37.8 **	10.6	31.0	8.9
<b>Compound</b>	49.4 <sup>A</sup> **	9.1	38.0 <sup>A</sup>	9.8
<b>Simple</b>	39.0 <sup>B</sup> **	9.0	31.8 <sup>AB</sup>	7.6
<b>Mixed</b>	33.9 **	9.5	27.4 <sup>B</sup>	9.0
<b>Conifer</b>	28.4 <sup>C</sup>	5.6	27.3 <sup>B</sup>	7.3

Superscripts (A,B,C) identify post-hoc Tukey test results. Means with the same superscripted letter are not statistically different (P=0.05). Within each row, leaf-off Cv values that are starred (\*\*) are statistically different when compared to leaf-on Cv values for that row (all plots or vegetation type). Statistical differences are not detected between leaf-on and leaf-off Cv values within conifer plots (p<0.05).

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**Fractional Canopy Cover**

Differences were observed between leaf-off and leaf-on lidar FC estimates and measured FC estimates. Leaf-off lidar FC ( $FC_{Loff}$ ) underestimates FC by 19–24% in deciduous canopies, however, represents measured FC ( $FC_{DHP}$ ) well within conifer and mixed canopies. Underestimation of FC in deciduous canopies is likely due to decreased leafy biomass yielding increased ground penetration. Interestingly, while a large underestimation of  $FC_{DHP}$  might be expected within mixed plots (due to deciduous vegetation), observed differences are small and similar to differences detected when using leaf-on lidar data. It is likely that a balance between decreased leafy biomass that facilitates ground penetration and dense needle cover that ensures within canopy responses (as observed in plot histograms, Fig. 4C) yields close estimates of  $FC_{DHP}$ . When compared to leaf-off lidar FC estimates, leaf-on lidar estimates relate well to but also overestimate  $FC_{DHP}$  within all vegetation types by 4–11%. Overestimation of FC is likely due to limited ground penetration, which is particularly evident in lidar point cloud histograms within conifer plots where few returns are elicited at the bottom of the point



**Figure 4. Example distributions of canopy laser pulse returns in leaf-off compared to leaf-on conditions in an A) deciduous compound and B) deciduous simple C) mixed conifer/deciduous and D) conifer plots.** Example distributions are representative of conditions observed within all plots for each vegetation type.  
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cloud distribution (Fig. 4D); subsequently FC is overestimated by the largest margin in conifer plots. Within deciduous simple leaved plots, a similar pattern of  $FC_{Lon}$  overestimation occurs. In contrast,  $FC_{DHP}$  is most closely estimated in deciduous compound leaved plots where increased pulse penetration is observed throughout the canopy (Fig. 4A).

Overestimation of fractional cover by lidar can be attributed in part to canopy density, composition and structure, which can limit pulse ground penetration [31,56]. However, over and underestimation of FC by lidar can also be attributed to flight configuration. Higher flight altitudes, and associated changes in pulse footprint and peak pulse power have been shown to yield increased single

**Table 8.** Mean differences ( $D$ , leaf-on lidar minus leaf-off lidar) between leaf-on and leaf-off lidar percentile height values and associated standard deviation ( $\sigma$ ) of mean differences in meters.

	All Plots		Deciduous Simple		Deciduous Compound		Conifer Needle		Mixed	
	$D$	$\sigma(D)$	$D$	$\sigma(D)$	$D$	$\sigma(D)$	$D$	$\sigma(D)$	$D$	$\sigma(D)$
$h_{99}$	0.49 <sup>A</sup>	0.72	0.59 <sup>A</sup>	0.60	**1.07 <sup>A</sup>	0.61	0.26	0.89	0.16 <sup>A</sup>	0.69
$h_{95}$	0.46 <sup>A</sup>	0.74	0.44 <sup>A</sup>	0.51	**1.25 <sup>A</sup>	1.12	0.15	0.75	0.19 <sup>A</sup>	0.51
$h_{90}$	0.38 <sup>A</sup>	0.82	0.32 <sup>A</sup>	0.63	**1.14 <sup>A</sup>	1.20	0.04	0.87	0.21 <sup>A</sup>	0.64
$h_{75}$	0.45 <sup>A</sup>	0.97	0.31 <sup>A</sup>	0.59	**1.37	1.41	-0.17	1.09	0.40 <sup>A</sup>	0.85
$h_{50}$	0.59 <sup>A</sup>	1.55	0.50	1.28	1.81	1.39	-0.75	1.99	0.64	1.40
$h_{25}$	1.36 <sup>B</sup>	3.48	1.40 <sup>B</sup>	3.72	3.15 <sup>B</sup>	1.82	-1.76	4.93	1.45 <sup>B</sup>	2.36
$h_{10}$	2.59	3.34	3.00	3.23	3.16	2.54	1.09	4.91	2.28	3.13

ANOVA was not run on 10<sup>th</sup> percentile ( $h_{10}$ ) values due to nonparametric distribution in leaf-off conditions. Superscripts (A,B,C) identify post-hoc Tukey test results. Means with the same superscripted letter are not statistically different ( $P=0.05$ ). Within each row, values that are starred (\*\*) are statistically different from other values at that percentile within that row.  
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returns and associated decreased second/multiple returns per pulse [58–60]. In some forest types, higher altitude collections may yield lidar overestimation of FC [61] due to a wider footprint which yields reduced ground response [60]. However, flight configuration has also been associated with underestimated FC due to reduced vegetation response and increased ground penetration [62]. In this study, within conifer plots,  $FC_{L_{off}}$  estimates are 20% lower than  $FC_{L_{on}}$  on average. However, it is important to note that in these same plots,  $FC_{L_{off}}$  and  $FC_{L_{on}}$  estimates are still within  $\pm 10\%$  of measured FC. Similarly, while vegetation type can influence lidar FC estimate accuracy [38], in this study, differences are less than the errors associated with digital hemispherical photography methods [55]. Therefore, as observed within the Spring Creek watershed, the degree of deviation of leaf-on (all plots) and leaf-off (mixed and conifer plots) lidar FC estimates from measured FC values is within the estimated error of DHP methods and thus likely acceptable for broadscale mapping purposes [27]. For example leaf-off lidar may be sufficient for detecting the 30% tree cover threshold often used to classify forest. However, it is also important to note that the range of variability of canopy cover sampled is narrow (60–90% cover) given dense riparian vegetation throughout the study watershed. Thus lidar estimates might be more variable within different vegetation types given lower density canopies.

### Vegetation Type & Lidar Flight/Configuration Influences on Lidar Estimates

Throughout the canopy, pulse penetration depth varies with both vegetation condition and type influencing lidar estimates of plot measurements. Variable penetration depth may be attributed to altitude differences between the two lidar surveys given that emitted light energy will attenuate and spread as it travels towards the earth's surface and through the canopy [58,62]. However, these differences, particularly at the top of the canopy, are likely small [58,60,61]. Leaf-on and leaf-off top of the canopy height estimates (e.g.  $h_{70}$ ) and the overall spread of laser pulse returns ( $Cv$ ) are similar within conifer plots. For example, throughout the top 25% of the lidar point cloud distribution, differences between leaf-on and leaf-off laser pulse penetration (represented by mean differences of percentile height values) range from  $-0.2$  m to  $0.3$  m (Table 8). Whereas differences observed within the top 25% of deciduous compound plots are larger and statistically significant when compared to conifer plots. The overall spread of laser pulse returns (represented by coefficient of variation) in leaf-on compared to leaf-off conditions is also within 1% in conifer plots (Table 7). In comparison, larger and statistically significant differences are observed within deciduous simple and deciduous compound plots. These results support findings in other studies. For example, Goodwin [58] found no significant difference between canopy height profiles derived from lidar flown at altitudes ranging from 1,000–3,000 m. Hopkinson [60] and Naesset [59] demonstrated that differences in altitude yield a small underestimation of maximum canopy height (0.2 m to 0.6 m on average), whereas Naesset [61] determined lidar estimates of forest biophysical conditions were robust regardless of flight altitude.

Therefore, differences in top of the canopy penetration depth are likely due to a combination of species-specific differences in canopy architecture (patterns of lateral branching and associated leaf angle and geometry) and leaf condition (leaf-on vs. leaf off). Specifically, in the Spring Creek watershed, largest differences are observed within deciduous compound plots. The spreading and open branch structure of vegetation within these plots (e.g. Black Walnut, *J. nigra*) most likely facilitates increased pulse penetration

in both leaf-off and leaf-on conditions. Variation in leaf and branch structure influences incident light energy reflection, transmission and absorption within canopies [63], maximizing light intake and ecosystem productivity [64]. Thus, it is not surprising that this variability can influence both the spread and allocation of laser pulses in leaf-on and leaf-off canopies [40–44,53,65,66]. Orka (2010) found top of the canopy lidar height estimates to be lower in leaf-off compared to leaf-on conditions for Aspen species whereas estimates are higher in leaf-off compared to leaf-on conditions for Birch species.

Interestingly, laser pulse penetration at the top of the canopy (used to estimate canopy height) is less variable (represented by a smaller standard deviation of mean differences between leaf-on and leaf-off lidar percentile values) compared to penetration values observed towards the bottom of the canopy (Table 8). Given this bottom of the canopy variability in penetration depth, it is expected that within canopy estimates of vegetation structure (e.g. canopy base height, sapling and understory cover) might yield a weaker correlation with measured values compared to top of the canopy height estimates. This decreased strength in within canopy lidar estimates has been observed when using lidar to estimate canopy base height (unpublished data) and understory canopy structure [67]. Bottom of the canopy differences in pulse penetration are likely a combined effect of system configuration and vegetation structure. Increased flight altitude, not only yields fewer multiple returns [58], but also can yield increased variability of within canopy pulse penetration depth [40,62]. However, this variability could also be attributed to branch volume and associated leaf area per branch which often increases lower in the canopy to maximize light absorption [68,69]. Thus, differences observed within canopy pulse penetration depth may also represent naturally occurring variability in leaf and branch structure.

### Conclusions

The implications of this work for the study of riparian forests are as follows:

1. Given diverse top of the canopy vertical structure and 1.4 m lidar point spacing, lidar CHM methods underestimate and deviate further from measured average canopy heights compared to lidar percentile methods. Lidar percentile methods to predict canopy height may be preferred for broadscale mapping purposes.
2. Lidar percentile estimates are similar to measured H within deciduous simple, conifer and mixed plots during leaf-on and leaf-off conditions, however, lidar percentile methods underestimate H in deciduous compound canopies. Further, field validation may be needed to assess potential error when using lidar to sample vegetation over broad geographic extents.
3. Lidar estimates of fractional cover are within 10% of measured in all plots during leaf-on periods, and in mixed deciduous/conifer canopies during leaf-off periods, but are greatly underestimated during leaf-off periods in deciduous canopies; leaf-on lidar therefore may be preferred for fractional cover estimates.
4. Depth of penetration lower in the canopy is more variable compared to top of the canopy penetration. Differences in penetration depth will likely influence accuracy of within canopy vegetation structure estimates such as canopy base height and understory cover.
5. Sensor and flight altitude effects observed within conifer plots account for small differences (less than 0.5 m) in top of the

canopy penetration. These effects may be more pronounced within and at the bottom of the canopy.

This study provides a viable rationale for further examination of lidar datasets that are not optimized for vegetation detection. It furthermore demonstrates the use of lidar to reliably estimate forested riparian buffer structure across a watershed given varying vegetation conditions. Lidar data surveyed during leaf-off conditions are sufficient to estimate forested riparian buffer canopy height and may be sufficient to estimate fractional cover in mixed forests when leaf-on datasets are not available. However, differences in laser pulse penetration in leaf-off compared to leaf-on conditions and within varying vegetation types will influence lidar estimate accuracy. Therefore, field calibration that considers vegetation type and structure may be required to both select best lidar methods and calibrate lidar models when measuring height for some purposes such as growth detection. However, there is great potential for existing leaf-off lidar data to support a host of broadscale inventory, analysis and change detection mapping purposes including detection of riparian

vegetation height classes, assessment of forested riparian buffer vegetation density and biomass and determination of forested buffer width. Broadscale mapping of riparian buffer structure efforts is essential to assess buffer and associated stream and wildlife population integrity in support of ecological monitoring that assesses disturbance impacts and associated restoration efforts.

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## Author Contributions

Conceived and designed the experiments: LAW LC. Performed the experiments: LAW. Analyzed the data: LAW. Contributed reagents/materials/analysis tools: LAW LC. Wrote the paper: LAW LC RD AT.

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