



Mapping tall shrub biomass in Alaska at landscape scale using structure-from-motion photogrammetry and lidar

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ABSTRACT

Warming in arctic and boreal regions is increasing shrub cover and biomass. In southcentral Alaska, willow (*Salix* spp.) and alder (*Alnus* spp.) shrubs grow taller than many tree species and account for a substantial proportion of aboveground biomass, yet they are not individually measured as part of the operational Forest Inventory and Analysis (FIA) Program. The goal of this research was to test methods for landscape-scale mapping of tall shrub biomass in upper montane and subalpine environments using FIA-type plot measurements ($n = 51$) and predictor variables from imagery-based structure-from-motion (SfM) and airborne lidar. Specifically, we compared biomass models constructed from imagery acquired by unmanned aerial vehicle (UAV; ~ 1.7 cm pixels), imagery from the NASA Goddard's Lidar, Hyperspectral, and Thermal Airborne Imager (G-LiHT; ~ 3.1 cm pixels), and concomitant G-LiHT small-footprint lidar. Tall shrub biomass was most accurately predicted at 5 m resolution ($R^2 = 0.81$, $RMSE = 1.09 \text{ kg m}^{-2}$) using G-LiHT SfM color and structure variables. Lidar-only models had lower precision ($R^2 = 0.74$, $RMSE = 1.26 \text{ kg m}^{-2}$), possibly due to reduced model information content from variable multicollinearity or lower data density. Separate models for upper montane zones with trees and shrubs and subalpine zones with only shrubs were always chosen over single models based on minimization of Akaike's Information Criterion, indicating the need for variable sets robust to overhanging tree canopy. Decreasing point density from UAV (5000–8000 pts. m^{-2}) to the G-LiHT SfM point cloud (500–2000 pts. m^{-2}) had little impact on model fit, suggesting that high-resolution airborne imagery can extend SfM approaches well beyond line-of-sight restrictions for UAV platforms. Overall, our results confirmed that SfM from high-resolution imagery is a viable approach to estimate shrub biomass in the boreal region, especially when an existing lidar terrain model and local field calibration data are available to quantify uncertainty in the SfM point cloud and landscape-scale estimates of shrub biomass.

1. Introduction

Rapid climate warming over the past half century has increased shrub cover and the size of individual shrubs across arctic and boreal ecosystems (Myers-Smith et al., 2019). This “shrubification” includes infilling among established shrub patches, growth of individual plants, and shrubline advance beyond previous range limits (Myers-Smith et al., 2011). Shrubification can initiate a cascade of ecosystem impacts (Elmendorf et al., 2012), as woody vegetation alters snowpack depth, permafrost (Lantz et al., 2013), above- and below-ground carbon pools (Mack et al., 2004), and albedo (Lorant et al., 2011; Pastick et al.,

2018). Although widespread, shrubification is neither ubiquitous nor homogeneous. Thus, efforts to characterize spatial variability and change in boreal shrub structure are key to understanding associated changes in ecosystem function (Gamm et al., 2018; Myers-Smith et al., 2011).

While arctic shrub expansion has been well documented (Elmendorf et al., 2012; Myers-Smith et al., 2011, 2019), few studies have quantified shrub abundance and expansion in the boreal forest biome. Shrubs in montane boreal forests, particularly N-fixing alders (*Alnus* spp.), may increase both soil C and N content (Wurtz, 1995), though the effects of shrubs on soils are complex (Crofts et al., 2018). Shrubs may

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also change habitat suitability for vertebrate herbivores: alders are avoided by moose, while willows are favored (Tape et al., 2016). Dial (2018) attributed 7% of aboveground biomass to shrubs in a mixed forest of southcentral Alaska, where upslope movement in response to warming is faster for shrubs than trees (Dial et al., 2007; Dial et al., 2016; Rinas et al., 2017), contributing to the rapid recent increase in the shrub component of aboveground biomass in the region.

Historically, understory vegetation (including shrubs) has been considered a minor component of the total carbon budget in national greenhouse gas inventories. Shrubs have therefore been under-emphasized or excluded altogether from the US forest carbon accounting framework (Woodall et al., 2015). For example, the USDA Forest Service Forest Inventory and Analysis (FIA) program currently does not measure individuals of species considered to be primarily shrubs, such as willow or alder (USDA Forest Service, 2018), regardless of size.

Given widespread evidence for shrubification, satellite remote sensing has been used to track shrub cover (Fraser et al., 2014; Ju and Masek, 2016; McManus et al., 2012; Pastick et al., 2018). However, moderate (e.g., 30 m – 500 m) pixel resolution and passive optical sensors may not capture important spatial heterogeneity in shrub growth (Duchesne et al., 2018); fine-scale information on both cover and structure provide important insight regarding the underlying ecological mechanisms for shrub expansion (Lantz et al., 2010). High-resolution (< 30 m) remote sensing has therefore played a key role in identifying shrubification, including repeat oblique aerial photography in the arctic (Sturm et al., 2001; Tape et al., 2006) and orthophotography in high-elevation boreal forests (Dial et al., 2007, 2016; Rinas et al., 2017). A number of studies have used lidar to quantify forest structure and biomass (e.g., Eitel et al., 2016; Goetz and Dubayah, 2011). However, the application of lidar to quantify shrubland structure is less well developed (Greaves et al., 2016; Martinuzzi et al., 2009; Wing et al., 2012).

Recently, unmanned aerial vehicles (UAV) have emerged as a less expensive means to acquire fine-scale information on ecosystem structure using high-resolution imagery and a structure-from-motion (SfM) approach. In contrast to earlier photogrammetry techniques that required mapping-grade cameras and precise aircraft positional and orientation information, SfM requires only that overlapping images capture objects from multiple angles (Dandois and Ellis, 2013). High-resolution imagery with high overlap allows for the creation of geometrically accurate, three-dimensional (3D) SfM point clouds more than $10\times$ as dense as airborne lidar (Cunliffe et al., 2016; Fraser et al., 2016). This ultra-high point density can be acquired with consumer-grade cameras because UAVs can fly arbitrarily low and slow, yielding small pixel sizes and high image overlap (Cunliffe et al., 2016). While point density is high, SfM is typically limited to depiction of the outer canopy surface because passive sensor-based point clouds contain little information on sub-canopy vegetation or terrain in areas with dense canopy cover (Lisein et al., 2013; Puliti et al., 2015). An additional concern with SfM workflows is that uncertainties associated with internal consistency of the point cloud are frequently underreported (James et al., 2017).

In addition to higher point density, SfM point clouds also provide red, green, and blue (RGB) color information unavailable from lidar. RGB point-cloud attributes have been shown to improve models of forest health (Michez et al., 2016), structure (Bonnet et al., 2017), vegetation phenology (Lisein et al., 2015), and species classification (Alonzo et al., 2018; Michez et al., 2016). For example, Alonzo et al. (2018) found that optimal separability among boreal forest tree species was achieved with predictors pertaining to tree height (maximum height), tree form (width and 98th percentile height), and color (median crown blueness). However, because UAV camera systems are typically radiometrically uncalibrated, variability in illumination and acquisition parameters (e.g., UAV position and orientation, lens/sensor properties) can influence color values, reducing model generalizability

(Alonzo et al., 2018; Puliti et al., 2015). To estimate forest inventory attributes, Tompalski et al. (2019) compared point cloud and spectral metrics from digital aerial photogrammetry (DAP) against an airborne lidar reference. In that study, the spectral-only model performed poorly and addition of spectral information to the DAP point cloud only minimally improved accuracy over structural information by itself.

Mapping shrub structure, particularly in open cover types, is well-suited for high-resolution SfM techniques because of high-resolution mapping capability and limited need for canopy penetration. In a dryland ecosystem, Cunliffe et al. (2016) mapped grasses and creosote shrub biomass using a ~ 0.5 cm resolution canopy height model (CHM). This extremely high-resolution dataset relied on UAV altitudes of 15–20 m above ground level (AGL). In a study of shrub tundra in the Canadian arctic, Fraser et al. (2016) generated an ultra-dense ($> 30,000$ pts. m^{-2}) point cloud to estimate individual shrub heights using color and structure metrics from UAV data. In these studies, the imagery detected gaps within and between shrubs, creating a digital terrain model (DTM) based on imagery alone. However, the degree to which shrub structure can be modeled using SfM in more complex environments with partial tree cover is not well known.

Given current technology and regulations (e.g., maximum flight altitudes, line-of-sight control), UAV-based maps of ecosystem structure are spatially restricted (Dandois and Ellis, 2013; Puliti et al., 2017). However, airborne and high-resolution satellite imagery (HSRI) permit application of photogrammetry for terrain modeling (e.g., ArcticDEM; Morin et al., 2016) and assessments of vegetation structure (Montesano et al., 2019) at landscape and regional scales. Recent studies have compared DAP and lidar-derived point clouds over forests. Given the lower point densities from 0.25–0.3 m DAP imagery (12–37 pts. m^{-2}), lidar yielded superior results for estimating common forest inventory variables and structural attributes, such as canopy gaps in a temperate rainforest. (Noordermeer et al., 2019; Tompalski et al., 2019; White et al., 2015, 2018). Comparison of structural measurements derived from photogrammetry to airborne lidar data has not, to our knowledge, been conducted for shrubs.

Here, we estimated tall shrub biomass in upper montane and sub-alpine boreal zones in southcentral Alaska using coincident field measurements, airborne lidar, and SfM photogrammetric point clouds from UAV and airborne platforms. One goal of this study was to explore the potential for remote sensing approaches to better capture the contribution from shrub species to total aboveground biomass in the region. Separating shrub and tree biomass is important to support FIA inventory objectives, and tracking changes in shrub cover, height, and biomass over large spatial extents (> 100 km²) is needed to quantify the impact of rapid climate warming in remote boreal landscapes. Our specific objectives were to: 1) Determine the best predictors of tall shrub biomass across upper montane and subalpine habitats through comparison of SfM point clouds derived from UAV imagery, SfM point clouds from NASA Goddard's Lidar, Hyperspectral, and Thermal (G-LiHT) Airborne Imager, and G-LiHT lidar; 2) Characterize tradeoffs among point density, color information, and canopy penetration from different point cloud data sources for biomass estimation; and 3) examine uncertainty propagation through the process of SfM data acquisition, processing, and analysis in a complex vegetated landscape. We demonstrate that low-cost, consumer-grade UAV platforms can be used to accurately estimate shrub biomass. Coincident G-LiHT SfM and lidar data have been collected over > 1 M ha of interior Alaska (Data portal: <https://glihtdata.gsfc.nasa.gov/>) providing a path forward for shrub mapping and change detection across large gradients in climate, soils, and elevation.

2. Methods

2.1. Study area

The study area was conducted between 300 and 1000 m above sea

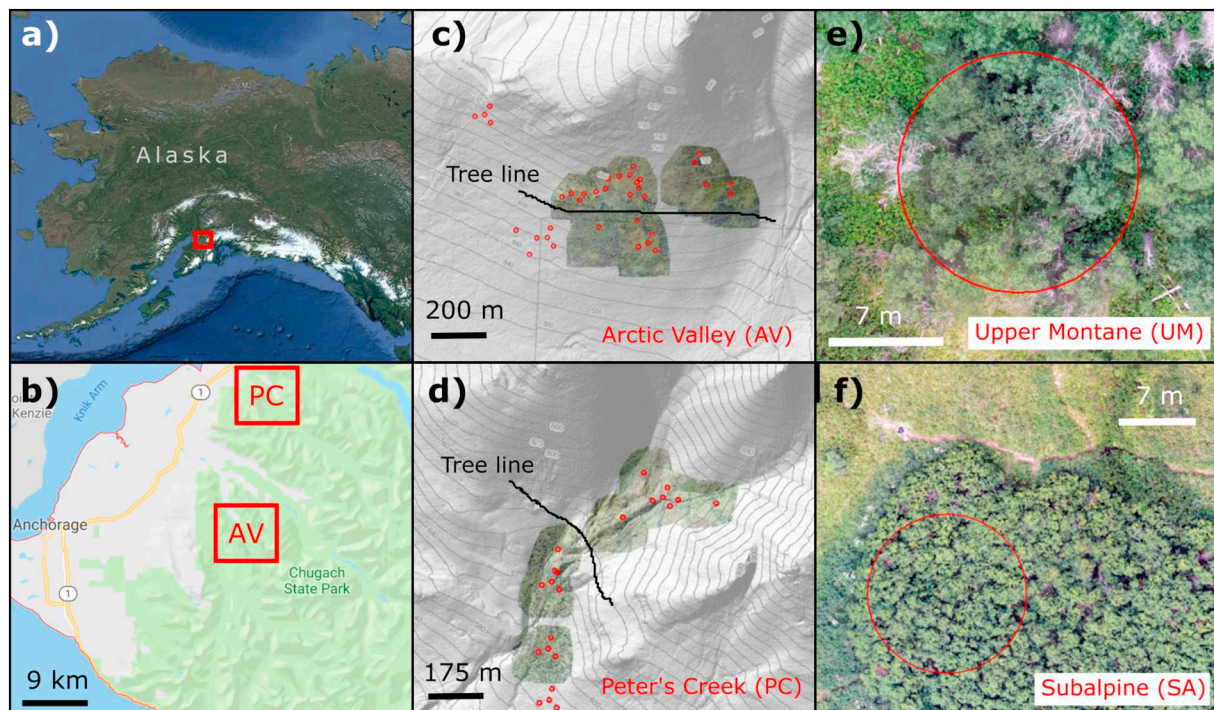


Fig. 1. a) Chugach State Park study area in Alaska, USA; b) Peters Creek (PC) and Arctic Valley (AV) shrub measurement areas; c) AV field measurement plots overlaid by UAV imagery. No imagery acquired westernmost portion of AV due to flight restrictions. d) Same but for PC. e) Example upper-montane plot with tree overstory (UAV orthomosaic). f) Example alder patch in subalpine zone (UAV orthomosaic).

level (masl) along the upper montane-subalpine ecotone of the Cook Inlet Basin Ecoregion of southcentral Alaska within the Chugach State Park (Fig. 1; views of data at landscape scale in **Supplemental Materials S1**). With extensive tall shrub cover (Dial et al., 2016) in both upper montane forest and subalpine communities, this study area was selected to test remote sensing methods under a range of canopy conditions. Upper montane forests of white spruce (*Picea glauca*), paper birch (*Betula papyrifera*), and balsam poplar (*Populus balsamifera*) generally grow between 300 and 500 masl. Tall (> 1.5 m) *Alnus* and *Salix* shrub species co-exist with canopy dominants in these upper montane forests but also form mixed-species and monospecific stands of tall shrub communities in the subalpine region (~450 to 760 masl) above tree line (Viereck et al., 1992). Mean shrub height in our study area was 4.6 m (se = 0.49 m).

Field measurements and remote sensing data were acquired for two study areas in Chugach State Park separated by approximately 20 km (Fig. 1). The northern Peters Creek (PC) study site (565–785 masl; 61.397°, –149.371°; $n = 19$ plots) is somewhat drier and higher in elevation than the Arctic Valley (AV) site (560–745 masl; 61.234°, –149.535°; $n = 32$ plots). Study sites were 0.25–1.25 km from former dirt roads, subject only to natural disturbances, and both sites had roughly south by southwest aspects. The mean slope of PC plots was 27% ($\sigma = 11.7\%$), and AV 25% ($\sigma = 7.5\%$). We chose sites across a range of shrub abundance from sparse to very dense with varying dispersion, conditional on ground access and permission to fly the UAV. Subalpine ($n = 32$) and upper montane ($n = 19$) plots were differentiated by presence or absence of trees. Subalpine plots were typically at higher elevations than upper montane plots. Mean tree height on upper montane plots was 8.5 m (range 3–18 m) corresponding with a mean tree biomass density of 2.31 kg m⁻² (0.12–11.0 kg m⁻²; **Supplemental Materials S2**). Dial et al. (2016) describe the general geology, climate, and vegetation.

2.2. Field plot measurements of tall shrub biomass

Field measurements were collected in 51 circular 1/24 acre (7.3 m radius, 168.6 m²) subplots that were part of 24 FIA-style plots (Bechtold & Patterson, 2005) in the summer of 2018. The plots consisted of a circular center subplot and up to three identically sized satellite subplots. Microplots (2.93 m radius) were located at an azimuth of 90° and 3.66 m distant from subplot center in each satellite subplot (USDA Forest Service, 2018). To facilitate alignment with remote sensing data, all subplot centers were geolocated precisely using mapping grade GPS with uncertainty < 0.25 m (GPS details in section 2.3).

We estimated individual shrub biomass from diameter at root collar (DRC) measurements and an existing, local allometric equation. We measured all shrubs with DRC ≥ 2.5 cm in center subplots; in satellite subplots we measured all shrubs with DRC > 12.7 cm and all shrubs ≥ 2.5 cm in the microplots. For stems with DRC > 12.7 cm, we also collected diameters at breast height (DBH). If the stem forked between the ground and breast height (1.37 m), we followed the FIA forking rules, which provide an objective, repeatable process for determining the location of stem diameter measurements (USDA Forest Service, 2018). To estimate individual tall shrub biomass, taxon-specific allometric equations were developed; however, willow and alder exhibited statistically similar allometry, allowing for a single power function: biomass = 0.85 * DRC^{2.4} ($R^2 > 0.9$; Lewis-Clark et al., 2018). We applied this allometric equation with DRC = DBH for each stem with a DBH, using a frustum to estimate stem volume from root-collar to breast-height.

We summed all individual shrub biomass calculations to generate total biomass in each central subplot. In satellite subplots, we summed the biomass of individual shrubs with DRC > 12.7 cm and expanded the shrub biomass density on microplots to the full subplot, generating subplot-level total shrub biomass estimates. We did not include shrubs with DRC < 2.5 cm or tree species (*Betula*, *Picea*, *Populus*) in these subplot-level biomass estimates. We established site-level biomass estimates by summing subplot estimates, establishing 95% confidence

intervals based on sampling from the model parameter variance-covariance matrix. This site-wide estimate does not account for potential model bias based on purposive plot selection to span the likely range of shrub biomass conditions. Finally, we determined that the among-plot variance in biomass was not significantly different than within-plot (i.e., among subplots in a single plot) variance (oneway-ANOVA, $F = 0.64$, $p = .84$), thus satisfying the assumption of independence among subplots. Following this section, for simplicity, FIA subplots will be referred to as “plots” since they are used in a remote sensing model calibration and validation context.

2.3. UAV data collection and processing

UAV data were collected near peak greenness between July 18–24, 2018. Flights were conducted between 11:00 and 17:00 local time under fair conditions ranging from full sun to high overcast. Imagery was acquired using the DJI Phantom 4 Pro (DJI, Shenzhen, China), a consumer-grade quadcopter with a 20 Megapixel camera. To generate data acquisition grids and flight parameters we used the iOS app Pix4DCapture (Pix4, Lausanne, Switzerland). We established 85 m × 85 m flight boxes capturing up to four plots at once in a double, perpendicular serpentine flight at nominal 55 m AGL with camera angle 20° off nadir and 90% image overlap (Alonzo et al., 2018). Off-nadir imagery was collected to improve image network geometry, spatial accuracy, and to reduce data gaps and other systematic errors in the final point cloud (James et al., 2017; Nesbit and Hugenholtz, 2019). Where elevation changed substantially over the width of a plot, two flights in a stair-step pattern (i.e., downslope flight with lower nominal AGL than upslope flight) maintained a consistent ground sample distance (GSD) of between 1.5 and 2.0 cm. Following Alonzo et al. (2018), we deployed five brightly-colored ground targets throughout the plot in areas with full sky view. Each target was located to a post-processing precision of 0.1 m using either a Trimble Geo7x (Trimble, Sunnyvale, CA, USA) or a Javad Triumph-2 (Javad GNSS, Inc., San Jose, CA, USA) GPS unit. Under open-sky conditions, we expect the absolute positional error from either of these GPS receivers to be close to the reported precision after post-processing.

Raw image data were processed to a sparse point cloud using SfM followed by densification, thereby leveraging multi-view stereo algorithms in the Pix4 software. We followed standard Pix4 processing procedures including: the computation of tie points among overlapping images and bundle block adjustment; manual alignment of the ground targets to differentially-corrected ground control points followed by re-optimization of computed camera positions and internal camera parameters; and generation of dense point cloud using default image scale and point density options (Pix4D, 2017). Across all UAV plots, the median absolute 3D positional error of our SfM point cloud was 0.25 m, based on evaluation at *checkpoints* (leave-one-out cross-validation of ground control points). Final point cloud densities ranged from ~5000 to > 8000 pts. m⁻² depending on site-specific vegetation structure, GSD, availability of viable tie points, and other acquisition parameters. Point elevations were translated to heights via subtraction of the 0.1 m resolution interpolated G-LiHT lidar-based DTM (details below; Alonzo et al., 2018; White et al., 2018). To facilitate calculation of raster-based vegetation structural variables, we also generated a CHM at 0.1 m resolution (Pingel et al., 2013) using the point with maximum height per grid cell.

2.4. Collection of G-LiHT airborne lidar and high-resolution imagery

In this study we had the unique opportunity to compare shrub biomass estimates derived from G-LiHT airborne lidar with biomass estimates derived using SfM from coincident high-resolution G-LiHT imagery (Cook et al., 2013). G-LiHT collects structural information using two 1550 nm Riegl VQ 480i scanning lidar sensors with a 300 kHz pulse repetition rate. At G-LiHT's typical flight altitude of 330 m, the

pulse footprint diameter is approximately 10 cm. G-LiHT imagery and lidar were collected on July 31, 2018. A DTM was generated following standard G-LiHT data processing protocols (Cook et al., 2013) and yielded a median absolute deviation compared to GPS validation points of 0.32 m. Lidar data were processed to normalized point clouds (i.e., heights) and a 0.5 m CHM using Matlab (R2018a, MathWorks) software following Pingel et al. (2013). RGB photos were taken using a mapping-grade Phase One iXU1000-R camera with a Rodenstock HR Digaron-W lens. This camera, well-suited for photogrammetric applications, minimizes radial distortion and internal deformation (e.g., “doming”; James and Robson, 2014) of the resultant SfM point cloud. Flying at 330 m with an air speed of 130 knots, the pixel GSD with this 100-megapixel camera was ~3.1 cm, image size was ~9.6 ha, and along-track overlap was ~75%. Based on onboard, high-grade GPS and Inertial Measurement Unit (IMU) we used direct georeferencing only (Turner et al., 2014), resulting in nominal post-processed horizontal and vertical absolute accuracies of 0.1 and 0.2 m respectively.

2.5. Processing G-LiHT RGB imagery to SfM point cloud

We followed similar image processing procedures for G-LiHT SfM (hereafter gSfM) imagery as for the UAV imagery (section 2.3). Forty-nine PC and 92 AV images were used to generate dense point clouds. Quality reports indicate that tie points from > 5 images were generally available at each point in both study areas and that average GSD was 3.14 cm. Output point densities ranged between 500 and 2000 pts. m⁻².

Due to fundamentally different sensor systems and processing methods, lidar and SfM surface models may suffer from complex misalignment in 3D space (White et al., 2018), even when generated concurrently from the same platform. To co-align gSfM data to G-LiHT lidar (hereafter gLID), we sampled the gSfM and gLID digital surface models (DSM) at 1000 random locations to develop a robust, bisquare linear correction. This process is a simplification of the terrain surface matching possible using an iterative closest point (ICP) method, where point clouds are aligned by finding the best rigid body transform (Johnson et al., 2014). In testing our set of 1000 DSM sample points, we found that both approaches prescribed similar shifts dominated by a vertical component (~10.1 m) with minimal horizontal re-alignment (< 0.1 m). Note that the vertical shift internalizes a shift between ellipsoidal (WGS84) and orthometric heights (EGM96) which is 10–15 m throughout much of Alaska. When evaluated only at points with minimal vegetation (lidar CHM < 0.25 m) to remove the discrepancies from sensor-specific depiction of canopy, we found the post-correction median absolute deviation in DSMs to be 0.17 m. The correction factor was then applied to all gSfM points before subtracting the gLID DTM values from gSfM points to arrive at heights above ground.

2.6. Variable generation from lidar and SfM 3D point clouds and CHMs

As in Tompalski et al. (2019), one goal of our study was to compare SfM structural-only and SfM structural + spectral models against field and lidar-predicted shrub biomass. To this end, we divided our variables into four categories: 1) SfM structural metrics (e.g., vegetation height, vertical distribution of points) from the 3D point cloud, 2) SfM spectral metrics from RGB color and vertical distribution thereof, 3) CHM-based metrics from the SfM point cloud distribution, 4) lidar-derived structural, CHM, and intensity-based metrics.

Vegetation structural variables were generated from the distribution of point heights in each plot (UAV $n = 39$, G-LiHT $n = 51$; Table 1, Supplemental Materials S3). These structural variables include percentile heights of all points (i.e. height at which a particular percentage of points lie below), moments of the height distribution of all points (e.g., mean, skewness), and percentiles and moments of only canopy points and “low” points only (0.1 to 5 m). It has been shown that structural metrics constructed directly from the point cloud can add

Table 1

Variables selected by at least one linear regression model for biomass. See Supplemental Materials S3 for the full set of variables evaluated.

Category	Metric	Description
CHM	<i>chm_can_med_frac</i>	Median canopy height * canopy fractional cover
	<i>chm_can_1_4_per</i>	Percent of canopy pixels between 1 and 4 m
	<i>chm_can_fcov_2_5</i>	Fractional cover in 2 to 5 m height range
	<i>chm_can_fcov_5_10</i>	Fractional cover in 5 to 10 m height range
Percentile Heights	<i>low_90</i>	90th percentile height of returns between 0.1 and 5 m
	<i>tot_med</i>	Median height of returns
	<i>tot_90</i>	90th percentile height of returns
	<i>tot_mu_div_med</i>	Mean height of returns divided by median height of returns
Distribution Moments	<i>low_mu</i>	Mean height of returns between 0.1 and 5 m
Lidar Intensity	<i>low_int_med</i>	Median intensity of returns between 0.1 and 5 m
Lidar Energy	<i>egy_low_gnd</i>	Energy between 1 and 5 m divided by energy at ground
SfM Color	<i>blue_skew</i>	Skewness of point blueness values
	<i>bright_skew</i>	Skewness of point brightness values (R + G + B)
	<i>low_green_90</i>	90th percentile greenness for points between 0.1 and 5 m
	<i>low_green_mu</i>	Mean greenness for points between 0.1 and 5 m

value compared to use of simpler, rasterized metrics (Alonzo, M., 2014; Li et al., 2017). Additionally, two topographic variables (elevation and slope) were calculated from the G-LiHT DTM.

Red, green, and blue color metrics were also generated from UAV SfM (hereafter uSfM) and gSfM point clouds. For example, we calculated mean normalized greenness as $green_mean = mean((green - red)/(green + red))$. See **Supplementary Materials S3** for additional formulations. While lidar data does not have color information per se, we did calculate variables pertaining to the distribution of uncalibrated intensity (e.g., median intensity of low points), which have proven useful in previous studies characterizing forest cover (Hopkinson and Chasmer, 2009) and composition (Kim et al., 2009).

To leverage lidar's forest/shrub patch penetration, we also created a small set of "energy" distribution variables inspired by plot-level pseudo-waveform techniques (Muss et al., 2011). These variables may consider the aggregated vertical height distribution or intensity distribution of returns in a plot to be functionally similar to the energy waveform produced via large-footprint lidar. Such metrics have been shown to be sensitive to leaf area index (Farid et al., 2008) and biomass (Popescu et al., 2011). In our application, we summed the number of returns within a height range (Fig. 2, middle row; **Supplementary Materials S4** for upper montane example) and then normalized by pulse density to mitigate effects of scan angle and flight-line overlap on data density (Table 1).

Finally, we calculated a suite of variables based on the CHM for each plot because previous studies have shown that CHM-based metrics are well suited to lower spatial precision of a single dataset or imperfect alignment among several co-registered datasets (Alonzo et al., 2017). We further assumed that variables related to plot fractional cover would be better represented as rasterized products than as irregularly sampled raw point data. Finally, CHM-based canopy volume has been found a useful predictor of shrub biomass using lidar (Cunliffe et al., 2016; Greaves et al., 2016). We calculated canopy volume (*chm_vol*) as the sum of pixel heights in a plot * pixel area.

2.7. Model calibration and validation

As in previous studies, we used linear regression to model the relationship between field-measured shrub biomass and remote sensing metrics (Estornell et al., 2012; Greaves et al., 2016; Puliti et al., 2017). We created "single" models to be applied across the entire landscape and "separated models" to separate subalpine and upper montane zones in order to evaluate the influence of tree cover on variable selection and model performance for shrub biomass prediction. A separated model is composed of two component linear models, one calibrated for SA and another for UM. The results of separated models are ultimately evaluated against field measurements as a combined output. A linear

regression approach, in contrast to nonlinear and machine learning methods, allows for more straightforward interpretation of the biophysical meaning of predictor variables and of the resultant model itself.

Shrub biomass models for uSfM, gSfM, and gLID were each constructed using the same general methodology. Variable sets were created by concatenation of point cloud and CHM variables. All variable combinations were evaluated (exhaustive search) and variable sets were selected based on minimization of root mean squared error (RMSE) in holdout cross-validation mode such that each plot's predicted biomass was independent of model calibration. Final model selection was based on minimization of Akaike's Information Criterion (AIC) paired with an acceptably low variance inflation factor ($VIF < 5$), an indicator of predictor variable multicollinearity (Puliti et al., 2017). Across single models and the individual components of separated models, we found diminishing returns with respect to model fit and AIC for > 5 variables, and so tested no models with > 6 variables. Final, "separated" models were created by selecting the individual SA and UM component models that had lowest AIC and acceptably low VIF. For example, in the gSfM structure + spectral category, if the optimal SA component model used 2 variables and the optimal UM component model required 3 variables, the final model would use 5. This model would be labeled as "gSfM5Sep" to indicate that it is G-LiHT SfM with 5 total variables from component models separated by ecosystem.

Ultimately, we selected four models for further evaluation: one each for uSfM, gSfM (structure only), gSfM (structure and spectral), and gLID. While G-LiHT models can be compared robustly at $n = 51$ plots, uSfM data were available at $n = 39$ plots due to UAV airspace restrictions. By chance, the uSfM data do not include the two highest biomass plots. Model uncertainty was reported as 95% confidence intervals constructed by bootstrap sampling from the multivariate normal distribution of model parameters generated from the parameter variance-covariance matrix.

2.8. Biomass maps at the landscape scale

We mapped shrub biomass at the landscape-scale using the three G-LiHT models (gSfM structure, gSfM structure + spectral, gLID) at several spatial resolutions. For methods development purposes, the box bounding our AV and PC study sites enclosed an area of 1.2 km². One reason for mapping beyond our field validation plots was to glean additional information about model performance through visual assessment of the biomass estimates and associated model uncertainty further afield (e.g., based on comparison with lidar CHM, local knowledge of other ground cover types). Additionally, we mapped shrub biomass at resolutions higher than the 13 m pixel (169 m² approximating FIA subplot size of ~168 m²), because it is unknown if models developed at

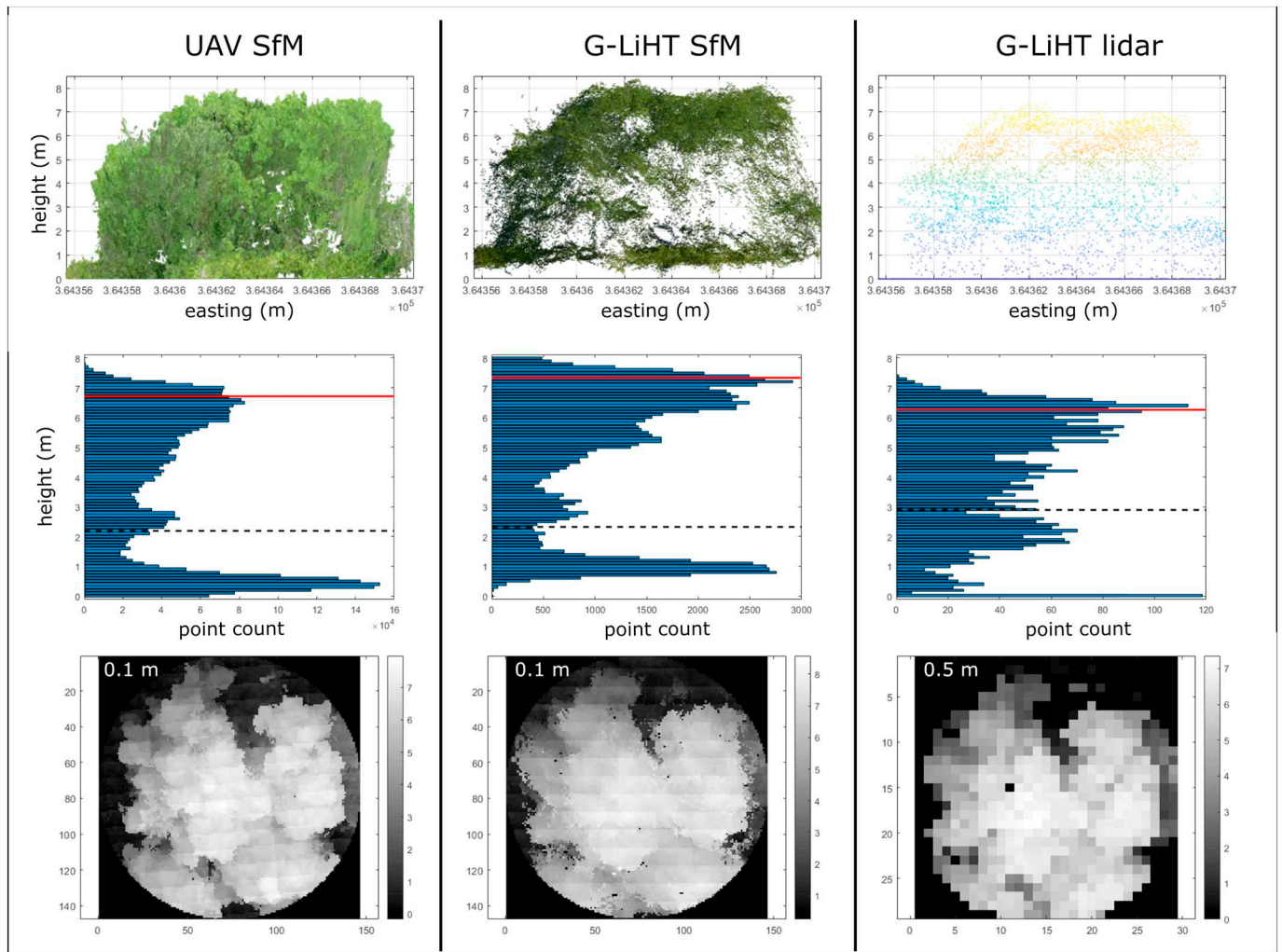


Fig. 2. Views of a single subalpine plot dominated by tall shrub biomass. Top row: side view of the point clouds from each sensor. The lidar point cloud is colored by height. Middle row: “pseudo waveforms” or vertical height distributions of points in plot. Red line is 90th percentile height of all points. Black dashed line is “low μ ” or “mean height of points between 0.1 and 5 m”. Note that the x-axis for the lidar height distribution is truncated because all ground returns are, by definition, exactly zero m. Bottom row: canopy height maps. See **Supplemental Materials S4** for an upper montane example. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

plot-resolution capture the spatial grain of shrub variability (e.g., 2 m pixels). While we were unable to validate individual pixel biomass values at resolutions less than plot size, we hoped to illustrate the strength and limitations of the modeling approaches for capturing fine-scale spatial heterogeneity in shrub cover and biomass. For example, we hypothesized that SfM models with their ultra-high data density would be less sensitive than lidar models to changes in model resolution. These understandings will better inform the tradeoff between resolution and pixel information content.

We produced maps at 2, 5, and 13 m spatial resolutions for both gLiD and gSfM. Maps were constructed by extending a grid over the point cloud and CHM at each resolution, removing scan angles > 20 degrees (lidar only), calculating the predictor variable values within each grid square, and then applying the linear model created during model calibration using the higher resolution values of the variables. We applied the SA and UM habitat-specific models across our study area, determining which values to use based on a 13 m resolution binary map of canopy height > 8 m. This height corresponded with the influential presence of tree overstory. Finally, we resampled all biomass maps (redundantly) to 1 m resolution to allow for reaggregation to plot scale for model evaluation while minimizing the impact of plot edge effects. Ninety five percent confidence intervals of sitewide

biomass predictions were established at the pixel scale as previously mentioned for plot-scale analyses. Plot-level biomass estimates and model uncertainty were calculated as averages of pixel-level results. In this study, given emphasis on relative changes in model uncertainty and bias, we do not include pairwise pixel covariance in our results (McRoberts, 2006).

3. Results

3.1. Field plot measurements of shrub biomass

Mean shrub biomass density in all plots was 2.58 kg m^{-2} (range $0\text{--}10.9 \text{ kg m}^{-2}$, $\text{se} = 0.35 \text{ kg m}^{-2}$, $n = 51$ plots). At the drier, higher-elevation PC site, mean biomass density was greater in UM habitat (2.01 kg m^{-2} , $\text{se} = 0.45$, $n = 13$) than in SA habitat (1.74 kg m^{-2} , $\text{se} = 0.34$, $n = 8$). By contrast, mean biomass density in UM habitat at the AV site (1.66 kg m^{-2} , $\text{se} = 0.69$, $n = 6$) was less than half the mean biomass density in SA habitat (3.41 kg m^{-2} , $\text{se} = 0.65$, $n = 24$). This information provided for site description only given small sample sizes after slicing the data by ecosystem and study area. Most plots ($n = 36$) were dominated by willow biomass; only nine plots had higher alder than willow biomass.

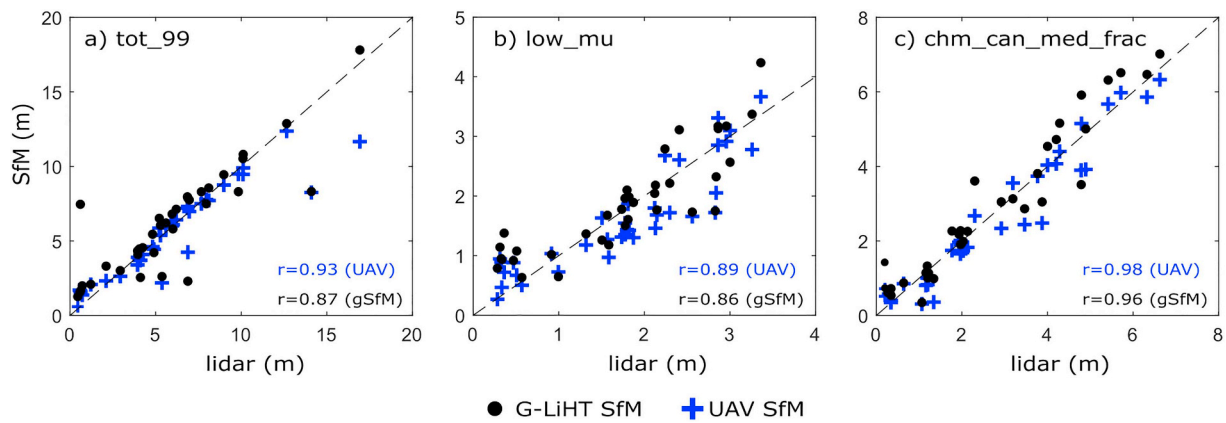


Fig. 3. Correlation between selected lidar-measured and SfM-measured structural variables from G-LiHT SfM (black dots) and UAV SfM (blue crosses) for $n = 37$ plots where data for each sensor available: a) 99th percentile height of all returns; b) mean height of returns between 0.1 and 5 m; c) Median canopy height * canopy fractional cover based on CHM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2

UAV and G-LiHT biomass models selected based on minimization of AIC and VIF. Final, “separated” models in bold evaluated at plots across both ecosystems based on combination of the two component models listed directly above. The reader is referred to Table 1, above, for explanation of variables.

Model	Zone	Category	# variables	R ²	RMSE	AIC
<i>uSfM3Sep-SA</i>	SA	UAV SfM structural	3	0.88	0.66	20.8
<i>uSfM3Sep-UM</i>	UM	and spectral	3	0.70	1.00	32.6
<i>uSfM6Sep</i>		($n = 39$ plots)	6	0.82	0.81	56.4
<i>gSfM1Sep-SA</i>	SA	G-LiHT structural	1	0.65	1.68	72.0
<i>gSfM1Sep-UM</i>	UM	only ($n = 51$ plots)	1	0.54	1.06	27.1
<i>gSfM2Sep</i>			2	0.65	1.48	117.7
<i>gSfM2Sep-SA</i>	SA	G-LiHT structural	2	0.75	1.44	63.1
<i>gSfM3Sep-UM</i>	UM	and spectral	3	0.68	0.89	35.2
<i>gSfM5Sep</i>		($n = 51$ plots)	5	0.75	1.26	100.6
<i>gLID3Sep-SA</i>	SA	G-LiHT lidar	3	0.78	1.34	69.7
<i>gLID3Sep-UM</i>	UM	($n = 51$ plots)	3	0.65	0.92	36.7
<i>gLID6Sep</i>			6	0.77	1.20	107.1

3.2. Biophysical variable correspondence among UAV and G-LiHT datasets

Shrub biomass models derived from uSfM, gSfM, and gLID data relied on similar remote sensing variables. At the plot scale, SfM and lidar derived variables were strongly correlated ($r > 0.85$; Fig. 3). Categories of variables with particularly strong correlations between SfM and gLID included overall percentile heights ($r_{uav} = 0.96$, $r_{gSfM} = 0.94$), low percentile heights ($r_{uav} = 0.95$, $r_{gSfM} = 0.94$), and fractional cover based on CHM ($r_{uav} = 0.98$, $r_{gSfM} = 0.95$). CHM-based variables were very similar across sensors (e.g., Fig. 3c), highlighting their transferability across sensor types.

Correlations between SfM and lidar-based estimates of higher moments such as skewness and kurtosis were generally moderate ($r_{uav} = 0.48$, $r_{gSfM} = 0.53$). In general, low SfM sensitivity to sub-canopy vegetation structure may partly explain the lower correlations. In some plots, SfM 99th percentile height underestimated the highest vegetation in cases where maximum shrub height was high but fractional cover at that height was quite low (seen as largest deviations from 1:1 line in Fig. 3a). This is likely a sampling issue where dense matching algorithms oversample (i.e., find more tie points) in dense vegetation and generally illustrates how order statistics closer to max and min are sensitive to sample size. Low mean, low 90th and low 99th percentile data were more consistent than expected among sensors (Fig. 3b; $r_{uav} = 0.89$, $r_{gSfM} = 0.87$) highlighting the ability for high density data to characterize small surface variations and gaps in canopy. The weakest correlations (e.g., overall fractional cover) between SfM and gLID arose because the height variance of the ground signal was larger in SfM than lidar profiles (Fig. 2, middle row). Thus, the ground signal may have been considered vegetation “cover” on occasion.

3.3. Biomass models

The best model from each of our four categories was selected for further examination: 1) uSfM (structural + spectral information), 2) gSfM (structural information only), 3) gSfM (structural + spectral information), and 4) gLID (Table 2). Models were selected on the basis of low AIC and low multicollinearity among predictors as indicated by their VIF. Despite greater model complexity from reliance on two component models, models separated by habitat (SA and UM) were always selected. For example, a single, 3-variable lidar model had higher AIC (124.3) and lower R² (0.60) compared to the separated model (*gLID6Sep*, AIC = 107.1, R² = 0.77), highlighting the need to account for tree presence in UM habitat. The maximum number of variables in separated models was six for uSfM structural + spectral (*uSfM6Sep*), five for gSfM, structural + spectral (*gSfM5Sep*), two for gSfM, structure only (*gSfM2Sep*), and six for gLID (*gLID6Sep*; Table 2). Inclusion of additional variables in each case either increased the AIC or only marginally reduced the AIC while increasing VIF from well below 5 to above 10 (Puliti et al., 2017).

The best uSfM model was *uSfM6Sep* (Table 2, Fig. 4a; R² = 0.82, RMSE = 0.81 kg m⁻², $n = 39$ plots); however, the two highest biomass plots located in a flight-restricted zone were excluded. For this model, variables were selected from the point cloud relating to both structure (e.g., *low_mu*) and color (e.g., *bright_skew*), and from the CHM (e.g., *chm_can_1_4_per*), suggesting complementary information among variable categories (Table 3).

The best gSfM model (structural + spectral) was *gSfM5Sep* (Table 2, Fig. 4b; R² = 0.75, RMSE = 1.26 kg m⁻²). For more direct comparison to uSfM data, model fit was also calculated after removing the two

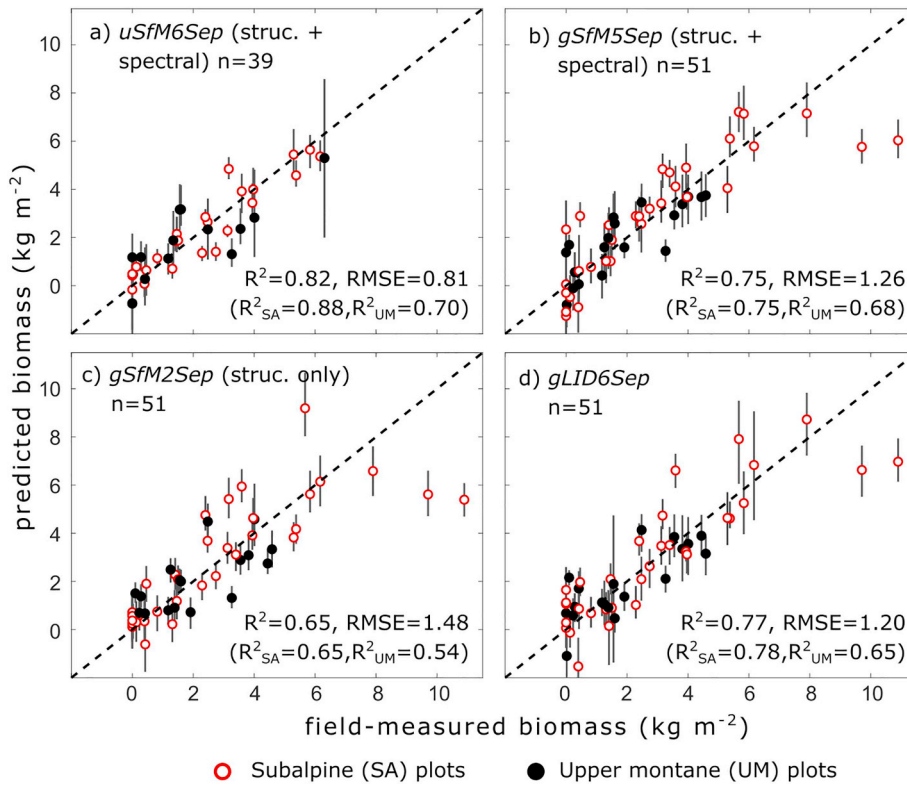


Fig. 4. The four selected models evaluated at the maximum number of field plots. Plots display the final result of separate SA and UM component models and the resultant uncertainty at each field plot. Component model fits for SA and UM are also shown. a) *uSfM6Sep* (structural and spectral), b) *gSfM5Sep* (structural and spectral), c) *gSfM2Sep* (structural only), d) *gLID6Sep* (all available lidar variables). Dashed line is 1:1.

anomalously high biomass plots, leading to revised fit statistics ($R^2 = 0.81$, $RMSE = 0.87$). To arrive at a model with different numbers of variables for SA and UM, we assessed AIC and VIF analysis on each SA and UM component model and determined that inclusion of three different SA variables was unwarranted, leading to a high degree of redundant information (VIF_{max} for 2 SA predictors = 1.1, VIF_{max} for 3 SA predictors = 15.6). For UM, however, three variables improved model fit, highlighting the challenge of the more complex upper montane environment. In the SA component model, the 90th percentile height of low points (0.1 and 5 m; *low_90*) was most important with respect to incremental reduction of model fit upon removal (Fig. 5). Addition of a spectral variable expressing the greenness of that pixel was also useful; in our study area shrub biomass was negatively associated with greenness (see standardized coefficients Table 3). The UM component model was dominated by the positive contribution of *chm_can_med_frac*, defined as the product of median canopy height and fractional cover. Still, spectral variables, skewness of blue (*blue_skw*) and greenness of low points (*low_green_90*) improved fit, likely by differentiating shrubs from ground cover and trees.

In order to separate the value of high-density data from the

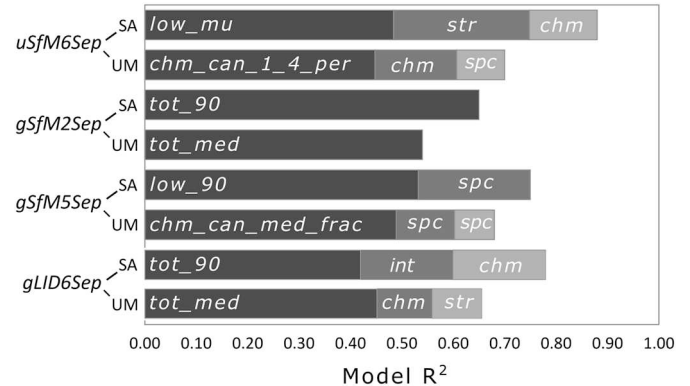


Fig. 5. Variable importance measured by reduction in scaled model R^2 upon removal. Most important variable specifically named in each case. Subsequent variables listed by category only where *str* = point cloud structural, *spc* = spectral, *int* = lidar intensity, and *chm* = chm. Four selected models shown, each with its subalpine (SA) and upper montane (UM) component models.

Table 3

UAV and G-LiHT biomass component model variables and standardized coefficients. Standardized coefficients correspond to each predictor variable as indicator of direction and importance of its relationship with biomass. The reader is referred to Table 1 for explanation of variables and Table 2 to see how component models are combined into final models.

Component models	Predictor variables in each component model			Standardized coefficients		
	x1	x2	x3	x1	x2	x3
<i>uSfM3Sep-SA</i>	<i>low_mu</i>	<i>tot_mu_div_med</i>	<i>chm_can_1_4_per</i>	0.62	0.27	−0.36
<i>uSfM3Sep-UM</i>	<i>chm_can_1_4_per</i>	<i>chm_can_fcov_2_5</i>	<i>bright_skw</i>	−0.83	0.43	−0.41
<i>gSfM1Sep-SA</i>	<i>tot_90</i>			0.84		
<i>gSfM1Sep-UM</i>	<i>tot_med</i>			0.80		
<i>gSfM2Sep-SA</i>	<i>low_90</i>	<i>low_green_mu</i>		0.65	−0.42	
<i>gSfM3Sep-UM</i>	<i>chm_can_med_frac</i>	<i>blue_skw</i>	<i>low_green_90</i>	0.97	0.52	−0.41
<i>gLID3Sep-SA</i>	<i>tot_90</i>	<i>low_int_med</i>	<i>chm_can_fcov_5_10</i>	0.88	0.68	0.65
<i>gLID3Sep-UM</i>	<i>tot_med</i>	<i>chm_can_fcov_2_5</i>	<i>egy_low_gnd</i>	1.01	0.91	−0.90

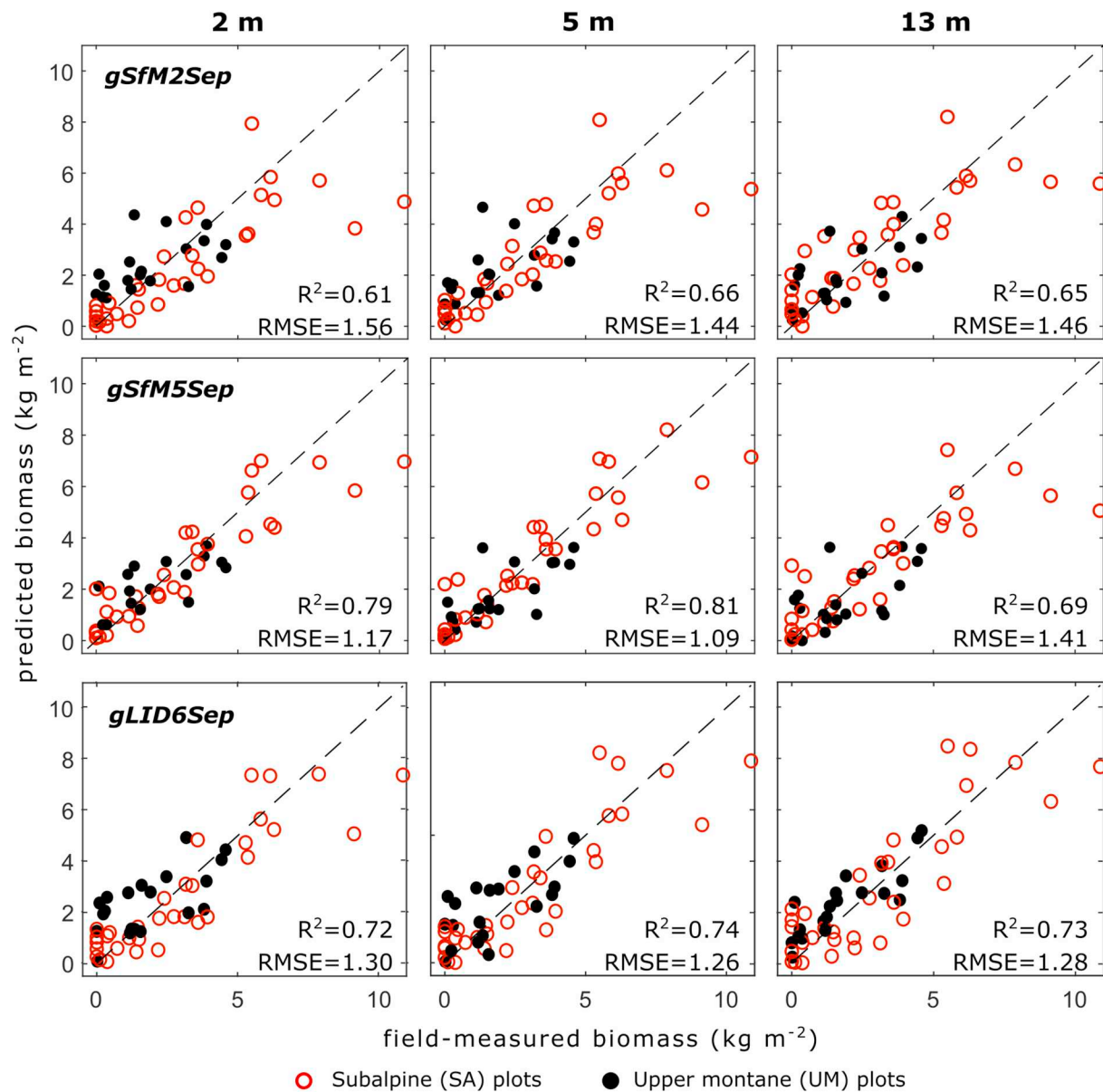


Fig. 6. Biomass mapping results re-aggregated to plot level for comparison with full set ($n = 51$) of field plots. Subalpine plots in open red circles and upper montane plots in black. Rows for each G-LiHT model and columns for pixel size of model variable generation. Dashed line is 1:1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

contribution of spectral variables, we created SfM models making use of only structural variables. Interestingly, the best of these models, *gSfM2Sep* (Table 2, Fig. 4c; $R^2 = 0.65$, $\text{RMSE} = 1.48 \text{ kg m}^{-2}$), employed a single variable for each habitat: 90th percentile height of all points (*tot_90*) for SA and median height of all points (*tot_med*) for UM. This was also the single-variable model selected when both spectral and structural metrics were available for inclusion highlighting the importance of these basic structural variables. As expected, the single-variable model performed worst overall in RMSE and R^2 (Fig. 4), even when the two highest biomass plots were excluded ($R^2 = 0.72$, $\text{RMSE} = 1.06$).

The best performing lidar model was *gLID6Sep* (Table 2, Fig. 4d; $R^2 = 0.77$, $\text{RMSE} = 1.20 \text{ kg m}^{-2}$), with three variables for each habitat (Table 3). By a small margin, this model best estimated biomass at the two highest biomass SA plots (Fig. 4). With those two plots removed, the revised fit for comparison yielded $R^2 = 0.78$ and $\text{RMSE} = 0.93$. Judging by scaled contribution to model R^2 , the SA lidar component model ($R^2 = 0.78$) used structural information primarily but also

benefited from inclusion of sub-canopy intensity information (Fig. 4). Variable multicollinearity was higher for this model with a mean $\text{VIF} = 4.4$ and a max $\text{VIF} = 5$. As with the single-variable, structure-only SfM model (*gSfM2Sep*), the UM component model ($R^2 = 0.65$) relied most heavily on the median height of points in the plot (Table 2).

3.4. Biomass maps and determination of optimal spatial resolution

We mapped biomass using the three G-LiHT models at 2, 5, and 13 m resolutions to understand the strengths and limitations of mapping at finer spatial resolutions than the model-calibration scale (plot area $\approx 13 \text{ m}$ pixel). The *gSfM5Sep* model applied at 5 m resolution was the most precise predictor of field-measured biomass once re-aggregated to the plot scale ($R^2 = 0.81$, $\text{RMSE} = 1.11 \text{ kg m}^{-2}$; Fig. 6 left middle panel). Model bias was low (Fig. 7); the predicted study area-mean biomass density ($2.51 \pm 1.01 \text{ kg m}^{-2}$) was within 3% of the field-measured sitewide biomass density (2.58 kg m^{-2}). While *gSfM2Sep* applied at 13 m performed substantially worse ($R^2 = 0.65$,

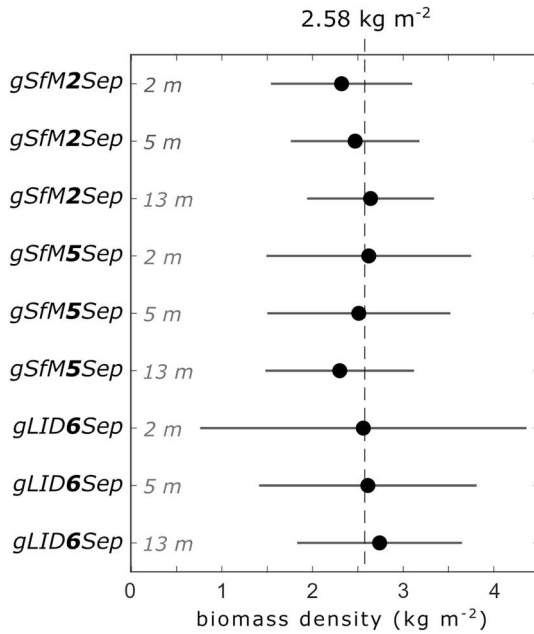


Fig. 7. Sitewide biomass density compared to field-measured value (2.58 kg m^{-2}) by model and pixel size of model construction. Horizontal bars are 95% confidence intervals of the estimate.

RMSE = 1.46 kg m^{-2}), it exhibited similarly low bias ($2.64 \pm 0.70 \text{ kg m}^{-2}$; Fig. 7) and demonstrated the lowest uncertainty.

The lidar model chosen for mapping, *gLID6Sep*, mapped with low bias but at 2 m resolution demonstrated the highest uncertainty ($2.56 \pm 1.80 \text{ kg m}^{-2}$) of all models and resolutions; at 13 m its bias was higher but uncertainty lower ($2.74 \pm 0.91 \text{ kg m}^{-2}$). Lidar mapping was stable across resolutions in terms of model fit but generally less good than high-resolution SfM (Fig. 6).

The *gSfM5Sep* and *gLID6Sep* models generated maps that were broadly similar in terms of spatial allocation of biomass and uncertainty (Fig. 8). Uncertainty in *gSfM5Sep* prediction was generally low to moderate. It was notably highest in areas with low woody vegetation cover. There, the relationship between color variables, such as low green mean, and biomass was inverted such that low greenness corresponded to very low shrub biomass (e.g., scree) but our model coefficients were not calibrated for these alpine zones, thus prescribing large overestimates (Table 3). Uncertainty in *gSfM5Sep* was also high along study area edges. There, reduced image overlap lowered data density (Fig. 8c, 1 and 2). Uncertainty in the lidar-based estimates (*gLID6Sep*) was more spatially uniform but highest in the UM habitat near its border with SA (Fig. 8d and f).

Along an elevational gradient, the best-performing G-LiHT models (*gSfM5Sep* and *gLID6Sep*) broadly corresponded, with continuing shrub biomass upslope from our fractional cover proxy for tree line at each study site (Fig. 9). The uncertainties in the best-performing gSfM model (*gSfM5Sep*) were lower than *gLID6Sep* at lower (UM) elevations, particularly at AV, but increased with increasing elevation at PC (Fig. 9b). This increasing uncertainty in the SfM model occurred where scree

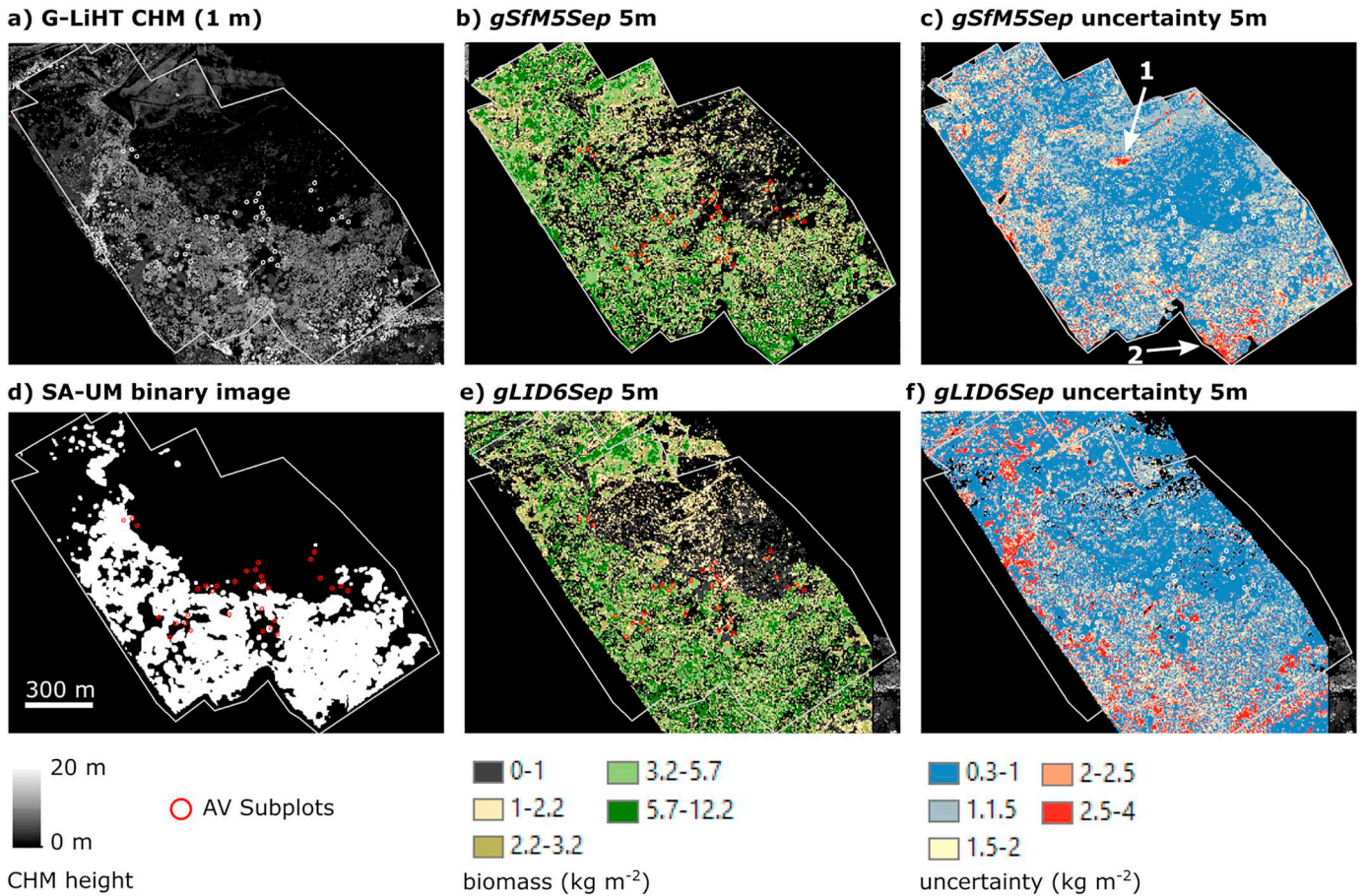


Fig. 8. Predicted biomass and uncertainty maps at Arctic Valley where outline depicts extent of G-LiHT SfM maps to visually orient the reader: a) G-LiHT lidar CHM for reference; b) *gSfM5Sep* 5 m biomass; c) *gSfM5Sep* uncertainty; d) Binary image based on vegetation height threshold used to determine whether SA or UM model applied (UM in white); e) *gLID6Sep* 5 m biomass; f) *gLID6Sep* uncertainty.

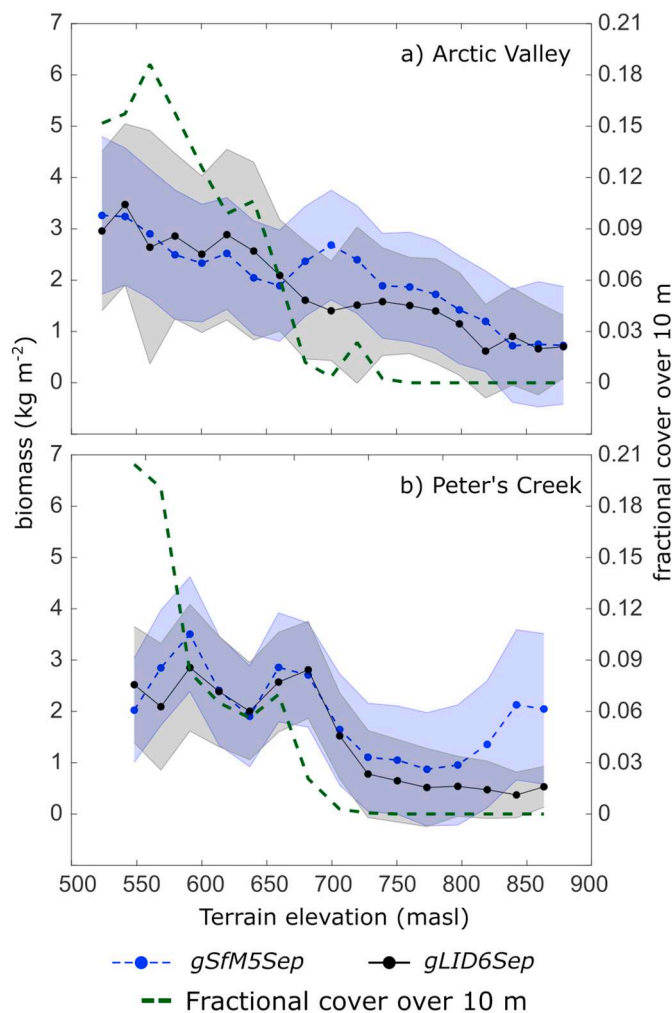


Fig. 9. Modeled shrub cover at each site along an elevational gradient shows broad agreement between SfM and lidar models. Fractional cover over 10 m is also plotted as a proxy for tree cover. Blue and grey shading denotes the average model uncertainty at each elevation band. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

cover surpassed vegetative cover, most likely because the coefficients of color variables were inappropriate for the landscape. While Fig. 9 depicts these high elevation issues with SfM spectral information for illustration purposes, this issue is easily corrected with implementation of a simple CHM threshold (not shown).

4. Discussion

This is the first study to map shrubs at the landscape scale using SfM techniques at high spatial resolution. We found that high-density SfM point clouds were suitable for estimating shrub structure and biomass in both subalpine and upper montane environments under discontinuous tree cover. These findings suggest that the benefits of ultra-dense point clouds can, in some cases, outweigh the drawbacks associated with lack of canopy penetration. The best performing UAV model and G-LiHT SfM model both included color variables, highlighting the unique contribution of imagery-based techniques for characterizing vegetation structure and composition. Even in the highest biomass plots, the G-LiHT SfM model performance was equivalent to the G-LiHT lidar model, despite the expectation of more consistent subcanopy information from lidar. It may be that low greenness varies in part with exposure of non-photosynthetic vegetation providing a proxy for sub-canopy

information. Models incorporating color information led to some overestimation of shrub biomass in higher-elevation areas not included in the training sample, such as exposed rock, soil, or ground cover that were similar to shrub vegetation with respect to low greenness. Coincident lidar data, as shown here, could provide an independent means to limit SfM estimates of shrub biomass to woody vegetation (e.g., based on a simple CHM threshold), thereby reducing the influence of lichen, moss, or other ground cover on shrub biomass estimates from SfM data using color variables.

4.1. Acquisition and point cloud comparisons across sensors

The use of UAV-based photogrammetric techniques for ecological monitoring is increasingly widespread (Anderson and Gaston, 2013). However, UAV studies are constrained by technological and regulatory restrictions to small study areas. One objective of this study was to determine whether UAV-based workflows could be transferred to imagery acquired by a piloted airborne platform flying at higher altitude with only a nadir-pointing camera, lower image overlap, and limited external ground control. While several studies have implemented methods involving SfM processing of images from aircraft systems (Dietrich, 2016; Nolan et al., 2015), none, to our knowledge, focus on vegetation applications which offer particular challenges in terms of identifying image tie points (Dandois et al., 2017) and quantifying salient characteristics (e.g., height, biomass).

We demonstrate that UAV and G-LiHT SfM datasets yielded similar results for shrub biomass estimation. Our UAV acquisition (GSD = 1.7 cm) employing a double-grid flight pattern and off-nadir image capture (Alonzo et al., 2018) provided convergent camera geometry (Dietrich, 2016; James and Robson, 2014) and low internal deformation of the dense point cloud (5000–8000 pts. m^{-2}) as evaluated through comparison with ground control and check points. External ground control using differentially corrected GPS was necessary to achieve decimeter positional accuracy given imprecise positional information collected aboard consumer-grade UAV. By contrast, the Phase One camera on G-LiHT was nadir-pointing, nominally producing parallel camera orientations which have been implicated in surface model deformation (Dietrich, 2016). However, as a “metric”, survey-grade camera with a well-defined camera model, the root cause of deformation—lens radial distortion—was negligible (James and Robson, 2014). Moreover, with GNSS-inertial direct georeferencing (Turner et al., 2014) leading to post-processed nominal positional accuracy of 0.1 m horizontal and 0.2 m vertical, we achieved similar absolute accuracy to that of the UAV point cloud after ground control.

High point cloud density and fidelity in our SfM models facilitated SfM mapping accuracies similar to those employing lidar data. While G-LiHT SfM point cloud densities (500–2000 pts. m^{-2}) were substantially lower than UAV, they were still much higher than G-LiHT lidar (~30 pts. m^{-2} in canopy) and notably higher than previous landscape scale DAP acquisitions ranging between 12 and 37 pts. m^{-2} based on image GSD between 0.25 and 0.3 m (Noordermeer et al., 2019; White et al., 2015, 2018). While there is a known, fundamental inability of image-based techniques to “penetrate” the canopy envelope (Dandois and Ellis, 2013), we argue that very high-resolution imagery does allow for proxy estimation of internal canopy structure. The definition of “canopy envelope” is scale-dependent and thus its evaluation is dependent on the resolution of the imagery in question as well as the focal length of the camera. Mapping grade cameras, with longer focal lengths, are better suited to detect small gaps due to smaller off-nadir, layover effects (Osborn et al., 2018). For example, with 0.3 m image resolution and 12 pts. m^{-2} both for lidar and DAP data, White et al., (2018) found that, on average, a gap must be twice as large to be detected using DAP compared to lidar. With similar illumination conditions and camera specifications, it would stand to reason that our 0.03 m resolution gSfM data with several orders of magnitude higher point density would detect substantially smaller gaps. In our study, we show evidence of

comparable sub-canopy performance with the high correlations among low mean height (*low_mu*) measurements across uSfM, gSfM, and gLID acquisitions ($r > 0.86$; Fig. 3). Indeed, one or more height-restricted variables were selected for modeling in all multi-variable models in UM habitat (Table 3).

4.2. Model performance and variables

We compared the precision and accuracy with which field-measured biomass could be predicted from lidar models, models constructed with all available SfM data (structural + spectral), and only SfM structural variables. We did not attempt to build SfM spectral-only models due to their known poor performance (Tompalski et al., 2019). We adopted a linear modeling approach (analogous to Puliti et al., 2017) for two reasons. First, we sought to evaluate the contribution of individual variables in simple models to better understand the tradeoffs among data density, canopy penetration, and color information. Second, the relationships between structural variables (e.g., 90th percentile height of points) and field-measured biomass were mostly linear. We tested nonlinear models in hopes of better characterizing our highest biomass plots, but they generally lowered precision and increased uncertainty across the full range of values. Nevertheless, our mapping results suggest probable nonlinear relationships between shrub cover and spectral information (e.g., low greenness), suggesting an application of machine learning approaches to classify land cover (e.g., Rinas et al., 2017), but only if field sampling covers the range of variability in land cover. While Greaves et al. (2016) found value in lidar canopy volume as a single predictor of tundra shrub biomass in a linear regression context, their precision improved when spectral metrics were ultimately added in a random forest regression model.

Our broad finding was that the both uSfM and gSfM models performed as well as the gLID model (Fig. 4), and SfM models performed even better than lidar for higher-resolution mapping (Fig. 6). Point cloud structural, CHM-based, and color variables were all present in both of the selected SfM structure + spectral models. Without color information, however, the SfM models underperformed the lidar-only models. Puliti et al. (2017) found a similar result predicting forest volume (lidar $R^2 = 0.88$ vs. UAV SfM $R^2 = 0.79$); they suggest it is due to lidar's ability to penetrate canopy. However, with inclusion of color and height-restricted structural information, the information content of our models increased to the point of rough equivalence with lidar models.

Height-restricted point cloud variables were important components of SfM models (Fig. 5). This result was expected, given the relatively short stature of even tall shrubs compared to overhanging tree canopy, and conceptually similar to the 1–2.5 m height variable used to isolate understory shrub species in a mixed conifer forest (Martinuzzi et al., 2009). In UM environments, the correlation between *low_90* (90th percentile height of points between 0.1 and 5 m) and field-measured biomass ($r = 0.64$) was nearly twice that of *tot_90* ($r = 0.37$; 90th percentile height of all points), demonstrating the importance in avoiding overstory trees when estimating shrub biomass. In SA habitat, the utility of the height-restricted variables may act as a proxy for sub-canopy biomass density. That is, after a certain height (~8 m) further increases in stature did not relate to higher biomass, an indication of the unstable relationship between basic structural metrics and biomass. This is consistent with previous work demonstrating discrepancies between biomass and simple structural measurements due to inconsistent species-volume relationships (Greaves et al., 2015), microtopographic variation (Greaves et al., 2016), and variability in sub-canopy woody density (Estornell et al., 2012).

Color information was important for mapping high biomass plots but the direction of the relationship between color predictor and biomass response are not always consistent. The combination of low structure and low greenness was particularly useful in the mapping phase (5 m pixels) where the two highest biomass plots were underestimated by a combined 48% by *gSfM2Sep* but only 37% by *gSfM5Sep*,

which was identical to the underestimate by *gLID6Sep*. Melin et al. (2017) showed that including spectral metrics when estimating boreal forest canopy cover slightly lowered RMSE, but improved estimates at high cover fractions. Estornell et al. (2012) made use of standard deviation of greenness for their best model of shrub dry-weight biomass in a Mediterranean environment. Greaves et al. (2016) also report of adding the normalized difference vegetation index (NDVI; Tucker, 1979) to a lidar dataset increased performance when estimating high biomass plots; however, they positively correlate NDVI with tundra shrub biomass. In our study, greenness was negatively associated with shrub biomass (Table 3), highlighting both the potential utility of spectral information for de facto species separation but also the challenge of interpretation and broader application of color information.

Previous work suggests the specific utility of color information for discriminating vegetation species (Alonzo et al., 2018; Michez et al., 2016). Alonzo et al. (2018) leveraged blueness with two structural variables to differentiate five boreal tree species (85% overall accuracy using UAV data), finding median blueness as the most useful single variable (60% overall accuracy). We found in this study that in the UM plots, skewness of overall brightness (*bright_skw*) and blueness (*blue_skw*) as well as low greenness (*low_green_90*) each could differentiate tree canopy from shrub understory. This relationship was effective along the forest-tundra ecotone where lower greenness likely indicated the presence of shrub species as opposed to herbaceous vegetation (see data views in **Supplementary Materials S1**). However, at higher elevations with minimal shrub cover and greater exposure of rocks and soil, lower greenness values related to lack of any vegetation. While there has been limited research evaluating color metrics for modeling structure at landscape and regional scales, it is known that color metrics (when not calibrated to surface reflectance) are susceptible to variability over space and time (Dandois et al., 2015; Puliti et al., 2015). Even species prediction models created from hyperspectral surface reflectance data can decrease markedly in accuracy when ported across space and time (Meerdink et al., 2019). Looking forward, it may be that the most efficacious use of color information is to facilitate species discrimination in advance of creating species-specific biomass models as has been demonstrated via fusion of lidar and hyperspectral data (Swatantran et al., 2011).

4.3. Mapping

Model-based estimation is useful for quantifying the spatial and temporal variability of shrub biomass over large spatial extents. We produced biomass maps at 2, 5, and 13 m resolutions to understand model stability at higher resolution than the resolution of the biomass sampling. Higher resolution biomass maps provide a useful visualization of spatial heterogeneity of shrub cover and biomass across the landscape (see visual example **Supplemental Materials S5**). Moreover, if segmenting the landscape along the SA and UM ecotone, higher resolution provides a higher percentage of pure pixels (i.e., those with only shrub or those with overhanging canopy). In our study, the latter advantage is observable in Fig. 6 where 2 m and 5 m models exhibit less scatter than those formulated at 13 m.

While model bias was minimally impacted by changes in model resolution, uncertainty increased with resolution, particularly for lidar models (Fig. 7). The increasing uncertainty highlights the difficulty of employing variables reliant on robust penetration (e.g., ratio of low lidar energy to ground energy, *egy_low_gnd*) at high resolution (**Supplemental Materials S6**). This finding is consistent with previous work. Alonzo et al. (2015) demonstrate the challenge of measuring LAI at the individual crown scale due to limited penetration of even high-pulse density lidar. In the present study, SfM color (low greenness; *low_green_mu*) and lidar intensity variables (low median intensity; *low_int_med*) were among the most stable and minimally biased across resolutions, suggesting broader utility in biomass mapping efforts (**Supplemental Materials S6**). This finding may inform researchers'

choice between lidar and SfM datasets, depending on whether they will prioritize fine spatial resolution mapping or, for instance, retrieval of sub-canopy information.

4.4. Outlook

Landscape to regional scale mapping of woody vegetation structure using ultra-dense SfM data is on the horizon. Lower-resolution implementations of these methods offer interesting and economically feasible possibilities such as countrywide forest canopy mapping (Ginzler and Hobi, 2015). While canopy penetration per se is not possible with image-based techniques, ultra-dense data (> 500 pts. m^{-2}) can characterize variation in canopy structure in novel ways. In this paper, SfM and lidar models performed similarly with respect to biomass estimation accuracy and uncertainty, with gSfM models offering better precision and lower uncertainty at higher spatial resolution. Moreover, both gLID and gSfM models yielded nearly identical estimates of biomass at the two highest biomass SA plots leading us to conclude that SfM color information and high point density can act as surrogate for subcanopy lidar information in certain applications. We found minimal loss of this canopy information between UAV imagery (1.5 cm) and gSfM imagery (3.1 cm).

Using SfM methods for sub-canopy estimation relies on an existing or concomitantly collected lidar terrain model (but see Puliti et al., 2019 for SfM-only work), particularly as vegetation density increases. Here, we collected lidar simultaneous with high-resolution imagery. While the need for a lidar-based DTM hampers proliferation of regional-scale SfM, the prioritization of lidar collections across large spatial extents (e.g., US States, <https://coast.noaa.gov/inventory/>) will make repeat SfM more likely in the future (e.g., repeat high-resolution stereo imagery from the USDA's National Agriculture Imagery Program). For example, in our peri-urban study area, we also had access to an existing, municipally collected 1 m DTM that could have been used instead of using G-LiHT lidar. The forest inventory research community currently is very interested in DAP or SfM techniques that can be efficiently and economically employed for periodic inventory updates in areas with existing DTMs (Goodbody et al., 2019). Even without lidar DTM, opportunities to characterize open vegetation in drylands (Cunliffe et al., 2016), tundra (Fraser et al., 2016), or woodlands (Alonzo et al., 2018) are available.

SfM practitioners must adhere to best practices with respect to point cloud quality, consistency across platforms and compared to lidar, and robust reporting of uncertainty. In this study we sought to minimize and report uncertainties related to 1) the internal structure of the SfM point cloud, 2) absolute geolocation of our UAV and G-LiHT data, and 3) biomass predictions based on model parameter selection. We were largely unable to report uncertainty in field-based biomass estimates such as DRC to biomass conversion, though these can represent a sizable proportion of the overall error budget in shrub environments (Cunliffe et al., 2016). Reporting strategies for absolute geolocation error as well as modeling and sampling-based uncertainties are common across many remote sensing studies (Dietrich, 2016; Greaves et al., 2016; Puliti et al., 2017). Most pertinent for elevating the utility of SfM data for quantifying vegetation is growing the expectation for reporting processes and uncertainties related to the internal consistency of the point cloud. If following commercial SfM workflows (e.g., Agisoft Photoscan, Pix4) it is not generally adequate to report only the precision estimated by software during initial point cloud generation. Instead, use of ground control points and independent checkpoints allow for confirmation against an external point of reference which is better for assessing the prevalence of artifacts such as doming (James et al., 2017).

We show in this work that shrub biomass can be mapped with reasonable precision and low bias using either SfM or lidar techniques. This helps to open the door to larger scale implementation of these methods to quantify the spatial variability of shrub biomass (e.g.,

Fig. 9). Isolating the shrub component of aboveground biomass in both upper montane and subalpine environments allows for more spatially continuous assessment of, for example, alterations to habitat and soil characteristics that are specific to shrub species. This targeted approach similarly facilitates simultaneous study of multiple dimensions of shrubification: shrubline advance upslope but also infilling and growth, processes that are more difficult to detect under forest canopy cover. With G-LiHT data strips currently available across large swaths of boreal Alaska and continued efforts to gather field calibration data, we are positioned to produce region-wide estimates of shrub structure in the near term. Moreover, with the addition of historical lidar data (e.g., 2004 in Alaska's Kenai peninsula) we can work to scale multitemporal studies of shrub change (e.g., Dial et al., 2007; Dial et al., 2016) across more meaningful spatial extents.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rse.2020.111841>.

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