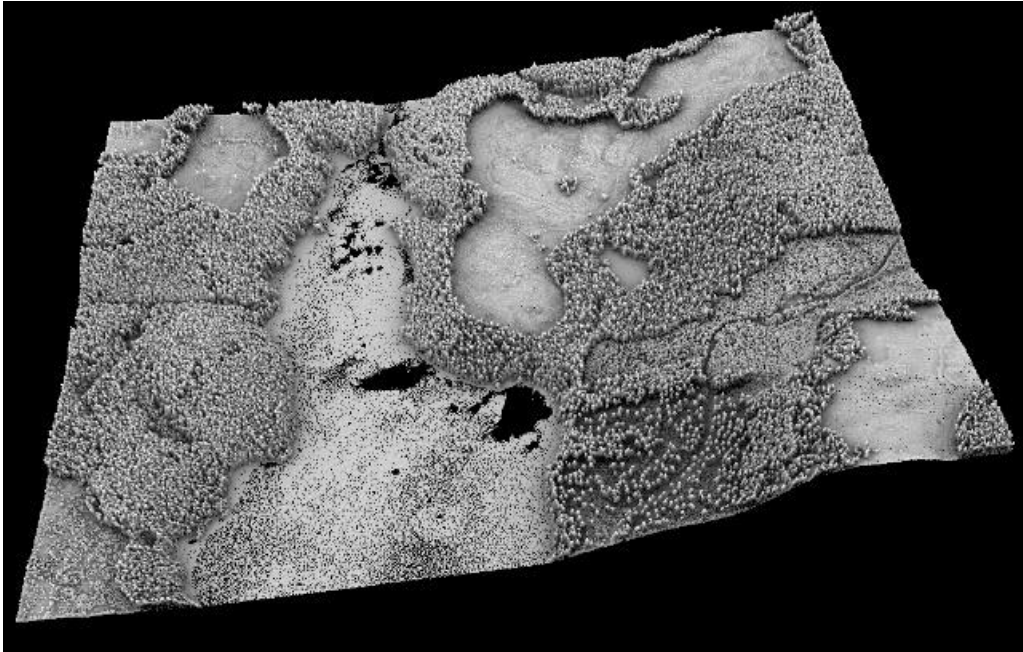
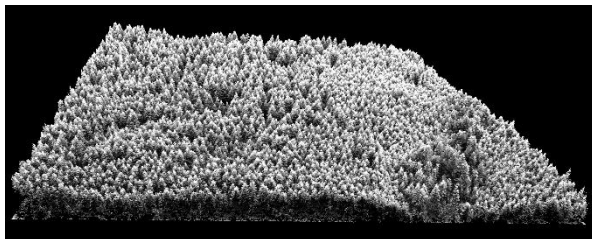
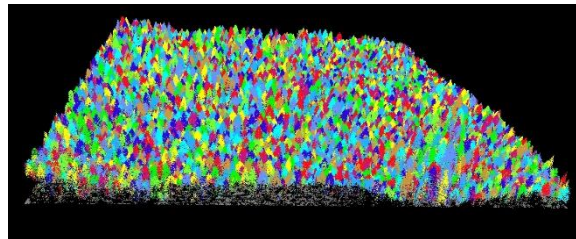


Exploring the use of full-feature Lidar data to inform Northern Goshawk habitat modeling



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Report prepared by: Matthew Wheatley, PhD., P.Biol., Solstice Environmental Management
(Edmonton, AB)
Todd Manning, MAsC, RPBio., RPF, Strategic Resource Solutions (Victoria, BC)

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Background and Introduction

The 3D structure of ecosystems has long been understood to have profound effects on animal communities (Davies and Anser 2014). As early as 1935, the vertical structure of vegetation was recognised as an important factor for bird assemblages (Dunlavy 1935), with the first attempts to quantify vertical-foliage density “drawn by eye” in 1961 (MacArthur and MacArthur 1961). These studies were based on the foliage height diversity (FHD) hypothesis (MacArthur and MacArthur 1961) which submits that avian diversity is positively associated with the vertical distribution of foliage among the forest vegetation layers. Although initial attempts were entirely analog and “by hand,” this early work demonstrated that avian diversity could be determined almost solely by vegetation structure, with plant species only becoming important when it influenced this structure (e.g., conifer versus deciduous). Accordingly, vertical structure has been found key in predicting species distributions and abundance (Muller et al. 2014, Flaspohler et al. 2010, Palminteri et al. 2012, Gouveia et al. 2014), animal behaviour (Loarie et al. 2013) and patterns of predation risk (Tambling et al. 2013, Lone et al. 2014).

Data to effectively address the FDH hypothesis for birds has until somewhat recently been restricted in spatial extent and accuracy, primarily because of the time and effort required for field crews to acquire accurate vertical-structure data from traditional field plots; vertical-structure data are exceedingly difficult to acquire particularly in dense vegetation. Light detection and ranging (or “lidar”) data, however, enables researchers to begin objectively and accurately quantifying vertical vegetation structure by removing observer subjectivity (especially in subjective percent-forest cover assessments) and by sampling the whole forest, removing the need to extrapolate relatively small or isolated veg-plot metrics across entire forests (Zellweger et al. 2013). As such, more recently there has been a growing body of literature examining the application of lidar-derived variables of forest structure to explain species-habitat relationships (Bradbury et al. 2005, Vierling et al. 2008).

Accordingly, lidar-derived vertical-structure measurements of forest elements have been found important in explaining the multi-year prevalence songbirds (Goetz et al. 2010), songbird diversity and richness (Goetz et al. 2007, Lesak et al. 2011, Clawges et al. 2008), and species distributions and habitat suitability (Hill et al. 2004; Seavy et al. 2009, Swatantran et al. 2012). Although 3D lidar-based data have been used somewhat extensively to examine geomorphology (Fonstad et al. 2013, Lucieer et al. 2014; Westoby et al. 2012), forestry (Dandois and Ellis 2013, Getzin et al. 2014; Mlambo et al. 2017, Zahawi et al. 2015) and vegetation classification (Dandois et al. 2017; Husson et al. 2017), these efforts have not yet been broadly translated to wildlife ecology (Osloy et al 2018), specifically for larger landscape-scale areas. Previous syntheses (e.g., Bradbury et al. 2005, Vierling et al. 2008, Hill 2014, Muller and Vierling 2014, Merrick et al. 2013) have focussed largely on lidar-based technology and its potential application to ecology (Hill 2014, Muller and Vierling 2014).

To assess the state of this science, Vogeler and Cohen (2016) conducted a keyword search within the Web of Science database using the phrases “lidar AND habitat AND forest” and “radar AND habitat AND forest.” They identified approximately 54 studies that incorporated lidar data in their examination of forest wildlife habitat or diversity measures, specifically to characterize forest for habitat modeling and/or mapping purposes. The majority of reviewed lidar studies characterized forest habitat through primary metrics that were either from, or comparable to, those available through the frequently used FUSION lidar processing software (McGaughey 2009). These included (but were not limited to) raster binned summary statistics at multiple spatial scales of: canopy height and densities; percentiles of heights; and

the density of lidar returns within specific height strata. Within these studies (many with a particular focus on the architecture of the understory stratum), many have found great promise in the ability of lidar to represent foliage height diversity in an ecologically meaningful way for multiple wildlife species as well as allowing for the mapping of this metric across whole landscapes (Clawges et al. 2008). In addition to diversity in foliage heights, some wildlife species respond to specific vertical foliage layers which lidar is able to quantify (Vogeler and Cohen 2016). For instance, Vogeler et al. (2013) found the upper canopy as represented by lidar, to be the driving factor in the occupancy of a late-seral specialist, the brown creeper (*Certhia americana*). The continuous nature of lidar data as opposed to field-sampled vegetation data also allows for extraction of landscape metrics in studies examining relationships at larger habitat-selection scales (Nelson et al. 2005). Even with just an emergent body of literature exploring lidar in the wildlife sciences, there is already a need to move the science beyond verification of the remote sensing method to its application across a range of habitats, animal communities, and ecological questions, using it to further unravel observed relations between animals and ecosystem structure.

Analyses of raptor habitat use have previously been limited by coarse-resolution habitat data that categorizes vegetation into broad categories based on tree-species composition, age or size classes, and canopy-cover classes, precluding opportunities to describe finer-resolution habitat use patterns at the patch-scale (Kramer et al. 2016). For example, in recovery efforts for northern spotted owls in the Pacific Northwest, high ($\geq 70\%$) levels of canopy cover within both owl territories and their core use areas have been associated with greater owl occupancy and survival (Tempel et al. 2014, Tempel et al. 2015), and higher reproduction at nest sites (North et al. 2000); and accordingly, high canopy cover is commonly used to identify potential habitat areas and determine management options. Yet, canopy cover can be a difficult management metric because estimates significantly vary depending on how many measurements are taken, the observer's viewing angle (i.e., closure vs. cover *sensu* Jennings et al. (1999)) and whether estimates are derived from direct field measurements (e.g., spherical densiometer or 'moosehorn'), indirect interpretation (i.e., using aerial photographs or Landsat imagery) or modeled from non-spatial plot data (Fiala et al. 2006, Korhonen et al. 2006, Christopher and Goodburn 2008, Paletto and Tosi 2009). Field plots are used to record tree size and foliage characteristics, but sample size is often small, which makes it difficult to extrapolate across the large, diverse forest conditions used by owls and many other raptors. In this sense, lidar can be a powerful tool for raptor research because it captures variation across the habitat-resolution spectrum these animals are known to respond within, from nest-site forest gaps to broad stand-level forest cover types, which emerging raptor research is beginning to demonstrate using lidar.

For example, North et al. (2017) used lidar to advance beyond coarse stand-level forest metrics and found that the specific within-stand height of canopy cover was important for spotted owls, and the retention and promotion of individual large trees and the cover they provide may more directly benefit owl habitat than high levels of total stand-level cover; forest variables that historically were left confounded together within stand-level data resolutions. Furthermore, using a height-stratified lidar analysis, they found that cover in the 2–16 m height strata was less near nests and within owl territories than the surrounding landscape, suggesting owls avoid excessive overstory complexity. Previous spotted owl research has been unable to decouple canopy cover from individual-tree characteristics, nor investigate specific height strata (Call et al. 1992, Verner et al. 1992, North et al. 2000, Tempel et al. 2014, Tempel et al. 2016). Similarly, Gallagher et al. (2019) hypothesized that spotted owls would forage in areas with higher canopy cover and a mosaic of small gaps, where small-mammal abundance at early

seral forest edges is combined with increased protection and movement offered by mature forest; both variables that were beyond the resolution of traditional forest inventories. They found the proportion of gaps within a stand was the most important vegetation covariate predicting owl habitat use, demonstrating how higher-resolution forest-structure data can not only augment known habitat relationships, but in some instances replace them with stronger independent variables.

In this project we are taking a similar approach for coastal Northern Goshawk (*Accipiter gentilis laingi*) habitat modeling, examining whether existing lidar data collected on Vancouver Island can effectively generate reliable high-resolution forest-structure data that could either refine existing goshawk habitat models, or potentially augment or replace some independent variables with more robust ones, such as crown canopy closure or indices of subcanopy structure. In doing so and at this time, we are only taking an exploratory approach to see whether meaningful forest-structure variables can be generated from full-feature lidar with sufficient computational efficiency to inform habitat modeling over larger landscape scales. To our knowledge, there are no studies that have published results linking lidar-derived habitat variables to goshawk ecology. Although we compare known goshawk nest sites with lidar-derived forest data, the analytics performed here are largely qualitative and visual and we have not attempted any empirical predictive modeling. Our primary objective is to assess whether lidar can be effectively used as a tool to improve the quality and type of data used in goshawk habitat modelling in coastal BC and determining which forest metrics generated by lidar hold the most promise in this context. Additional questions such as optimum scale for lidar data acquisition, processing and application, and complementary use of other remote sensing technologies (e.g., satellite) are also discussed.

Current Goshawk Predictive Model

The current coastal Northern Goshawk habitat model is based on a suitability-index approach for nesting habitat and foraging habitat and consists of a combination of habitat variables thought or known to be important to goshawk ecology (

Table 1). In the development of these models, a list of habitat variables commonly associated with goshawk ecology was generated, but not all these variables were included in the final models, mostly because not all of them could not be reliably generated from existing forest-inventory data. Notable examples of variables thought to be important but not included in the current model include canopy closure, number of stems, and subcanopy closure or flyways in the mid-canopy stratum. The exclusion of these important variables is a primary rationale for this current project; because many of these can be quantified using full-feature lidar it becomes important to know whether they can be efficiently calculated to improve the current habitat models.

Table 1. From Mahon et al. (2015; Table 2 therein), a summary of habitat variables commonly associated with goshawk habitat from published literature and regional studies, with an indication of whether they were included in the final models. *Text below highlighted in bold was inserted by this project, and indicates gaps in these variables that can be filled using lidar data.*

Habitat Variable	Included in Model?	Comments
Stand Age	Yes	Frequently used to assess structural maturity of a stand.
Stand Height	Yes	Frequently used to assess structural maturity of a stand. (Lidar can determine sub-stand or within-stand heights and spatial relationships)
Forest Composition	Yes	Suitability of branching platforms for nests and subcanopy flyways are related to the form of different tree species. Subcanopy flyways can be determined from lidar using height-stratified compositional analysis of forest structure.
Canopy Closure	No	Mid-high canopy closures were consistently identified as a common characteristic of used nesting habitat (relates to subcanopy flyways), but this variable was often not available or inaccurate in many forest cover databases. Lidar can generate canopy cover at a sub-stand resolution removing the observer bias in its estimation.
Average Stand Diameter/ No. Large Trees	No	These two variables were commonly associated with goshawk nesting studies in the USA. Not available in FC database; correlated to height. and age. Lidar data can determine stem density and tree-crown morphologies with sub-meter resolution.
Distance from Forest Edge	Yes	Data from Coastal BC show strong avoidance of edges for nest sites. Lidar can be used to assess edge hardness and morphology.
Patch Size	No	Issue more appropriately captured by edge.
Slope	Yes	Nest sites often on low-moderate slopes. Local data indicate no nests on slopes >60%. Lidar-derived digital elevation models (DEMs) can produce elevation and slope surfaces at 1-m accuracy.
Aspect	No	Identified as a significant variable in dry SW USA. No selection noted in any study in BC.
Elevation	Yes	Local data indicates avoidance of higher elevations.
Mesoslope Position	No	Weak selection noted in a couple of studies but no consistent relationship; no relationship in BC studies. Effect observed likely related to slope.
Site Index	No	Considered as a local variable. No nests in poorest or richest sites, but forest composition and height more directly capture structure.
Distance to Water	No	Significant variable only in dry SW USA; no relationship in BC studies. Water sources not likely limiting in Coastal BC.
Biogeoclimatic Variant	Yes	Apparent avoidance of the higher elevation Mountain Hemlock and hypermaritime Coastal Western Hemlock zone; none of the ca.165 nest areas occur in these variants.

Importantly, and regarding the application of these models, Mahon et al. (2015) clarified that the model resolution is 100 m² and indicated that:

Outputs from this model should generally be restricted to large-scale strategic purposes. This is primarily due to the relatively poor stand level accuracy of some of the forest cover data. In addition, some variables that are known to affect goshawk habitat suitability (notably canopy closure), and which we recommend should be included in models used for stand-level purposes, such as operational management, could not be included in these models because they were not available in all forest cover databases across the study area. (Mahon et al. 2015, pg. 2).

With these limitations in mind, our objectives were to explore the use of lidar data in efficiently generating the forest-structure variables that would enable the effective delineation of good versus poor goshawk habitat (e.g., Figure 1), much of which ostensibly requires the defensible high-resolution measurement of forest canopy and its associated understory structure. Specifically, we investigated the ability of existing lidar data to calculate high-resolution metrics for stem density, stand height, subcanopy flyways, crown closure, elevation, slope, forest edge, and ground cover.



Figure 1. From Mahon et al. (2015; Figures 2 and 3 therein), examples of good goshawk habitat (left) and relative to poor habitat (right), with notable differences in the forest structure particularly in the height of the canopy cover and complexity (openness, closedness) of the sub-canopy forest structure.

Methods and Results

Field sampling

When exploring the generation of novel lidar-based forest metrics, it becomes useful to have a set of field-plot data from which to compare measurements. We completed this using existing field-plot data from government sources (Jeff Shatford, BC Min. FLNRORD, pers. comm.) collected during habitat assessments of goshawk territories on Vancouver Island. We specifically selected lidar data that covered the areas where these field-plot vegetation data were available.

Ministry field data were collected in fixed-area plots (500m² = 1/20th ha) with a radius of 12.6 meters. Within these plots, all trees > 2 cm diameter at breast height (DBH) were recorded. Each live tree was

counted within the plot, and the height for all trees was estimated from equations developed for coastal forests using DBH (Staudhammer and Lemay 2000). A subset of live trees from each canopy class were measured for top height and height to live crown using the Haglof vertex or Electronic Clinometer. Understory seedlings and sapling (< 2cm DBH) were tallied for the plot, and if hyper-abundant, an estimate was derived by subsampling the plot (e.g. tallied in $\frac{1}{2}$ or $\frac{1}{4}$ the full plot). To compare field-plot data to the lidar-derived metrics, we used the UTM coordinates recorded for the field-plot center and buffered these by 12.6 m, within which we calculated the same metrics from the lidar data. Effectively, the field plots we compared were using lidar derived from the same location, plus or minus any associated GPS error (typically < 3 m).

Lidar Data

All lidar data for this project were acquired directly from BCTS who have archived lidar coverage of their management areas consisting of lidar data from different service providers. When BCTS tenders their data-acquisition projects, they request between 50% and 70% flight-swath overlap with minimum point density targets of $1/\text{m}^2$ for ground returns, and a minimum of $7/\text{m}^2$ for non-ground returns. Because the data come from multiple providers, the file sizes and formats were slightly different between the study areas that we examined; however, we found above-ground point densities to range from 15 to upwards of $30 \text{ points}/\text{m}^2$ (and over $40/\text{m}^2$ where flight swaths overlapped). All files were acquired in LAS format uncorrected for elevation, outliers, or terrain, and contained XYZ coordinates, intensity, scan angle, and GPS time. To explore these data, we used a combination of ArcGIS 3D and Spatial Analysts with LAStools, Fusion (McGaughey 2009), QGIS, and Lidar360 software. Details for methods are included below in each lidar-metric section. We focused our analyses on three study areas that contained both known goshawk nests and associated vegetation data from recent field-plot sampling; we term these study areas Sayward, Rosewall, and Sutton Pass (Figure 2), the former two being managed second growth commercial forests, and the latter one being an old-growth forest.

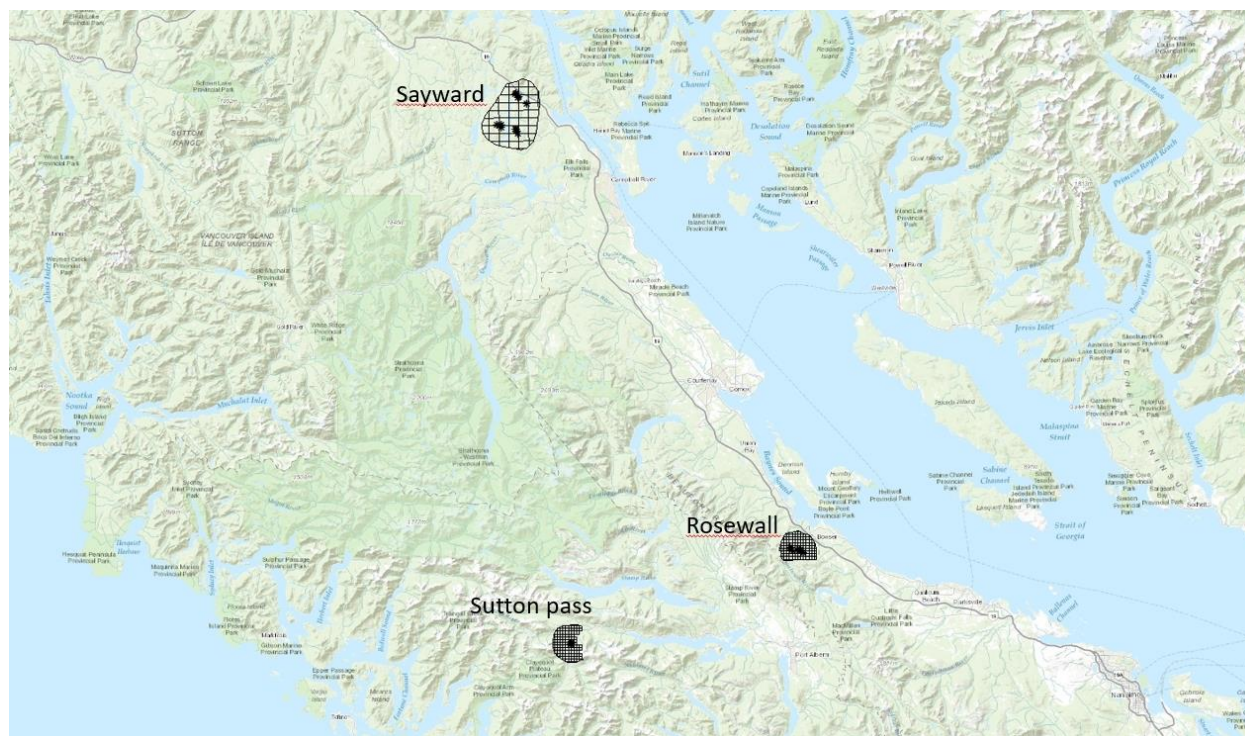


Figure 2. Three study areas on Vancouver Island examined with Lidar data in this project.

Below is an investigation of various forest-structure metrics that we derived from the lidar data and that are relevant to goshawk ecology. We chose these based on

Table 1 above, focusing on metrics that are currently absent but important to the current goshawk predictive habitat models, as well as metrics that are included in the current models but which can be improved in terms of spatial resolution (i.e., below 100 m²). Specifically, these include stand stem density, stand height, subcanopy flyways, crown closure, elevation, slope, forest edge, and shrub ground cover.

Lidar Metrics

Lidar Data Quality

Many lidar-data quality issues are typically dealt with and reported by the data provider. Beyond this, however, it is important to explore the point-cloud files for outliers; a common step in the creation of surface DEMs and normalized point-cloud files (i.e., correcting for terrain). Within the context of species-habitat modeling, however, many lidar derivatives rely on point-density measurements, so it becomes important to scan the delivered lidar data to determine whether the sampling effort is relatively uniform across a study area. We did this using a density-quality scan for the Sutton Pass, Rosewall and Sayward study areas. These scans were comprised of a visual inspection of point-cloud density for each study area. From these we found uniform point-cloud data in Sutton Pass and Rosewall, but considerable density patterning in Sayward (Figure 3); patterning indicative of uncorrected flight-line overlap. Overlap is where any point in one flight-line or swath is within the boundary of another flight-line. Whether or not points overlap is typically determined at the time of flight by the operator. If this has not been done, and if the data have been delivered without flight-line, scan angle, and GPS timing information, for most GIS users overlap is an immutable characteristic that will affect any wildlife-habitat forest-structure derivatives calculated from subsequent analyses. Somewhat advanced sampling methods do exist to extract or identify overlap using GPS timing (Figure 4), but these techniques are beyond the majority of users, particularly when dealing with time gradients versus discrete flight-line identifiers.

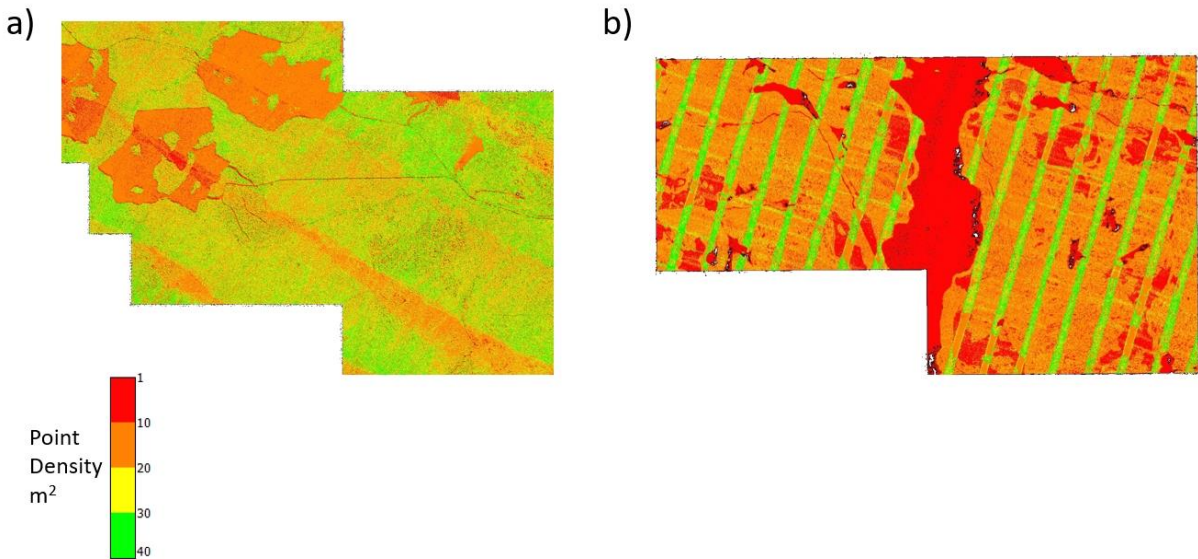


Figure 3. Lidar point density per square meter for (a) the Rosewall study area versus (b) the Sayward study area. Note the more uniform point density in Rosewall versus the flight-line overlap patterning in Sayward. If not corrected *a priori*, any forest metrics derived from point densities acquired from overlap data can be misleading.

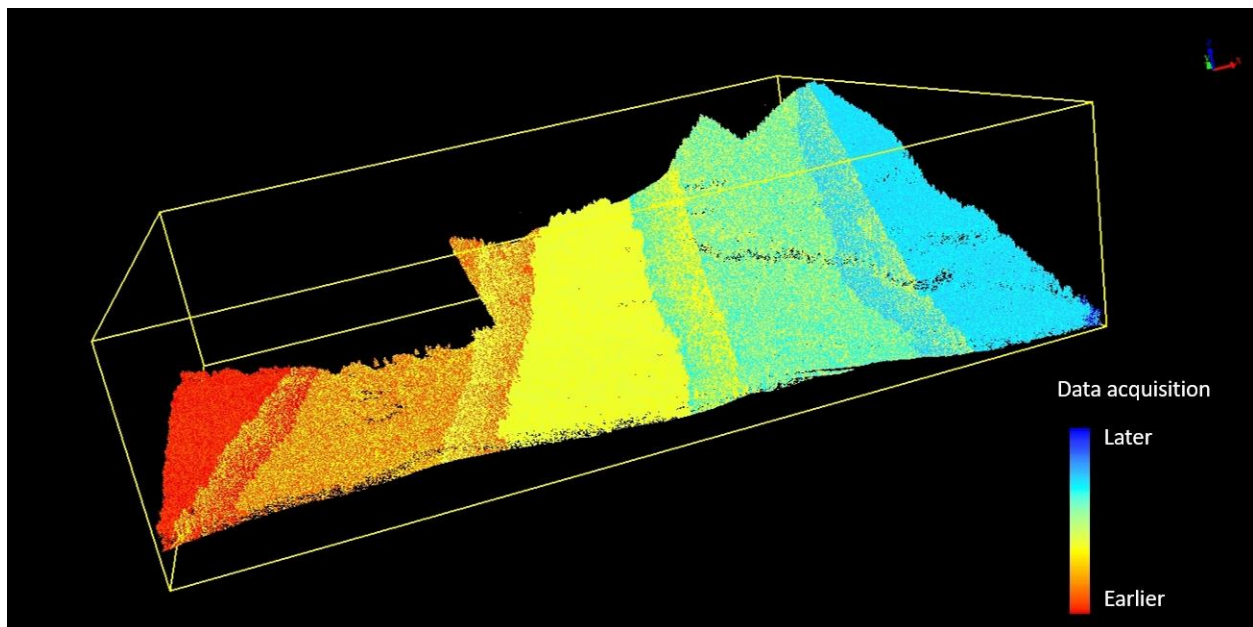


Figure 4. Tile 3411 from the Sayward Forest indicating GPS time stamps for data acquisition. These can be used to correct for data overlap and correct point-cloud densities if flight-line data are not available.

Stem Density

To determine stem densities, we used point-cloud segmentation. There are numerous methods proposed to delineate individual trees using point-cloud segmentation. For example, Popescu and Wynne (2004) used a local-maximum filtering technique to locate and measure individual trees. Tiede et al. (2005) used a similar local maximum algorithm to identify tree tops and then developed a “growing algorithm” to delineate tree crowns, effectively clustering point clouds based on user-defined inputs.

We employed a point-cloud segmentation algorithm described by Li et al. (2012) to locate the local maximum of point clusters based on a user-defined tree spacing characteristic approximating forest structure. Users interested in replicating these methods are referred to the detailed methods in Li et al. (2012) and TerraSolid’s TerraScan (<http://terrasolid.fi>) software. The algorithm first locates the highest point and uses this as the seed point of the first segmented tree. It then locates the next tree’s seed point by identifying points that are farther away than the user-defined spacing distance; at lower elevations it allows for sub-canopy trees to be clustered as independent trees where canopy-tree structure thins and subcanopy trees can be clustered (unlike methods based upon canopy height models). Points that are equidistant to two trees define the boundary point between stems. With this technique, the spacing threshold is important and should be set to approximate the crown radius of a typical tree. When the spacing threshold is too large or too small, under-segmentation or over-segmentation may occur. To explore the data in this project, we used a tree spacing of 2 m (crown radius). Other inter-tree spacings can be explored.

This segmentation routine first removes any outliers in the point cloud data, then uses a digital elevation model to correct and normalize the data to reflect height above ground and to remove variability associated with terrain. Using a digital surface model and the user-defined tree-spacing threshold, a subset of individual points are identified as treetops, and then all associated points are clustered around each of these and segmented into individual trees. The output of this process is a point layer identifying individual tree locations, and a point-cloud layer with all points identified by individual tree ID. Associated information from this technique also includes crown diameter, crown volume, and stem height for each identified tree (

Figure 5).

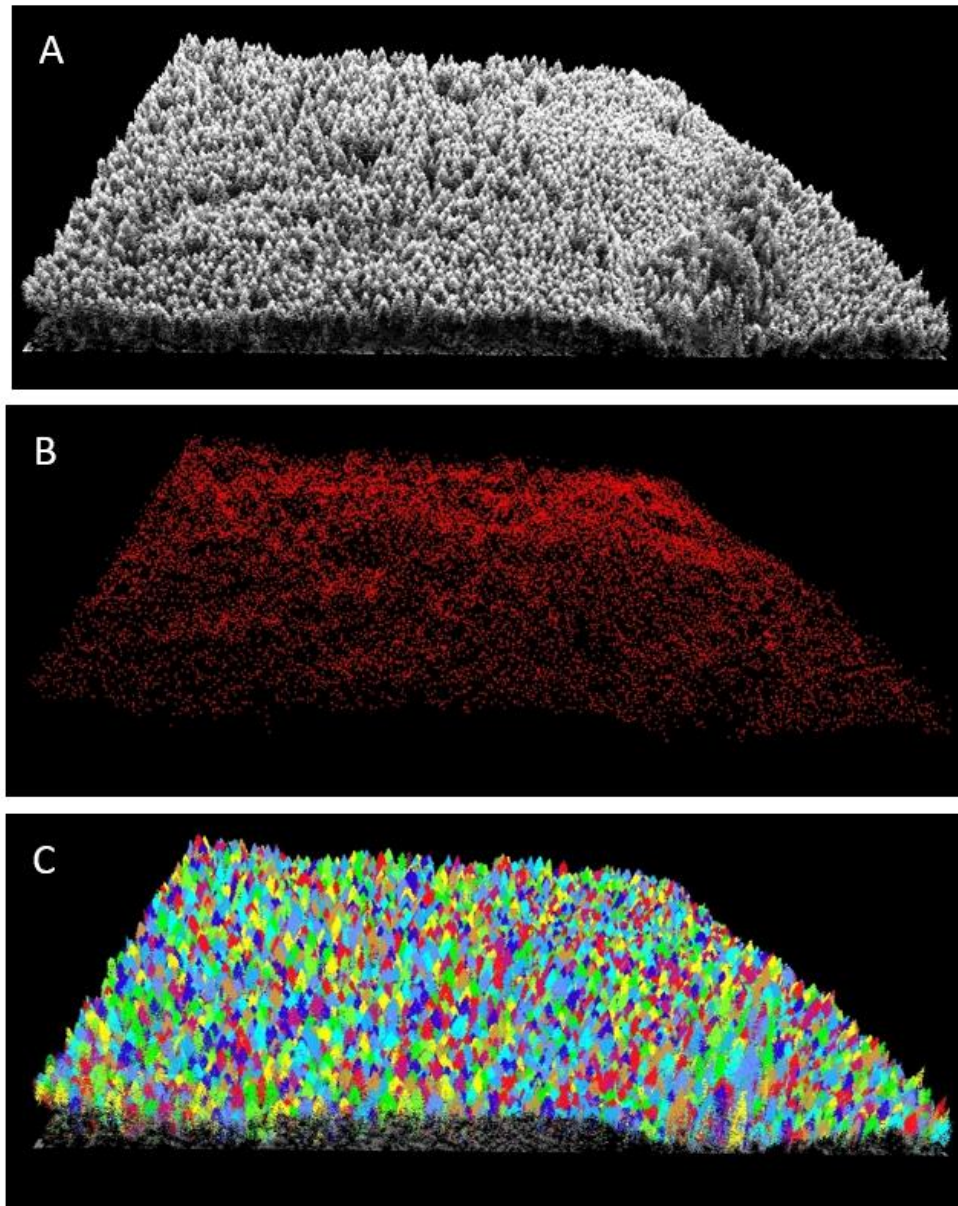


Figure 5. Example imagery showing the workflow for stem density (for Rosewall Lidar tile ADE343). A) point-cloud adjusted for heights to a normalized elevation model; (B) Tree-tops identified by local height maximums spaced out by a user-defined tree spacing threshold; and, (C) point clouds clustered into individual trees, here displayed using random colors for each individual tree.

Within our sub-set of data, we had comparable lidar and field-plot data for 26 stations. Stem-density information was generated for each of these stations and we then compared the average differences between field plots and lidar segmentation. In comparison to the field-plot data, our point-cloud segmentation quantified on average 8.6 less stems than what was counted in the field plots (

Table 2, note that the median difference was only 1.0 stems less). In terms of a data comparison, this average difference should not be surprising, particularly since the field-sampling program was designed to quantify all stems and associated structure within a plot and was not tailored specifically to the potential limitations of airborne lidar reaching the lower elevations of the understory, which is the primary visual domain of the field sampler. Given the common understory complexity found in most forest stands used in this project, where younger sapling trees could be occluded from lidar by taller trees, or where understory structure is particularly dense (e.g., Figure 6) and better sampled by observers completing vegetation plots than by lidar, an underestimation of stem density by lidar should be expected. This underestimation is simply a limitation of the lidar physically not reaching the ground and thus the clustering algorithm not segmenting sapling-sized trees, but instead clustering them with adjacent more mature trees.

Whether this underestimation is biologically relevant and represents a meaningful limitation for goshawk data interpretation would require further study (see “Shrub Cover” below). It should be noted that the variability in plot differences had a notable range. Some plots were relatively close in total stems and thus had negligible differences between plot and lidar data; however, 8 of the 26 plots had differences above 15 stems, some upwards of 66 stems. However, it may be that the larger differences represent plots which had a higher density of smaller stems that were tallied, and thus could be accounted for using multi-height segmentation (i.e., separate segmentation of near-ground versus taller point clouds).

Table 2. Comparison between tree stems counted by lidar segmentation versus those quantified in the same location by field-plot sampling.

Station	Lidar Number of Trees	Field Number of Trees	Difference
CC_UT1	40	50	-10
CC_UT2	31	97	-66
CC1	32	19	13
CC2	32	27	5
CC3	30	36	-6
CC4	23	28	-5
CC5	38	33	5
CC6	24	15	9
CC7	32	57	-25
CC8	30	45	-15
Cook Creek 2016 nest	37	68	-31
S2	27	26	1
Stn 23	33	80	-47
Stn 25	16	12	4
Stn 26	32	12	20
Stn 3	43	24	19
Stn 41	21	22	-1
Stn 42	31	45	-14
Stn 50	36	29	7
Stn 51	37	30	7
Stn 52	30	21	9
Stn 53	29	31	-2
Stn 54	29	29	0
Stn 55	37	97	-60
Stn 56	25	66	-41
Sutton (S1)	30	31	-1
AVERAGE	30.96	39.62	-8.6±23* Median -1.0

*Lidar measurements, on average, count 8.6 less trees than field-plot measurements.



Figure 6. Goshawk habitat sampling on Vancouver Island in a forest with abundant near-ground shrub and sapling structure that could create significant differences between what field-based observers would count for total stems versus what lidar and subsequent segmentation algorithms might quantify (photo: J. Shatford).

Stand Height

To determine stand height, we used two approaches. First, we used point-cloud segmentation as described above for Stem Density (i.e., Li et al. 2012). As noted above, this method also derives individual tree heights for each identified stem. When averaged, these stem heights provide a relatively detailed quantification of stand height, accounting for both overstory and understory heights.

The resulting output of this analysis allows the user to quantify a substantial amount of detail within an individual stand; this is information that is well below the resolution of a VRI polygon (Figure 7). This detail includes not only the average height of any given area within an individual VRI polygon, but it also offers the quantification of spatial structure with respect to tree heights and their relative spatial organization. For example, understanding whether an individual stand is homogeneous versus heterogeneous with respect to tree heights (or even crown volumes and diameters) is an arguably powerful advancement with respect to goshawk habitat information.

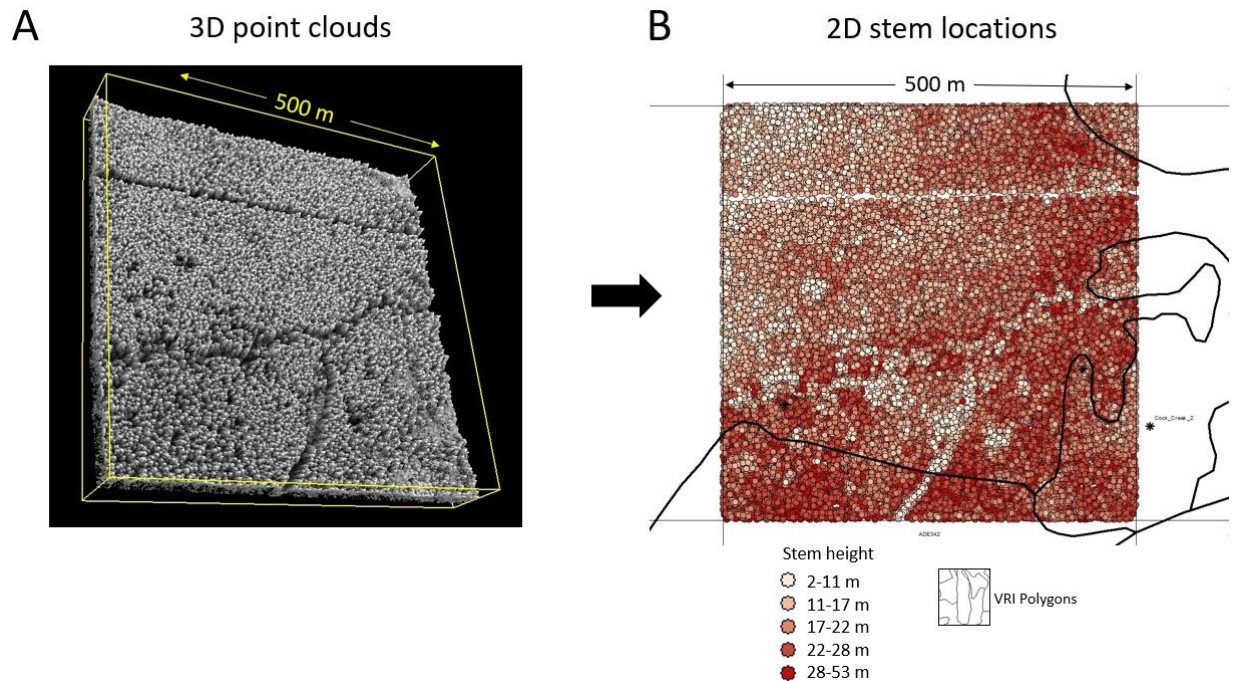


Figure 7. Conversion of 3D point clouds (panel A; Rosewall lidar tile ADF342) into individual-stem locations with associated heights (panel B) using point-cloud segmentation. Resulting data can provide high-resolution spatial information on tree heights within a single VRI polygon, enabling the analyst to quantify not only average heights but also their spatial properties, like whether they are randomly spaced or clustered in some biologically relevant way. Note in panel B, the spatial arrangement of taller versus shorter trees and the identification of trails or old roads (potentially serving as flyways), all within a single VRI polygon.

In our field plot data, there were 25 field plot stations with information to compare to lidar data for tree height. On average, lidar measurements quantified tree heights approximately 2.5 m lower than those measured in field plots (Table 3). Unlike the data for stem densities described previously, the range of differences were lower between field plot data and lidar. Average differences ranged from close to zero, to upwards of 11 meters in height. Again, whether these differences are biologically relevant is a question for further study. It could be argued that information acquired from lidar is more accurate in terms of correcting for site-specific terrain variation when calculating or measuring an individual tree height. This is especially cogent in relatively rugged west-coast forests where it may be sufficiently challenging for field observers to accurately measure tree heights, as many tree-tops (and bottoms) can be occluded from view either by thick over or understory structure. Further, the average tree height from lidar is derived from the entire surrounding landscape rather than just from a sub-sample within a vegetation plot circle. In this sense, there are strong arguments that lidar tree height data are more accurate and reliable.

Table 3. Comparison between tree heights measured by lidar segmentation versus those quantified in the same location by field-plot sampling.

Row Labels	Lidar Average Tree Height (m)	Field Average Tree Height (m)	Difference (m)
CC_UT1	29.76	32.25	-2.49
CC_UT2	33.05		
CC1	25.66	33.20	-7.54
CC2	33.21	34.80	-1.59
CC3	32.72	40.52	-7.80
CC4	37.57	28.30	9.27
CC5	35.35	31.44	3.91
CC6	26.87	31.75	-4.88
CC7	21.89	32.88	-10.99
CC8	25.50	31.98	-6.47
Cook Creek 2016 nest	27.02	22.87	4.15
S2	30.33	38.20	-7.87
Stn 23	28.78	29.56	-0.78
Stn 25	35.73	40.73	-4.99
Stn 26	36.54	42.60	-6.06
Stn 3	27.91	26.03	1.87
Stn 41	34.82	32.26	2.56
Stn 42	33.41	39.03	-5.62
Stn 50	26.88	29.72	-2.83
Stn 51	32.39	34.30	-1.91
Stn 52	30.34	35.18	-4.84
Stn 53	30.62	31.91	-1.30
Stn 54	31.68	34.30	-2.62
Stn 55	28.12	27.39	0.72
Stn 56	28.99	29.69	-0.69
Sutton (S1)	30.85	34.25	-3.40
TOTAL AVERAGE (m)	30.62	33.01	-2.49 ±4.5* Median -2.6

*Lidar measurements are, on average, 2.5 m lower than field-plot measurements.

The second method we used to determine stand height is based on the segmentation of a canopy height model (CHM). This is different from the point-cloud segmentation described above in that the CHM method first calculates a surface-elevation model of the tree canopy, which is a relatively detailed description of the canopy-top texture; it is analogous to a terrain model but one that includes all associated vegetation structure. The CHM segmentation (described by Chen et al. 2006) uses a “hydrological surface-watershed” modeling approach, whereby the CHM is inverted in 3D space then, from the lowest point, each inverted tree is “flooded” and where the different water sources meet,

boundaries are drawn separating individual trees. Most contemporary GIS platforms come with terrain analyses modules capable of delineating watershed boundaries and flow characteristics of terrain models (e.g., ESRI's watershed Tool in Spatial Analyst, or QGIS's Hydrological Analysis Catchment Area tool). From these "tree watershed boundaries" with different individual tree metrics are generated, including tree location, tree height, crown diameter, crown area, and tree-canopy boundaries. Comparable methods have been derived by Koch et al. (2006) who delineated tree crowns with a combination of a pouring algorithm, knowledge-based assumptions on the shape of trees, and a final detection of the crown edges. Similarly, Korpela et al. (2007) used a multi-scale template matching approach for tree detection and measurement using elliptical and other shaped templates to represent tree models. Sovern et al. (2019) used a similar approach to measure forest canopy cover in Northern Spotted Owl activity centers; they found that using lidar can provide "...an accurate direct measurement of entire stands and larger areas, whereas ground plots need to be extrapolated or correlated with other remote-sensed data". The CHM segmentation approach is appealing because it creates an intuitive vector-based canopy layer (i.e., a shapefile of tree-top polygons coded by height, volume, and diameter); however, this method can still underestimate stem densities depending on the forest type and its associated understory structure. Within relatively complex forests, understory stems will be included as part of taller, more mature trees; whereas the point-cloud method described earlier would segment these younger stems more often than clustering them into taller trees.

The derivative of output of the CHM method is a relatively detailed polygon layer of the dominant trees in the canopy (Figure 8). Consequently, any average-stand height metrics calculated from this output would overestimate the general stem height in the stand because many of the understory-structure trees would be clustered into the larger more mature stems. As such, this method may not give the desired stand-height metrics required in some instances, but this information is still important and biologically relevant to goshawks. Although we did not quantify anything from these data here (primarily because we do not have comparable field plot data), we would submit that this type of information layer might be analytically relevant for goshawk habitat modeling. Specifically, it splits any VRI polygon into its constituent parts, and although this layer focuses only on the dominant tree canopy, it may be a relevant way to derive higher-resolution information for VRI polygons. Similar to the stem-density data described above, the CHM-segmentation output enables the quantification of the spatial heterogeneity of tree morphology within any given VRI polygon. This spatial distribution may be important in describing variation in goshawk habitat selection, particularly for foraging habitat where stem density and related understory composition likely influence habitat suitability for goshawk prey species.

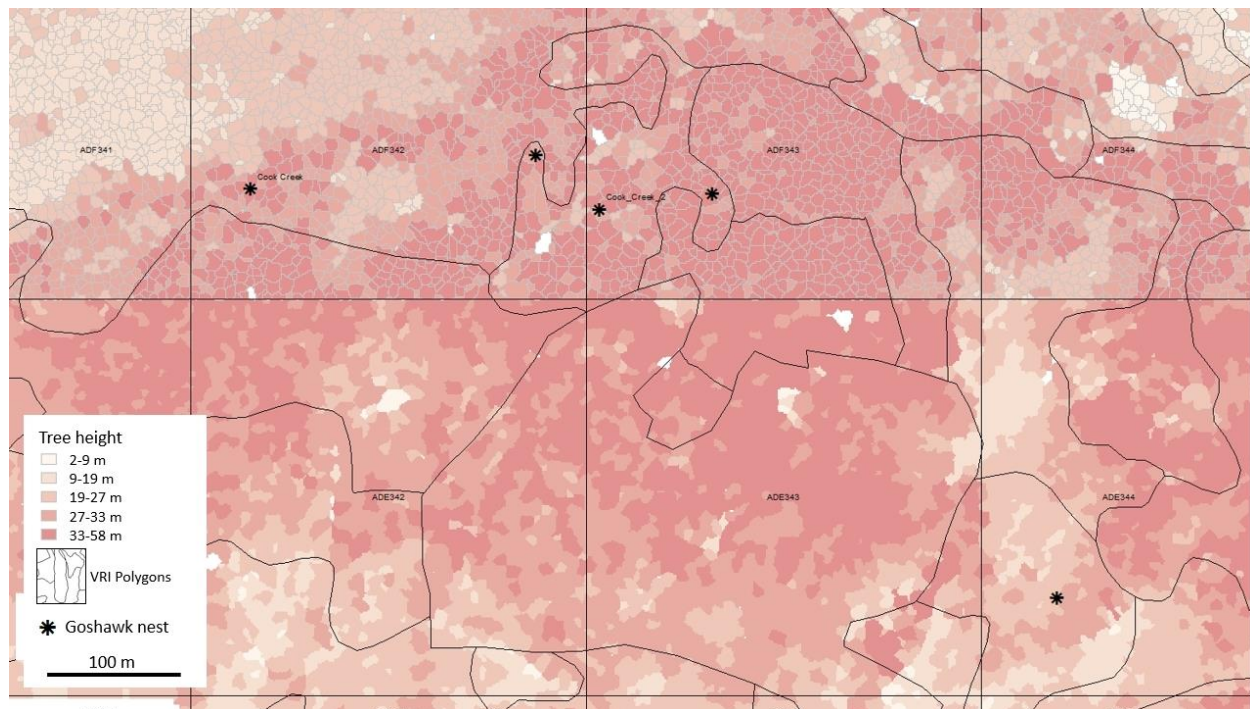


Figure 8. Canopy height model tree segmentation indicating lidar-based canopy-tree polygons and associated heights, depicting both height and spatial heterogeneity within any given VRI polygon.

Subcanopy flyways (lower and middle understory structure)

Methods for lidar-derived height to live crown (HTLC) estimation are either regression-based (Holmgren and Persson 2004, Solberg et al. 2006) or are estimations based directly from point-cloud data (Popescu and Zhao 2008, Vauhkonen 2010). The regression-based methods require a relationship between field-measured HTLC and LiDAR data, linking (for example) tree height and crown width (Popescu and Zhao 2008, Holmgren and Persson 2004, Solberg et al. 2006); HTLC is then predicted based on regression relationships in areas without field measurements. The accuracy of regression-based methods relies entirely on field-plot data quality (Vauhkonen 2010, Kelly et al. 2017). In contrast, direct methods estimate HTLC directly from the lidar point-cloud data without the requirement of field measurements (Popescu and Zhao 2008, Vauhkonen 2010). For example, Popescu and Zhao (2008) generated vertical-forest profiles based on the density and intensity of voxelized lidar points for each tree, and then calculated HTLC as an inflection point of the polynomial curve fitted from the vertical profiles, and Vauhkonen (2010) presented a 3D geometry-based algorithm to estimate the HTLC for scots pine trees (*Pinus sylvestris*). Similar methods have examined the histogram profile of vertically stratified point-cloud densities, using spline analyses or k-means clustering to identify inflection points of point densities indicating the height where tree crown begins (e.g., Mund et al. 2015). Although these methods show promise in extracting HTLC directly from lidar data without the need for field sampling, they can only be applied to limited species in relatively simple-structured forests (e.g., agricultural trees or monocultures) because of the high computational costs associated with the complex procedures of generating vertical profiles or reconstructing the 3D convex of individual trees. Such methods also exclude most GIS users when applying them over relevant spatial extents. Therefore, it is necessary and important to develop

new methods which are simple and computationally efficient, and can be applied defensibly in more complex or rugged terrain. Moreover, given the computational and analytical requirements to complete these more complex methods, it becomes important to ask whether such measurements would be more easily captured by a similar and correlated metric that can be extracted from point-cloud data. For this project, we explored the use of “subcanopy gaps” to achieve a more intuitive and computationally efficient metric in order to quantify understory vegetation structure.

Subcanopy gaps

Exploring forest structure below the canopy is an emerging area of research, particularly in the wildlife sciences. To examine this for Northern Goshawk, we focused on the elevation band known to be relevant to goshawks which typically fly below the upper canopy, and specifically between 5 and 25 m from the ground depending on the overall stand height and forest structure. For demonstration purposes within this project, we focused on 5 to 15 m in height; other height stratification can easily be explored, and we would recommend exploring this variable in multiple height increments, such as 5 to 15 meters in height and another 15 to 25 m in height. Similar to Sesnie et al. (2016), we examined relative point-density measurements at different height strata (e.g., Sesnie et al. (2016) used 1–3 m, 3–5 m, 5–10 m, and 10–15 m) to characterize vegetation understory conditions. We assumed that subcanopy gaps would be highly correlated with any measurement of HTLC, whereby lower crown heights would mean more understory complexity (i.e., less subcanopy gaps or flyways), and that both subcanopy gaps and HTLC would be capturing similar aspects of forest structure, with the former being significantly easier to calculate.

The quantification of vegetation structure within the mid canopy requires the assumption that more structured subcanopy forest is indicative of increased lidar-point returns. In this context, analysts can quantify both relative density of points within a height stratification, or they can look at gradients of point density per cubic meter. Determining the relative validity of either approach would require analytical exploration with respect to either goshawk nest locations or individual-bird behavioral and foraging activity data. In other words, although we can derive understory structure from point density returns in a number of different ways, the point-density threshold at which goshawks begin to respond to understory structure is something that would require more detailed study; something beyond the scope of this current project.

For this project, we were interested to see if there were any visual correlations between known goshawk nest sites and the spatial patterning of understory structure, in this case between 5 and 15 m height above ground. To do this we extracted all points between 5 and 15 m in height above the ground (correcting initially for outliers and terrain), then calculated point densities per cubic meter for areas surrounding these known goshawk nest locations. Although we admittedly only focused on three relatively small study areas, we found identifiable consistencies in understory structure surrounding known goshawk nests at all locations (Figure 9). Specifically, nest areas had evident sub canopy flyways adjacent to all known nests, and we did not find nest locations associated with dense understory cover (e.g., Figure 9, Panel B). It should be noted that this relationship was not mathematically quantified, but it is a striking visual pattern that requires further investigation.

This pattern is likely as important to nest sites as it is to foraging areas. The output of this assessment allows the analyst to identify areas within the forest that facilitate both subcanopy foraging for prey species (e.g., Figure 10, Panel C) and ideal nest-approach flyways for potential nesting sites.

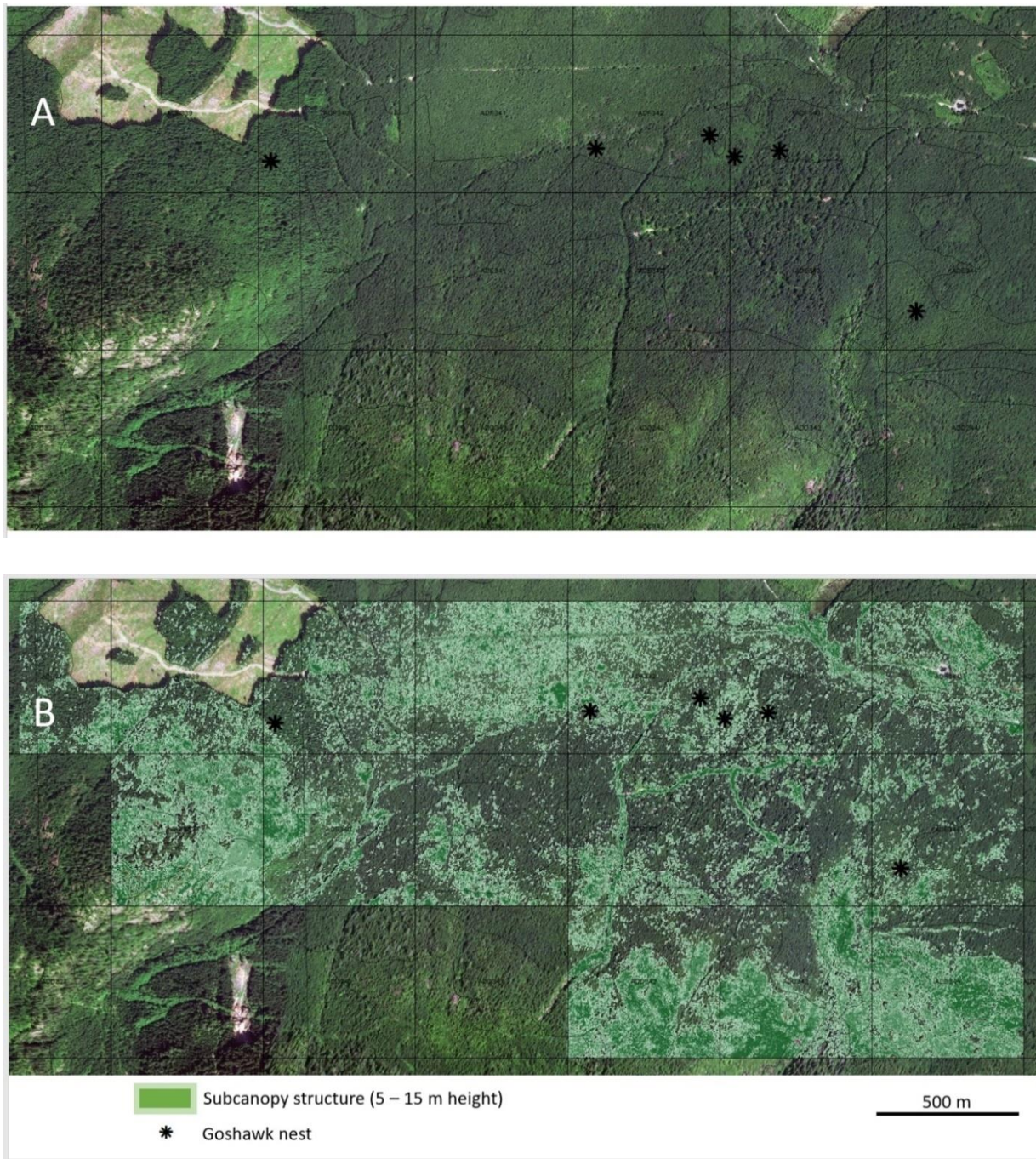


Figure 9. A) Typical canopy view using traditional ortho-photography whereby sub-canopy structure cannot be assessed effectively. B) Lidar-derived subcanopy structure from 5-15 m in height above ground. Areas in darkest green indicate areas that have denser subcanopy structure within this height band, whereby more open areas within this band width (colored pale green) indicate sites where goshawks could more easily fly under the forest crown and through the middle-lower canopy layers. Note how known nest sites are all adjacent to open subcanopy areas, suggesting that nests likely require more open sub-canopy approach avenues.

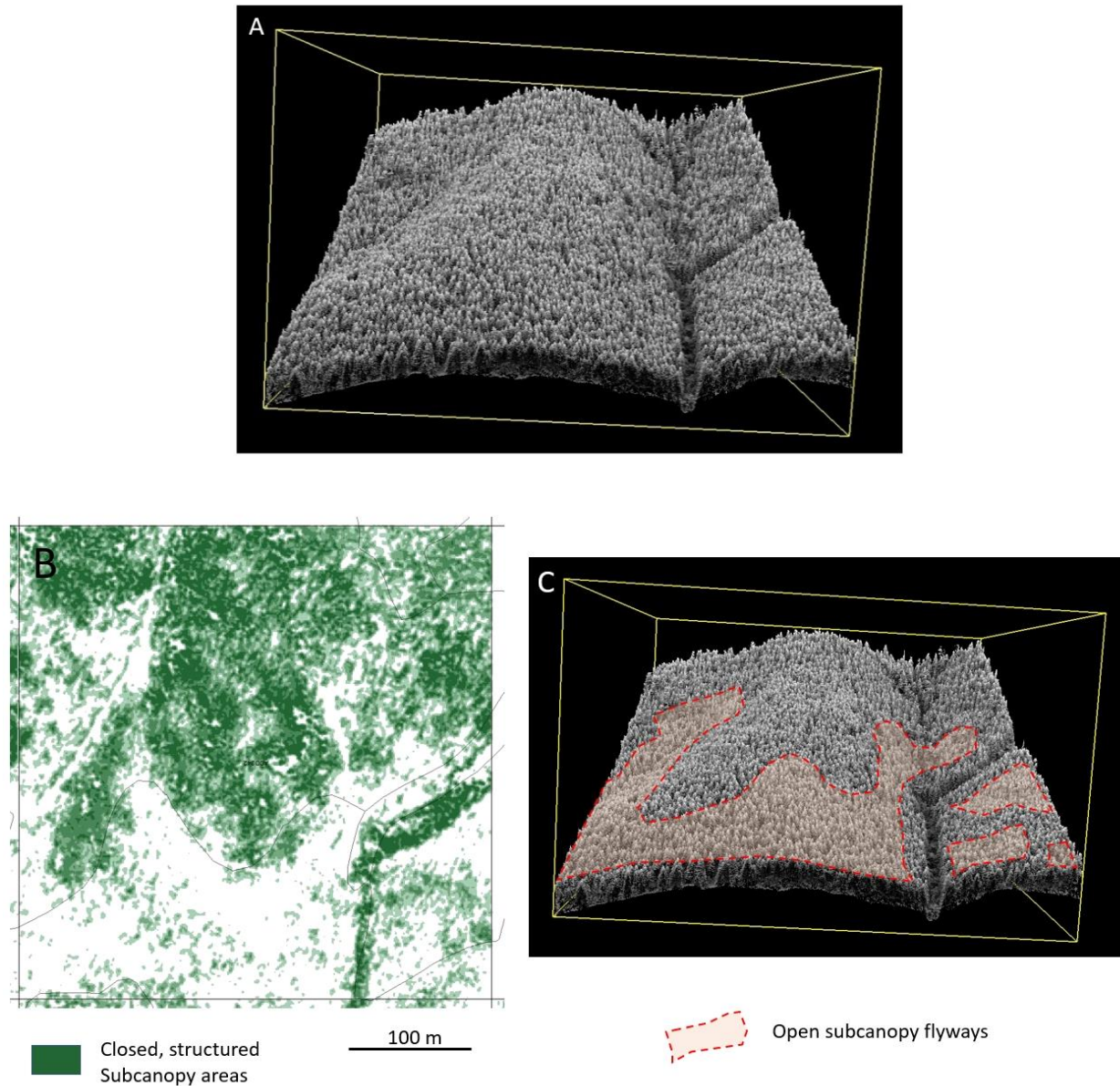


Figure 10. A) 3D point-cloud of lidar tile Rosewall ADD342 within which we extracted the 5-15 m height profile, corrected for elevation and terrain, and quantified the amount of sub-canopy structure as a relative proportion of lidar-point returns in 1-m resolution 3D space. B) the derivative raster output indicating areas that are physically obstructed with more forest structure (green) versus those that are physically open (white areas) within the sub-canopy. C) A 3D representation of the point-cloud indicating areas (approximated for demonstration purposes) which contain sub-canopy flyways within the lidar tile.

Again, for demonstration purposes within this project, we acquired ground-truthing data from trained goshawk habitat-assessment biologists who visited nest or territory areas and ranked the forest with respect to presence of subcanopy flyways. Using a set of standardized criteria, observers visited these areas and ranked the subcanopy as good, moderate, poor, or very poor with respect to abundance of

flight pathways within the forest. We took these data and mapped the location of each ranking with respect to the subcanopy structure derived from lidar (Figure 11). This comparison had mixed results. In some instances, good flyway rankings were found in areas where lidar data indicated as relatively open. However, we also identified areas using lidar that were relatively open but that were ranked moderate or poor in the field. We also found sites that were ranked good in the field, but using lidar were not found to be particularly open with respect to sub canopy flyways. Striking visual patterns were not evident when comparing ocular field assessments with lidar-derived subcanopy structure (see Figure 11).

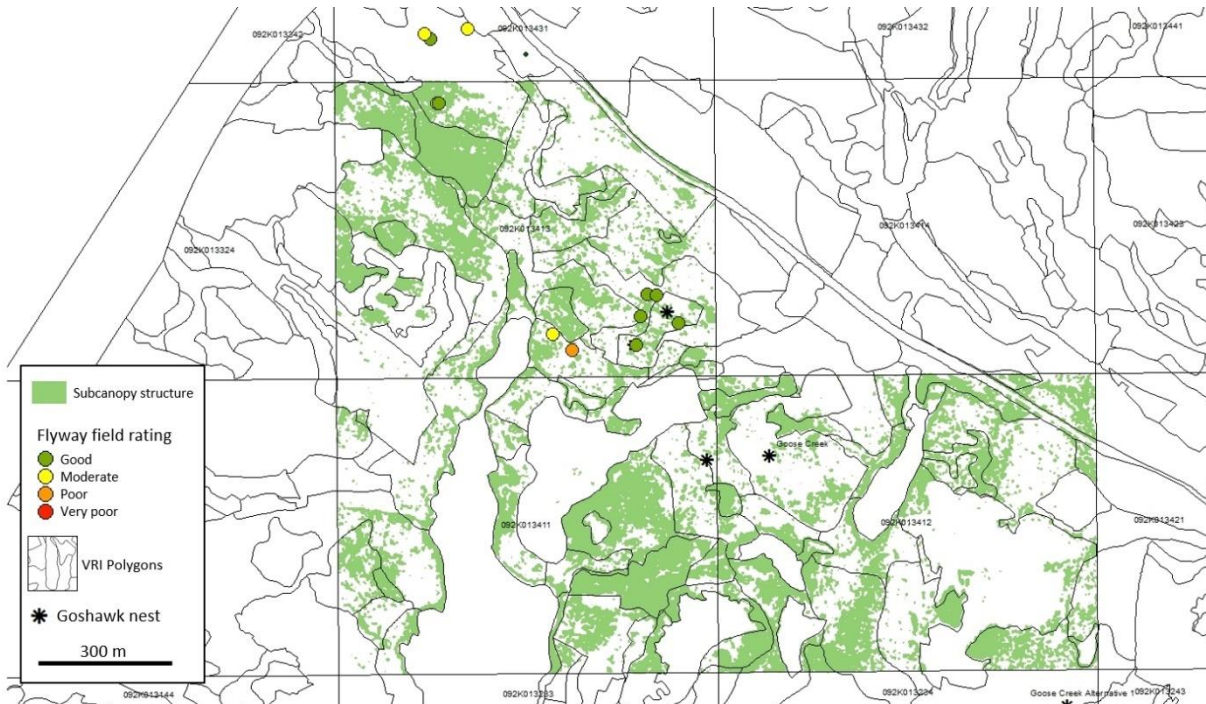


Figure 11. Three lidar tiles from the Sayward study area that have both subcanopy forest structure and goshawk-flyway field-based habitat assessments. Areas with more open flyways (i.e., areas relatively devoid of green forest structure) have mixed flyway ratings ranging from good to poor, indicating variability between field assessments and lidar-derived sub-canopy forest structure.

Crown Closure (canopy cover)

There are two common methods to generate canopy closure using point-cloud data. The first uses only the number of vegetation first returns as a proportion of the total number of returns per unit area. The second uses the total number of above-ground returns (typically adjusted to a minimum height above ground) as a proportion of total returns per unit area. The second method tends to generate higher average estimates of canopy cover, but the choice of method is typically governed by whether subcanopy or near-ground structure is important for inclusion into a canopy-cover measure. Both methods are computationally similar in terms of computing time and file size, so for this project we used the total number of above-ground returns to capture both top-canopy and mid-to-low canopy structure known to be ecologically important to goshawks. We limited the above-ground points to those >2 m in

height, and merged lidar point-cloud tiles together into larger landscapes (Figure 12) until the software/hardware file-size limit was reached, enabling more efficient batch processing of lidar data.

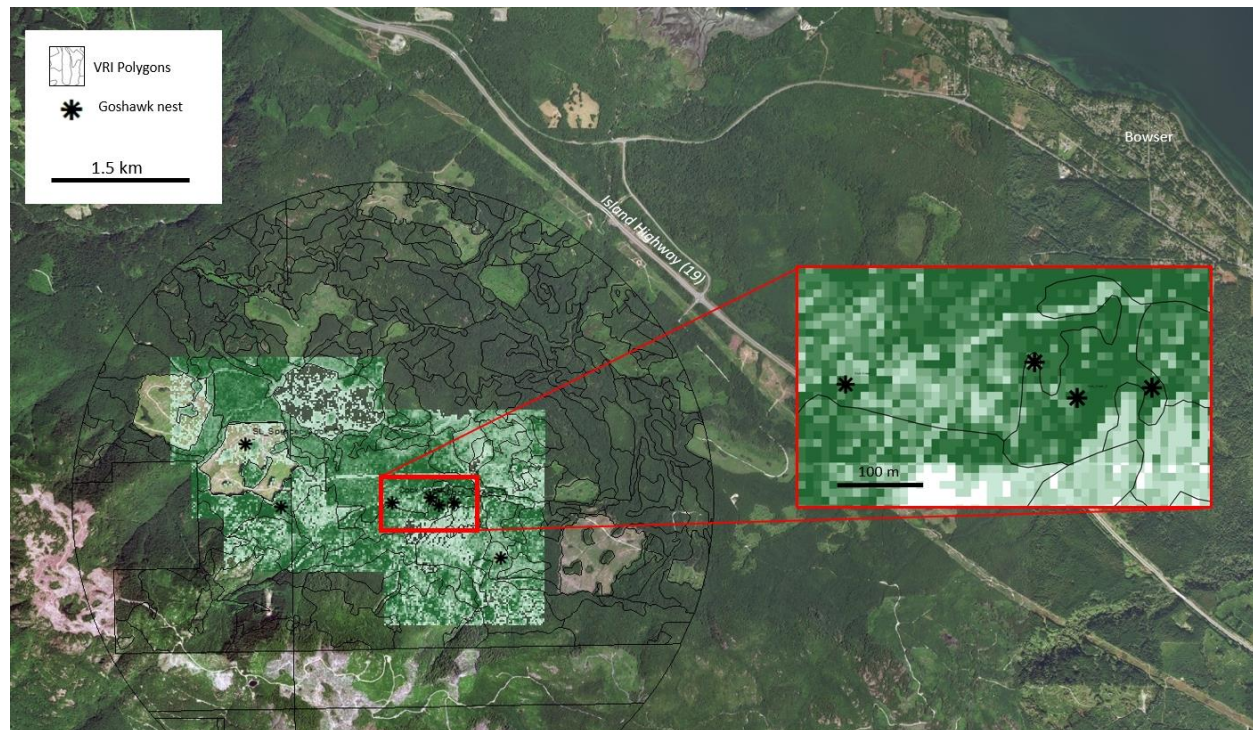


Figure 12. Canopy closure for the Rosewall study area calculated at a 15-m resolution. Darker shading indicates higher canopy closure.

For this project we had a total of 21 sampling stations where we could compare lidar versus field-plot canopy-cover data. To account for site-specific variability in canopy-cover measurements, we resampled the canopy-cover to a 15-m resolution using a focal-mean approach. We did this based on expert opinion, but whether these measurements should be rolled into a lower resolution is an emerging area of research. Creating a lower resolution output has the advantage of capturing more variability within each pixel, but it also potentially reduces the resolution of the final modeling product in that all other associated input layers would need to be resampled up to a coarser 15- m resolution from initial 1-m or 2-m resolution.

When comparing our lidar canopy cover to field-plot canopy cover, we found that, on average, lidar measurements were 23% higher than field measurements (Table 4). Also, we found that the range of these differences was from 4% upwards of 66%, indicating notable variability depending on what was likely site-specific context. The difference between lidar and field measurements for canopy cover is perhaps not entirely surprising, in that ground-based observers in many instances are unable to visualize the tree canopy in the same detail that lidar can accomplish, especially in densely forested areas. Moreover, field-based canopy cover estimates have traditionally been known to be highly variable and

subjective, whereas lidar canopy measurements would have more objectivity with any biases arguably equal across the entire study area. And like both stem density and stand height measurements, the lidar-derived canopy cover is from the entire stand, not just a representative field plot. In these aspects, lidar is arguably the more accurate and more reliable measure of canopy cover. One notable aspect of our lidar-data approach was that we did not remove near-ground lidar points from the data prior to determining canopy cover; thus, our estimates are arguably over-estimates, whereby field observers likely would have focussed more on near-canopy cover than near-ground cover. Future applications of this calculation may be more defensible if near-ground data are filtered out before canopy cover is determined from the lidar data.

Table 4. Comparison between canopy cover derived from lidar versus those quantified in the same location by field-plot sampling.

Station	Lidar Canopy	Field Canopy	Difference
CC_UT1	99		
CC_UT2	99		
CC1	97	64	33
CC2	97	72	25
CC3	93	77	16
CC4	95	74	21
CC5	100	89	11
CC6	97	73	24
CC7	82	77	5
CC8	92	26	66
Cook Creek 2016 nest	99		
S2	95		
Stn 23	100	96	4
Stn 25	72	58	14
Stn 26	94	65	29
Stn 3	96	35	61
Stn 41	81	42	39
Stn 42	98	79	19
Stn 50	94	86	8
Stn 51	99	82	17
Stn 52	89	67	22
Stn 53	97	86	11
Stn 54	97	78	19
Stn 55	94	68	26
Stn 56	96	73	23
Sutton (S1)	97		
Averages	94	70	23 ±15* Median 21

*Lidar measurements are, on average, 23% higher than field-plot measurements.

Elevation and Slope

Elevation and slope are perhaps the most common derivatives of lidar data. There are relatively extensive applications of lidar-surface models in many aspects of both natural and engineering-based planning. The elemental data derived from point-cloud returns are simply elevations, which are directly representative of slope. The advantages of lidar-derived slope and elevation are the resolution achievable from lidar, versus more contemporary sources which typically include space-based (satellite) measurements from radar over continental extents. Although these space-based measurements have shown remarkable improvements in spatial resolution, they are still in the order of 10 to 20 meters; whereas in comparison, lidar-derived slope and elevation can accurately and reliably be derived at a sub one-meter resolution, and these products can be used to explore surface-flow modeling which has been shown to be predictive of microsite hydrology, including wetlands and site-level biodiversity.

For this project we required slope and elevation models as derivatives before we could generate other habitat metrics such as subcanopy flyways. In this sense, elevation and slope models are easily derived from full-feature lidar data and, in the context of goshawk ecology, can provide high-resolution information surrounding nest areas (e.g., Figure 13). Slope and elevation are computationally simple to derive, and multiple tiles of lidar can be mosaiced to create landscape-level surface models with relative analytical ease. As a simple exercise here, we plotted known goshawk nest locations on top of the slope model derived from the lidar data. In general, we found that goshawk nests tend to be in areas below 50% slope, but that some nests can be within close proximity to steep slopes (i.e., <20 m), suggesting that this level of spatial resolution is important for slope to be a meaningful variable within a predictive-habitat model. That is, if slope above 30 or 50 m resolution is used, the signal with respect to nesting ecology may be obscured when compared to high-resolution slope data (e.g., Figure 13, Panel C).

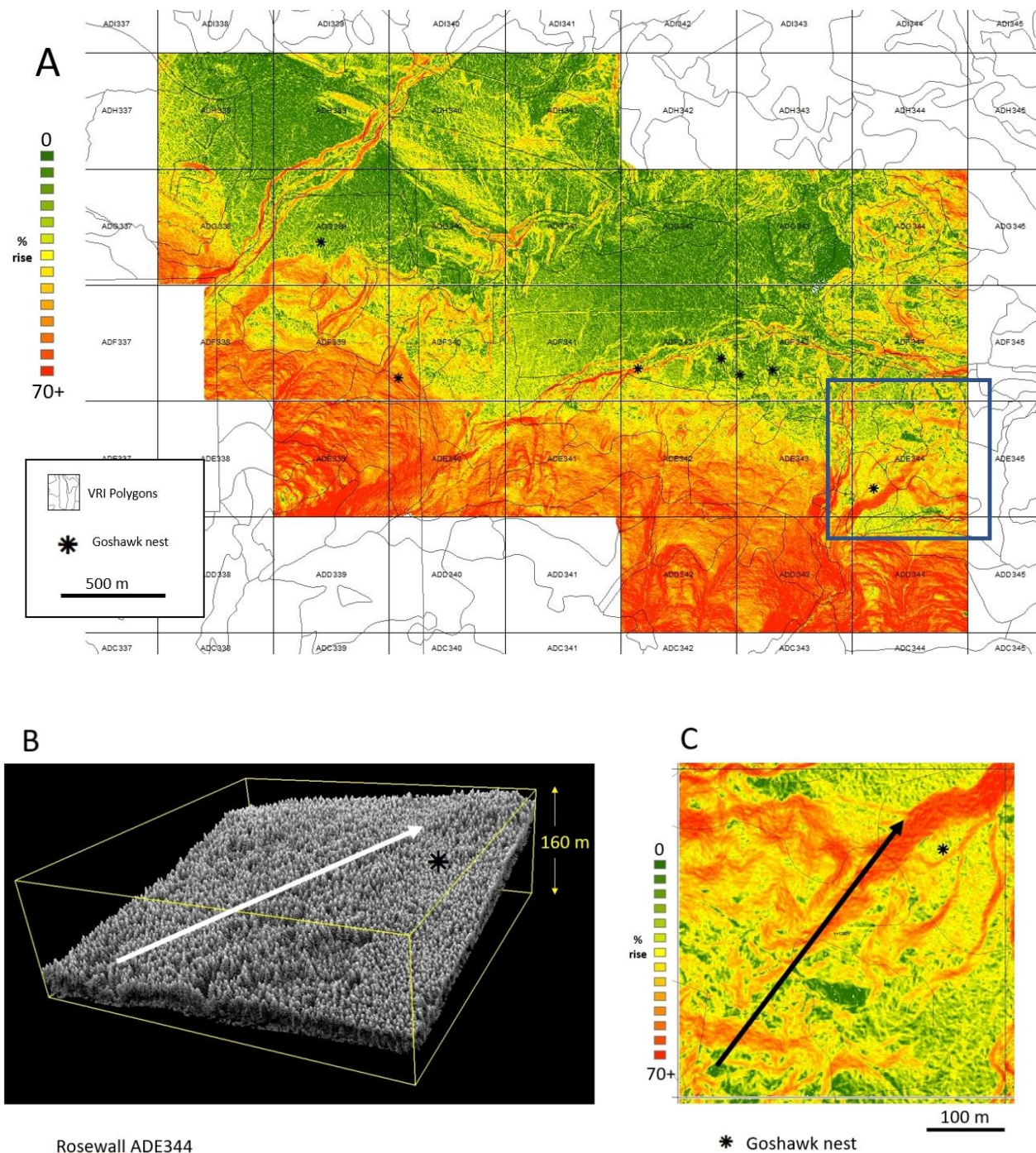


Figure 13. A) Slope as percent rise for the Rosewall study area at a 2-m resolution, with one lidar-tile area (Rosewall ADE344) shown in detail in B and C. B) Point-cloud visualization of the ADE344 lidar tile in 3-dimensional space with a known goshawk nest inlaid. C) The same ADE344 lidar tile in 2-dimensions indicating slope as 2-m resolution percent rise, with the known goshawk nest location included. Arrows indicate the same line-of-sight between the 3D and 2D projections.

Distance from Forest Edge

In the current goshawk habitat model, distance to forest edge is listed as an important and strong variable. Although a considerable amount of information regarding edge location, and in many instances edge type, can be acquired using VRI data (e.g., proximity to polygons with early seral age class and dominant tree layer height class), we wanted to explore whether lidar could provide a more objective and empirical identification of edge location and type, and perhaps explore whether each edge could be objectively quantified with respect to its hardness or softness.

To do this, we chose a lidar tile of data that contained both natural and anthropogenic edge types, including those that were regenerating versus those that were natural or relatively new. After correcting for elevation and terrain, we generated a canopy-height model at a 2 m pixel resolution. Then, using a combination of raster-curvature and focal-pixel elevation differences, the former assessing the shape of edges and the latter assessing their heights (both available tools in common GIS workstations), we explored whether this combination of data could efficiently identify edges and also quantify them with respect to their abruptness or degree of “hardness”.

We found the lidar data of sufficient resolution to effectively identify and rank different edge types within a landscape with an objective score (Figure 14). Although admittedly this analysis is exploratory, early results are analytically simple and the output is both intuitive and clear. The advantage of this approach is that it can delineate spatially accurate height thresholds for different edge types, while simultaneously ranking them based on their physical structure or anthropogenic hardness. Whether this type of output offers advantages over existing edge information from general forest inventory classification should be explored further. Within the context of goshawk ecology, this approach not only identifies obvious edge types between, for example, two different cutblock types, but it also identifies natural forest gaps that may not be evident from typical VRI data. Further, it can quantify different values of hardness along a single edge continuum, whereas a VRI-derived edge would have a single ranking its entire length. The lidar-derived edge values would offer more spatially explicit and objective information.

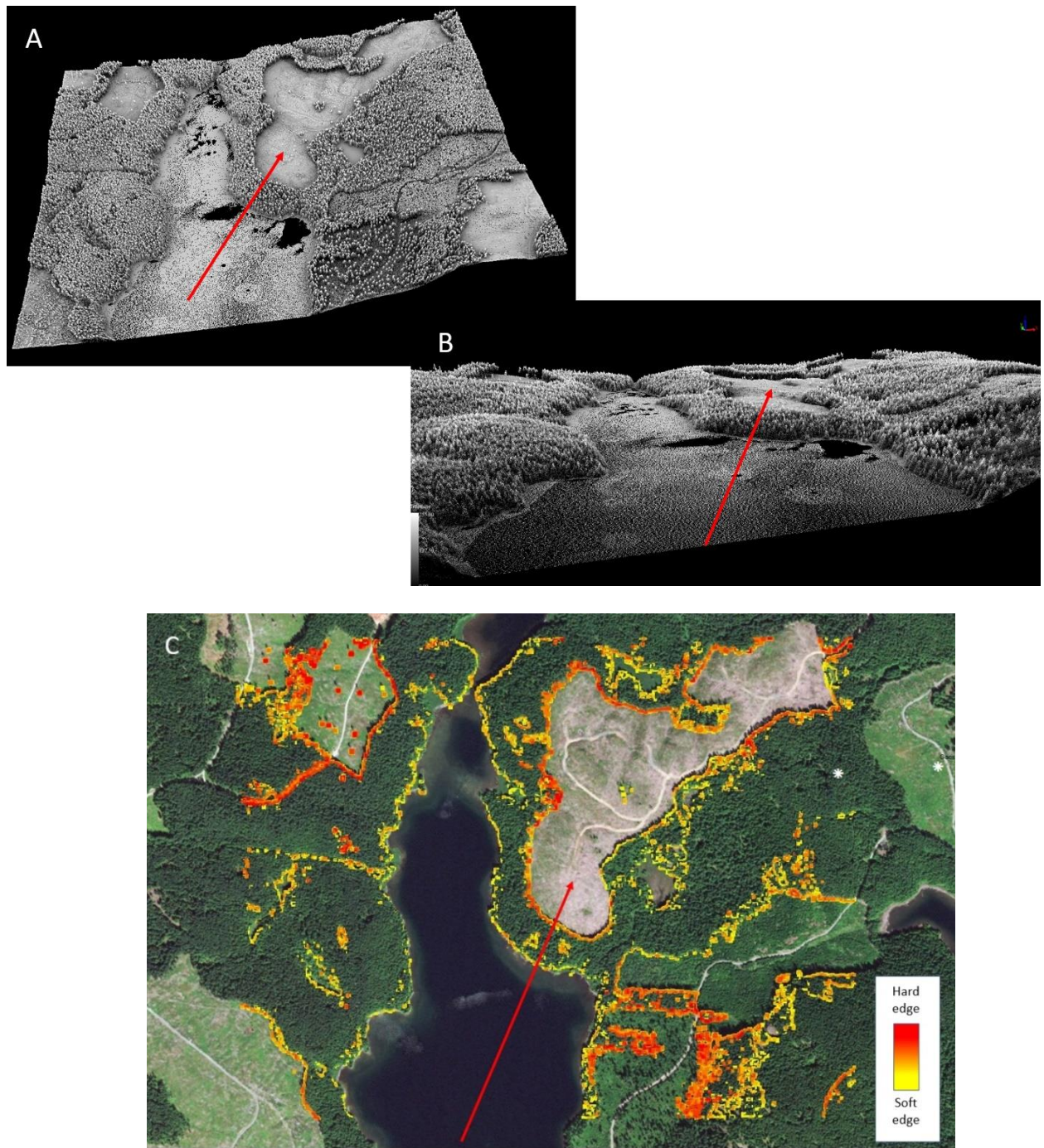


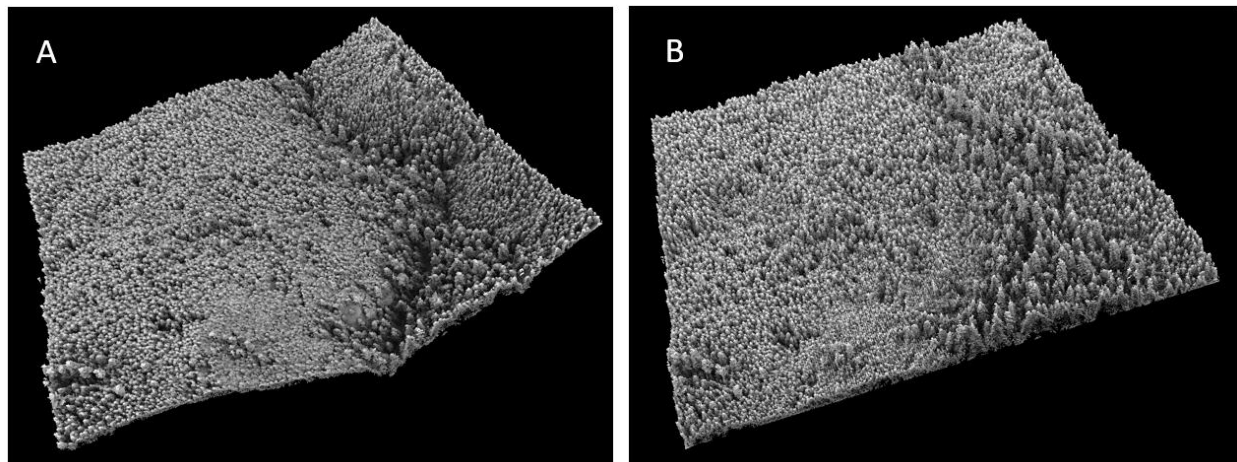
Figure 14. A) Semi-oblique 3D point-cloud visualization of a Sayward Forest lidar tile for an area with multiple forms of forest-edge types, including both natural and anthropogenic edges. B) Edge types in this area are both hard and soft in nature, which can be seen in the point-cloud data that shows hard cutblock edges versus softer edges next to the lake and regenerating forests. C) Lidar data are of sufficient resolution to discriminate texture, shape, and elevational differences along edge types to effectively identify these areas as edges and rate them objectively with an edge-hardness score. Edges shown in yellow indicate more gradual (soft) edges along riparian/lakeshore or gradually maturing vegetation in regenerating cutblocks.

Shrub Cover

Using lidar to explore near-ground vegetation structure (i.e., herb and shrub layers) can be contentious. Some studies argue that minimum point density must be over 100 per square meter to do this effectively, while others argue there may be meaningful signals in lidar data even at lower point densities. The issue with near-ground airborne lidar is that the forest canopy physically prevents the lidar beam from penetrating down to the ground level. Consequently, point densities can be remarkably lower near the ground, and it is debatable, depending on the forest type, whether meaningful ground-level metrics of vegetation structure can be generated, not only in terms of point densities but also in terms of spatial consistency across a landscape, with more detailed ground data retrievable in areas with a more open top canopy.

While exploring sub canopy structure in this project, it was a natural extension to also explore near-ground cover using similar methods. Goshawks are known to forage within the forest canopy for prey species that often require or are linked to ground cover (e.g., berry producing shrubs, large woody debris, etc.). Therefore, we wanted to explore whether meaningful ground cover could be derived from the lidar, or whether there were obvious occlusion effects; namely, areas where ground cover was consistently absent when overhead canopy cover was dense, or the inverse.

To explore this and after correcting for elevation and terrain, we extracted all points above ground but below 5 m in height and completed the point-cloud segmentation algorithms using both methods described above for stand height. Using this technique, we identified point-height maxima of what were assumed to be sapling and shrub-sized individual stems, and then clustered the points around them into individual shrubs. We then visually explored whether this output was spatially correlated with dense canopy or sub canopy structure (Figure 15).



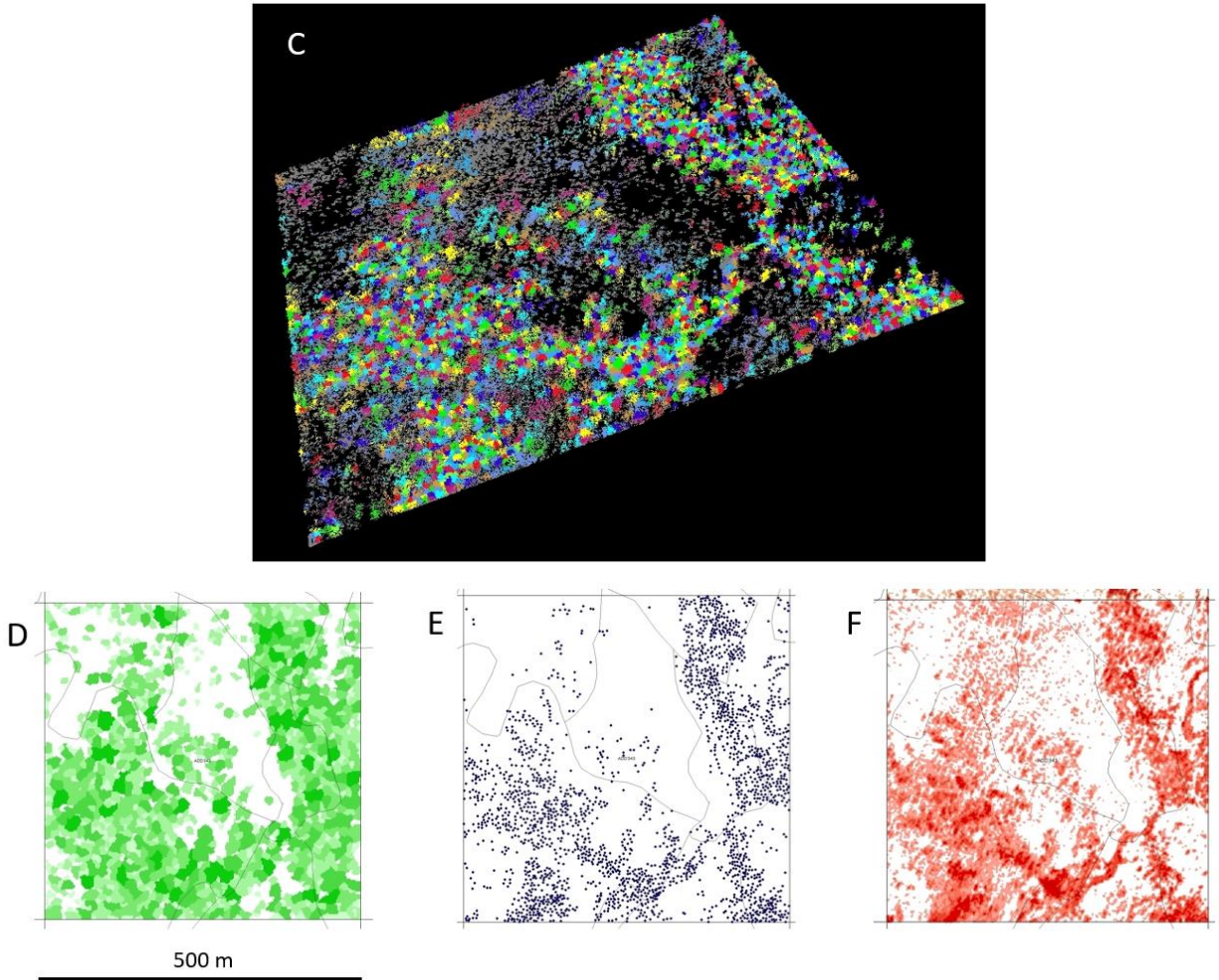


Figure 15. A) Raw point-cloud data in 3D space. B) Raw point-cloud data corrected for elevation and terrain. C) The 0 to 5 m point-cloud extracted and segmented into individual understory clusters for this height band, denoted here by a random color palette. D) Canopy height model watershed segmentation polygon output denoting individual shrub-cover polygons. E) point-cloud segmentation output denoting the seed points used to cluster lidar-point returns into shrub-layer individuals. F) Point-density raster of near-ground lidar returns per square meter.

These analyses produced three different outputs, including a polygon layer of shrub cover, a point Layer of shrub stems, and a point density layer of lidar returns per square meter, all between 0 and 5 m in height above ground (Figure 15, panels D, E, and F, respectively). Visual inspection of these layers with reference to the canopy models generated from the stem-density and stand-height methods were intriguing but require a more in-depth analysis. That is, we found areas where ground cover was identified even with a relatively structured and dense top canopy (Figure 16), suggesting sufficient canopy penetration from the airborne lidar. However, we also found areas where shrub-level cover was clearly correlated with open canopy trees, which may indicate a real effect of increased light and forest-floor vegetation release, or it may simply be an artifact of canopy density where decreased ground cover

is simply a function of lidar occlusion resulting from a developed canopy layer. Our very preliminary results suggest that ground cover may be a potential variable to derive from lidar. For example, after the ground layer was extracted from the full-feature lidar files, we found the resulting point density to be consistently below 3 points per square meter; however, this level of resolution is something the emerging literature on required point-densities would not necessarily support. Whether completing segmentation algorithms using three points per square meter is defensible is still an emerging area of research.

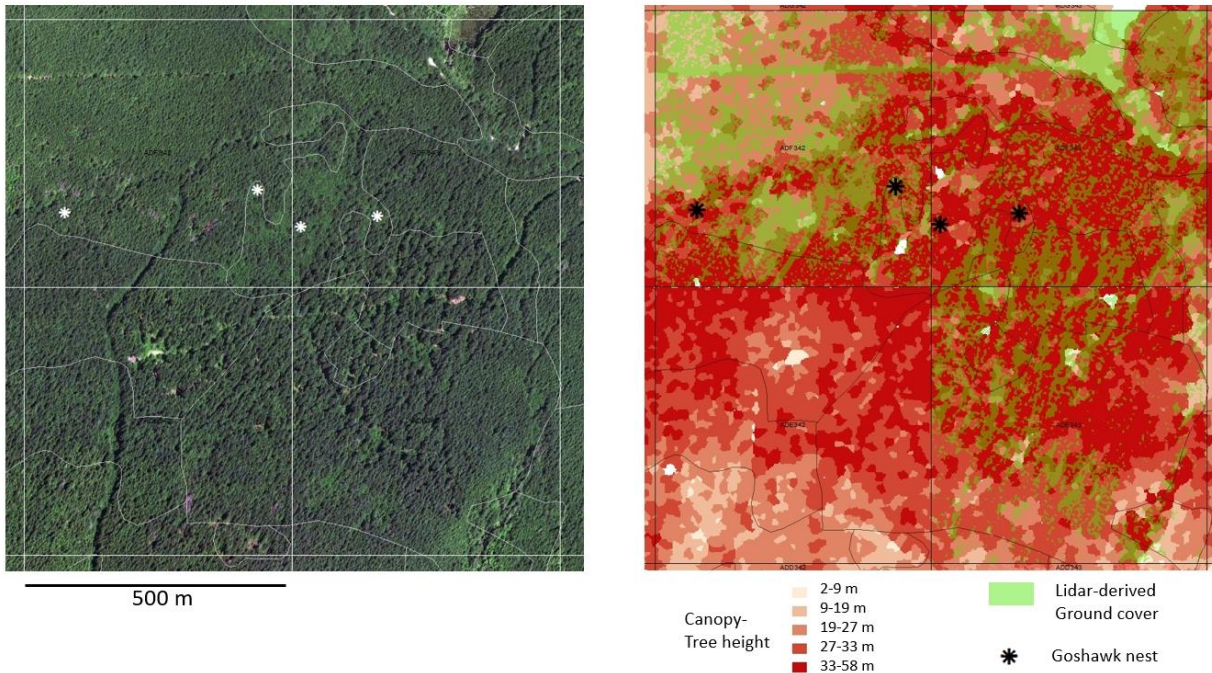


Figure 16. An air photo of a Resewall lidar-tile area (left) with the combined layers (right) of tree height (red gradient) and segmented ground cover (green) from the 0 to 5 m height point cloud. Note areas on the right panel that have both mature taller canopy trees and segmented ground cover, but also areas that have lower more open canopy and associated segmented ground cover. Whether ground cover identification from lidar is a function of canopy occlusion or vegetation release remains to be determined.

Summary

In this project we were able to compare field versus lidar data for three metrics; stem density, stand height, and canopy closure. Previous research comparing field versus lidar data has tended to focus on silvicultural applications, many comparing tree and canopy heights. These have found variable accuracies between data platforms with R^2 values ranging from 0.30 to 0.87 (Dandois and Ellis 2013, Messinger et al. 2016, Puliti et al. 2015, Zahawi et al. 2015). Li et al. (2016) compared the height of maize crops to lidar data and found an R^2 of 0.74, whereas Puliti et al. (2015) found an R^2 of 0.85 predicting tree volume in conifer-dominated boreal forest, and Osloy et al. (2018) found an R^2 of 0.65 for tree volume at the patch scale. In general, comparisons between field data and its lidar derivatives have shown mixed results. However, whether these differences are meaningful becomes questionable when the advantages of lidar-derived metrics are contextualized.

Field-based surveys of vegetation structure, per cent cover and availability of forage on the other hand can provide valuable information at resolutions that are relevant to individual organisms, but such measurements are limited in spatial and temporal extents, and usually quality of data (Osloy et al. 2018). Generalizing field-based assessments to broader spatial scales and in rapidly changing habitats can be challenging, particularly when fine-scale variability in habitat quality is important, as may be the case for many vertebrates (Wiens 1989) and, according to emerging research (e.g., Gallagher et al. 2019, North et al. 2017) this includes raptor species. For example, Jamie-Gonzales et al. (2017) compared habitat models built using lidar, vegetation-plot data, and both combined, and found that the lidar-based models accounted for 27% of the variability in predicting the abundance of wood mice, whereas adding field-plot data only slightly increased the fraction of variability explained to 30% (i.e., field-plot plus lidar data only added 3% additional explanatory power). These types of emerging results will likely question the utility and cost of collecting field-plot data beyond a structured ground-truthing or site-visit or validation program (i.e., collecting field data, but not with the intent of analysing them empirically in a modeling context).

Software and Processing Considerations

Until relatively recently, the use of lidar data has been primarily limited by the computing power required to ingest and process the raw lidar data files. And, perhaps equally as important, these data have not been the focus of many common spatial-analysis software platforms. This has changed remarkably even over the past decade, but it is still useful to assess potential variables with respect to their computational requirements in terms of both hardware and software, and with respect to the expertise required to defensively process and analyze these types of three-dimensional point cloud data.

With this in mind, we ranked each one of the metrics explored in this project with respect to its computational complexity, and the hardware requirements to create lidar derivatives at larger landscape scales (

Table 5). As new software platforms emerge, the metrics we explored here will become more automated so that users can ingest multiple lidar tiles simultaneously and create landscape-level forest structure coverages; this is factored into our rankings.

For example, stem density and stand height are computationally intense because they both require the full-feature point-cloud data, however software enabling these analyses to be completed in batch form are emerging rapidly, and the only real limitations for completing these efficiently are analytical expertise and hardware capacity, both of which are also increasing; thus, we ranked stem density and stand height as relatively easy metrics to generate.

Subcanopy flyway analysis requires a multi-step process that currently is not pre-packaged in any current software. However, the steps required to calculate these layers can be scripted and run in batch, making the primary limitation analytical expertise, more than hardware or software.

Metrics such as crown closure, elevation, and slope are all traditional elevation surfaces all essentially pre-packaged in existing software across multiple platforms. As such, these are computationally simple “point-and-click” layers.

Detecting and ranking forest edge is perhaps the most difficult metric we explored, namely because there are no published methods or inclusive software packages outlining streamlined methods for this measurement. There is some subjectivity inherent in this method, namely to determine thresholds for both contour and elevation differences that would denote and detect relevant edge types, and the output requires some data cleaning which likely cannot be easily automated. In this sense edge detection would be a relatively difficult metric to calculate over a large spatial extent.

Shrub cover was computationally identical to subcanopy flyways; however, this metric requires empirical validation with respect to lidar return occlusion close to the ground. Prior to using this metric over a large spatial extent, exploration linking canopy cover to shrub cover and field plot data would be required to ensure meaningful signals are being generated similarly in areas of dense forest cover versus more open canopy areas. Some emerging research has suggested that point densities exceeding 150 points/m² are required to defensibly quantify near-ground forest structure (e.g., Hamraz et al. 2017), although alternative methods are actively being explored.

Table 5. Subjective rankings of the computational efforts and feasibility of employing the abovementioned lidar-derived forest-structure metrics in studies with large landscape-level spatial extents.

Metric	Easy	Moderate	Difficult	Comments
Stem Density	X			Computationally intense but is automated in most software packages to complete in batch mode. File sizes and computer RAM are notable limitations.
Stand Height	X			Automated in most lidar software packages to complete in batch mode. Methods based on CHM are computationally easier because larger areas can be mosaiced into a CHM surface raster; where as point-cloud segmentation methods require more effort to section-up the study areas into smaller files.
Subcanopy flyways		X		Effort is required initially to extract height-stratified points from original LAS files, but these steps can be scripted in batch form and, once height profiles are extracted, these smaller files can be batched together or mosaiced and analysed together simultaneously.
Crown Closure	X			Automated in most lidar software packages to complete in batch mode.
Elevation and Slope	X			These are the basic outputs of lidar and all available software packages can create these with ease at any specified resolution.
Edge			X	Requires a standard CHM which is computationally simple to create but must then be processed though some raster-analysis tools for contour and elevation ranges, followed by some output data cleaning. Could be scripted for automation once the technique is further explored.
Shrub Cover		X		Exactly the same workflow process and requirements for subcanopy flyways.

Additional data platforms to augment LiDAR.

Emerging research has shown promise in the fusion of lidar data with space-borne satellite imagery. Historically, satellite images have been difficult and expensive to acquire; however, with the somewhat recent release of both LandSat and European Sentinel data into the open-source public realm, and with the rapidly expanding Google Earth Engine platform supporting this, users now have access to satellite imagery at 5-10 m resolution, with some acquiring multiple repeat images daily. Further, image-classification software to process these multi-band images effectively is now common both in commercial and open-source GIS platforms, creating a wealth of current information for land managers. Image segmentation (i.e., classification of satellite imagery into relevant land cover types based on pixel characteristics) is an active area of research. Land-cover classification error is known to occur most notably where features of interest mix spatially or where compositional overlap between vegetation assemblages produces similar spectral signatures (Irwin and Bockstael 2007, Wickham et al. 2010). These errors have been documented in a number of studies using a variety of both satellite and airborne imagery, particularly for differentiating forest and vegetated open-canopy (sometimes explicitly shrubland-based) classes (Koetz et al. 2008, Verrelst et al. 2009, Singh et al. 2012). For example, forest and shrub classes are often confused during image classification due to intergrading species compositions (e.g., regenerating forest stands) that differ only in vegetation height or canopy structure that is not directly inferred from passive multispectral sensors (Xie et al. 2008). However, the imagery acquired from satellite data can offer much insight into the spatial heterogeneity of individual stands, below the resolution of a VRI polygon.

The canopy height model (CHM), representing maximum vegetation height values (quantified by subtracting the DEM from the DSM), is the most basic and commonly used measurement of lidar-derived vegetation structure (Zimble et al. 2003). Thus, perhaps the most straightforward approach to improve image segmentation of forest-habitat types is the fusion of lidar-derived CHM with satellite imagery. In this approach, the image and LiDAR data are fused at the pixel level and processed together during model calibration (Leckie et al. 2005). This is referred to as multi-sensor fusion (Hall and Llinas 1997), and the mixture of LiDAR and optical remote sensing data have been explored in applications involving land-cover classifications (Koetz et al. 2008, Singh et al. 2012) and vegetation mapping (Verrelst et al. 2009, Gu et al. 2015) with promising results.

In the context of Northern Goshawk habitat, lidar and satellite imagery can be seen to provide similar but complementary information, the fusion of which could provide additional and synergistic results to enhance future modeling efforts. For example, we accessed the publicly available Sentinel satellite imagery and downloaded a recent image acquired for the Sayward study area (Figure 17). Using bands 4, 8, and 12 of this multispectral image (i.e., those known to be indicative of vegetation and moisture), we generated a supervised classification of landcover types into broad cover classifications in order to examine whether these data could provide additional stand-level or VRI-polygon level information on forest structure. Once classified, we could accurately detect broad cover types such as open conifer, closed conifer, bare areas, and wetlands, all of which could be further refined using lidar fusion. For instance, Adams and Matthews (2018) fused LandSat with Lidar CHMs to improve land-cover information. They found that fusion data produced a 12% improvement in total accuracy of landcover classification and improved overall class accuracies 4–63% over Landsat imagery alone. They found especially large improvements in overall class accuracy for shrublands (63% accuracy improvement). Such results support the fusion of LiDAR data with optical remote sensing data for the landscape

monitoring of forest structure and growth stage. With this additional information, spatial characteristics of individual VRI polygons can be further quantified (e.g., within-polygon patch or gap distribution and spatial arrangement; e.g., panel D in Figure 17) to augment habitat modeling with higher-resolution habitat data. Processing satellite imagery over large spatial extents is orders of magnitude easier than processing lidar data, and the subsequent examination of their combined derivative products (even combining leading-tree species from VRI) would create a more detailed and higher-resolution product upon which to base future predictive-habitat models.

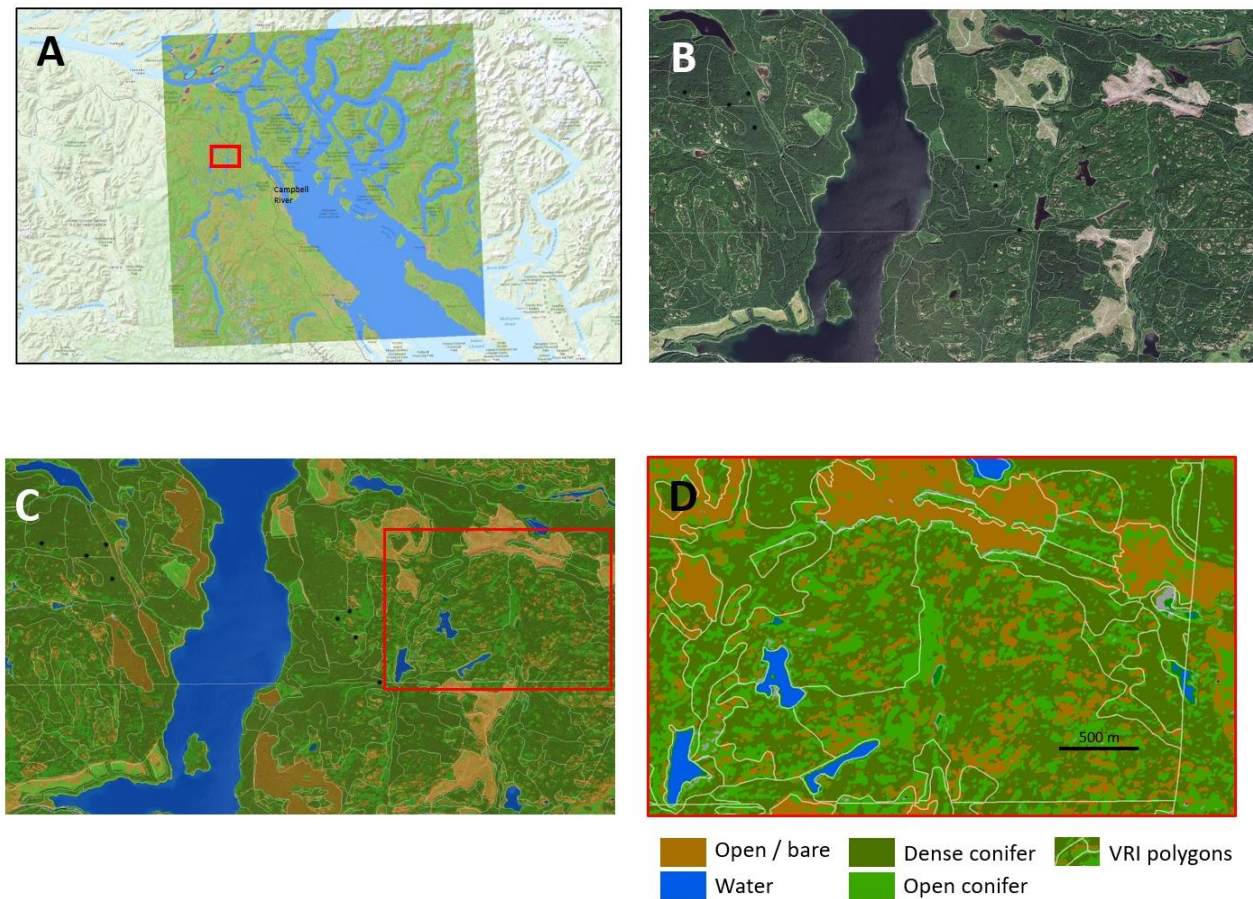


Figure 17. A) Sentinel image acquired for the Sayward study area indicating the spatial extent of the single image (darker landcover colors) and the Sayward study area (inset red rectangle). B) Air-photo image of the red inset rectangle. C) local-level perspective of the broad landcover classes for the Sayward study area. D) VRI-polygon scale perspective of the spatial heterogeneity that can be acquired from Sentinel imagery alone. This heterogeneity of forest types can be further refined using CHM from lidar data, effectively delineating regenerating forests from shrubs and more mature-forest areas.

Scale and management-unit size.

Within the context of habitat modeling, there is a difference between scale and management-unit size. Scale refers to the spatial grain, extent, and time chosen to quantify the variables of interest in a habitat model, including both dependent and independent variables, whereas the management-unit size refers to the typical area within which the habitat-model output is applied. These are discussed in more detail below.

Scale is defined ecologically as “the spatial or temporal dimension of an object or process, characterized by both grain and extent” (Turner et al. 1989, Gustafson 1998, Dungan et al. 2002, Schneider 2001). Several authors have urged for more focus on scale per se (Sandel and Smith 2009 and references therein), including the addition of scale as an explicit factor in investigations (Meetenmyer and Box 1989, Weins 1989, Wheatley 2010, Laforge et al. 2015), and recent reviews consistently identify scale as fundamental to research design and interpretation (Wheatley and Johnson 2009, Jackson and Fahrig 2014, McGarigal et al. 2016). Nonetheless, our general understanding of scale in ecology remains limited, a fact evidenced by its continued uninformed use in study design (Wheatley and Johnson 2009, McGarigal et al. 2016), even though the empirical implications of scale to any ecological investigation are potentially profound (e.g., de Knegt et al. 2010, Wheatley 2010, Lechner et al. 2012, Martin and Fahrig 2012).

The scale at which a model is built could be analogous to the resolution of available data, or it could be a function of how the data are aggregated or averaged into biologically relevant observational units. The choice of scale size is a function of both the resolution of available data and how this is linked to a species’ ecology, which is an active area of research within species-environment modeling. Not all aspects of an animal’s biology can be observed using one observational scale. Each life-history stage has different spatial requirements, and these will be scale-dependent; thus, different observational scales are often required to examine or compare (say) local foraging movements versus natal dispersal movements. Interestingly, there are no set rules on how to choose the best observational scale.

Most often this is done arbitrarily, while some studies rely on more meaningful approaches linked to the spatial extents of home ranges, or choose scales based on Johnson’s orders of resource selection (Johnson 1980). However, perhaps the most defensible emerging approach is to generate the same set of habitat models across a continuum of scales, whereby both the independent and dependent variables are quantified using multiple sample-plot sizes, and the relative model support amongst plot or scale sizes are compared (e.g., Wheatley and Larsen 2018).

Scale choice has implications for both means and variances of sampled metrics, an effect commonly referred to in the geographical sciences as the modifiable area unit problem, or MAUP (Openshaw and Taylor 1979, Jelinski and Wu 1996). Generally the MAUP indicates that, depending on how a researcher chooses to aggregate their observations, different variance structures can be produced from the same data. Because different variance structures are associated with scale, we must then expect different mathematical relationships between dependent and independent variables as a function of scale; and it then becomes an insightful exercise, both methodologically and ecologically, to explore model fit and

selection for the same set of model variables among observational scales; lidar-derived habitat data significantly facilitate this exercise.

The resolution of available data almost always limits or prohibits these cross-scale comparisons. Data resolution will define the smallest analytical unit in model construction, and thus the coarsest resolution variable is what all other variables must be resampled or aggregated to fit. As such, many argue that scale can remain as a lurking variable in species-environment modeling, as important scales of observation are effectively hidden by the limits of data resolution. Lidar data resolves many of these issues, most importantly by providing vegetation structure measurements at resolutions that are often below those (i.e., finer resolution) collected by field-plot sampling, largely removed from observer biases, and in a format that can be investigated (not extrapolated) over landscape scales. Most notably, lidar data facilitates the use of small sample-plot sizes within which data can be aggregated, and also allows for the systematic incremental increase in sample-plot size to explore how predictive-model fit changes based on how the vegetation data are aggregated. Once the best-fit model is identified at the most appropriate scale, the output of this can be applied to management units.

The management unit, as opposed to the scale of observation, is typically the spatial unit within which the model output is contextualized for operational purposes. For goshawks on coastal BC, this will arguably always be the VRI polygon or the forest stand, or something analogous. This is the unit with which many forestry operations are planned and there are several planning, operational, and logistical advantages to maintaining this unit even when using higher-resolution tools such as lidar. The improvement we are seeking in this project is to demonstrate how a spatially refined predictive habitat model can improve the use of management units such as VRI polygons; namely, how the use of lidar can bridge the resolution gap between HSI-model output and VRI polygons.

Even just from our preliminary output, we were able to quickly identify examples of where lidar derived data could begin to inform forest management at the VRI-polygon scale beyond which is currently possible (Figure 18). For example, in the Sutton Pass area, an old growth forest which from aerial photography looks relatively homogeneous, appears after lidar analysis to show distinct forest-structure patterning within the individual VRI polygons. Similarly, we found the same patterning using different lidar variables in the Rosewall study area (Figure 19). Even from a cursory visual examination of these data with respect to both VRI-polygon boundaries and goshawk nest-site locations, it would be surprising if marked mathematical relationships were not evident that could predict these patterns over larger landscapes. From an operational perspective, this higher-resolution lidar data would enable forest managers to target not only individual VRI polygons with respect to goshawk habitat, but they could also assess the spatial heterogeneity of lidar derived features *within* individual polygons and contemplate management alternatives at the sub-stand level. In this sense, an appropriate management unit for goshawks could range anywhere from the sub-stand or the within-VRI polygon unit, upwards to the birds' territory size (e.g., 4000+ ha). Choice of a suitable analysis and management unit size will depend on the relevant modeling scale (i.e., pixel resolution) and the particular management area of interest where the analysis is applied.

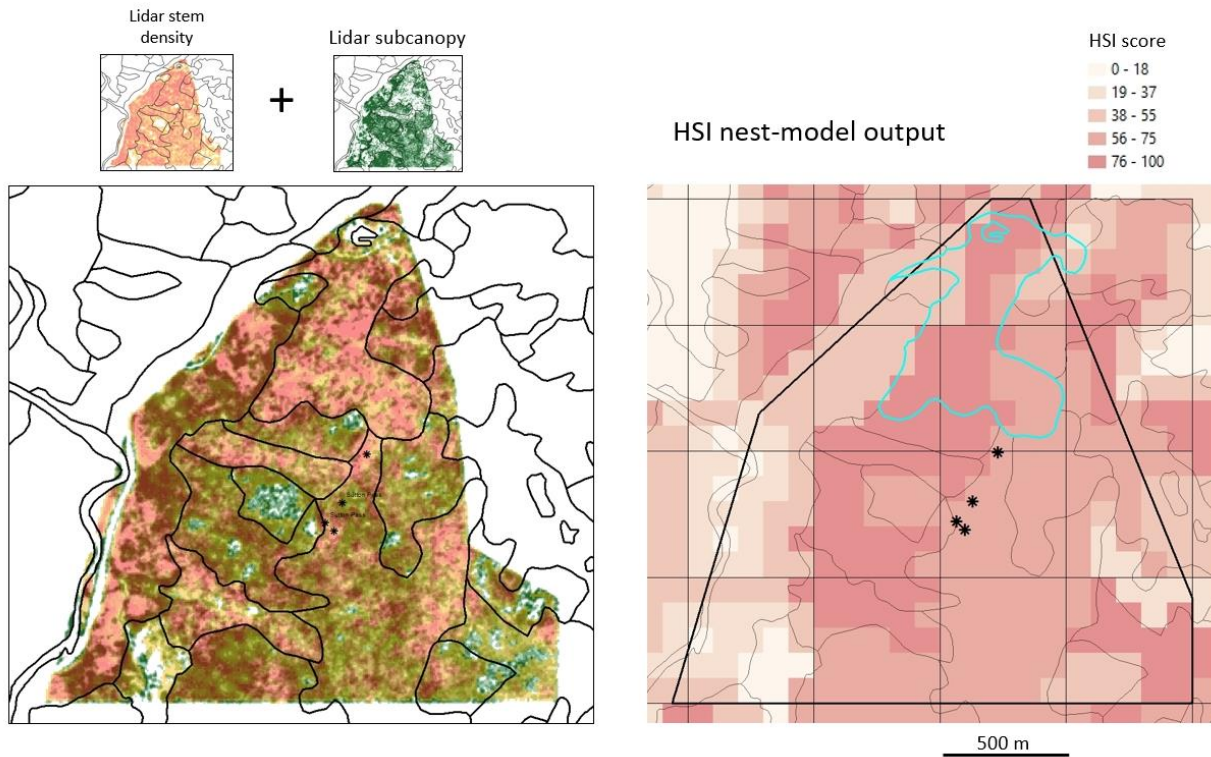


Figure 18. A simple overlay of lidar-derived stem density and subcanopy structure for Sutton Pass (left), versus the HSI nest-model output for same (right). VRI polygons and goshawk nest locations are indicated in both. Note for the single selected VRI polygon on the right (outlined in blue), HSI scores therein range anywhere from coarse scores of nil/low 19 to moderate/high 100. In comparison, just the lidar data (left) for the same polygon would clarify that the entirety of this stand polygon is high-quality habitat because of its relatively high stem density in combination with an open subcanopy. Although this is not a quantified predictive-model interpretation, it serves to demonstrate how the resolution of a lidar-derived model would differ from the existing HSI outputs.

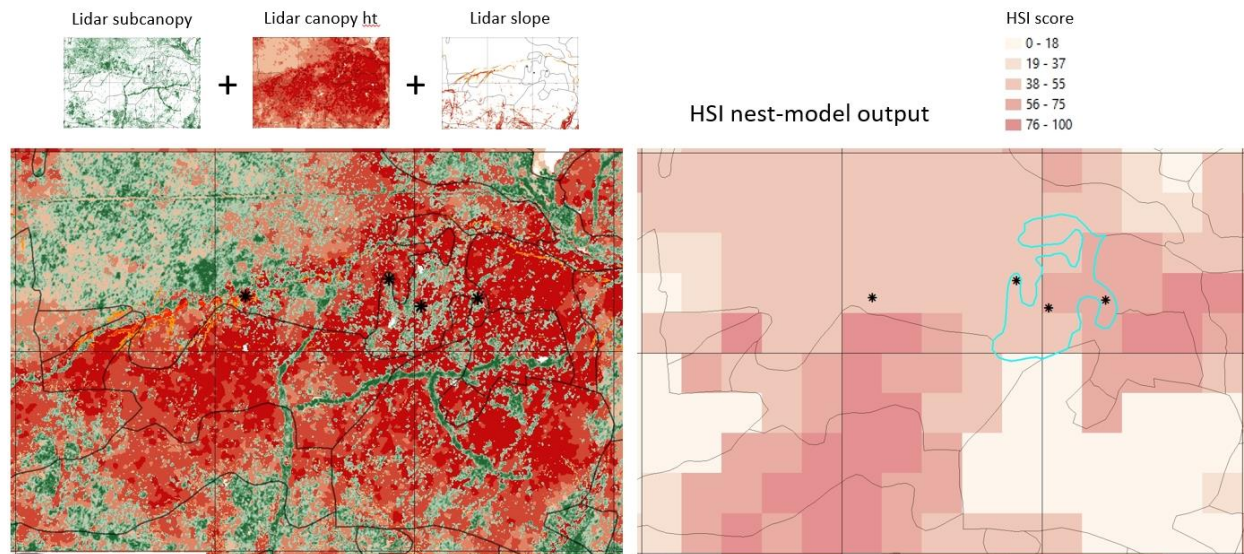


Figure 19. A simple overlay of lidar-derived subcanopy structure, canopy height, and slope for the Rosewall study area (left), versus the HSI nest-model output for same (right). VRI polygons and goshawk nest locations are indicated in both. Note for the single selected VRI polygon on the right (in blue), HSI scores therein range anywhere from nil/low 19 to high 100. In comparison, just the lidar data (left) for the same polygon would clarify that nest areas in this single VRI polygon are likely linked to the relative openness of the subcanopy in areas of relatively high tree height. Further, for the fourth nest to the far left, its location is likely more strongly linked to the mature forest (dark red indicates tall stand height) to the south which also has evident open subcanopy (light green), than the VRI polygon to the north that is shorter and more structured/dense within the subcanopy flyway band.

Conclusions and Recommendations

From the above examinations of lidar data and its derivative products, the following conclusions and recommendations can be made within the context of Northern Goshawk habitat modeling:

1. Existing lidar can reliably generate high-resolution (i.e., 1 – 5 m²) forest-structure data for stem density, stand height, subcanopy flyways, crown closure, slope, and elevation. With appropriate analytical scripting and batch-processing, these variables could be created and integrated immediately into a lidar-based goshawk habitat modeling effort, in some cases increasing independent variable resolution by almost an order of magnitude and enabling habitat-conservation or mitigation decisions to occur at the sub-VRI polygon level. In doing so, we offer the following metric-specific recommendations:
 - a. Stem Density: When determining stem densities using point-cloud segmentation, different parameters can be examined that might be more relevant to the forest structure being quantified. Most notably, users should explore different tree-spacing parameters in efforts to better approximate stem densities that are relevant to the

ecology of goshawks. For example, we used a minimum 2-m tree spacing which can be adjusted in future analyses to cluster lidar points differently among individual trees.

b. Canopy Closure: Future analyses of canopy closure should explore the removal of near-ground lidar points before determining canopy cover. We used all point returns in the data including the near-ground and sub-canopy points, which likely overestimated a canopy cover. This recommendation was not apparent to us until we had summarized and compared our estimates to the field data; while it is not a common practice in the emerging peer-reviewed literature, this should be examined in depth moving forward.

c. Sub-canopy Flyways: Two key aspects of this metric should be examined in detail moving forward. First, this metric contains a continuous variable for point density and thus the point density above which goshawks respond ecologically in relation to the lidar-derived forest structure flyway classification needs to be examined. In other words, at what point density do we classify a pixel of subcanopy as open, versus one which is more closed and “occupied” by forest structure? Second, it is likely that different elevation bands (i.e., height above ground within the vertical forest stand profile) might work synergistically in the context of sub-canopy structure modeling. That is, multiple elevational bands of sub-canopy should be created and then explored in a statistical context to see whether they act additively in a multi-variate context. For example, better model support might be found for lidar-derived habitat models that include both the 5-15m structure and the 15-25m structure both as variables in the same predictive model.

d. Slope: Areas with >60% slope (or variants on this) should be explored as spatial features within predictive models. That is, rather than using a slope raster and quantifying average slope values from proximate pixels, slope could be pre-processed into spatial features (i.e., polygons) delineating slope-class areas, from which spatial variables can then be determined as model variables (e.g., distance to sloped area, spatial arrangement from sloped area, etc.). This may be specifically relevant to nesting area predictions where spatial statistics can be integrated as predictive variables.

2. The lidar-derived variables (from #1 above) should be explored relative to improving the existing goshawk HSI models. However, because there are differences in the resolution of data used in the lidar versus HSI approach (i.e., upwards of 100-fold, from 1 m² to 100 m² pixel size, respectively), a defensible choice of resolutions will be essential; perhaps by developing lidar-only models for smaller, focused study areas (e.g., 100-400 ha potential breeding areas) while relying on coarse-grain HSI model outputs for larger areas (e.g., 2000-4000 ha foraging areas). Ground-based habitat assessments of these types of lidar-derived candidate breeding areas would be an important validation step.
3. The lidar-derived variables (from #1 above) should form the basis of a high-resolution statistical analysis using known goshawk nest-site locations and lidar-derived forest-structure variables to predict additional high-probability nesting/breeding areas across lidar-sampled landscapes. This

analysis should take the form of a use-availability or occupancy-probability analysis using multiple working hypotheses and a model-selection approach applied over multiple observational scales. For this approach it will be important to match as closely as is defensible, the acquisition date of the LiDAR data to when nests were first established.

4. A simultaneous exploration of existing HSI models in a statistical modeling context would be synergistic; however, on statistical grounds we do not recommend the fusion of 100-m resolution HSI models with newly derived sub-5-m lidar-derived variables. The two approaches should be separate modeling efforts using coarse HSI models for large landscape areas while refining lidar-derived models for high-resolution stand-scale applications.
5. Based on review of lidar-derived metrics (as per #1 above), a suitable analysis/management unit for assembling, processing, analyzing and applying lidar data], is the VRI polygon. This unit is routinely used in forest and habitat inventory and planning, and can easily be “scaled up” to aggregated multi-polygons or landscape unit areas, if desired for management planning purposes.
6. Further work should be completed examining lidar-derived variables for forest-edge detection. There appears much promise in the existing lidar’s ability to generate objective forest-edge scores (i.e., edge type incorporating a hard-to-soft gradient) relevant to goshawk nesting and foraging ecology.
7. Further work should be completed examining lidar-derived near-ground vegetation (shrub layer) cover using existing lidar data (augmented with field plots). This analysis should focus on lidar-point density across a gradient of forest-canopy cover (dense to open) to explore whether meaningful near-ground forest structure (e.g., shrubs, large woody debris) can be quantified, or whether higher-quality lidar data are required before including this variable into future goshawk predictive models. This type of near-ground vegetation metric may prove useful in informing better identification and quantification of goshawk foraging habitats.
8. Minimum suitable lidar quality (resolution in laser points/m²) necessary to enable reliable acquisition of the forest structure metrics described in #1 above, is approximately 20 points/m². Thus, when requesting lidar data sets for use in habitat modelling, this resolution should be requested as a minimum deliverable. As lidar hardware technology and associated processing software continue to improve, lidar data in the order of 100-300 points/m² will become available (Morsdorf et al. 2017). This high level of resolution may revolutionize our ability to discern detailed subcanopy forest structure (e.g., large mossy platform limbs below the canopy).
9. The lidar variables derived here for goshawk habitat analysis could also inform other species-habitat or forest community-level predictive models (e.g., deer winter range quality and selection, Spotted Owl or Marbled Murrelet nesting habitat classification).
10. Further work should be completed examining the fusion of lidar data with satellite-derived land cover classifications, specifically to quantify forest-structure metrics at a higher resolution than the VRI polygon over large areas. With respect to goshawks, this could include analysis of

within-stand spatial structure of forest gaps or broad forest types (e.g., age classes, tree species composition, open vs. closed canopy). Understanding how this information could be used to augment existing VRI coverage and improve species-habitat modeling would benefit both multi-species recovery efforts and enhanced-forest inventory methods. Because tree species cannot be acquired via LiDAR, particularly where recent VRI data are lacking, it will be worth examining whether satellite-based remote sensing data can be used to estimate forest-species composition, at least to broad classes, if not down to actual tree species percentages. Additionally, both lidar and satellite imagery should be examined for integration with Terrestrial Ecosystem Mapping (TEM) data, such that both over and understory variables may be incorporated into new land-cover coverages (e.g., like derived Sentinel data); this may enable qualification of additional goshawk predictive variables that could be used to predict foraging and understory cover important to goshawks and their prey species.

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