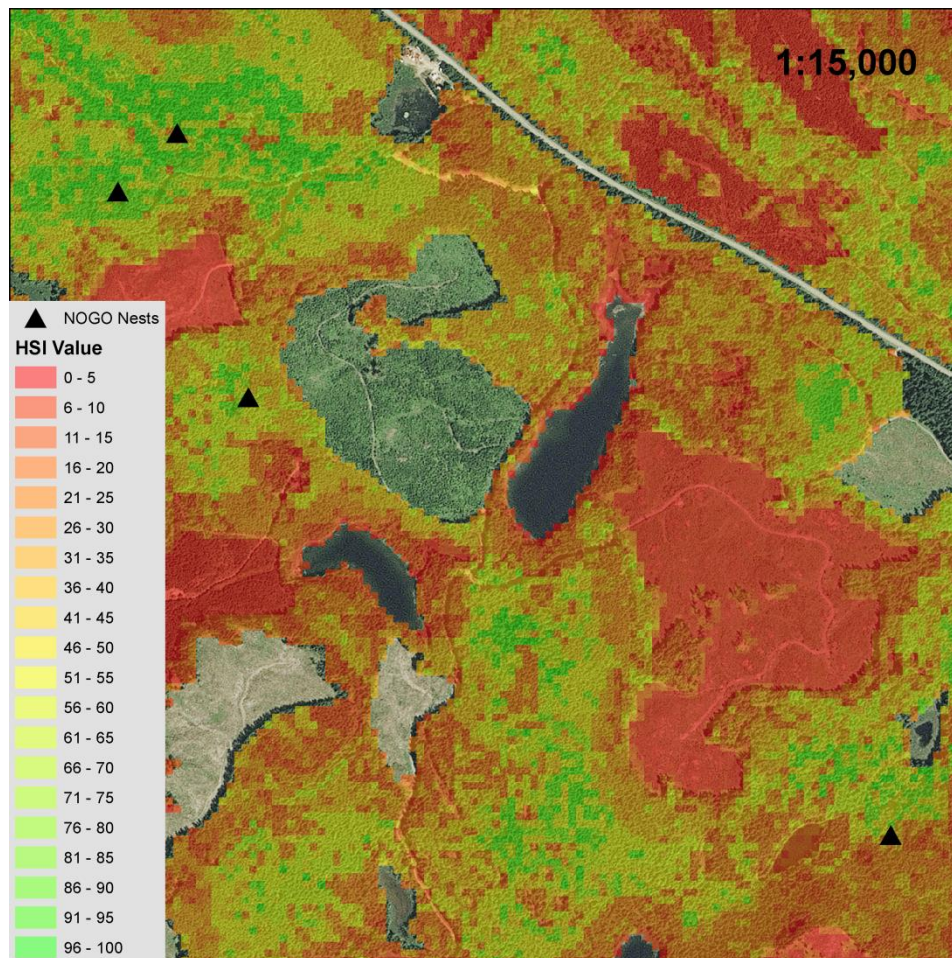


Using LiDAR to Improve the Identification of Northern Goshawk (*laingi*) and Ungulate Winter Range Habitats



Prepared for: BC Ministry of Forests, Lands, Natural Resource Operations & Rural Development

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Background and Objectives

BC Ministry of Forests, Lands, Natural Resource Operations & Rural Development initiated a project in 2018 to determine if currently available LiDAR data (BC Timber Sales source from Vancouver Island, BC) could be used to discriminate forest structure variables relevant to the assessment and modeling of Northern Goshawk (*Accipiter gentilis laingi*) nesting and foraging habitat. Results of this project (Wheatley and Manning 2019) concluded that LiDAR-derived data layers for various forest structure attributes (e.g., canopy height, canopy closure, stem density, etc.) can be used to identify and model suitable goshawk habitat, and that high resolution LiDAR data can discern subcanopy forest structure such as canopy gaps and flyways which are not available from provincial Vegetation Resources Inventory (VRI) or other traditional data sets; having such data can in turn lead to improvements or revisions to current goshawk habitat suitability index (HSI) models. This project also provided recommendations about LiDAR-data quality, optimum analysis/management unit size, and the use of other remote sensing, GIS tools and inventory layers (e.g., Terrestrial Ecosystem Mapping) that can be used in conjunction with LiDAR to improve wildlife habitat assessment and modelling for goshawks as well as other applications such as ungulate winter range. Consequently, the initial 2018-2019 pilot project provided as an excellent "stepping stone" for the current project, with the goal to further use LiDAR to improve habitat suitability modelling for Northern Goshawk and ungulate winter range.

There were six main objectives in this current LiDAR project, as follows.

Objective 1: Determine where existing field information (e.g., LiDAR coverage, goshawk habitat assessment ground plots) are available to verify the accuracy of derivative mapping products such as canopy height and canopy closure.

Objective 2: Generate forest structure derivative mapping layers outputs (see a-j listed below) at a spatial scale and resolution suitable for use in goshawk habitat modeling. Stand height, crown closure, subcanopy flyways, distance from hard edge, slope and aspect are LiDAR point cloud derived, while the remaining variables are VRI derived. The variables below were chosen in order to be consistent with the current BC Northern Goshawk nesting habitat suitability model (Mahon et al. 2019), but also amenable for incorporation into a revised HSI model based on modelling parameterization recommendations from Mahon et al. (2008, 2015), Smith (2008) and Wheatley and Manning (2019).

- a) Stand height (dominant canopy layer)
- b) Crown closure
- c) Subcanopy flyways (at 5-15 m above ground) in the lower-mid forest canopy
- d) Distance from forest edge
- e) Slope
- f) Forest age class (dominant tree layer, derived from VRI)
- g) Leading tree species composition (2 dominant tree species, derived from VRI)
- h) Elevation a.s.l.
- i) Aspect (applicable to ungulate winter range suitability)
- j) Biogeoclimatic unit (BEC) - subzone variant

Objective 3: Explore the use of the derivative layers listed in Objective #2 for improving the accuracy of the existing goshawk nesting habitat suitability index (HSI) model (Mahon et al. 2019), as well as incorporation into a new/revised nesting habitat HSI algorithm (see Methods below). New model LiDAR

inputs (i.e., independent variables) include stand height, crown canopy closure, subcanopy flyways and slope, in conjunction with traditional VRI data (e.g., age class, tree species composition, elevation, etc.).

Objective 4: Generate preliminary statistical comparisons using LiDAR-derived variables (e.g., stand height, canopy closure and subcanopy flyways) incorporated into a new HSI model, to identify suitable goshawk nesting habitat at selected LiDAR-sampled landscapes. Comparisons of these results to corresponding outputs from the current HSI nesting habitat model will be made. Results from this analysis will directly inform the development of a new LiDAR-based goshawk habitat model.

Objective 5: Determine the most defensible scale and management-unit size for modelling and mapping goshawk habitats. Appropriate spatial scale remains an unresolved issue in species-habitat modeling, and is conflated by data resolution, experimental design, and the biological rationale used to justify an observational scale. LiDAR data typically resolves many of these issues, enabling the same data to be used from qualifying micro-sites to characterizing landscapes, and revealing important scale-based signatures in a species' ecology (e.g., areas with a combination of suitable habitat characteristics such as tree height, canopy closure and canopy gaps).

Objective 6: Generate appropriate data layers generated (refer to Objective #2 above, particularly tree species composition, canopy height, canopy closure, slope, aspect, elevation, BEC subzone unit) which can be used to identify suitable ungulate winter range (UWR) habitat (i.e., for Columbian black-tailed deer and Roosevelt elk).

Methods

In order to fulfill the above Objectives, the following steps and associated methodology were applied, including initial acquisition of LiDAR files and relevant ground plot assessment data for areas of interest.

1. Data

1.1 Field Plot and Ancillary Data

The following field plot and ancillary data were provided by the provincial government (BC Min. Forests, Lands, Natural Resource Operations & Rural Development, Coast Region):

- field ground plot habitat suitability data from several years (2013 - 2019) in the form of GIS point layers. These data included measurements or ratings for important habitat variables such as canopy closure, flyway quality, dominant tree species composition and overall nesting habitat suitability
- a Northern Goshawk nest location point layer (current to 2018)
- existing HSI model outputs for 3 years (2015 - 2017) in GIS polygon format

Additional forest structure plot data compiled by Jeff Shatford (BC MFLNRORD, 2016) at known goshawk nest sites were also obtained. These were particularly useful in that canopy closure was measured more accurately using a "Moose horn" ocular device. These data were provided in spreadsheet format.

1.2 LiDAR Data

LiDAR point cloud data in LAS format were obtained from the provincial government (BC Timber Sales) for tile areas of interest on Vancouver Island, and an appropriate data sharing agreement was initiated. Acquisition dates for the LiDAR data were a combination of 2015,

2017 and 2018 for the Sayward forest area, and 2016 for the Rosewall / Qualicum area. Average pulse density for these LiDAR data was found to be approximately 10 pulses / m² for Sayward, and 12 pulses / m² for Rosewall / Qualicum.

2. Data Processing and Analysis

2.1 Field Plot Data

Field plot points for the Sayward and Rosewall / Qualicum areas were selected from the original government field plot data. In the interest of keeping the plot data relatively temporally consistent with the LiDAR data, only plots established within 2 years of LiDAR acquisition were retained and used for analyses.

The “Jeff Shatford plot data” was initially non-spatial in nature; however, plot coordinates in latitude / longitude were provided as fields in the data spreadsheets. These coordinates were used to generate GIS-compatible spatial data point layers in the same geographic projection as the LiDAR data and government GIS data (i.e. BC Albers).

2.2 LiDAR Data

A Digital Elevation Model (DEM) was created from the original LiDAR point cloud data. This point cloud was then height-normalized (i.e. converted to height-above-ground rather than elevation). A column of LiDAR was then extracted from the height-normalized data at each plot location [12.6m radius from plot center as per the Northern Goshawk habitat survey protocols document (Heckford 2016)]. A series of 70+ standard LiDAR-derived forest canopy metrics were calculated from the point cloud for each ground plot and summarized in tabular format by plot. In addition, lidar-derived canopy closure was calculated for each plot. Key plot attributes (obtained from the field data) including flyway ratings, canopy closure measurements, and plot comments / descriptors, were appended to the LiDAR metrics tables; these summary tables were provided to the *SRS* lead author on this project for evaluation, and eventually formed the basis for developing inputs into the new HSI model Equations (see Eq. HSI_A and HSI_B below).

Selected LiDAR-derived raster layers (at 20m spatial resolution) were generated across the entire Sayward and Rosewall / Qualicum study areas for subsequent input into an HSI model calculation.

These variables (layers) were as follows:

- **Stand Height**
 - p95 of LiDAR height within each 20m x 20m grid cell
- **Canopy Closure (%)**

$CC_{Ground\ return} = 1 - \frac{\sum R_{Ground(First)}}{\sum R_{Ground(All)}}$	<p>Using only the returns in the point cloud with height<3m, what proportion are first returns – then take inverse of this proportion. This test determines the percent of pulses that get below 3m without striking any canopy vegetation first (i.e., clear gaps) – and the inverse is the percent that does hit canopy.</p>
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- **Subcanopy Flyway Metric**
 - LiDAR point count proportion within the 5-15m above ground canopy stratum.
Calculated as Count Proportion = *(return count in the 5-15 m layer/total return count)*
- **Slope (Percent or Degrees)**
 - Calculated from the LiDAR-derived DEM
 - For ground slope, which has been described as a “weak habitat predictor variable” (Mahon et al. 2019), nesting habitat suitability decreases linearly between the HSI rating curve inflection points at slope 30°, slope 60° and slope 90°.
 - For the HSI Equation A model runs conducted in this project, we used % slope data inputs with HSI rating inflection points and corresponding r value changes at 60% and 100%; these slope percent cutoffs are consistent with the suitability rating scores recommended for slope in McClaren et al. (2015) and Mahon et al. (2008). Table 1 also provides HSI ratings (r values) for slopes measured in degrees.
- **Aspect**
 - Calculated from the LiDAR-derived DEM
 - Not used in the Northern Goshawk HSI model, but generated for potential use in UWR modelling

- **Distance to Edge**

Initially, we attempted to build on the exploratory approach for identifying edges developed in the 2019 pilot project (Wheatley and Manning 2019) which was based on finding height differences between groups of pixels in a LiDAR-derived canopy height model (CHM). Although that approach showed promise when optimized over small areas such as individual data tiles, results were mixed when applied across the full project area (i.e., at a landscape scale or larger). The main issues were that obvious hard edges^a were sometimes incompletely defined resulting in gaps in contiguous edges, and “false positives” were often detected where no clear edges were present, which then led to many areas being incorrectly identified as being near edges.

In the interest of saving time and coming up with an approach that could be easily applied across large areas, we developed an approach for identifying Natural and Anthropogenic edges based on available VRI and Harvest Depletions GIS polygon data.

The Depletions dataset included harvest boundary polygons dating back more than 50 years, but still represented edges due to height differences between these boundaries and adjacent forest. Harvest polygons <20 years old were considered anthropogenic edges while the older (and now regenerated) cutblocks were considered natural edges.

^a A hard edge is defined as >12 m in height difference between adjacent forest stands or habitat types.

In terms of the VRI data, queries were developed by a *Forsite Consultants'* certified VRI photo-interpreter, to identify polygons representing natural and anthropogenic edges using the R-script process below. Definitions of Natural and Anthropogenic edges are consistent with those used in the current goshawk nesting habitat HSI model (Mahon et al. 2019).

Natural Edges

```
(NON_VEG_COVER_PCT_1 >=50 AND (NON_VEG_COVER_TYPE_1 = 'BR' OR  
NON_VEG_COVER_TYPE_1 = 'DW' OR NON_VEG_COVER_TYPE_1 = 'LA' OR  
NON_VEG_COVER_TYPE_1 = 'OC' OR NON_VEG_COVER_TYPE_1 = 'RI' OR  
NON_VEG_COVER_TYPE_1 = 'TA'))
```

OR

```
((NON_VEG_COVER_PCT_1 <=10 AND NON_VEG_COVER_PCT_1 <50)
```

AND

```
(NON_VEG_COVER_TYPE_1 = 'BR' OR NON_VEG_COVER_TYPE_1 = 'DW' OR  
NON_VEG_COVER_TYPE_1 = 'LA' OR NON_VEG_COVER_TYPE_1 = 'OC' OR  
NON_VEG_COVER_TYPE_1 = 'RI' OR NON_VEG_COVER_TYPE_1 = 'TA'))
```

AND

```
(LAND_COVER_CLASS_CD_1 <> 'TB' AND LAND_COVER_CLASS_CD_1 <> 'TC' AND  
LAND_COVER_CLASS_CD_1 <> 'TM'))
```

AND OPENING_IND = 'N'

Anthropogenic Edges

```
NON_VEG_COVER_PCT_1 >=50 AND (NON_VEG_COVER_TYPE_1 = 'ES' OR  
NON_VEG_COVER_TYPE_1 = 'GP' OR NON_VEG_COVER_TYPE_1 = 'LL' OR  
NON_VEG_COVER_TYPE_1 = 'RN' OR NON_VEG_COVER_TYPE_1 = 'RZ' OR  
NON_VEG_COVER_TYPE_1 = 'UR')
```

OR

```
((NON_VEG_COVER_PCT_1 >=10 AND NON_VEG_COVER_PCT_1 < 50) AND  
(NON_VEG_COVER_TYPE_1 = 'ES' OR NON_VEG_COVER_TYPE_1 = 'GP' OR  
NON_VEG_COVER_TYPE_1 = 'LL' OR NON_VEG_COVER_TYPE_1 = 'RN' OR  
NON_VEG_COVER_TYPE_1 = 'RZ' OR NON_VEG_COVER_TYPE_1 = 'UR') AND  
(LAND_COVER_CLASS_CD_1 <> 'TB' AND LAND_COVER_CLASS_CD_1 <> 'TC' AND  
LAND_COVER_CLASS_CD_1 <> 'TM'))
```

AND OPENING_IND = 'N'

Although the above approach of identifying edge features from existing polygon data worked well, we suggest that in future, if time and budget permit, to manually edit the query results in order to “fine tune” the edge layer where applicable.

Finally, GIS spatial analysis was used to generate distance-from-edge rasters, and the edge vector layers were converted to raster for input into the revised HSI model (see Equation HSI_A below).

3. HSI Model Calculation and Implementation

Algorithm calculations were done using the *R programming language*. VRI was read in using the ArcGIS R Binding package and corrected for topology errors. The hard edge layer was read in maintaining X and Y coordinates.

The seven raster datasets (Table 1) were read in and intersected with the VRI dataset. X, Y coordinates were maintained as variables, and the data was reduced to a single table. Each r-value metric (algorithm variable) was calculated as per the criteria and weightings shown in Table 1. These criteria (i.e., ranges or limits) are consistent with the current HSI nesting habitat model (Mahon et al. 2019), applicable to the Vancouver Island and South Coast Goshawk Conservation Regions, with canopy closure and subcanopy flyway variables incorporated as new variables into the HSI algorithm.

For the canopy closure and flyway variables, criteria ranges and associated r values (see Table 1) were developed by the SRS lead author based on the following rationale:

- a) review of the point cloud metrics described in sec. 2.2 above;
- b) correlation (non-statistical) of point cloud metrics to ground plot observer-based ratings at known goshawk nesting areas in the Sayward and Rosewall/Qualicum forest areas (J. Shatford 2016 forest structure plot data; BC MFLNRORD 2017 habitat suitability assessment plot data) for these two variables;
- c) knowledge of goshawk breeding habitat structure and recommendations for habitat model variable inclusion and sensitivity (Mahon et al. 2019, 2015, 2008; McClaren et al. 2015; Smith 2008). All calculated r values were rounded to the nearest 1/100th decimal.

The habitat suitability r values used for canopy closure corresponded to five percentage categories (<20%, 20-34.99%, 35-49.99%, 50-80% and >80%), instead of the four-category system generally used in government ground plot assessments (i.e., <25%, 21-34%, 35-45% and >45%, see Heckford 2016). However, because of the resolution of the LiDAR point cloud data (see CC_{groundreturn} calculation equation on p. 4) compared to much coarser and less accurate ocular estimates of canopy closure, we were able to discriminate canopy closure more finely and utilized corresponding r values in the HSI Equation A; this is consistent with known goshawk ecological data from coastal BC which tallied “... >90% of breeding areas were associated with relatively close-canopy stands (50-80%), which often correspond to good subcanopy flyway development” (McClaren et al. 2015, p. 27). Stands with higher canopy closure (i.e., >80%) are often dense with poor subcanopy flyway structure, thereby downgrading habitat suitability (i.e., r=0.25 or Low, see Table 1).

The habitat suitability criteria and associated r values used for subcanopy flyways (Table 1) were derived by comparing the point cloud metrics (e.g., <0.1000 LiDAR point count return proportion within the 5-15 m above ground stratum = 1.00 HSI score; see flyway calculation equation on p.5) to the ground plot observer visual assessment ratings for subcanopy flyways (i.e., Very Poor, Poor, Moderate

and Common). However, ground plot ratings are subjective and can vary widely depending on the density of the stand, topography, ability of the observer to adequately “see through” the stand from their particular vantage position, as well as observer experience in assessing and rating stands for habitat suitability. The 5-15 m above ground stratum was chosen because this height “slices nicely through” the lower-middle forest canopy height layer, including the tall shrub vegetation layer (B1) and the lower-intermediate portion of the main tree height stratum (A3). Structures suitable for perching and nest platform construction are often found within this stratum, and it offers horizontal sightlines and aerial flyways through the mid-canopy layer for hunting and nest site access/egress. Goshawk nests are often situated within the 15-25 m height band above ground in order to take advantage of overhead canopy protection for nesting and to facilitate good sightlines and access to and from the nest (Manning 2012).

The two new habitat variables [mean (canopy closure + subcanopy flyways)] that have been added in HSI Equation A below maintain the same linear, non-compensatory algorithmic function as the current HSI nesting habitat model; that is, when the suitability rating of one variable is low or below its optimal range it decreases the overall suitability by that amount, and the value of one variable cannot compensate for a deficiency in another; in addition, suboptimal ratings in two or more variables are combined through a multiplicative function to decrease the overall HSI score (Mahon et al. 2019, Mahon et al. 2008). Because canopy closure and flyway condition are structurally related (e.g., highly closed canopies can result in dense stands with nil or few flyways, while highly open canopies either have few trees with very little overhead protection and poorly defined flyways, or more vegetation growth in the tall shrub and subcanopy tree layers, resulting in obstructed flyways), we felt that averaging these two indicator variables would yield meaningful results both in terms of the variables’ weighting and continued rigour of the algorithm equation (i.e., a deterministic model with fixed parameter relationships; T. Mahon, *pers. comm.* March 2020).

We decided to keep all of the other variables (e.g., age, height, edge, ITG, etc.) and equation format in HSI_A consistent with the formula used in the current HSI nesting habitat model. Thus, this allowed us to improve the robustness of some of the input data (LiDAR-derived canopy height, hard edge, slope), as well as add two new variables into the HSI_A equation (canopy closure and subcanopy flyways). We feel these are significant improvements supported by the algorithm sensitivity analysis conducted by Smith (2008) which concluded that canopy height was the single variable which, when added or removed sequentially from the equation (i.e., only a partial algorithm equation remains that doesn’t include height as an input variable), produced the closest approximation to the results of the full model (which includes all algorithm input variables). Furthermore, the inclusion of canopy closure (and by inference subcanopy flyways) into the nesting habitat HSI equation was recommended by both Mahon et al. (2019) and McClaren et al. (2015), when data for these variables becomes available or more accurate.

The new HSI algorithms (HSI_A, HSI_B) shown below can be easily applied to other areas by modifying and running the *R script* developed within this project (also refer to the “*ReadMe*” text file which accompanies this script).

Table 1. *r*-value assignments for forest structure and other variables used in a LiDAR-derived Northern Goshawk nesting habitat HSI algorithm (optimized for the Vancouver Island and South Coast Conservation Regions).

Variable	Source	Criteria		r value (weighting)	
Stand Age (years)	VRI				
		0-39		0.00	
		40-90		$r=0.02*\text{age}-0.80$	
		>90		1.00	
Canopy Height (m)	Raster				
		0-13.99		0.00	
		14-31.55		$r=0.0572*\text{height}-0.80$	
		31.56 m and greater		1.00	
Canopy Closure (%)	Raster				
		<20 %		0.00	
		20-34.99		0.25	
		35-49.99		0.50	
		50-80		1.00	
		>80		0.25	
Hard Edge	Two Rasters			Anthropogenic Edge	Natural Edge
		0-100 m from hard edge		0.40	0.60
		>100 from hard edge		0.80	0.90
		>200 from hard edge		1.00	1.00
ITG (2 dominant tree species)	VRI	1 st Dominant	2 nd Dominant		
		Fd, Hw, or SS	Any Except YC, PL	1.00	
		Mixed Forest (Dr,AC,AT)	Any coniferous	0.90	
		Ba	Any Except YC, PL	0.80	
		Cw <80%	Any Except YC, PL	0.65	
		Cw >80%	Any Except YC, PL	0.45	
		other	other	0.45	
Subcanopy Flyway (5-15 m above ground stratum)	Raster (point count return proportion)				
		< 0.1000		1.00	
		0.1000-0.1300		0.70	
		> 0.1300		0.30	
Slope (%); Slope (°)	Raster				
		0-59%; or 0-30°		1.00	
		60-100%; or 31-60°		$r=0.70$ if using slope category; or $r=-0.0133*\text{slopedegrees}+1.40$	
		>100%; or >60°		0.50	
Elevation (m asl)	Raster				
		0-857		1.00	
		858-1300		$r=(-0.00105*\text{elev})+1.90$	
		>1300		0.00	
BEC subzone	VRI				
		CDF all		1.00	
		CWH except vh		1.00	
		CWH vh1 and vh2		0.80	
		MH all		0.80	
		Alpine parkland, tundra		0.40	

Based on the criteria and calculated r values listed in Table 1, two new HSI algorithm Equations were derived, calculated and stored in the data frame:

$$HSI_A = \frac{StandAge_r + Canopy Height_r}{2} * \frac{Canopy Closure_r + Flyways_r}{2} * Edge_r * ITG_r Elev_r * Slope_r * BEC_r$$

$$HSI_B = \frac{StandAge_r + Canopy Height_r}{2} * Canopy Closure_r * Edge_r * ITG_r Elev_r * Slope_r * BEC_r$$

A point layer of the data frame with the metrics, r values and final HSI values was saved. A raster for each HSI_A and HSI_B was then created.

Note that **Equation HSI_A incorporates a flyways variable (averaged with canopy closure)**, while Equation HSI_B does not.

Results

Results for the Sayward and Rosewall areas are presented separately below. Cells that overlap null VRI polygons (i.e., null Age, BEC or Tree Species 1), result in the corresponding r value set to zero.

Sayward

This section describes the results from the Sayward analysis area. **Figure 1** shows the distribution of r values for each of the algorithm indicators used in HSI Equation A. The count metric represents the number of 400 m² (20x20m) rasters that are in each variable category. Metrics including canopy height, stand age, canopy closure and hard edge, have r values that range from 0-1.00, but values for slope and ITG have a large proportion of their r values as 1.00. Elev_r and BEC_r both consist of a single r value (1.00), which is shown by the single bar in those graphs.

For the new LiDAR-derived metrics (canopy closure, flyways) which are included in the revised nesting habitat algorithm (HSI Equation A), r values tended to cluster at either Nil-Low suitability, or high suitability, with smaller amounts of Moderate suitability, as follows (see Figure 1).

Canopy Closure

There were approximately 410,000 raster cells (or 16,400 ha, r=0.25) of Low rated and approximately 225,000 cells (9000 ha, r=1.00) of High rated canopy closure habitat in the Sayward analysis area.

Subcanopy Flyways (5-15 m above ground stratum)

There were approximately 360,000 raster cells (or 14,400 ha, r=0.00) of Nil-Low rated, approximately 55,000 raster cells (2200 ha, r=0.70) of Moderate rated, and approximately 470,000 cells (18,800 ha, r=1.00) of High rated flyway habitat in the Sayward analysis area.

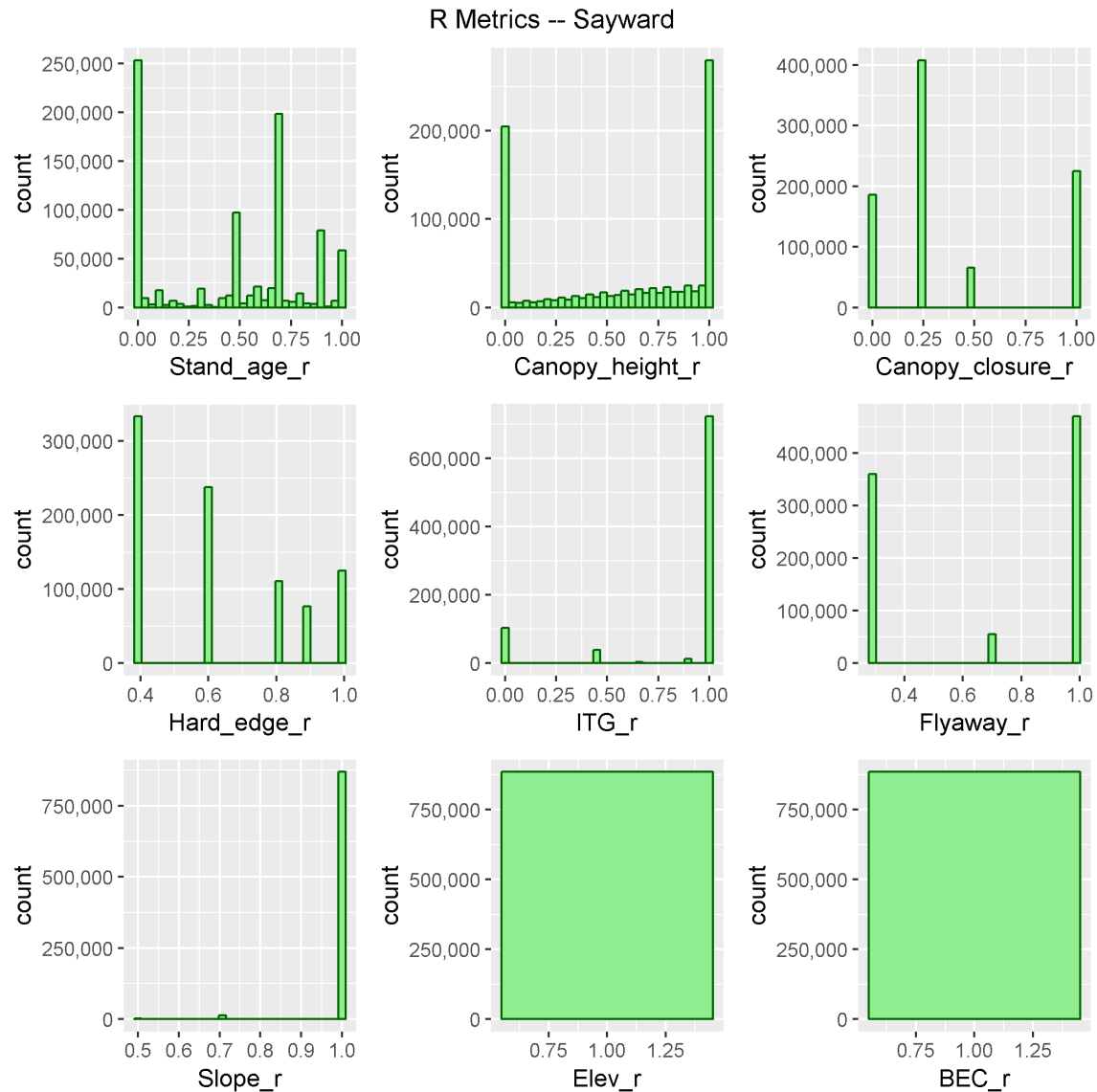


Figure 1. Distribution of each *r* value (HSI Equation A) – Sayward

Figure 2 shows the distribution of HSI values for both Equation A and Equation B, and the resulting habitat suitability scores (0-1.00) and corresponding suitability classes (low, moderate or high). In both cases, the majority of the total raster counts (20m x 20m cells) in the Sayward land base fall within the Nil and Low goshawk habitat suitability classes.

Note that HSI Equation A (which includes the mean *r* value of [canopy closure + subcanopy flyway] in the algorithm calculation), captures less Nil (20,025 ha) and more Low suitability habitat (7958 ha) than Equation B (24,396 ha Nil and 3975 ha Low). Equation A also captures more Moderate + High suitability habitat (3250 ha), while Equation B captures less (2862 ha). Thus, while both Equations have similar overall outputs (area captured by HSI class), these initial results indicate that Equation A (which includes the flyways metric) is able to more finely discriminate habitat into respective habitat classes.

Equation Results -- Sayward

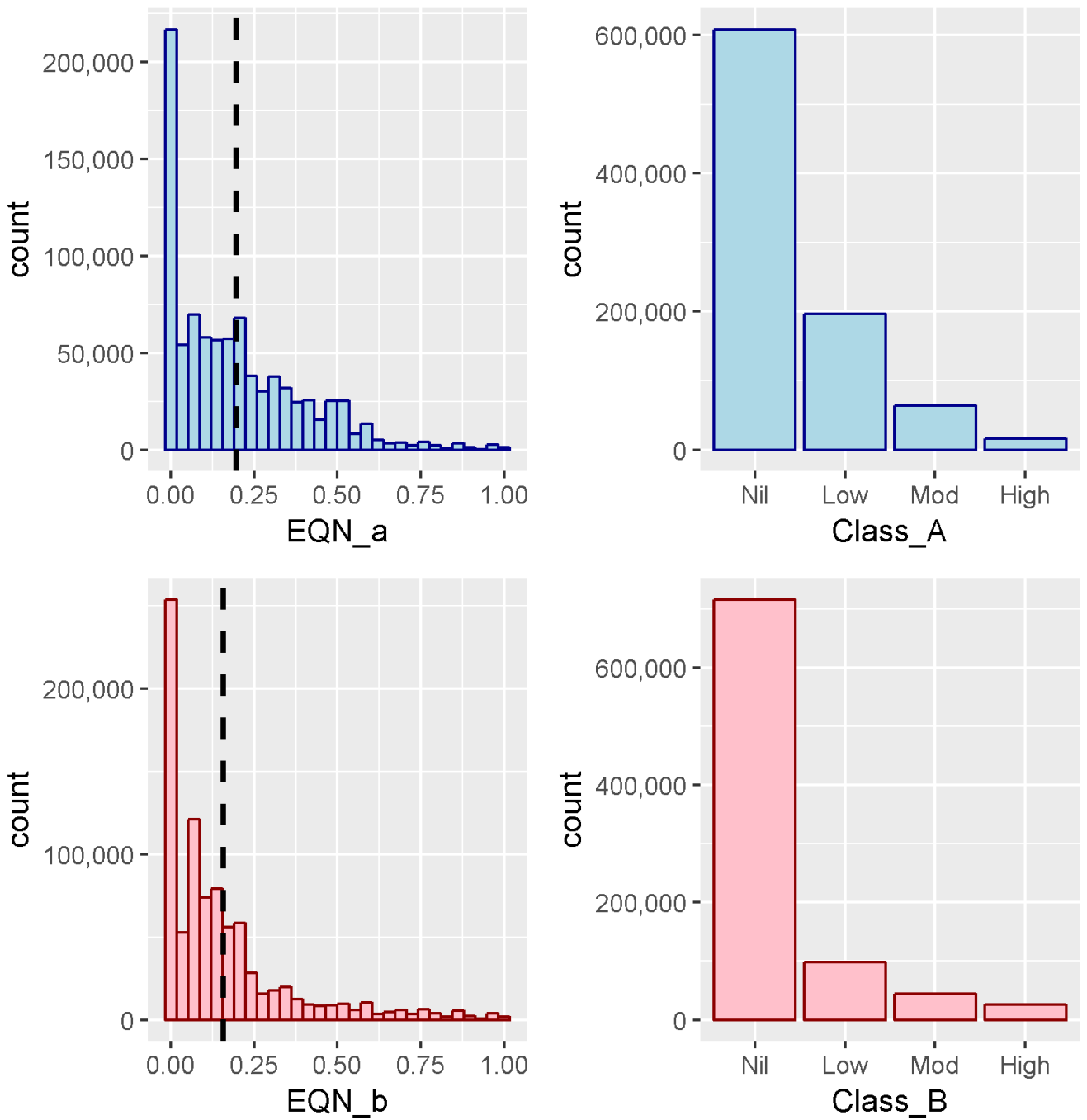


Figure 2. HSI values from Equations A and B, showing raster counts (20mx20m cells) by HSI score (at left) and HSI class (at right). The black dashed lines are the mean HSI scores: 0.22 mean HSI Equation A, 0.18 mean HSI Equation B.

Comparison of HSI outputs between HSI Equation A and the 2017 BC HSI nesting habitat algorithm for the Sayward analysis area (Figure 3), showed that the new algorithm captured less Low suitability habitat (7958 ha versus 9395 ha), and substantially less Moderate + High habitat (2609 ha and 641 ha, respectively), versus the 2017 BC HSI nesting habitat algorithm (7426 ha Moderate, 4451 ha High).

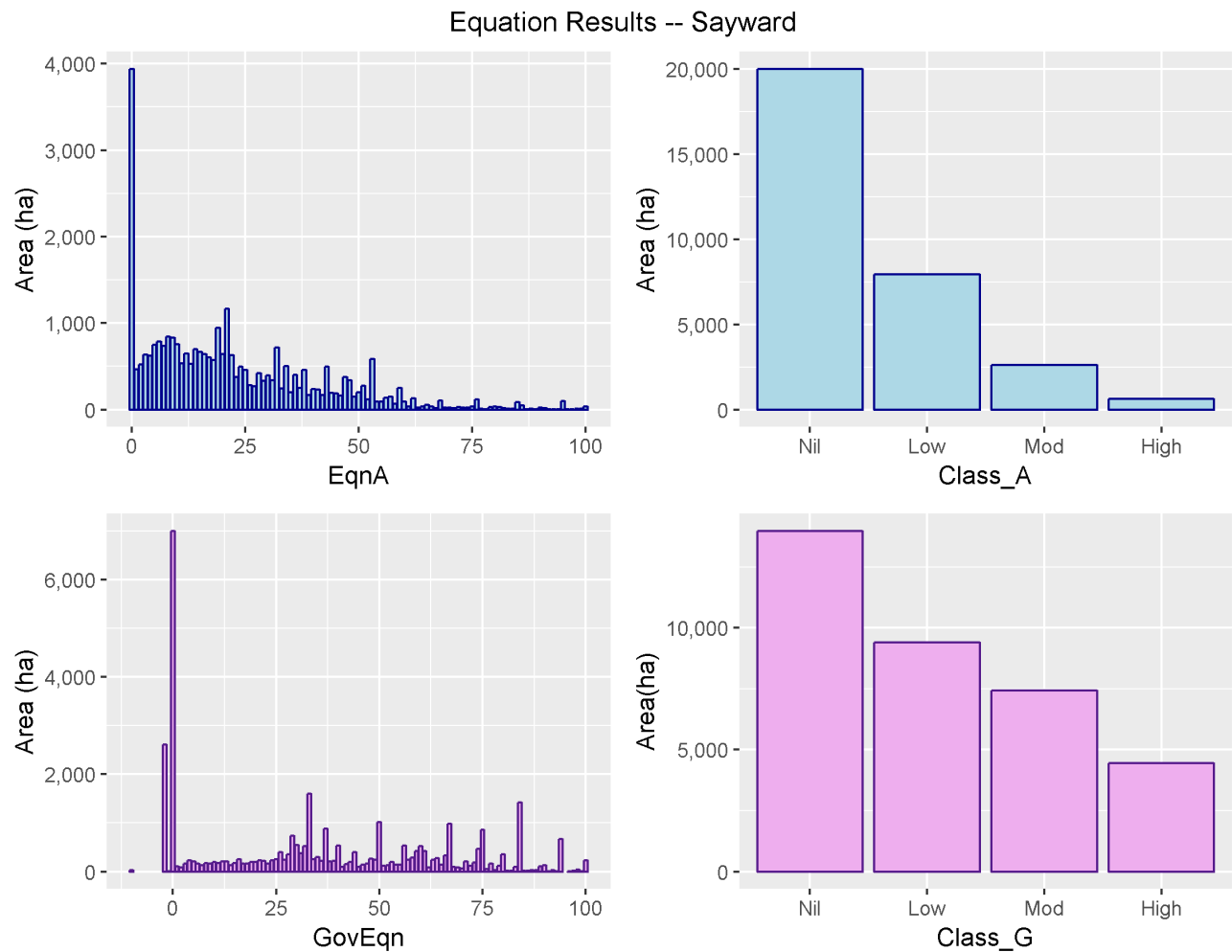


Figure 3. Comparison between Equation A and the 2017 BC HSI nesting habitat model results — Sayward

Rosewall

The Rosewall analysis area (8312 ha) is about ¼ the size of the Sayward area (35,284 ha), yet the r values for both areas show similar ranges and trends (Figure 4). Stand age, canopy height and crown canopy closure have wide r value ranges between 0 and 1.00. In Rosewall, there are some areas where elevation spans between 0.75 and 1.00 for the Elevation r value. There are also two different classifications of BEC-r value, 0.80 and 1.00.

The LiDAR-derived r metrics for canopy closure and flyways again showed a similar trend to that shown for the Sayward area; r values tended to cluster at either Low suitability (4944 ha crown closure, 4164 ha flyways @ $r=0.30$) or High suitability (2644 ha crown closure @ $r=1.00$, 4017 ha flyways @ $r=1.00$), with much smaller amounts of Moderate suitability habitat.

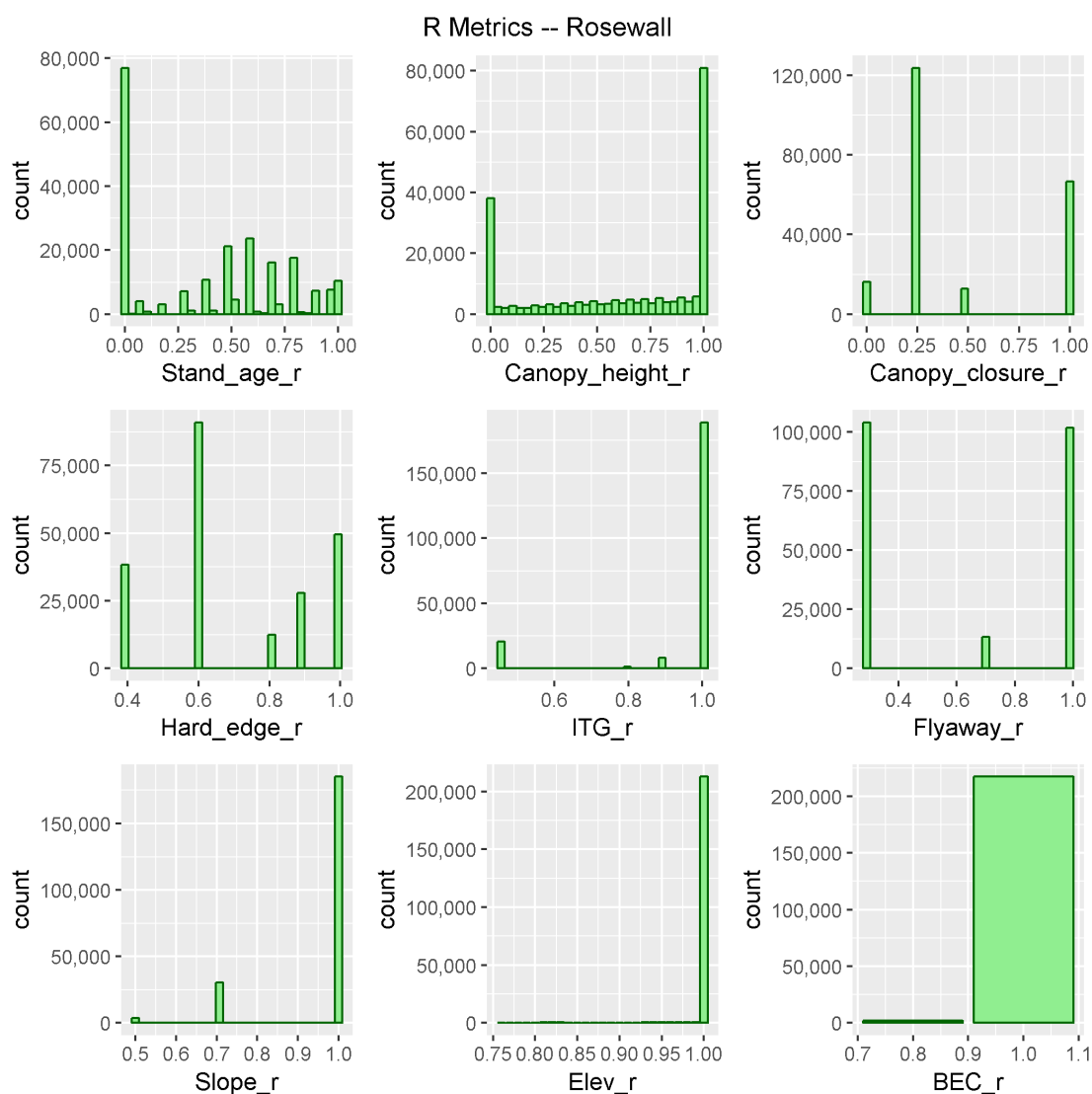


Figure 4. Distribution of r values for each HSI Equation A algorithm variable – Rosewall

Figure 5 compares the HSI outputs ratings (HSI value and class) between LiDAR-derived Equations A and B. These results were similar to the same comparison for the Sayward analysis area (Figure 2), with Equation A capturing much more Low habitat (2284 ha) than Equation B (796 ha); and slightly more Moderate and High habitat (774 ha combined) than Equation B (701 ha combined). The mean HSI scores for Equation A (0.23) and Equation B (0.18) were very similar to those for Sayward (0.22 and 0.18 respectively).

Again, while the outputs of Equations A and B are similar, these results suggest that Equation A (which includes the flyways metric) is able to more finely discriminate habitat into respective habitat classes.

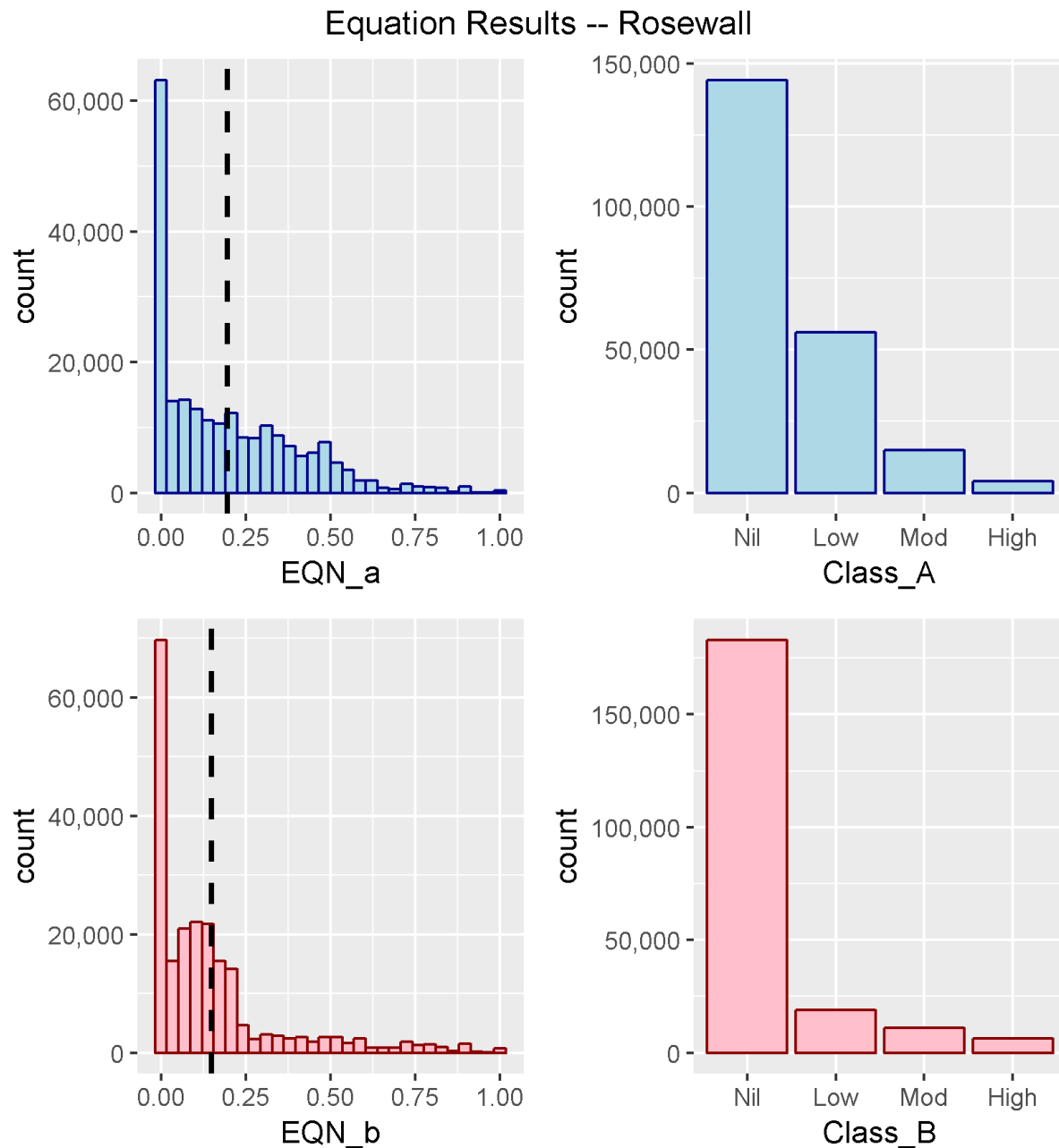


Figure 5. Raster counts and HSI value (at left) and suitability class (at right) from HSI Equations A and B. The black dashed line is the mean HSI score – Rosewall

Figure 6 compares the overall HSI scores and suitability class ratings for the Rosewall area, for Equation A and the 2017 BC HSI nesting habitat model algorithm. Again, the results are consistent to those for Sayward (Figure 3), with the LiDAR-derived Equation A capturing much less Nil and Low suitability habitat (2327 ha versus 5752 ha BC HSI nesting habitat model algorithm) and much less Moderate + High habitat (774 ha) than the BC HSI nesting habitat model algorithm (2560 ha).

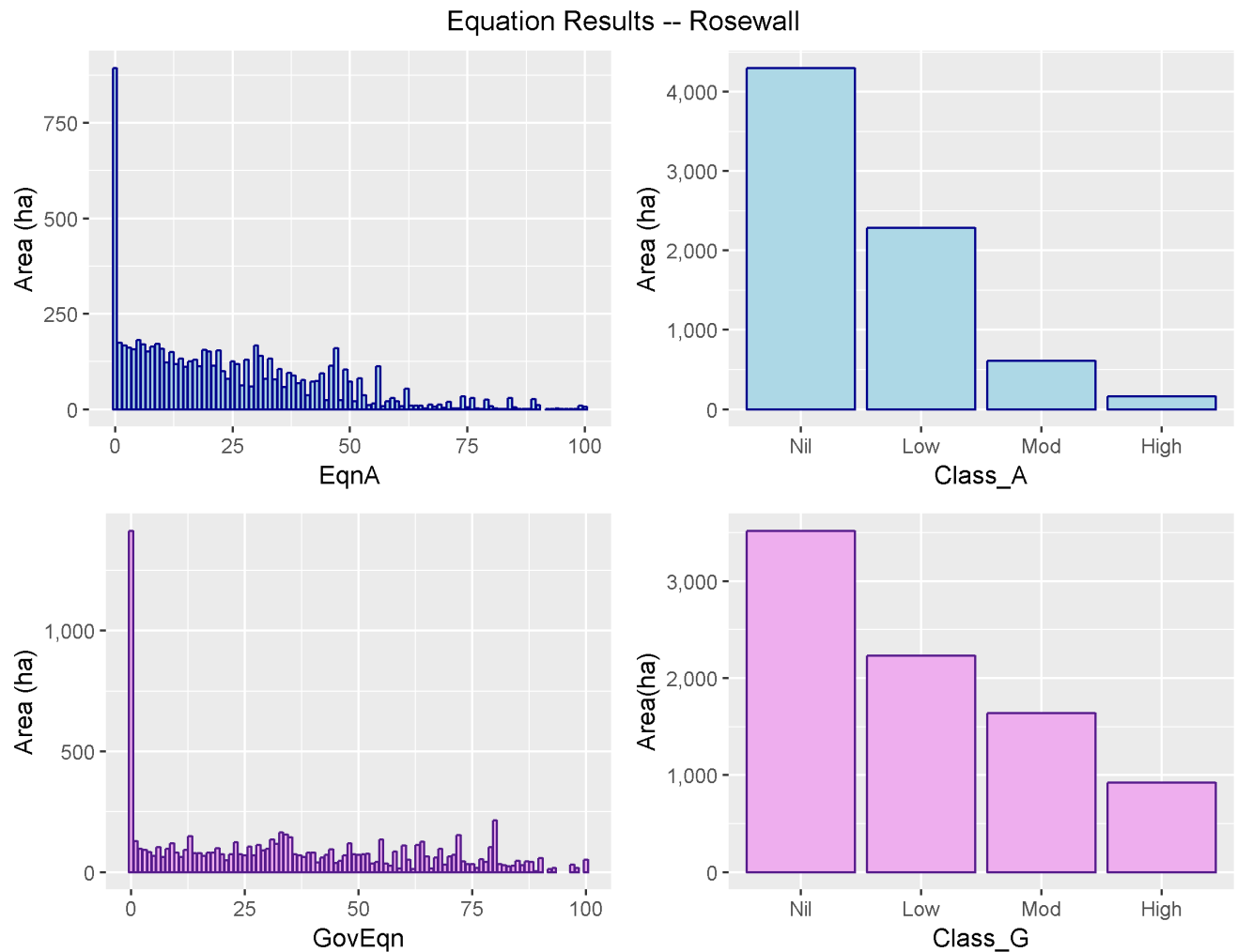


Figure 6. Comparison between Equation A and the 2017 BC HSI nesting habitat model results — Rosewall. HSI score at left, HSI class at right

Provision of Data Layers

The following data layers were generated for both areas of interest and for input into the new HSI models. They are provided as companion data to this report and are saved in ESRI geodatabase format (*.gdb).

- Canopy height (dominant tree layer)
- Canopy closure (%)
- Subcanopy flyway metric (@5-15 m above ground level)
- Elevation (m asl)
- Slope (%). A slope layer using slope degrees can be generated by converting slope% to degrees, then referring to the applicable r values for slope in Table 1. Convert percent slope to degrees as follows: $\text{Slope degrees} = \tan^{-1} * \text{slope\%}$
- Edge category (i.e., hard edge, either natural or anthropogenic)
- Edge distance (i.e., distance of raster cell from a hard edge)
- Terrain aspect (bearing in degrees) – this variable was not used in the goshawk HSI algorithm, but can be used for future UWR habitat modelling

Conclusions

The results obtained in this project demonstrate that incorporation of LiDAR-derived habitat metrics into a revised HSI algorithm with application over potentially large areas, can be done efficiently where high quality LiDAR data exists (i.e., using Table 1 input variables and the *R script* coded for this project). In particular, HSI Equation A developed in this project and which includes more accurate LiDAR-derived stand height and slope measurements, as well as new algorithm metrics for canopy closure and subcanopy flyways, yields HSI outputs which are fully comparable to, and perhaps more informative than, the current VRI-based HSI model outputs. The LiDAR-derived inputs (20 m x 20 m raster cell size) were both higher resolution and more accurate in comparison to the coarser scale (100 m x 100 m) and often inaccurate VRI-sourced inputs used in the current HSI model; particularly for canopy tree height, canopy closure and subcanopy flyways (which were recommended for use once LiDAR data became available, see Mahon et al. 2015, Wheatley and Manning 2019).

A new HSI algorithm integrating LiDAR-derived habitat variables (such as Equation A herein) is not only analytically possible over large areas, but will result in a higher-resolution habitat suitability rating. Based on our results here (also see Wheatley and Manning 2019), we suggest this will result in a more accurate future HSI model (though we do not test this hypothesis here; see below). For example, Figure 3 and Figure 6 for the Sayward and Rosewall areas respectively, demonstrate where the LiDAR-based Equation A consistently identified less Nil and Low suitability habitat and less Moderate + High suitability habitat, than the current HSI nesting habitat model. In other words, the Equation A algorithm (which includes metrics for canopy closure and subcanopy flyways) rated more habitat as having some suitability (i.e., Low), while being “more selective” in identifying Moderate + High suitability habitats. This is apparent in Figure 7, where the 2017 HSI nesting habitat model shows two known goshawk nests located in areas ranked Nil-Very Low for habitat suitability, versus the LiDAR-based Equation A indicating the same two nests situated within High-quality habitat polygons; we contend this is a function of both the improved accuracy in quantifying habitat such as tree heights, and the much higher resolution of the LiDAR data which enables

extraction of structural metrics such as canopy closure from the point cloud (i.e., 1-2 m accuracy rendered at a 20 m rasterized scale). Mahon et al. (2015) suggested the current 100-m VRI-based HSI model should generally be limited to large-scale management units for strategic planning purposes only. In comparison, we demonstrate here how more accurate (i.e., tree heights) and finer resolution LiDAR-based modeling can generate outputs and inform management decisions at both the stand and landscape scales.

It is worthwhile discussing implications of incorporating subcanopy flyways into the HSI algorithm. It is well recognized that the presence of abundant flyways and good sightlines in the lower-middle forest canopy is a key structural attribute of high suitability goshawk habitat. Until the advent of LiDAR, this metric has been impossible to measure quantitatively; thus flyway ratings are either not collected and are assumed to be correlated with overhead crown canopy closure, or they are rated into coarse categories (i.e., “common, somewhat limited, very limited, none”) based on ground plot observations. Similar to potential observer errors associated with measuring canopy closure, ground-based ratings of flyway condition are highly variable, biased by observer position and vantage, topography, stand type, and observer knowledge and experience. Results of the LiDAR-derived flyway quantifications for both the Sayward and Rosewall areas (see Figures 1 and 4), indicate much higher proportions of “High” and “Low” rated flyway condition (based on laser point count return proportion), and much less “Moderate” rated flyways. This finding is different from the ground plot observer ratings of flyway condition for these same areas which, even though sample size is not that large (N=152 plots), indicates a more normalized proportion (40:40:20, respectively) of “Good, Moderate and Low” rated flyway condition. Observer comments from these data revealed that most of the “Moderate-rated flyway” plot sites had been downgraded from “Good” due to an abundance of lateral branching in the B1 and A3 vegetation height layers (which roughly correspond to the 5-15 m LiDAR data height band).

Thus, the LiDAR-based flyway calculation would have downgraded occurrences with high point count return proportion (meaning presence of branches and foliage which reduce openness within this height stratum) to a Low rating, whereas a ground-based observer might have difficulty reliably distinguishing between flyway rating classes, particularly between “Moderate and Good”.

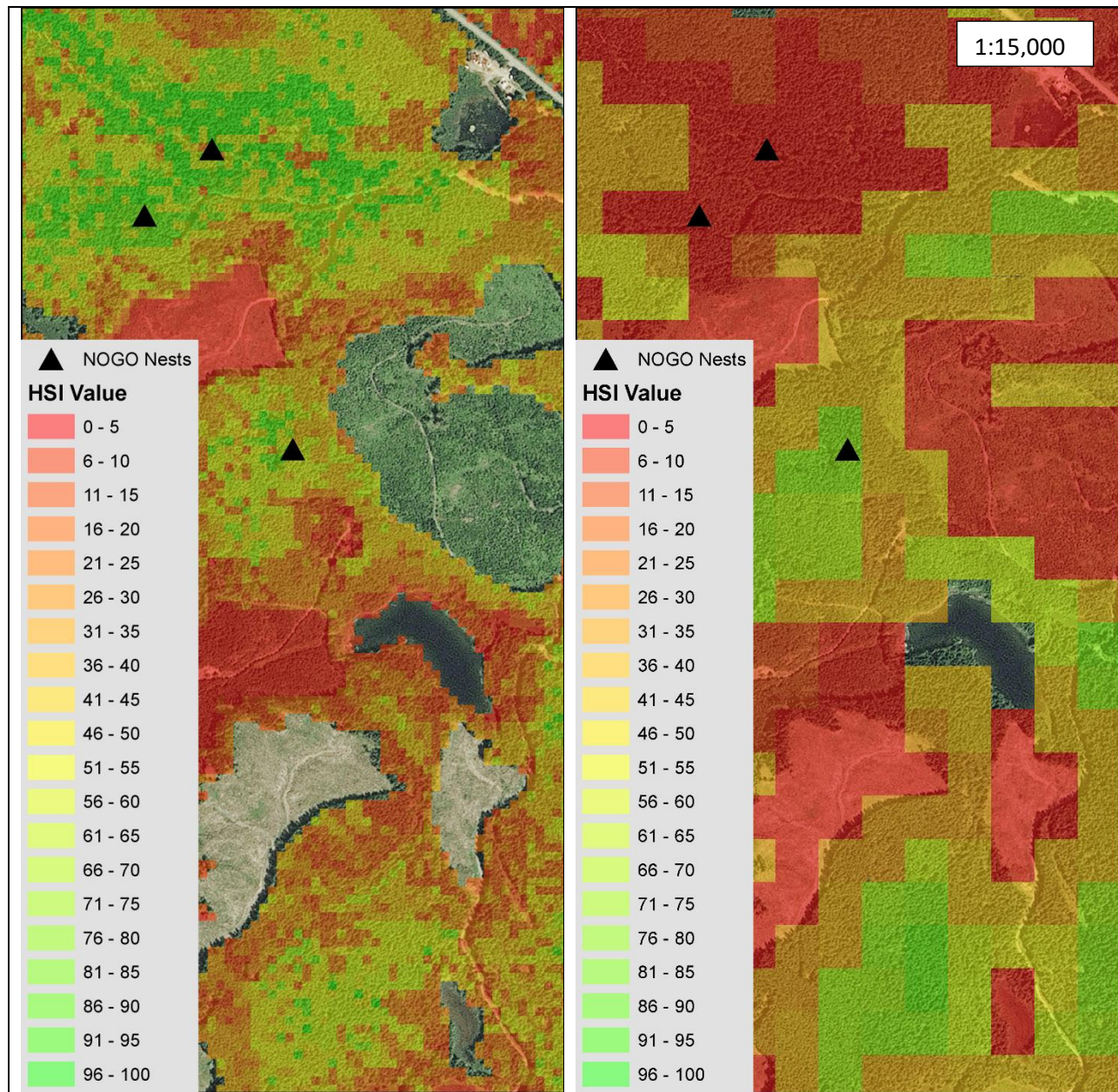


Figure 7. Comparative HSI outputs shown for a known goshawk nesting area in the Sayward analysis area. Equation A output at left, with 2017 HSI nesting habitat model output at right. Note the two goshawk nests located in the upper left part of the respective maps. The higher resolution 20 m x 20 m raster cells are visible in the HSI Equation A output map.

Recommendations

1. Determine whether other remote-sensing products can be integrated with LiDAR to improve Northern Goshawk habitat modeling. For example, both *Landsat* and *Sentinel* satellite imagery are publicly available, and can be used to generate land-cover classifications at higher resolutions than VRI, or fill gaps where VRI data are missing. A powerful addition to goshawk habitat modeling in this context would be the ability of LiDAR to differentiate the approximate stand age (using detailed height data) of high resolution (5 m) forested areas identified from satellite imagery (e.g., *Sentinel*), whereby younger stands can be differentiated using LiDAR (for height and thus age) and *Sentinel* for stand type and configuration.
2. Explore and expand the use of LiDAR-based terrain analysis (DEM) to further inform site or landscape-level variables important to goshawk ecology. For instance, LiDAR facilitates the micro-siting of shallow slopes or midslope flat-bench areas which are often used for nesting areas by goshawks.
3. Complete simple comparisons of 100-m VRI-based versus 20-m LiDAR-based HSI model outputs to better understand the differences between the two, and how these might apply to forest management. However, these should remain analytically simple (see #4 below); for example, by comparing the number of known goshawk nests located in high-quality habitat between the two models. Further, this should be completed with the understanding that HSI models are by definition derived through expert opinion in situations where ecological data are not available. HSI models are mathematical approximations of expert opinion and should be replaced by more objective ecological-occupancy models (statistical models) when appropriate data become available. Typically, when there are sufficient data to begin validating HSI models (i.e., a common conversation during this project), these same data are better used to develop new, independent statistical models. As such, we would suggest that sufficient data are available in many (but not all) areas of coastal BC to develop statistical models of goshawk nesting habitat (i.e., at the 20-m or higher resolution), and perhaps for foraging habitat where goshawk radio telemetry data exist. Advancements and refinements of the HSI modeling approach should become secondary to statistical analyses of ground plot nest-site data (e.g., T. Mahon “expert assessment habitat plot database”) and telemetry data (e.g., M. Wilson south coast goshawk radio-tagging) as response variables, while primarily using LiDAR-derived forest-habitat data as independent variables. This exercise can be viewed as a verification process for any new LiDAR-based habitat model.
4. Begin work to develop new LiDAR-based statistical models for goshawk nesting habitat. This could be accomplished by employing a use-availability or occupancy-probability multiple regression analysis using multiple working hypotheses and a model-selection approach to create new statistical models. LiDAR-derived data would generate the majority of habitat metrics for use as independent variables, and known goshawk nest site locations would be used as the response variable. This would not preclude the use of non-LIDAR data for some independent variables, similar to Equation A examined herein. Care must be used in linking the dates of goshawk nest occupancy with the acquisition of LiDAR data, but this would be the most statistically robust and by extension the most defensible habitat modelling approach moving forward. It would require the development of LiDAR-derived habitat metrics throughout any region of interest, but we have demonstrated herein that

this is entirely possible both in the contexts of data availability and contemporary computing power and expertise.

There are many different and valid statistical approaches and observational scales one could choose in the development of a new goshawk habitat model. Many of these will be determined by a combination of analytical assumptions and the characteristics of the final data set, so it is challenging at this stage to identify and suggest an exact methodology. However, based on our findings herein and in Wheatley and Manning (2019), we would generally recommend an analytical approach based upon Mackenzie et al. (2017), estimating species occurrence and occupancy using nest locations, telemetry data (where available) and both LIDAR and VRI-based forest metrics. These approaches are generally termed resource selection functions (see Johnson et al. 2006) based on multiple working hypotheses, and over the past 20 years there has been a veritable explosion in the development and application of occupancy models in wildlife-habitat work integrating population and community processes, spatial and temporal scales, and occupancy states (e.g., habitat adjacency, multiple species interactions, time-scale seasonality, etc.).

In developing new occupancy models, we would suggest including different combinations of the habitat variables derived herein, basing these combinations on working hypotheses of goshawk habitat use. This would not preclude the creation of additional independent variables or the combination of variables into non-linear algorithmic contexts, nor the use of both LiDAR-derived and VRI-based data inputs. However, each of these “exploratory combinations” would form the basis of a working hypothesis which can be compared statistically to other combinations; the one that best represents the “data in-hand” (e.g., nest site locations, radio telemetry locations, ground-verified stand structure data such as canopy closure, subcanopy flyway characteristics, nest platform structure abundance, etc.) would ultimately become the new validation goshawk habitat model.

The size of and shape of observational scale should also be considered. The most common sampling-plot shape in habitat-use studies has become the hexagon, but the size of the hexagon remains a topic of active investigation in ecology. Some researchers base the size of observational scale on Johnson’s orders of resource selection (Johnson 1980), choosing a separate scale for first, second, and third-order selection, typically corresponding to local, home-range, and landscape-scale habitat use. Although common in the literature, recent studies have identified that this 3-level process can hide or overlook important scale-based inflection points whereby important habitat-use signals occur at intermediate scales in-between the three observed scales. For this reason, we would recommend using a scale continuum approach whereby the same set of habitat-use models are compared amongst a series of objective observational scales (from ~5 ha upwards of 100 ha), while exploring which model best represents the actual/observed data at each scale. This approach enables the researcher to identify changes in habitat use among scales, which is a key parameter in understanding a species’ habitat selection. For instance, a smaller observational scale may indicate nest-site selection for certain forest characteristics immediately surrounding the nest, while different variables from the same data set may be important (e.g., perhaps for foraging) at larger observational scales (see Wheatley and Larsen 2018 for an application of this method; and McGarigal et al. 2016 for an alternative). Thus, rather than recommending any specific observational scales, we would encourage an exploration of multiple scales, addressing scale as a key factor in the design of future modelling work.

5. Some of the habitat indicator variables and continuous data sets that were produced in this project can also be used to assess or model ungulate winter ranges at varying spatial scales. Key LiDAR-derived variables and associated habitat criteria (BC Min. WLAP 2004; Manning et al. 2004; Nyberg and Janz 1990) that may be used for this purpose are shown below for Columbian black-tailed deer and Roosevelt elk winter range. A new UWR HSI algorithm would likely incorporate both LiDAR and VRI sourced variable inputs.

Habitat Indicator Variable	Criteria for High-ranked Winter Range	Source	Comments
Elevation (m asl)	600-800 deer	DEM raster	
	200-700 elk		
Forest canopy crown closure (%)	50-90 deer	raster	
	60-80 elk		
Aspect (bearing in degrees)	110-250	DEM raster	Generally south aspect slopes preferred; west usually better than east
Slope (%)	50-90 deer	DEM raster	Columbian black-tailed deer. Moderate to steep slopes preferred
	0-50 elk		Roosevelt elk. Flat to moderate slopes preferred
Stand height (dominant tree layer)	Likely >30 m	raster	Investigate height correlation with age class and leading tree species composition. Higher proportions of Douglas-fir and western hemlock are preferred overstory composition

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