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# An index for tracking old-growth value in disturbance-prone forest landscapes

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ABSTRACT

Forests in their later stages of development attain attributes that support biodiversity and provide a variety of ecological benefits (e.g. clean water and carbon storage). Despite their values, old-growth forests are declining worldwide in part due to anthropogenic pressures. A persistent challenge to managing and conserving old-growth forest has been establishing a reliable method for measuring old-growth values across large landscapes at an appropriately fine ecological and spatial scale. Using data from a community-managed forest in central British Columbia, Canada, an Aerial Laser Scanning (ALS) based metric was developed, using a random forest modeling framework, to predict an old-growth index across the forest. Using this old-growth index, we estimated that forests with “Very-high” old-growth values cover 14.7% of the study area (18,183.2 ha), and that only 25% (4,545.9 ha) of this “very-high” old growth value areas are current inside designated old-growth management areas (OGMAs). Additionally, the forests with “very-high” old-growth values that are currently inside OGMAs are fragmented, as only 1 out of 40 OGMAs have more than 50% of its area covered by forests with “Very-high” old-growth value. This research provides a clear ecological indicator that uses fine-scale remotely sensed data to measure old-growth and assess its conservation status within reserves. While the index developed is specific to the study site, the framework, is generic enough to be adapted to other forest types and ecosystems. More importantly, the identification of the amount and location of old-growth forests over the landscape can aid in the management and conservation of this rare resource and its services.

## 1. Introduction

Forests that are at an advanced development stage, often referred to as old-growth (Mosseler et al., 2003c; Spies, 2004; Hilbert and Wiensczyk, 2007), provide a range of ecological and socio-economic benefits, such as ecotourism (FAO and UNEP, 2020), genetic resources (Mosseler et al., 2003b), carbon storage and sequestration (Luyssaert et al., 2008; Maxwell et al., 2019), water provision (Bithell and Brasington, 2009), indigenous cultural values, and the maintenance of human health (Wirth et al., 2009a; Watson et al., 2018). Strategies to promote the retention of old-growth forests are often incorporated into landscape level forest planning (Arsenault, 2003; Gillis et al., 2003; Environmental Law Centre, 2013). However, the identification of old-growth is a difficult task due to the lack of a standard definition for what constitutes an old-growth forest (Hilbert and Wiensczyk, 2007). Old-growth forests are often defined in terms of longevity of dominant species, return period of natural disturbances, degree of human intervention, shade tolerance, and abundance of specific structures such as the number of large trees, snags, accumulated woody debris (Mosseler et al., 2003c, 2003a; Spies, 2004; Bauhus et al., 2009). These ecological differences with regard to the definition of old-growth across forest types pose a significant methodological challenge to the characterization of these forests only based on disturbance frequency.

There are multiple definitions and approaches to define and locate old-growth forests (Wirth et al., 2009b), but tree or forest age is often used as a simple proxy. For example, according to British Columbia’s Ministry of Forest, Lands, Natural Resource Operations and Rural Development (MFLNRORD, 2003), the province’s coastal forests are considered old-growth if trees are >250 years old. For forests dominated by lodgepole pine or broadleaf species in the northern interior, old-growth are forests with stands >120 years of age. In these landscapes, the longevity of trees tends to be shorter, and disturbances more

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frequent. Although age is a useful proxy, its measurement with traditional field methods is costly (Racine et al., 2014), and intractable at landscape scales. More importantly, essential structural elements of old-growth can be omitted using only an age threshold (Arsenault, 2003; Gillis et al., 2003; Holt et al., 2008; McMullin and Wiersma, 2019). This inaccuracy can lead to management that under represents old-growth forest in the landscape, or incorrectly identifies forests as being old-growth even though they do not exhibit the desired characteristics. As a result, in many areas, it may be prudent to compliment simple age dependent thresholds for old-growth definition with a more ecologically based representation of forest structures (Mosseler et al., 2003a; Spies, 2004; Hilbert and Wiensczyk, 2007).

Compared with old forests, young natural forests or intensively managed forest plantations have a simpler structure (Spies, 2004; McElhinny et al., 2006a). Thus, the abundance of old-growth attributes (e.g. large trees, snags, and accumulated woody debris), which contributes to the structural complexity in the old-growth forest, can be used as a proxy for old-growth forest mapping (Mosseler et al., 2003c, 2003a; Bauhus et al., 2009). A myriad of work has been conducted using a traditional field-based measurement of forest attributes to classify forest succession and assess the quality of old-growth forests (McElhinny et al., 2006a) (See also Table S01-Supplementary 1 for an overview of methods used to characterize old-growth forest). While field-based methods are essential for almost all forest studies, they are costly and normally cannot provide a fine grain assessment of forest state across a full landscape.

The emergence of new technologies has allowed the development of precise measures of forest condition across broad areas (White et al., 2016). For example, optical sensors have proven to be suitable for identifying forest succession at broad scales (Song and Woodcock, 2002). Nevertheless, remotely sensed images are often constrained to two-dimensional interpretation, which can limit the ability to detect important three-dimensional structural characteristics of old-growth forests (Lefsky et al., 2002). On the other hand, Aerial Laser Scanning (ALS, or airborne LiDAR) has been proven to be an effective technique to estimate 3D forest attributes, particularly for height and biomass (Næsset and Økland, 2002; Hyde et al., 2006). ALS has been rapidly incorporated into forest management (Reutebuch et al., 2005; Wulder et al., 2008), wildlife habitat assessment (Hyde et al., 2006; Martinuzzi et al., 2009), evaluation the effect of pests (Bright et al., 2013), and other applications. In addition to height and biomass, a variety of other old-growth forest attributes can be accurately estimated with ALS (Bater et al., 2009; Bright et al., 2013; Wing et al., 2015; White et al., 2018). While ALS has the potential to be an effective way of generating an old-growth index to effectively map old-growth forests, models that allow old-growth to be identified using ALS data are needed.

Being able to identify, quantify and map old-growth forests is a required precursor to effectively managing them within a landscape, and imperative for their conservation and maintenance in managed landscapes. Previous studies have developed a range of criteria for identifying and mapping old-growth forests (Table S01-Supplementary 1). However, few have used old-growth attributes to create an index for old-growth value that evaluates forest structure at a fine ecological grain at a landscape scale extent.

In this work, we aim to: (1) develop an old-growth index based on forest structures measured with traditional field methods; (2) evaluate a range of categorical and continuous old-growth indices that are derived from empirical forest attributes; (3) extrapolate the old-growth index to the landscape utilizing ALS-derived metrics; and (4) evaluate the amount and quality of old-growth forest for the study site, simultaneously evaluating the set-aside old-growth forests currently present in the landscape.

## 2. Material and method

### 2.1. Study area

The Chinook Community Forest (CCF) is located within the Skeena region of British Columbia, Canada, and overlaps with six First Nations' and Bands' territories: Cheslatta Carrier Nation; Lake Babine Nation; Burns Lake Band; Wet'suwet'en First Nation; Skin Tyee Nation; and Nee Tahi Buhn Band. Community forests are area-based tenures managed by a local government, community group, or First Nation, generally for multiple objectives. The forests contain two forest types or biogeoclimatic (BEC), the Englemann Spruce – Subalpine Fir (ESSF) and Sub-Boreal Spruce (SBS) (Williams et al., 2001). CCF is 123,695.73 ha and currently encompasses 40 old-growth management areas (OGMAs) with a combined area of 8,618.69 ha, or 6.96% of the tenure. CCF is comprised of five management blocks (Fig. 1); for the remainder of the paper we depict only block 04 to facilitate visualization, but the analysis and numeric results are for the whole tenure. The overall commercial intent for the CCF is to produce and harvest wood fiber for sale. However, as the area is a community forest, other non-commercial ESs such as cultural heritage, recreation, and water quality are taken into account when planning forest management and operations.

### 2.2. Field Data:

Empirical measurement of forest composition and structural attributes were collected from 120, 10 m radius, plots (Table 1; 5222 trees sampled). The location of the sample plots was determined using stratified random sampling (stratifying across the 5 blocks, Fig. 1), such that plots were representative of the CCF land base. All trees >4 cm DBH were measured to ensure that forest structure in disturbed and young forests was captured (Keränen et al., 2015). In addition, trees with a diameter smaller than 4 cm were tallied to obtain the density of small trees and seedlings. The inventory followed the Change Monitoring Inventory (CMI) procedures used by B.C. Ministry (MFLNRORD, 2017). High precision GPS was used to obtain two measurements of ±2 m accuracy from the plot center.

### 2.3. Old-growth attributes

From the list of thirteen old-growth attributes indicated by (Bauhus et al., 2009), we were able to produce eleven of them for the Chinook Community Forest (Table 1). In addition, we also included maximum tree height as it has a strong correlation with age in old-growth assessment (Kneeshaw and Burton, 1998; Hao et al., 2007). Tree diversity was also included, as old-growth is expected to have higher tree diversity (Mosseler et al., 2003b; McElhinny et al., 2006b). Here we utilized these attributes as the basis for forest classification and the development of an old-growth index. Aboveground biomass estimates were based only on the value of DBH in the form of an exponential curve developed by Jenkins et al. (2003). DBH and height are the base for volume estimates calculated using volume equations developed by Penner et al. (1997) and Standish et al. (1985). A description of the equations and associated parameters utilized in this study are included in Supplementary 2.

### 2.4. Plot-level definitions of old-growth

We developed and evaluated eight empirical indices of old-growth forests using field measured forest attributes (Table 1 and Fig. 2). All empirical attributes used to develop the indices were normalized (i.e. scale from 0 to 1 by dividing each variable by its maximum value), such that all variable had the same weight in the index development. The first five of these indices were categorical and divided the forest into old-growth classes. The first index was based only on estimated stand age and divided the forest into four provincially defined forest age classes (MFLNRORD, 1995): initiation (0 – 40 year), young (40 – 70 year),

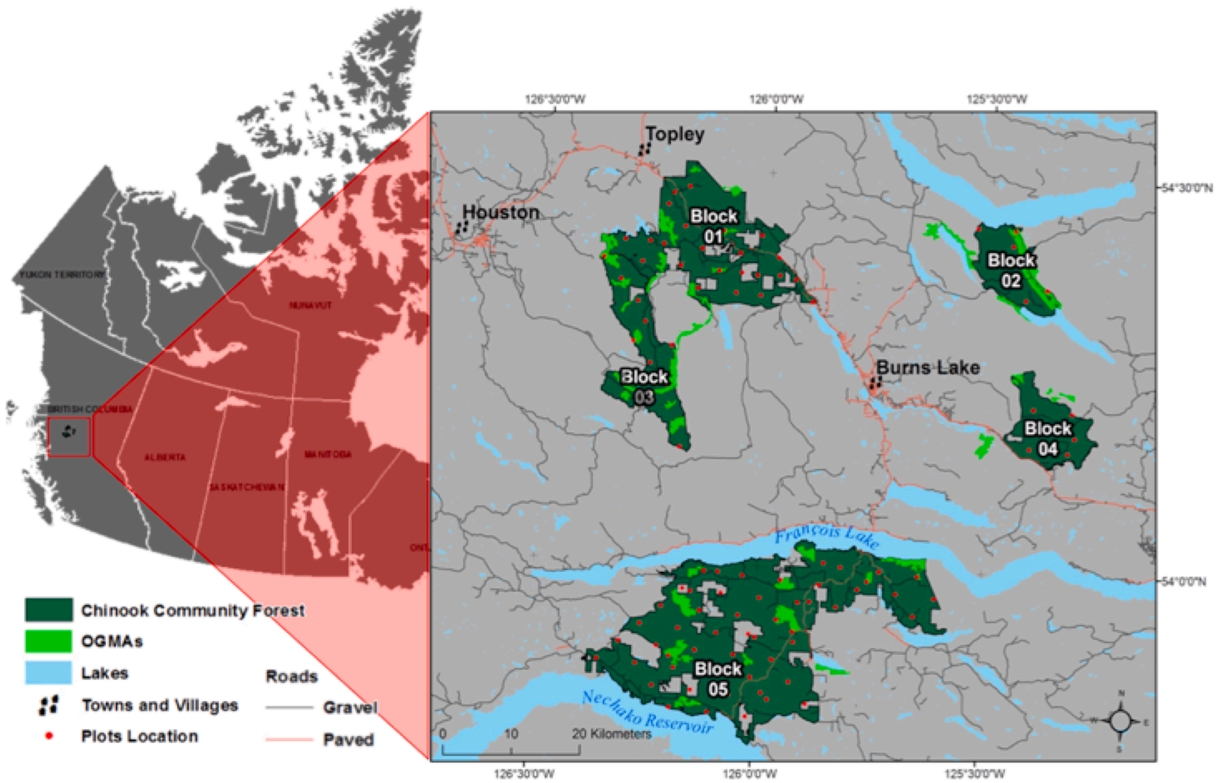


**Fig. 1.** Location of Chinook community forest tenure areas and distribution of Old-growth management areas (OGMAs).

**Table 1**
Field measurement of Old-growth attributes.

| | Old-growth Attribute | Mean | Range |
|---|---|---|---|
| **1** | Large trees density (number of trees - dbh > 40 cm/ha) | 14.47 | 0–222.82 |
| **2** | Presence of regeneration (number of trees < 1.3 m/ha); | 4,564 | 0–37,179 |
| **3** | Biomass of late succession species (Spruce, Balsam fir, tons/ha) | 912.10 | 0–7,289.30 |
| **4** | Coefficient of variation of DBH (Horizontal Complexity) | 47.52 | 0–125.84 |
| **5** | Coefficient of variation of height (Vertical Complexity) | 37.08 | 0–110.79 |
| **6** | Density of dead standing trees (stems/ha) | 180.38 | 0–1,655.21 |
| **7** | Volume of dead fallen trees ($m^3$/ha) | 13.08 | 0–115.16 |
| **8** | Wide decay class distribution (Std of decay class) | 1.32 | 0–3.56 |
| **9** | Total Volume ($m^3$/ha) | 105.58 | 0–375.98 |
| **10** | Biomass (tons/ha) | 3,297 | 0–14,322 |
| **11** | Basal area ($m^2$/ha) | 9.82 | 0–37.91 |
| **12** | Abundance of special attributes (broken top, fork, scars, and etc) | 3.19 | 0–14.49 |
| **13** | Age (year) | 63.81 | 0–262 |

mature (70 – 140 year) and old-growth (>140 years). Four additional forest classification indices were developed including stand structural attributes (Fig. 2). For two of them, stand structural attributes (Table 1) were delimitated into classes using unsupervised k-means classification including age (index 2) and without age as a stand attribute (Index 3) (Fig. 2). For the indices 4 and 5, we utilized a stepwise procedure that used a random forest routine to reduce the dimensionality of the data prior to applying k-means classification (Shi and Horvath, 2006; Afanador et al., 2016). The reduction in dimensionality works similar to a Principal Component Analysis (PCA), where all variables were reduced to a measurement of proximity to improve clustering of plots with similar stand structure.

We also created thee different old-growth indexes to capture the continuous nature of the forest structures. To allow the combination of multiple measures to form single indices and give the same weight to all variables, we normalized all old-growth attributes (Table 1) to range from 0 to 1 by dividing each variable by its maximum value. For the indices' development, each old-growth attribute was given the same weight. Age was utilized as a continuous variable to create the first continuous old-growth index (Fig. 2). The other two indexes were created utilizing all old-growth attributes, with and without age.

### 2.5. ALS data processing

ALS data was collected in a leaf-on condition with an average density of 14 pulses/m2, a half-scan angle of 12.5° from NADIR, with a 50% overlap. The footprint is estimated to be from 30 to 70 cm. LAStools (version 161114) was used to process the ALS point cloud data. Additional information on the methods and processing of the ALS data is provided in Supplementary 2 and a literature review on the use of ALS data for estimation of old-growth attribute in Table S2 - Supplementary 1. From the ALS data, we calculate a range of forest structure metrics (Table 2) at a 20 m by 20 m raster resolution (i.e.400 $m^2$ corresponding to the plot size from which empirical forest structure data was collected). Tree height is one of the most fundamental measurements in the forest industry and has a critical role in the quantitative assessment of forest biomass, carbon stocks, growth, and site productivity (Andersen et al., 2006), and was incorporated into our metric using ALS height percentiles. In addition, tree height is dynamic throughout forest succession, and it is considered an important old-growth attribute (Spies, 2004; McElhinny et al., 2006b). We incorporated tree and stand height into our metrics. The size, area and shape of forest gaps are also expected to reflect a forests development and succession stage (White et al., 2018). We assessed gap structure by calculating canopy cover using vegetation point > 3 m high (STH4_Cov in Table 2). While this metric does not measure the canopy gap directly, canopy closure depicts the differences in canopy openness in different forest succession, especially when combined with other old-growth attributes, such as vertical

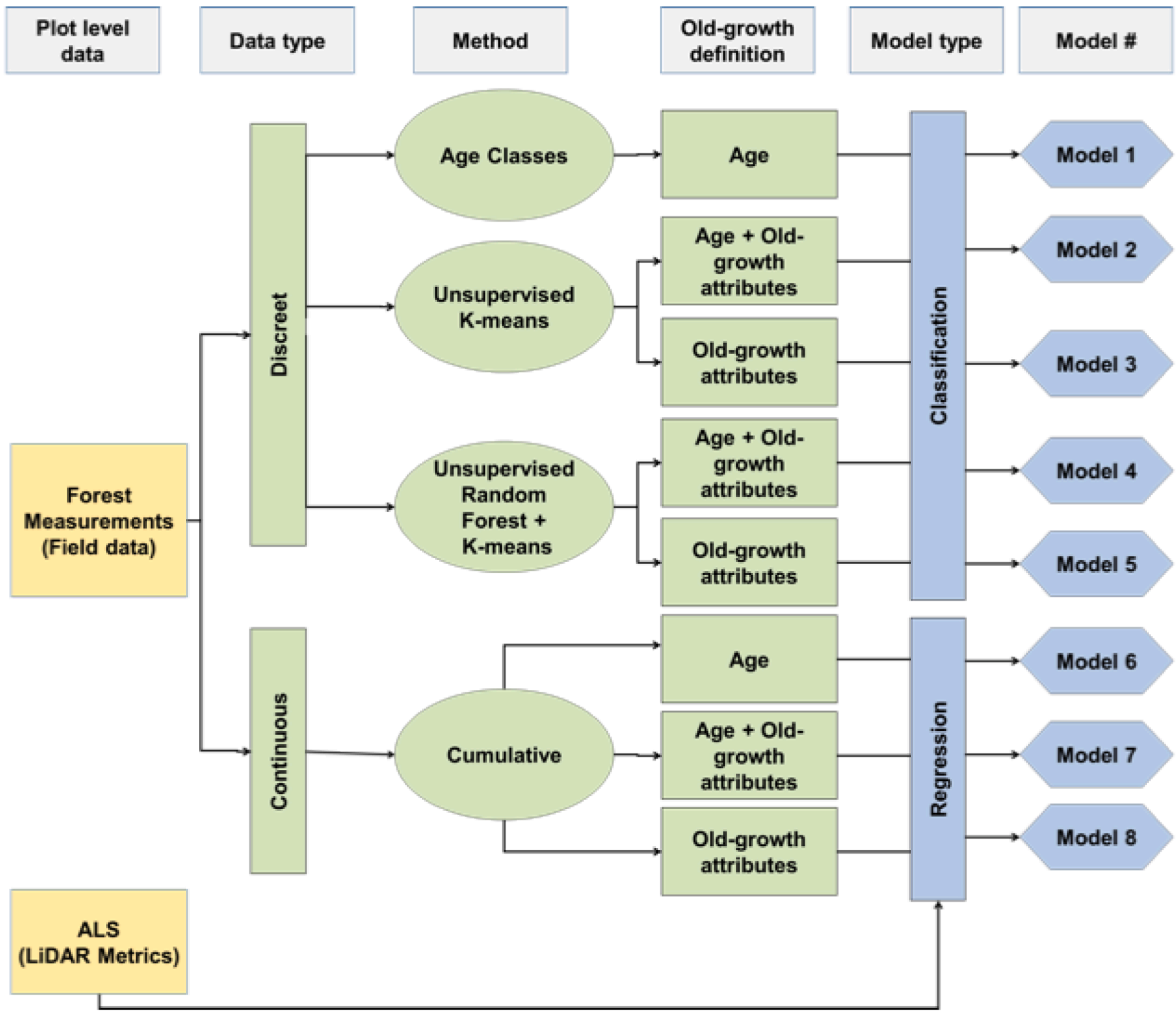


**Fig. 2.** Analysis schematic for the development of the old-growth empirical and ALS models. Field measured (plot-level) old-growth attributes (Table 1) were used to develop the response variables for the five classification and three regression models. Model 1 is an age-based classification of forest succession. For Model 2 through 5, old-growth attributes, with or without age, were used to align plots with old growth forest classes. Model 6 uses "age" as a continuous response for old-growth. For Model 7 and 8, old-growth attributes, with and without age, were used to develop continuous old-growth indices. A detailed description of each model is available on Supplementary Material 4.

complexity. We used the coefficient of variation (CV) of ALS-derived tree heights to estimate the number and complexity of canopy strata (Zimble et al., 2003). Old-growth forests are expected to have higher complexity not only in the crown height but also in the understory. Thus, a metric for vertical complexity was calculated using multiple strata heights (0.2 – 1 m, 1 – 2 m, 2 – 3 m, and > 3 m).

### *2.6. Statistical analysis:*

We used a Random Forest (RF) framework to develop classification and regression trees to model the empirically measured old growth attributes using ALS derived predictor variables (Belgiu and Drăguţ, 2016; Cutler and Wiener, 2018). We implemented the random forest (RF) models using the "randomforest" package (Cutler and Wiener, 2018) in the R (R Development Core Team, 2018) programming environment to connect field delivered metrics to ALS metrics.

Eight random forest models were generated, one for each of the old-growth indices described in Fig. 2. The models use the plot-level classification and old-growth indices delivered from fieldwork data as response variable. The predicting variables were the set of ALS metrics listed in Table 3. Each random forest model generated 10,000 decision trees to ensure the stabilization of the model. For each tree a subset of 12 out of the 36 predicting variables was used as suggested by (Breiman and Cutler, 2003). For each tree, we tested subsets of predictors from 6 to 12 out of the 36 predicting variables as suggested by Gareth et al. (2013) and Breiman and Cutler (2003). Most of the models had slightly better explained variation when 12 predicting variables were used in each tree in the random forest. Thus, we set 12 out of 36 predictors to growth each tree in all random forest models. In addition, we applied a K-fold cross validation (k = 4) procedure with the r package "Caret" to divide the data into training and validation data set (Kuhn, 2020). Thus, each random forest model was generated with a subsample of 75% of the available data and validated with the remaining 25%. This procedure was repeated ten (10) times for each model. Mean accuracy, kappa and balanced class accuracy was reported. For modeling the continuous old-growth indices (Model 6–8 in Table 2) random forest was implemented as a regression tree. For the regression, we reported the means and standard deviation of the r-squared and the mean square error of the ten repetitions.

The R package "raster" (Hijmans, 2019) was used to generate old-growth maps from the different old-growth models developed in this work. The five Random forest models ran with the plot-level forest succession classification were compared in terms of out of bag error and the old-growth misclassification error (Belgiu and Drăguţ, 2016). The

**Table 2**
ALS metrics utilized in the random forest models.

| Metric name | Metric Description |
|---|---|
| AHR_Avg | Average of all height returns |
| AHR_Kur | Kurtoses of all height returns |
| AHR_Max | Max of all height returns |
| AHR_Qva | Average of squared height of all height returns |
| AHR_Ske | Skewness of all height returns |
| AHR_Std | Standard Deviation of all height returns |
| AHR_Dns | Number of all points above 1.3 m / number of all returns. |
| H10PercT | Height 10th Percentile |
| H25PercT | Height 25th Percentile |
| H50PercT | Height 50th Percentile |
| H75PercT | Height 75th Percentile |
| H90PercT | Height 90th Percentile |
| H95PercT | Height 95th Percentile |
| STH1_Com | Coefficient of variation of returns of height > 0.2 m and bellow < 1.0 m |
| STH1_Den | Density of points for returns > 0.2 m and < 1.0 m / Density of ground returns |
| STH1_Ske | Skewness of all height returns |
| STH1_Kur | Kurtoses of all height returns |
| STH1_Cov | Canopy cover (First returns at height > 3.0 m/ all first returns*100) |
| STH2_Com | Coefficient of variation of returns of height > 1.0 m and bellow < 2.0 m |
| STH2_Den | Density of points for returns > 1.0 m and < 2.0 m / Density of ground returns |
| STH2_Ske | Skewness of all height returns |
| STH2_Kur | Kurtoses of all height returns |
| STH2_Cov | Canopy cover (First returns at height > 3.0 m/ all first returns*100) |
| STH3_Com | Coefficient of variation of returns of height > 2.0 m and bellow < 3.0 m |
| STH3_Den | Density of points for returns > 2.0 m and < 3.0 m / Density of ground returns |
| STH3_Ske | Skewness of all height returns |
| STH3_Kur | Kurtoses of all height returns |
| STH3_Cov | Canopy cover (First returns at height > 3.0 m/ all first returns*100) |
| STH4_Com | Coefficient of variation of returns of height > 3.0 m |
| STH4_Den | Density of points for returns > 3.0 m / Density of ground returns |
| STH4_Ske | Skewness of all height returns |
| STH4_Kur | Kurtoses of all height returns |
| STH4_Cov | Canopy cover (First returns at height > 3.0 m/ all first returns*100) |
| UNDEN | Density of points for returns > 0.2 m and < 3.0 m / Density of ground returns |
| VERCOMP | Coefficient of variation of all height returns |

**Table 3**
Number of plots per each level of old-growth classification. Model 1 is a pure age classification. Model 2 and 4 are classification of the abundance of old-growth attributes, including age. Model 3 and 5 are also classification of the abundance of old-growth attributes, except they do not include age.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Very-low | 7 | 35 | 35 | 13 | 14 |
| Low | 29 | 26 | 26 | 15 | 17 |
| Intermediate | 29 | 23 | 23 | 19 | 18 |
| High | 22 | 6 | 6 | 22 | 25 |
| Very-high | 11 | 8 | 8 | 29 | 24 |

three Random forest models generated from the two old-growth indices and age estimates were compared in terms of mean squared error. The most robust models were used to generate old-growth maps for the whole study area. To make comparisons between the categorical and continuous models, we broke the continuous model into classes. We used the natural breaks (Jerks) option from the ArcGIS classification method to create five classes analogous to the other categorical definitions of old-growth.

## 3. Results

### 3.1. Fieldwork data

None of the field measured old-growth attributes displayed a normal distribution (Fig. 3), highlighting the importance of choosing a non-parametric statistical framework, such as "random forest", for the development of old-growth models. Nine out of the ten non-age based variables selected to be included in the development of the old-growth indices were listed by Bauhus et al. (2009) as important old-growth attributes.

### 3.2. Fixed old-growth definitions

The classification models that utilized old-growth attributes without transformation (Model 2 and 3, Fig. 2), tended to underrepresent the high and very-high old-growth classes (Table 3). Including stand age as an attribute in the models did not substantially modify the old-growth classification (Models 2,3,4 and 5). The models that were based on reduced dimensionality prior to classification (Model 4 and 5) more closely approximated the age based old-growth classification groups. However, Model 4 and Model 5 had a higher number of plots classified as with very-high value for old-growth than any other classification, likely overestimating of old-growth in the landscape.

K-means old-growth classification based on old-growth attributes separated plots with stand age higher than 140, even though the remaining classes completely overlapped (Fig. 4 a and b). On the other hand, stand age overlapped throughout old-growth classes based on reduced dimensionality old-growth classes (Fig. 4 c and d). Although the oldest stands were mostly classified into "High" and "Very-high" old-growth values in all classifications, there were some apparent misclassifications (Supplementary 3, Fig. S3). The plot where the oldest tree was sampled was classified as either "Low" (Supplementary 3, Fig. S3 b and c) or "High" (Supplementary 3, Fig. S3 d and e) old-growth value, where it is expected to be in the "Very-high" old-growth value. Similar to age, the other old-growth attributes were not well differentiated into clear and consistent classes by any of the classification routines (Supplementary 3, Fig. S2 to Fig. S5). However, for the pure age classification (Model 1, Fig. 2), all old-growth attributes seem to follow a trend from very low abundance of old-growth attributes for the "Very-low" and "Low" classes to high abundance for the "High" and "Very-high" classes (Supplementary 3 – Fig. S1). Similar trends were also present for the other classifications (Model 2 to 5, Fig. 2), particularly for the old-growth attributes "maximum tree height", "Biomass" and "Basal Areas". The old-growth attributes differed with regard to how well they clearly differentiated into different classes. For example, "maximum tree-height" and "biomass" separated well the "very-high" class from the remaining classes in all models, except for pure age classification (Supplementary 3, Fig. S1). "Horizontal complexity" and "Volume" separated well the "Very-low" and "Low" old-growth value classes from the remaining classes. Yet, while one attribute separated well one class from the others, there were still overlapping between at least two classes in all classification for all attributes (Supplementary 3, Fig. S1 to S5). In addition, no single attribute provided a clear differentiation of all classes, likely because there is not a clear threshold to indicate when a forest enters the old-growth stage since stand development is continuous (Wirth et al., 2009b).

Reducing the dimensionality of the old-growth attributes prior to classification substantially improved the models' mean accuracy once compared to the K-means classification of old-growth attributes; from 0.53 (+/−0.03) to 0.69 (+/−0.02) for Model 2 and 4, and 0.55 (+/−0.02) to 0.68 (+/−0.02) for the models 3 and 5 (Table 4). The reduced dimensionality models (Model 4 and 5) had not only the best overall accuracy but also best class accuracy for "Intermediate," "High," and "Very-high" classes. While the model based on all attributes including age has greater predicting power for class "very-low" and

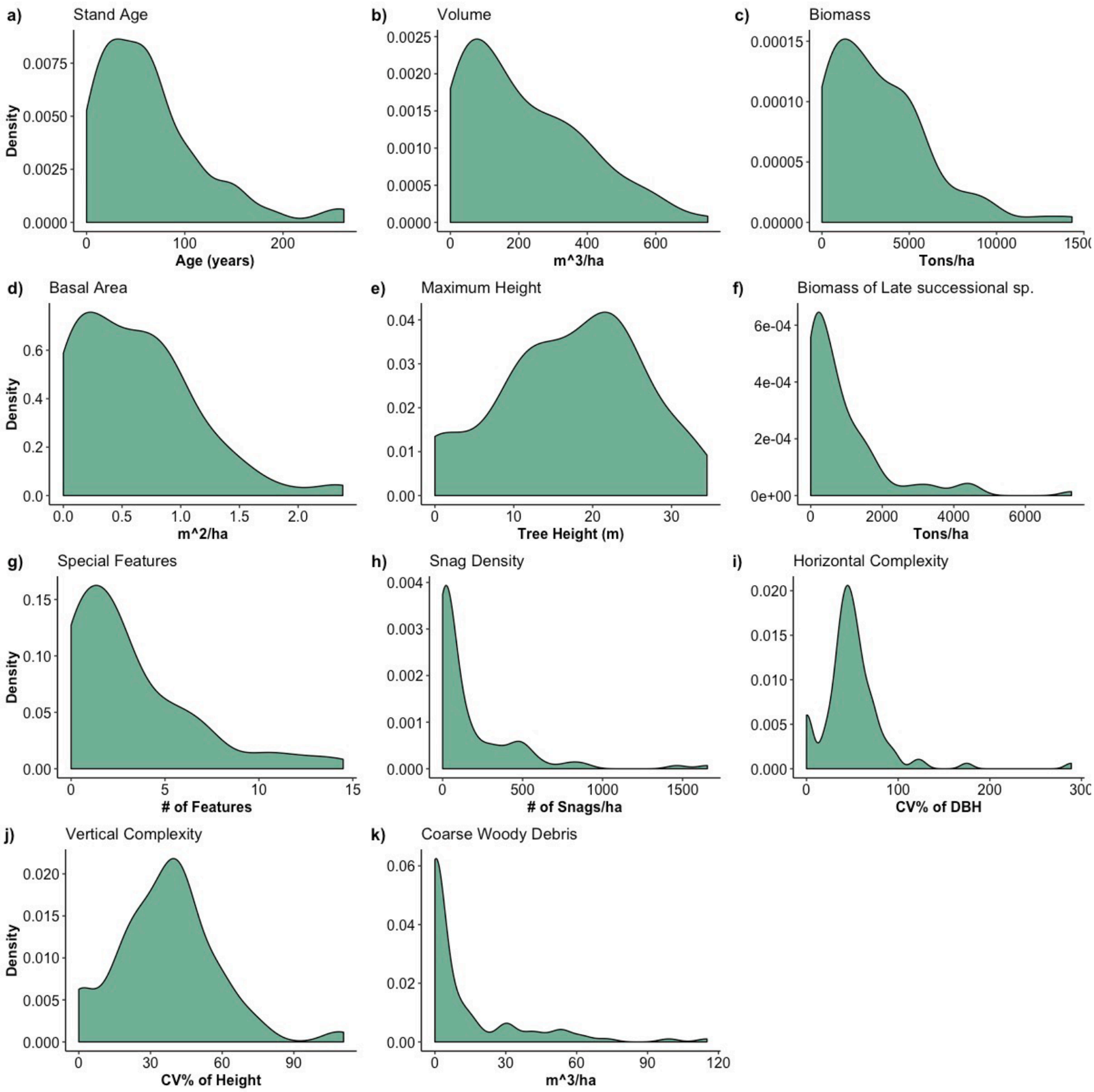


**Fig. 3.** Histograms of old-growth attributes best correlated with age, displaying the distribution of the data density of a) age, b) volume of live trees ($m^3$), c) above ground live biomass (tons/ha), d) basal area of live trees, e) maximum tree height (m), f) biomass of late successional species (tons/ha of Spruce and Balsam fir), g) number of species features (ex. scars, fork and broken tops), h) density of dead standing tree per hectare, i) coefficient of variation of dbh as a proxy for horizontal complexity, j) coefficient of variation of height as a proxy for vertical complexity, and k) volume of dead fallen trees/ha as a proxy for coarse woody debris.

"Intermediate" (Model 4) the model that excluded age performed better in class "Low," "High," and "Very-high." In particular, the reduced dimensionality models were better at identifying forests with "High" and "Very-high" old-growth value than any categorical definition utilized here (Table 4, Model 4 and 5). However, the stepwise framework of these models involved the use of two classification methods ("random forest" and K-means) to reach the final classification. Using random forest to reduce dimensionality of the data added randomness to the plot classification, which was stabilized after multiple k-means classification on the data results of the unsupervised random forest. Thus, while the final classifications based on reduced dimensionality old-growth attributes have better performance than the others, the accuracy of the classification only increased from 0.53 in pure age definition to 0.69 when old-growth attributes were included.

### 3.3. Continuous old-growth definition

When comparing the continuous old-growth indices (Table 5), we focused on the overall abundance of old-growth attributes. The old-growth attributes that had the highest correlation with pure age model (Age-Model 6) were the "Maximum Tree height and "Biomass" (r-squared > 40%) (Supplementary 3, Table S1). No attributes had r-squared >45% with AGE.

The continuous age-based model (Model 6, Fig. 2) represents age and

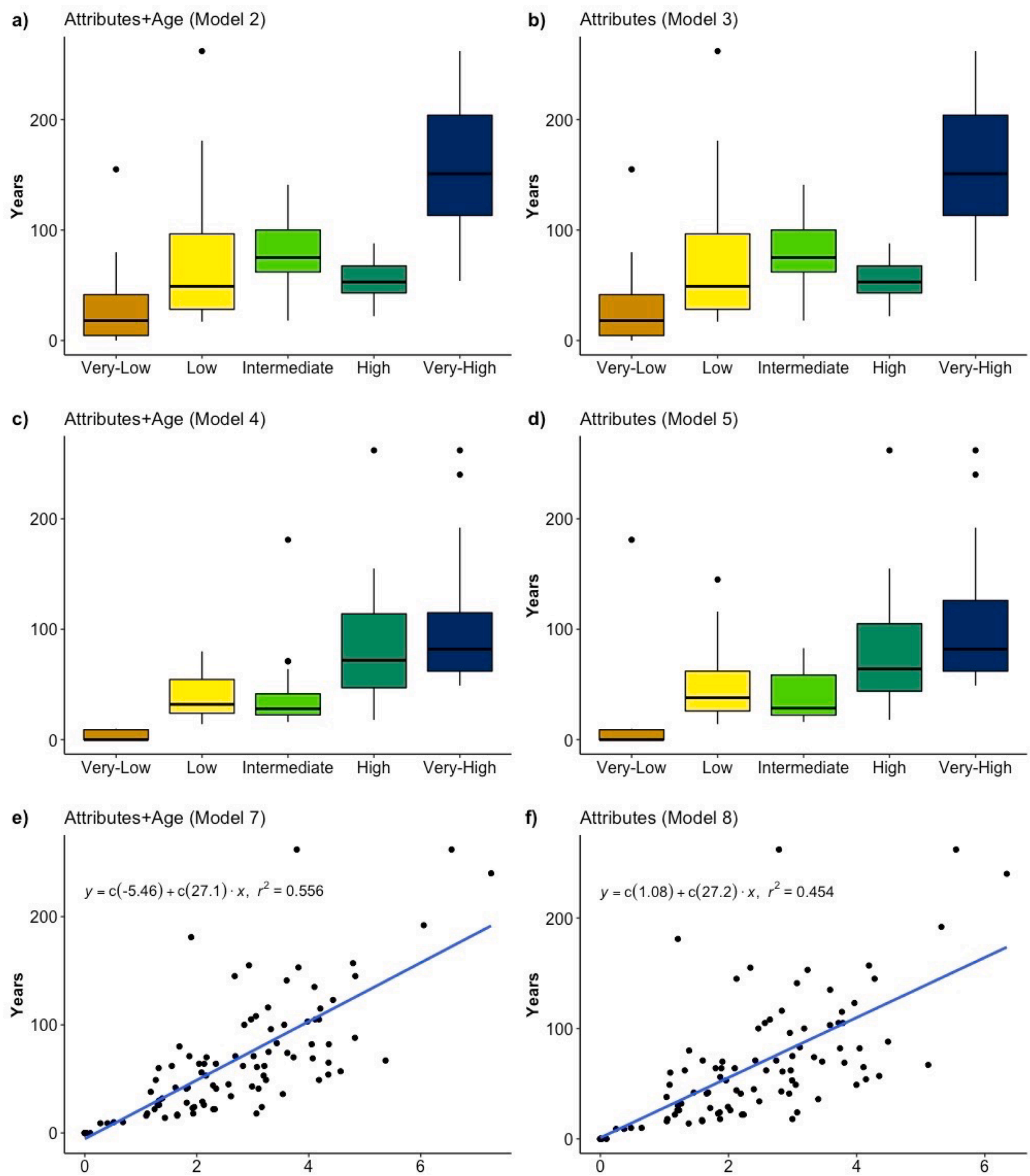


**Fig. 4.** Age distribution according to each different old-growth definition developed in this study: a) old-growth classification based on the k-means classification of old-growth attributes including age and b) without age, old-growth classification based on the k-means classfication of old-growth attributes pre-processed with unsupervised random forest c) including age and d) without age, and countinous old-growth definition based on old-growth attribute e) including age and f) without age. From a) to d), figures displays the median and ± interquartile intervals, while figures e) and f) the linear regression between Model 7 and 8 (x-axis), respectively, against age (y-axis). The names on top of each graph represent the definition and are listed and depicted in Fig. 2. See Supplementary 3 – Fig. S1 for Model 1 and Supplementary 3 – Fig. S6 for Model 6.

a few other old-growth attributes quite well, but fail to represent other important features, such as the vertical and horizontal complexity, coarse woody material, dead standing trees, volume and etc. (Supplementary 3, Fig. S6). The continuous old-growth attributed models (Model 7 and 8), had lower correlations with age, r-squared 56% and 45% respectively (Fig. 4 e and f), but better represented all other old-growth attributes (Supplementary 3 – Fig. S9 and S10). For example, "Late succession species" and "Dead Standing Trees" had their r-squared increased from < 10% in Model 6 (age definition) to over 32% for Model 7 and 8. Even the "Maximum tree height" and "Biomass", best-represented old-growth attributes in Model 6 (Supplementary 3, Fig. S6 b and c) were significantly increased in Model 7 and Model 8 (Supplementary 3, Fig. S7 and S8).

The regression model generated with age only (AGE) did not perform as well as the old-growth index models (OGA + AGE and OGA) (Table 5). In addition, there was no difference between the performances of the old-growth index models when age not included. Correlations between OGA definitions and old-growth attributes were low

**Table 4**
Summary of statistics for the five old-growth classification random forest models. All statistics represent the predictive power of models calibrated with ALS metrics as predictors and five classifications of old-growth as the response variable. Model 1 was contructed purely with age, as a discreet metric of old-growth, while Model 2 represent classes of abundance of all old-growth attributes, including age. Model 3 is similar to Model 2, except that it does not include age. Model 4 and 5 are also classification the abundance of old-growth attributes, but it has a unsupervised random forest classification as a further step to improve clustering.

| Classification | Accuracy Mean (+/−SD) | Kappa Mean (+/−SD) | Very-Low | Low | Intermediate | High | Very-High |
|---|---|---|---|---|---|---|---|
| Model 1 | 0.54 (+/−0.03) | 0.39 (+/−0.04) | 0.95 | 0.86 | 0.61 | 0.53 | 0.63 |
| Model 2 | 0.53 (+/−0.03) | 0.34 (+/−0.05) | 0.86 | 0.58 | 0.62 | 0.50 | 0.52 |
| Model 3 | 0.55 (+/−0.02) | 0.37 (+/−0.03) | 0.86 | 0.61 | 0.64 | 0.51 | 0.53 |
| Model 4 | 0.69 (+/−0.02) | 0.60 (+/−0.03) | 0.92 | 0.71 | 0.83 | 0.73 | 0.84 |
| Model 5 | 0.68 (+/−0.02) | 0.59 (+/−0.03) | 0.89 | 0.75 | 0.74 | 0.75 | 0.86 |

**Table 5**
Statistical summaries of old-growth index models. All statistics represent the predictive power of models calibrated with ALS metrics are predictors and continous old-growth indices as the response variable. Model 6 is contructed purely with age, as a continuos metric of old-growth, while Model 7 takes into the present and abundance of all old-growth attributes, including age. Model 8 is similar to Model 7, except that it does not include age.

| Regression | Adj. R-squared (+/−SD) | Residual standard error (+/−SD) |
|---|---|---|
| Model 6 | 0.35 (+/−0.04) | 31.19 (+/−1.84) |
| Model 7 | 0.71 (+/−0.01) | 0.68 (+/−0.02) |
| Model 8 | 0.71 (+/−0.01) | 0.55 (+/−0.01) |

(Supplementary 3 – Fig. S7 and S8).

From all eight models developed, we selected three to project old-growth values across the whole study site. First was age classification, because it is the method currently used for defining and location old-growth forests (MFLNRORD, 1995). Second, reduced dimensionality attribute-based classification (Model 5) because this was the model with the highest accuracy among the categorical models for the "high" and "very-high" old-growth values. The third and last model was continuous measure attribute-based definition (Model 8), because the model has a higher performance than pure age model (Model 6), and it did not include age, which is a costly attribute to be measured.

### 3.4. Comparison between old-growth maps

The attribute-based classification (Model 5) and old-growth index (Model 8) diverged from pure age classification (Model 1) in a similar way, both underestimated old-growth value classes (Table 6). Model 5 and 1 showed the greatest divergence for the "Intermediate", "High", and "Very-high" old-growth value classes. Model 1 one overestimated "Very-low" and "Very-high" old-growth classes while failing on classifying "High" old-growth value areas. Model 5 underrepresented the areas with the "Very-low" and "Low" old-growth values and overrepresented "Very-high" old-growth class. While both Model 1 and 5 classified a similar percentage of the landscape as "Very-high" old-growth value, 36.9% and 35.1%, they disagree in 17.6% of the "Very-high" old-growth classification and 52.6% of the total landscape classification (Table 6). Compared to the Model 1 the Model 5 map underestimated old-growth value by at least 1 class in 48.7% of the landscape. This percentage is much lower when comparing pure age classification with the old-growth index map (28.1%), Model 1 and 8 respectively. The high percentage of underestimation suggests that pure age classification map overestimated the old-growth value, especially for the "Intermediate" and "Very-high" class.

**Table 6**
Comparison between models to assess and locate the differences between classes. The column "<-1" shows underestimations (%) and ">1" the overestimations (%) made by the different models once compared to one another. Model 1 represents a typical age classification; Model 5 is a classification based on abundance of old-growth attributes, and Model 8 is continous meansure of the accumulation of old-growth attributes.

| Class | Model 5 – Model 1 Class Error (%) | | Model 8 – Model 1 Class Error (%) | | Model 8 – Model 5 Class Error (%) | |
|---|---|---|---|---|---|---|
| | < −1 | > 1 | < −1 | > 1 | < −1 | > 1 |
| Very-low | 0.1 | 3.8 | 3.4 | 0.2 | 0.0 | 33.4 |
| Low | 11.3 | 0.0 | 5.0 | 0.1 | 0.0 | 1.7 |
| Intermediate | 19.8 | 0.0 | 15.0 | 0.2 | 12.9 | 0.0 |
| High | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 0.0 |
| Very-high | 17.5 | 0.1 | 4.7 | 6.1 | 0.5 | 0.0 |
| **Total** | **48.7** | **3.9** | **28.1** | **6.6** | **15.5** | **35.1** |

Model 1 map has a higher percentage of the areas classified as "Very-high" old-growth value than old-growth index (Model 8), 36.9% and 11.8%. However, those areas were more scattered and do not exhibit the same degree of spatial clustering observed in Model 5 and Model 8 (Fig. 5 b and c). When we compared the Model 5 and 8 maps, Model 5 overrepresented "Intermediate" and "High" old-growth value classes, while Model 8 overestimated the "Very-low" old-growth value. Both models have similar total percent "Very-low" class, 4.5% and 4.0% for Model 5 and 8 respectively. However, the biggest disagreement between Model 5 and 8 is in the "Very-low" old-growth class, where Model 8 overestimated 33.4% of the areas classified as "Very-low" old-growth value by Model 5. Out of 50.6% of the areas that Model 8 and 5 showed classification disagreement, 35.1% were in the "Very-low" and "Low" old-growth class. For the "High" and "Very-high" old-growth classes, the disagreement between Model 8 and 5 was <2.5%. This means that, Model 8 and 5 mostly concurred in terms of "High" and "Very-high" old-growth classes, areas mostly likely to allocate old-growth forests.

Our results suggest that the pure age Model 1 is not capturing the distribution of old-growth attributes, and that Model 5 is overly representing "high" and "very-high" old-growth classes. Model 8 not only captured the continuous nature of the old-growth value, but also had a high correlation with each individual old-growth attribute (Supplementary 3, Fig. S7), high $R^2$ (Table 5), and has the most conservative definition of "Very-high" old-growth values (11.8%) when compared to the old-growth classification of Model 1 and 5, 36.9% and 35.1%. Finally, we also compared the difference between model Model 7 and 8 to make sure the exclusion of "age" as one of the old-growth attributes did not alter the patterns of distribution of old-growth values. We found that no pixel had a difference higher than +/−0.66 (13%), which is less than one class difference. This suggests that the exclusion of the age did not affect old-growth mapping.

### 3.5. Landscape level projection

We performed a post classification independent accuracy assessment in 14 sites (Supplementary 3, Fig. S9). Four plots were classified as "Very-high" old-growth value by Model 8 and one plot as "Intermediate," which concurred with what we observed during the field survey. The old-growth index (Model 8) captured the accumulation of old-growth attributes. However, wetlands received low old-growth values in both models since they do not attain the characteristics we were tracking as important old-growth attributes (ex. tree height, canopy complexity and basal area).

Using our old-growth index (Model 8), we estimated that 14.7% of

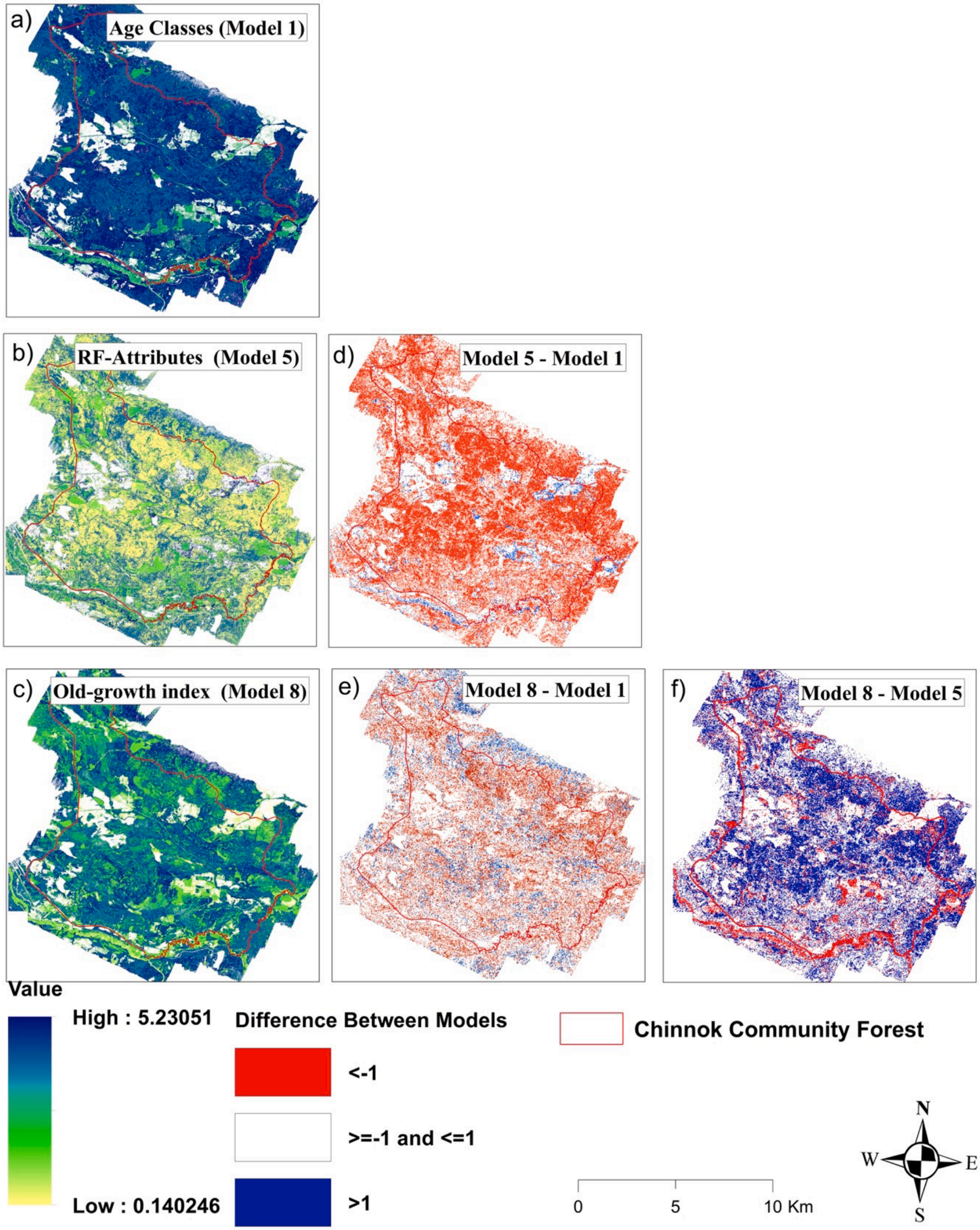


**Fig. 5.** Spatial correlations and constraints between a) pure age classication (Model 1), b) reduced dimensionality old-growth attribute based classification (Model 5), and c) a continuous definition of old-growth index based on old-growth attributes (Model 8), where d) represents the differences between Model 5 and 1, e) Model 8 and 1, and f) Model 8 and 5 with red representing underestimation and blue overestimations of old-growth value.

the tenure area has "Very-high" old-growth value (Fig. 6). When combined with "High" old-growth class this increases to 41.6%. However, from the 14.7% of the estimated "Very-high" old-growth forests in the landscape, only 13.5% is "protected" inside OGMAs. Additionally, only 2.55% of the OGMAs have an estimated "Very-high" old-growth value cover >50%, and more half of OGMAs had <25%. These results suggest a high fragmentation of "Very-high" old-growth value forest within OGMAs. It is worth noting that the predictive old-growth map inherited the error from the model (Model 8). In addition, the classes used to identify areas with "very-high" old-growth value are arbitrary and applied as a proof of concept. Thus, although the results above displayed the rarity and fragmentation of forest with "very-high" old-growth

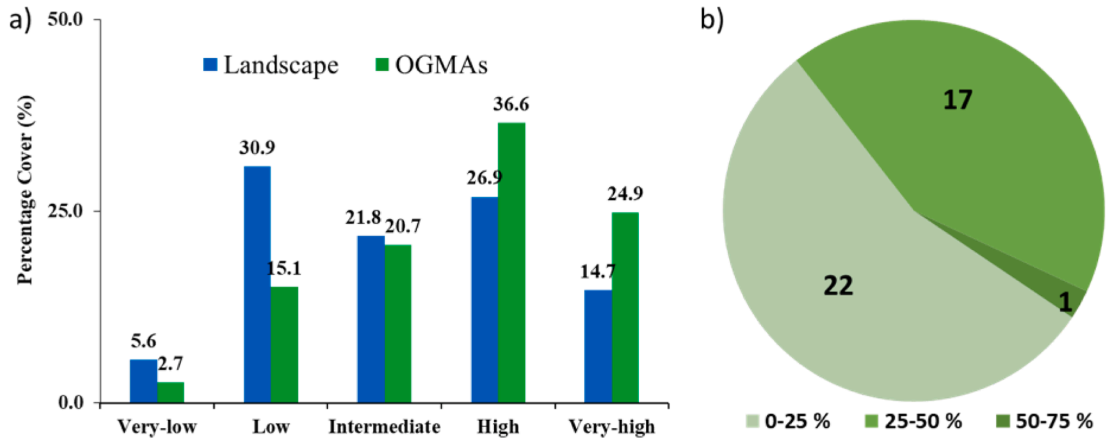


**Fig. 6.** Summary of old-growth assessment in the study area, utilizing the old-growth model 8, where a) displays the percentage cover of each old-growth value class for the whole landscape and only for the areas within OGMAs, and b) depicts the number of OGMAs per percentage forest cover of "Very-high" old-growth value.

values in the landscape, there is still the need for further work regarding the uncertainties and improvement of the model.

## 4. Discussion

### *4.1. Characterizing old-growth index*

Our results indicate that a structure-based old-growth definition can better capture the continuous nature of forest development, and more effectively reflect the ecological functions that old-grow forests epitomize, compared with old-growth categories that focus only on age. The incorporation of tree age into our old-growth models did not substantially improve the models' overall performance. Moreover, although age has been a useful indicator of old-growth under some conditions, it is less valuable when the dominant species in old-growth forests are multi-aged (Gillis et al., 2003).

Forest dynamics in the northern interior of British Columbia, Canada, have historically been defined by a regime of frequent large-scale disturbances (DellaSala et al., 1996; Spies et al., 2006). In these forests, estimating age can be difficult given the patchy nature of the disturbances, and the fact that legacy features such as surviving trees and woody debris often remain on the landscape. The inclusions or exclusion of these legacies features during inventories could lead to the overestimation or underestimate of stand age and drive false conclusion about the forest succession and old-growth functional value. Therefore, for forests that experience more frequent natural disturbances, or disturbances that vary in intensity and propagate heterogeneous landscapes, a structure-based old-growth definition, such as the one we developed, will likely be more appropriate than an age-based definitions (Kneeshaw and Gauthier, 2003; Wirth et al., 2009b).

The model based on our old-growth forest index not only had better overall statistical performances than the age-based models but also better captured actual field measurements of old-growth attributes. Consequently, the old-growth index has a better chance to capture the ecological function of old-growth forests in the landscape, as opposed to a forest with few old-trees. This is important because evidence suggests that many species typically found in old-growth are linked to specific structural attributes, and associated environmental conditions and not to old-growth as such (Mosseler et al., 2003c; McElhinny et al., 2006b; Lonsdale et al., 2008). Thus, the strict separation of forested landscapes in old-growth and non-old-growth may not represent a suitable conservation strategy for the provision of habitats in the landscape (Bauhus et al., 2009).

Stand development is continuous, and hence there is not a clear threshold to indicate when a forest enters the old-growth stage (Spies and Franklin, 1991; Wirth et al., 2009b). Therefore, a classification of forest succession, either age- or structure-based, will always be somewhat arbitrary (Hilbert and Wiensczyk, 2007; Wirth et al., 2009b; McMullin and Wiersma, 2019). The use of the old-growth index instead of binary classes is essential in dealing with the continuous nature of forest structural development and capturing functional old-growth forests.

### *4.2. Management Implications*

Despite advances in the definition of old-growth attributes and old-growth forests there are still challenges with evaluating old-growth at the landscape scale. For example, due to the diversity of old-growth forests, a consensus on a single ecological definition of old-growth will never be reached and may not be desirable given the diversity of forest conditions (Spies, 2004; Wirth et al., 2009b). The framework we developed here can be used to devise local definitions based on measurable structural features and biophysical site conditions, as has been advocated by past studies (Braumandl and Holt, 2000; Mosseler et al., 2003c; McElhinny et al., 2006a; Hilbert and Wiensczyk, 2007; Wirth et al., 2009b).

The degree to which old-growth forests and old-growth structures should be maintained or restored at the landscape level remains a complex political question (MFLNRORD, 1995; Environmental Law Centre, 2013). The methods current used to select set-aside old-growth forests might be increasing the risk of old-growth loss as they are mostly based on stand-age (MFLNRORD, 1995; Gillis et al., 2003; Environmental Law Centre, 2013). Our old-growth index allows for a more holistic view of the landscape's old-growth values, which indicate the level of abundance or rarity of old-growth in a specific location. As such it can be used for developing benchmarks for local or regional targets for conservation and management activities, as well as being used to design new old-growth reserves, assess current reserves, and monitor old-growth values.

Old-growth forest reserves may be prone to natural disturbances, especially in boreal and sub-boreal regions (Spies et al., 2006). Protecting old-growth forests should therefore be only part of the strategy to maintain old-growth value in the landscape (Burton et al., 1999). Areas outside reserves facilitate gene flow and migration of populations as well as provide complementary habitat (Lindenmayer and McCarthy, 2002). Using a continuous old-growth index can aid in the planning of long-term strategies as it can accommodate a dynamic population of old-growth stands in multiple stages of development within landscapes subjected to wildfire, pathogens, and climate change (Spies, 2004). For example, our old-growth index can track old-growth values throughout the whole landscape, thereby allowing set-aside forests to be complemented with managed forests that also retain key attributes of primary and old-growth forests. Such a strategy has been previously proposed by Beese et al. (2003), who suggested that set-aside old-growth should be combined with uneven-aged stand management to maintain late-successional forest attributes. This strategy is particularly important in areas where reserves are too small to ensure the occurrence of natural disturbances within their boundaries or to accommodate all developmental stages of forest succession (Kneeshaw and Gauthier, 2003).

### 4.3. Caveats

A continuous old-growth index derived from ALS and calculated at a landscape extent does require additional work regarding the identification of suitable thresholds and targets. In many applications, the local management objectives and constraints can be used to inform what these old-growth thresholds and targets should be. For example, the Chinook Community Forest is managed for timber in a region that historically has a high frequency of large-scale disturbances. In these conditions, it is expected that stands with high old-growth value will be rare (DellaSala et al., 1996; Spies et al., 2006). Thus, a threshold for old-growth can be set such that set-aside old-growth forests include forest with intermediate old-growth value.

The use of a continuous old-growth index for old-growth mapping should not be done without a critical evaluation of how the index characterizes other ecotypes and unique forest types. For example, in our case study region the index classifies wetlands as areas of low old-growth value, even though they can play a significant role in the provision of ESs and biodiversity (Adhikari et al., 2009; Kayranli et al., 2010). A similar challenge with the old-growth index is that it does not include any estimates of human or natural disturbance. Similar to natural disturbances, human disturbances often reduce the structural variability that is typical of many naturally developed older forests (Spies, 2004), and this may not be captured. Nevertheless, the source of the disturbance (e.g., human or fire) are irrelevant when stands are defined primarily based on structural development (Spies, 2004).

## 5. Conclusion

In this work, we developed an old-growth index based on forest structures measured with traditional field methods. While the index is specific to the study site, the methodology is adaptable to other forest types and ecosystems. We utilized the old-growth index to map old-growth value on the landscape and evaluate the amount and quality of the old-growth forest for the study site. Our assessment showed that <14% of the forests in the landscape have very high old-growth value, and <25% of forest protected in OGMAs have old-growth status. The old-growth index allows for the holistic assessment and monitoring of old-growth value in the landscape, which can aid managers to not only track the amount and quality of old-growth in the landscape but also set targets for old-growth retention in a transparent manner. Most importantly, mapping old-growth value can aid in the conservation of this rare resource and its services in managed landscapes.

## CRediT authorship contribution statement

**Luizmar Assis Barros:** Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Ché Elkin:** Conceptualization, Supervision, Writing - review & editing, Funding acquisition.

## Declaration of Competing Interest

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

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## Appendix A. Supplementary data

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