ASSESSING SET ASIDE OLD-GROWTH FORESTS WITH AIRBORNE LiDAR METRICS

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Abstract: Old-growth forest provide a variety of services to human populations such as water, carbon storage and ecotourism. Despite the value of old-growth forests, this resource is constantly under anthropogenic pressure. Old-growth management areas (OGMAs) are legal restrictions meant to retain old-growth forest attributes in managed landscapes. However, it is uncertain if this strategy has set aside forests with characteristics/attributes expected in old-growth forests. While researchers have attempted to measure and evaluate different forest attributes and succession, the effectiveness of OGMAs in retaining old-growth forests in a managed landscape has rarely been tested. In this work, I applied LiDAR delivered metrics to estimate attributes of old-growth forests (ex. height, canopy cover, vertical complexity, understory density) and develop an index for old-growth forests. This index can aid in tracking the location and quality of old-growth forest in the landscape based on quantitative and transparent evaluation of forest structure, which solves the problems of multiple definitions of old-growth forest. Thus, using a scale from 0-1, where “0” indicates the area with the least presence of old-growth attributes and “1” the highest, I assessed the quality of existing OGMAs, and evaluated the potential for recruitment of other prospective OGMA’s location. This research brings light to OGMAs’ definition and their evaluation through the use of a relatively new technique, LiDAR. More importantly, the identification of the amount and location of old-growth forests over the landscape can aid to the conservation of this rare resource and its services.

Key words: Community Forest, Conservation, OGMAs, Airborne LiDAR

1. INTRODUCTION:

Old-growth forest is a forest in advanced development stage, associated with specific structures, natural processes, and no significant anthropogenic interference (Mosseler et al. 2003c, Spies 2004, Hilbert and Wiensczyk 2007). When a forest is allowed to reach older stages of development, it attains attributes critical for the maintenance of biodiversity in the landscape (DellaSala et al. 1996, Spies 2004, Bauhus et al. 2009). Forests with these characteristics are valuable and rare resources in rapid decline in the world (Watson et al. 2016, 2018). In addition, the location and abundance of old-growth attributes enables the provision of a range of ecosystem services (ESs) that directly or indirectly beneficiate human populations (MA 2005, Isbell et al. 2011). Some of these services include ecotourism (FAO 2016), genetic variability (Mosseler et al. 2003b), carbon storage and sink (Luyssaert et al. 2008), water provision, indigenous culture and the maintenance of human health (Watson et al. 2018). Therefore, identifying and retaining old-growth forests can aid to their conservation and the maintenance of important ESs in the landscape.

In Canada, old-growth forest retention in managed landscapes is promoted by the Old-Growth Management Areas - OGMAs (Mosseler et al. 2003c, Environmental Law Centre 2013). Notwithstanding, the selection of OGMAs is a difficult task due to the lack of a common definition for what constitutes an old-growth forest (Hilbert and Wiensczyk 2007). Old-growth forest types vary in terms of longevity of dominant species, return period of natural disturbances, human intervention, shade tolerance, and abundance of specific structures such as number of large trees, snags, accumulated woody debris (Mosseler et al. 2003c, Spies 2004, Bauhus et al. 2009). For example, Douglas-fir forests may grow for centuries without disturbances, whereas ponderosa pine forest are often disturbed by fires (Spies 2004), posing an important methodological challenge on the characterization of these forests only based on disturbance frequency.

Age is a common proxy that has long been used to define and locate old-growth forests. For example, according to MFLNRORD (2003), BC's coastal forests are considered old-growth if trees are more than 250 years old. In the Interior, where the longevity of trees tends to be shorter and disturbances more frequent, old-growth is defined as more than 120 years of age for forests dominated by lodgepole pine or broadleaf species. Although age is a useful proxy, its measurement with traditional field methods can be quite costly (Racine et al. 2014). In addition, important structural old-growth elements can be omitted using only an age threshold (Holt et al. 2008). More importantly, forest cover maps currently used to locate old-growth forests does not correspond to the age class distribution in the landscape (Holt et al. 2008). This inaccuracy can lead to a management that underrepresents old-growth forest in the landscape. As a result, in many areas it may be prudent to move away from a simple age threshold for old-growth definition towards a more ecologically based representation of forest structures.

Different authors have pointed out the need to develop an index that could be used to track old-growth forest in the landscape, rather than only using stand age (Mosseler et al. 2003c, Hilbert and Wiensczyk 2007). Compared with old forests, young natural forests or intensively managed forest plantations have simpler structure (Spies 2004). Thus, the abundance of old-growth attributes (e.g. large trees, snags, accumulated woody debris, etc.), which contributes to the structural complexity in old-growth forest, can be used as proxy for old-growth forest mapping (Mosseler et al. 2003c, 2003a, Bauhus et al. 2009). A myriad of work has been conducted using traditional field based measurement of forest attributes to classify forest succession and assess the quality of old-growth forests (Table 1). Even though field based methods are essential for most forest studies, they are less applicable for landscape scale evaluation.

The rapid emergence of new technologies have allowed us to develop highly precise measures of forest condition across broad areas, which was never possible using traditional field based and areal interpretation methods (Cohen et al. 1995, Song and Woodcock 2002, Hyyppä et al. 2008, Kane et al. 2010b). Typical applications of passive and/or active optical sensors have proven to be useful for a variety of ecological studies, enabling researchers to, for instance, identify forest succession in broad scales (Table 1). Nevertheless, remote sensed images are only two-dimensional (x and y), which cannot fully represent the nuances of the three-dimensional (3D) structures present in old-growth forests (Lefsky et al. 2002). On the other hand, 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). Starting with civil engineering applications (Meng et al. 2010), airborne LiDAR has been rapidly incorporated in 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 airborne LiDAR (table 2). Thus, airborne LiDAR may be an effective way of generating an old-growth index and effectively mapping old-growth forests.

The definition and mapping of old-growth forests with measurable structural and biophysical features, considering the continuous nature of forest structure, is imperative for their conservation and maintenance in managed landscapes. Throughout the years, different authors have attempted to map forest succession in the landscape (table 1). However, very few have looked at the quality of the set aside old-growth forests or OGMAs, and none has done it in landscape scale. In this work, I aim to: (1) develop an old-growth index based on forest structures measured with traditional field methods; (2) extrapolate the old-growth index to the landscape utilizing ecological based old-growth attributes delivered from airborne LiDAR; and (3) evaluate the amount and quality of old-growth forest for the study site, simultaneously evaluating the OGMAs currently present in the landscape.

2. MATERIAL AND METHOD:

2.1. Study Area:

A community forest can be defined as "any forestry operation managed by a local government, community group, or First Nation for the benefit of the entire community"(MFLNRORD 2017a). The Chinook Community Forest (CCF), located within the Skeena region, 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. The tenure area for CCF operations is approximately 123,679 ha, encompassing around 40 OGMAs (~7,431 ha). Further information about CCF can be found in the supplementary materials (S1). The overall commercial intent for the CCF is to produce and harvest fibers for sale. However, due to the nature of the partnership that created this community forest, not only timber but also other ESs such as cultural heritage, agriculture, recreation, and water quality receive also great importance in the management of the community.

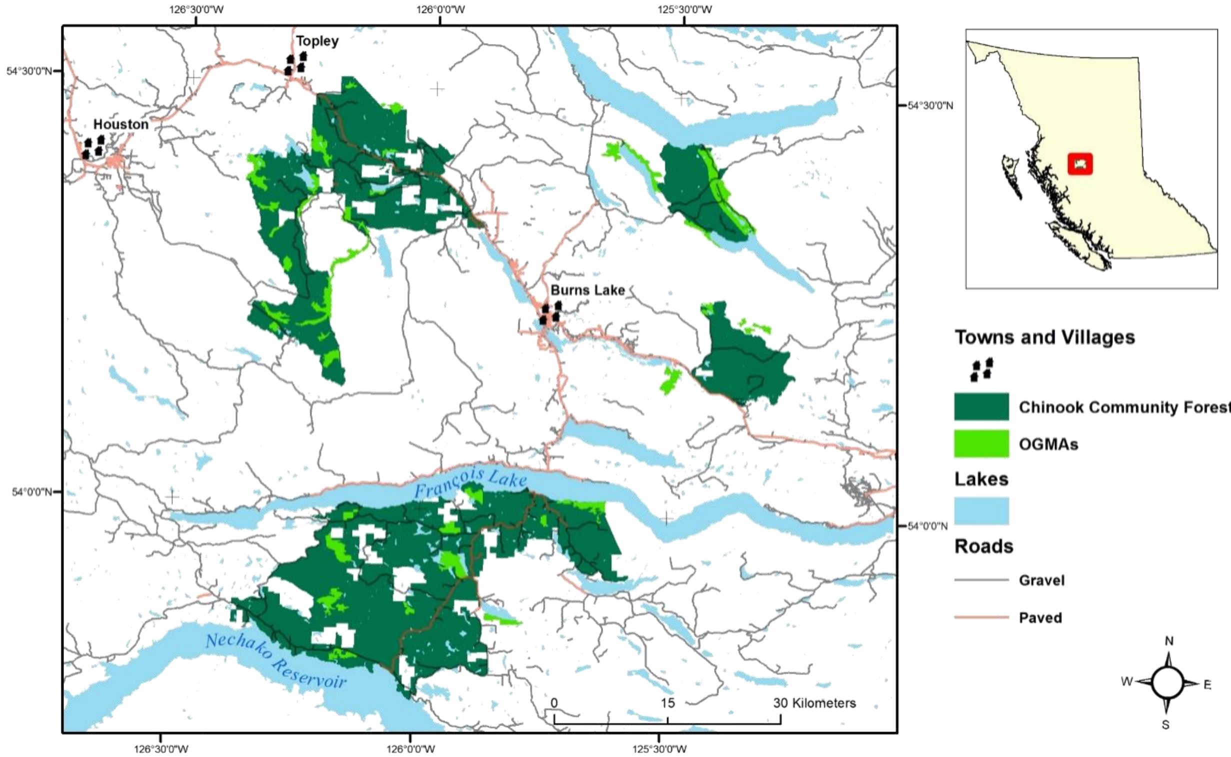

Figure 3 OGMAs' distribution in Chinook Community Forest tenure areas (unpublished L. Barros, UNBC, 2018).

2.2. Data:

Airborne LiDAR was collected in a leaf-on condition with minimum density of 2 pulses/m^2; half-scan angle of 12.5^o from NADIR, with 50% overlap. Footprint is estimated to be from 30 to 70 cm. To process the LiDAR's point cloud, I utilized the LAStools software (version 161114). A complete scheme of the LiDAR process can be seen in Figure 5. To validate ALS data, permanent ground plots were designed to capture the variation observed from the airborne LiDAR cloud points. Ground measurement of forest features was collected from a minimum of 110 plots of 10 m radius (Table 1). All trees down to 4 cm (at 1.30 m height) were measured to obtain better LiDAR metrics estimates for disturbed and/or young forests (Keränen et al. 2015). The inventory followed the Change Monitoring Inventory (CMI) procedures (MFLNRORD 2017b). High precision GPS was used to obtain two measurements of ± 2m accuracy from the plot center. Airborne LiDAR and ground survey were incorporated into geographic information system (GIS) exercises to map and evaluate old-growth forests.

Table 1 List of forest attributes measured during the field work

Data Collected	Description
Tree # :	
Species (2 Letter Code):	e.g. Pl =Lodgepole Pine, At= Trembling Aspen, Sx= Hybrid Spruce
Diameter:	DBH (cm) Measured or Estimated
Height:	Tree Length (m) Measured or Estimated
Loss Factor Information:	Tree Class; Conk; Blind Conk; Scar; Fork/ Crook; Frost Crack; Mistletoe; Rotten Branch; Dead/ Br. Top; Root Rot Code; Insect Code; Fire Code; and Blowdown Code
Sector (1-8):	
Live or Dead:	
Standing or Fallen:	
Crown Class (D, C, I, S):	D= dominant, C= Codominant, I= Intermediate, S= Suppressed
Height to Live Crown (m):	
Broken Trees:	Broken Top Diameter (cm) Projected Height (m)
Borderline Trees:	Horizontal Distance (m) Bearing from Plot Center
Site Tree Ages:	Age at DBH Counted - Field Agea at DBH Counted - Office Reach Pith? Yes/No If Can't Reach Pith - Enter Core Length (mm) 5 yr. Growth (mm) 10 yr. Growth (mm) 20 yr. Growth (mm)
General Comments:	
# of small tree (DBH<4cm):	Species code; Length class: 10-30cm, 31cm-1.3m, >1.3m
Stumps >= 4cm DIB and length <1.3m:	Species code, frequency, DIB(cm), length(m), and %Sound

2.3. Methods:

For this work, I combined traditional field based measurement with airborne LiDAR to track and evaluate old-growth forest in the landscape. I obtained an old-growth index from empirical data collected for each of the permanent plots present in the landscape. K-mean clustering was applied to the empirical data to try to identify different clusters, which was here assigned as forest succession. Plots were then used as training dataset to build two random forest models with the LiDAR delivered metrics: a classification model and regression model. For a random forest regression method, I utilized the old-growth index from empirical data, and extrapolated it to the landscape using the same airborne LiDAR metrics, assigning an old-growth level from 0-1 for each plot.

2.3.1. Empirical data processing:

Forest structural attributes obtained from field measurement was used to obtain a forest succession classification and an old-growth index. K-means clustering statistics is powerful unsupervised classification method that identifies patterns for the available variables. These statistics were applied to old-growth attributes measured in a plot level. The attributes were, tree height, coefficient of variation, understory density (down wood, small trees, and samplings), number of snags and snag DAP classes, broken top trees, number of large trees, and other important old-growth attributes (Table 3). PCA was previously used to ordinate plots as forest succession and old-growth evaluation with the forest attributes (Braumandl and Holt 2000, Table 2). This statistical analysis was used to select the attributes that better classify forest, which were then used to create an old-growth index.

Table 2 Method utilized to identify and map old-growth forests

Method	Description	Reference
Field metrics	Classification of forest succession in a stand level based on age thresholds defined for each Biogeoclimatic (BEC) zone and fire return interval, utilizing outdated forest cover maps.	(MFLNRORD 1995)
	Use a series of forest attributes associated with old-growth forest to create an old-growth index succession and evaluate old-growth forest reserves in different BEC zones.	(Braumandl and Holt 2000, Holt 2000, Holt et al. 2001, 2002, DeLong et al. 2004)
	Reviewed and listed a series of forest attributes strongly associated with old-growth forest to identify silvicultural approaches that could promote old-growth forests.	(Bauhus et al. 2009)
	Evaluated different plot sizes to determine the minimum plot that still captures old-growth indicators (e.g. number of living trees, trees with DBH >50cm, dead wood volume, etc).	(Lombardi et al. 2015)
	Review of old-growth static and dynamic attributes and use of cohort basal area ratio (understory cohort/post-disturbance cohort) as a proxy for old-growth forests in boreal forest, simultaneously addressing the dynamic nature of forest.	(Kneeshaw and Burton 1998, Kneeshaw and Gauthier 2003)
	Mapping of individual stems and their respective features (e.g. height, crown area) in temperate old-growth forests to study forest structure and dynamics.	(Chen and Bradshaw 1999, Hao et al. 2007)
Optical Sensors	Forest succession model (ZELIG) and a canopy reflectance model (GORT) were applied to compare with forest succession from Landsat TM and test the potential of remote sensing on mapping successional stages.	(Song et al. 2007)
	Landsat ETM+ combined with ecological land unit classifications.	(Bergen and Dronova 2007)
	Landsat TM image resampled to 25m cell size and 106 ground reference stands of tree density, basal area.	(Cohen et al. 1995)
	Mapping of structural stage classes with Landsat TM data through ISODATA analysist technique.	(Miller et al. 2003)
	Spatial manifestation of forest succession in optical imagery (Landsat TM) through three types of model.	(Song and Woodcock 2002)

LiDAR	Use of Lidar delivered metrics (e.g. height percentiles and statistics, % of vegetation returns, % of first returns, and etc.) with Random Forests statistical analysis to identify seven stages of forest succession.	(Falkowski et al. 2009)
	Documented increasing vertical structure complexity along five development stages in western coastal forests with five field, six LiDAR metrics, and their combination.	(Kane et al. 2010b)
	Use of LiDAR-delivered tree height variance to distinguish between single-story (young forests) and multistory vertical structural classes (old forests).	(Zimble et al. 2003)
	Use of two principal components (PCA) of the Integration of airborne LiDAR (canopy height model) and spectral data (12 wavebands of HyMap) to perform an unsupervised classification of forest classes.	(Hill and Thomson 2005)
	Estimated stand age across 158 plots in managed Boreal forest with forest structures and site attributes delivered from LiDAR.	(Racine et al. 2014)

2.3.2. Lidar processing:

LAStools were utilized to process LiDAR point cloud and obtain ecological meaningful metrics for old-growth forests (Figure 2). Table 3 summarizes important studies using LiDAR to measure old-growth attributes. For vegetation estimates, the production of an accurate DTM is a major output from ALS, since DTM errors are propagated into vegetation estimates (Goodwin et al. 2006). Two operational steps are employed to produce DTMs out of an ALS point cloud: separation of the ground (last returns) and non-ground points (first returns), and then interpolation of the separated ground points (Aryal et al. 2017). 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). In addition, it has been shown to be highly variable throughout forest succession, being considered an important old-growth attribute (Table 2). Tree height is extracted from the difference between the Digital Surface Model (DSM) and DTM, where DSM is derived from the first returns and DTM from the last (Hopkinson et al. 2006, Andersen et al. 2006, Aryal et al. 2017).

Forest gap properties have a great role on forest dynamics and composition (Koukoulas and Blackburn 2004a). Moreover, White et al. (2018) and others (Table 2) observed that ALS could derive accurate information of canopy gaps in a landscape scale. Gaps' size, area and shape differ greatly depending on forest stage (White et al. 2018), and thus could be used to differentiate forest succession. For the purpose of this work, I obtained a LiDAR metric for canopy cover (vegetation point >3m high/ground points) to represent these differences. While this metric does not measure canopy gap directly, canopy closure seems to be enough to depict the differences in canopy openness in different forest successions once used together with other old-growth attributes developed for this work, such as vertical complexity.

Old-growth stands seem to display a complex canopy structure throughout the height range of the stands, whereas young stands have more clearly defined canopy layers (Spies and Franklin 1991). Vertical complexity attribute has been estimated in a variety of manners (Table 2), but I will utilized the coefficient of variation (CV) of ALS-derived tree heights according as it has been proven to have high correlation with the number and complexity of canopy strata (Zimble et al. 2003).

Another important ecological attribute that can be used to differentiate between forest successions is understory density. Here, I applied the method described by (Wing et al. 2012), where they created raster for ground returns density and understory density. Most studies used only understory density. However, due to overlapping flight lines and other factors, the density of points are usually higher on the edge of the LiDAR and not only on the amount of intercepting objects on the ground. Thus, I described here understory density as a ratio between the point density of the understory strata and ground returns, minimizing the effect of flight lines with the point density.

As listed in Table 3, some studies have used the intensity values of each LiDAR return to determine rather or not the return is from a living or dead material. While such techniques seems to deliver accurate predictions, it requires a calibration of the LiDAR instrument prior to the data collection. The LiDAR data collected for this study do not count with such pre calibration. Thus, I will use statistical models to predict snags' density, since I cannot count with intensity values to obtain it directly from LiDAR metrics.

Table 3 Airborne LiDAR delivered metrics for old-growth forest attributes with area based approach (ABA) and individual tree detection (IDT)

Old-Growth Attribute*	Lidar Estimators	Scale	Reference
Tree height	Treetops were detected with the highest return of point cloud from each tree and compared with high precision field measured of treetops.	ITD	(Andersen et al. 2006)
	Estimation of plot based height measurements (e.g. average, maximum, standard deviation) with LiDAR delivered metrics, indicating correlation close to 1:1.	ABA	(Hopkinson et al. 2006, Goodwin et al. 2006)
Basal area	Random Forest models were developed with LiDAR delivered metrics with and without intensity metrics to predict total, live and dead basal area.	ABA	(Bright et al. 2013)
Number of dead standing trees (snags)	Filtering algorithm based on density and intensity statistics to remove points associated with living trees, followed by an individual tree detection procedure.	ITD	(Wing et al. 2015)
	Correlation of height metrics with field observed frequency of snags to estimate snag frequency for the landscape.	ABA	(Bater et al. 2009)
	Median absolute deviation of height was associated with the abundance of snags in different DBH classes, as well as different other canopy and topography metrics, using Random forest algorithm	ABA	(Martinuzzi et al. 2009)

	Intensity, density and height statistics were used to estimate basal area (BA) of live, dead trees, and total BA through Random Forest models	ABA	(Bright et al. 2013)
Structural Complexity	Canopy volume profile estimates and leaf area index (LAI)	ABA	(Lefsky et al. 1999, Coops et al. 2007)
	Complexity of vertical forest structure was estimated with LiDAR derived height variance	ABA	(Zimble et al. 2003)
	Indicates that the 95th height percentile, rumple (ratio of canopy outer surface area to ground surface area), and canopy density had the strongest correlation with field measured stand complexity.	ABA	(Kane et al. 2010b, 2010a)
Biomass	LiDAR height percentile (h80) and crown width (CW) measurement were the best metrics for aboveground biomass (AGB) estimates using a multilinear model	ITD	(Wan-Mohd-Jaafar et al. 2017)
	Quantiles and full returns against field measurement, and other simple LiDAR metrics were tested against field estimates with correlation analysis and multilinear models	ABA	(Næsset 2011, Ahmed et al. 2013, Næsset et al. 2013)
Understory Density	First returns in a specific range of intensity in lower strata of the canopy was utilized to estimate live understory distribution	ABA	(Koukoulas and Blackburn 2004a, Vepakomma et al. 2008, Wing et al. 2012, White et al. 2018)
	Proportion of ground returns, vegetation return between 1 and 2.5 m in height and percent slope times cosine of aspect were fed to a random forest model to predict presence and absence of understory vegetation	ABA	(Martinuzzi et al. 2009)

	LiDAR delivered metrics were proven more accurate predictors of coarse woody debris (CWD) than field measurement of living trees, and indicated as important auxiliaries in the prediction of CWD in the landscape	ABA	(Seielstad and Queen 2003, Pesonen et al. 2008, 2009)
Canopy Gap	Canopy gap was measured based on a canopy height mode (CHM) with a height threshold measured during field (4-5m) and gap area of $5m^2$. Slope from CHM was also an important feature to map canopy gaps.	ABA	(Koukoulas and Blackburn 2004b, Vepakomma et al. 2008)
	Applied a fixed and variable height thresholds to a 1m resolution CHM to detect gaps, further filtered by area. Gap areas $<5m^2$ and >2ha were excluded.	ABA	(White et al. 2018)

***** Old-growth attributes listed above were the most common attributes found in different studies (Table 1), with Bauhus et al. (2009) as the main source

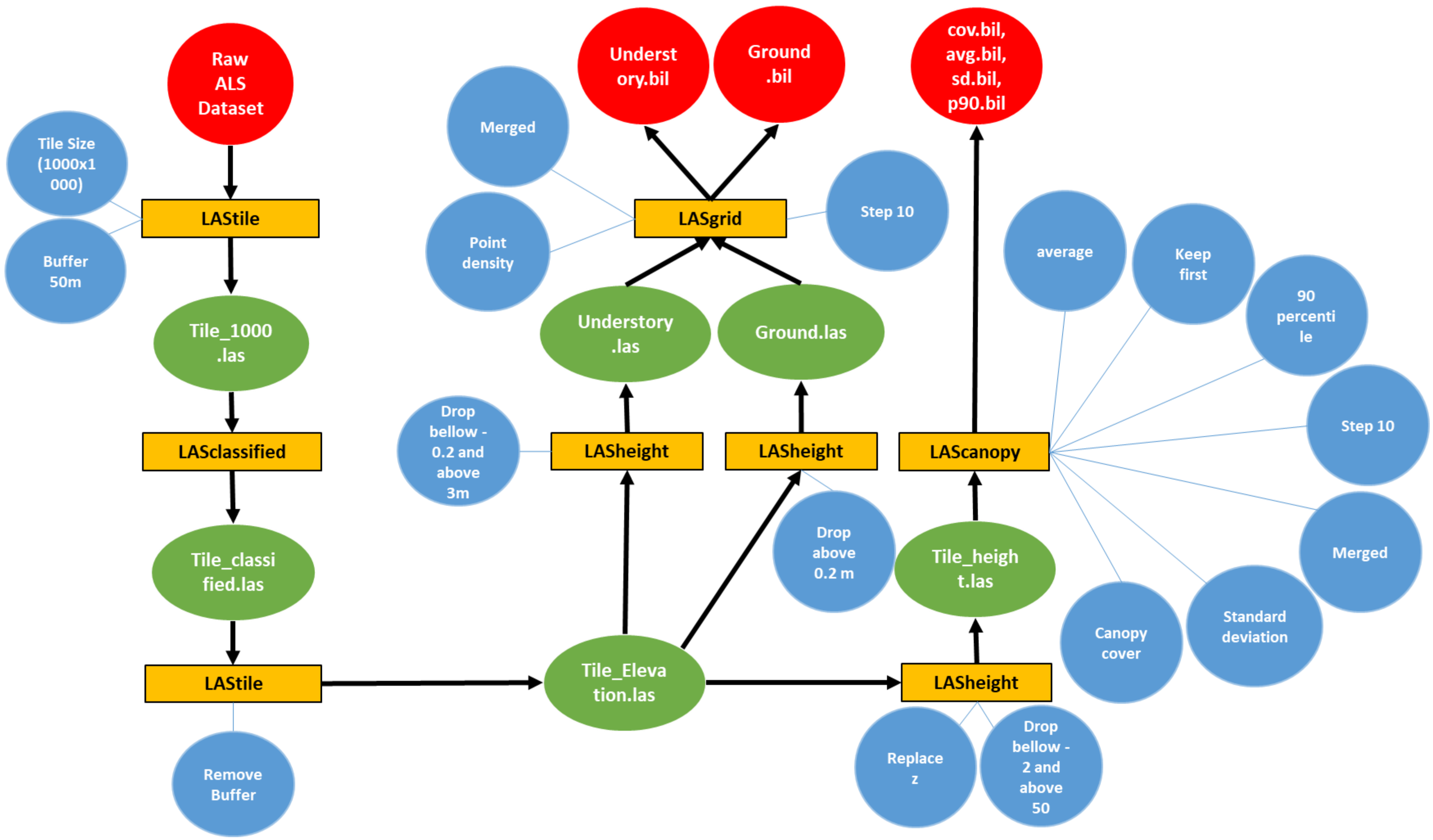

Figure 1 Pipeline of LiDAR processing using LASTools from the raw LiDAR files (.las) to the raster outputs (.bil) used to create ecological meaningful metrics for old-growth attributes

2.4. Statistical analysis:

I applied the random forest (RF) statistical model, using the "randomforest" package (Therneau et al. 2011, Cutler and Wiener 2018) in the R (R Development Core Team 2018) programming environment. RF is a machine learning method that adds randomness by randomly selecting subsets of the data without replacement, which increases the diversity of decision trees ("Regression Trees"). RF combines decision trees, considering the values of an independent random sample, with the same distribution for all the trees in the forest (Breiman 2001).

Breiman and Cutler (2003) recommend that one-third of the total number of explanatory variables be randomly selected. As 4 independent variables were used in this study, 2 were considered in each division. I set the random forest model to produce 1000 decision trees to ensure stabilization of the model, each tree using a subsample from 70% of the available data. The remaining 30% of the data were reserved for validation of the model as a test sample. Random forest was applied in its regression and classification mode to generate two different models to predict old-growth forest in the landscape.

3. RESULTS:

Since I still do not yet have access to the empirical data to perform a PCA and K-mean clustering analysis, the old-growth index was delivered from the sum of all old-growth attributes delivered from LiDAR.

I first perform a Pearson's correlation to observe how the metrics developed in this study were correlated with the old-growth index developed from "empirical data" (Figure 2). Canopy cover and 90th percentile of height were the most correlated metrics (0.83 and 0.68), although they have strong correlation among themselves (0.68). Both metrics are derived from a similar portion of the LiDAR point clound. While canopy cover is generated from the density of returns from the strata higher than 3m, 90th percentile is delivered from all return between 1.3m high and the 90% of the height distribution within the pixel. As well, vertical complexity, which is delivered from the coefficient of variation of heights from all returns greater than 1.3m, had a high correlation with the 90th percentile of height distribution. Even though the 90th percentile have a strong correlation with vertical complexity and canopy cover, each helped to differentiate a different forest succession (Figure 3). In addition, all metrics had a strong correlation with the old-growth index, except wetness index (Figure 2).

Wetness index is a topographic metric, which indicates values to areas depending on the likelihood of retaining moisture. Higher values are assigned to concave topography features such as creeks, and lower values to convex such as mountain's tops. Since fire is the main natural disturbance in the study area, it was expected that areas that would contain higher values for old-growth attributes to be in wetter regions, less likely to be affected by the fires. This would generate a bias in old-growth forest mapping, as old-growth forest are not present only on areas less affected by fires (DellaSala et al. 1996). However, wetness index had a very small correlation with the old-growth index, which can also be observed in the boxplot in Figure 3.

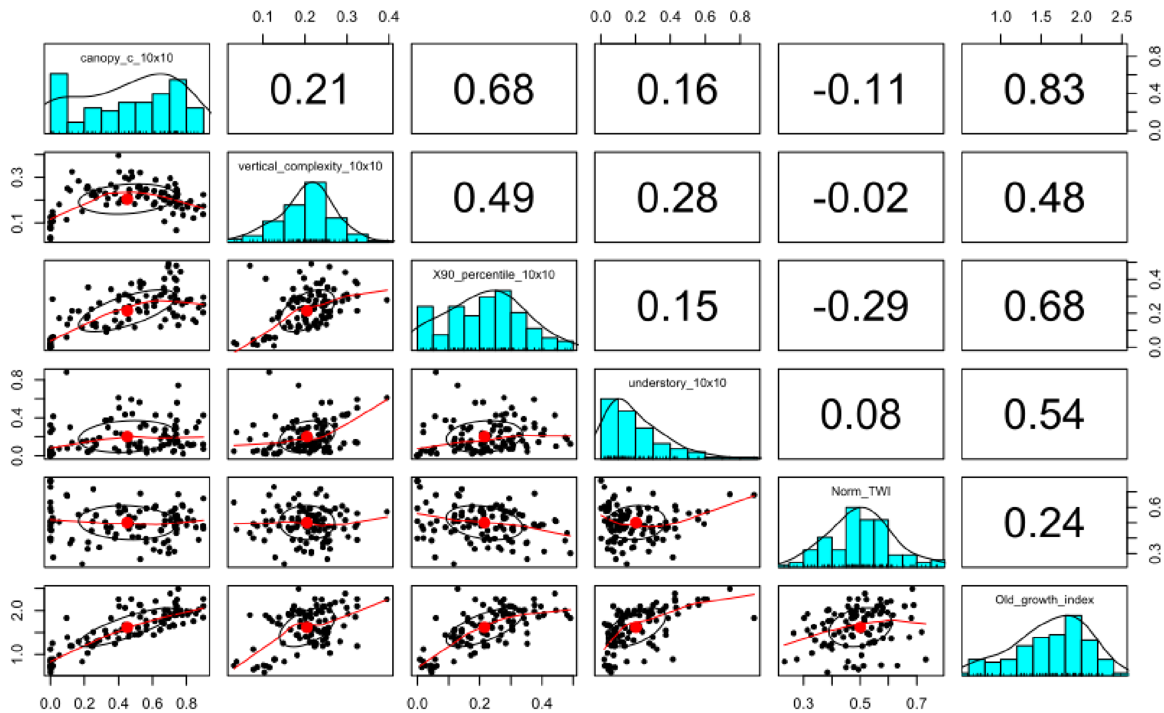

Figure 2 Pearson's correlation for old-growth attributes and old-growth index

Figure 3 depicts the distribution of LiDAR metrics in each forest succession for the plots measured on the field. Canopy cover was highest for plots in mature stands, average of 70%, where trees crown would be denser right before tree gap dynamics start creating more opening in the upper strata due to tree fall. In both young and old-growth stand, canopy cover is less dense. However, while the average of canopy cover for young stand were 30%, it was approximately 50% for old-growth stands. Vertical complexity displayed similar results for young and mature stands. However, regeneration and old-growth stands were clearly differentiated from the other forest succession types. In the same way, the mean for 90th percentile of height had similar results for mature and old-growth stands, even though the range of height distribution was wider for old-growth stands. Understory density was the metric that most differentiated old-growth stands from the others. Wetness index shows very little difference between the forest succession types (not statistical), which suggested a well distribution of forest succession types in all wetness ranges. While each metric, except wetness index, contributed individually to differentiate one or two forest succession, only the combination of the four metrics generates an increase gradient of old-growth index from regeneration to old-growth plots.

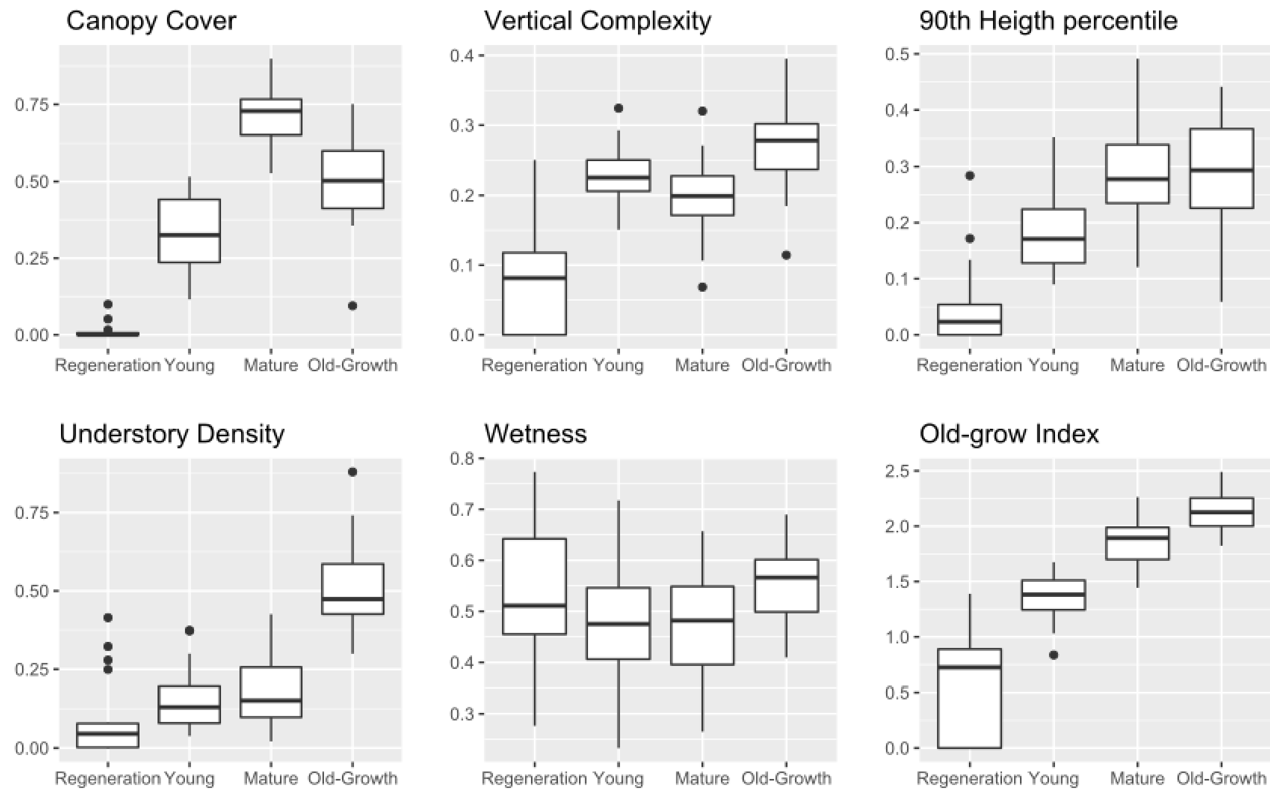

Figure 3 Boxplot distributions for all old-growth attributes, wetness index and the old-growth index for the 110 plots measure on the ground.

3.1. Random forest:

I developed two type of random forest models: one for classification (Table 4 and 5) and other for regression (Table 6). For both models, canopy cover was the most important metric followed by understory densidy, the later being the most important for the old-growth class.

As classification:

Table 4 Level of importance of each LiDAR metric in prediction old-growth forest

	Regeneration	Young	Mature	Old-Growth	MDA*	MDG**
Canopy Cover	37.586	67.273	85.898	5.163	84.335	35.008
Vertical complexity	13.900	17.763	8.411	14.152	24.407	10.599
90% Height	16.670	21.341	20.035	8.595	28.005	12.857
Understory Density	6.298	17.800	21.638	43.072	41.154	12.684
Wetness Index	-0.829	1.074	9.866	2.481	8.963	2.983

*Mean Decrease Accuracy

**Mean Decrease Gini

Table 5 Confusion matrix for forest succession classification

	Regeneration	Young	Mature	Old-Growth	class.error
Regeneration	18	2	0	0	0.100
Young	0	28	0	0	0.000
Mature	0	0	43	1	0.023
Old-Growth	1	1	4	8	0.429

* OOB estimate of error rate: 8.49%
**1000 decision trees were created with 2 variables tried at each split with a classification method

As regresssion:

Table 6 Level of importance of each LiDAR metric in the regression model for the landscape prediction of old-growth index

Variables	%IncMSE	IncNodePurity
Canopy Cover	45.213	12.385
Vertical complexity	18.842	5.012
90% Height	27.209	9.881
Understory Density	32.231	5.034
Wetness Index	13.223	1.170

*****Mean of squared residuals: 0.02464584, % Variance explained: 92.33
** Number of trees: 1000, No. of variables tried at each split: 2

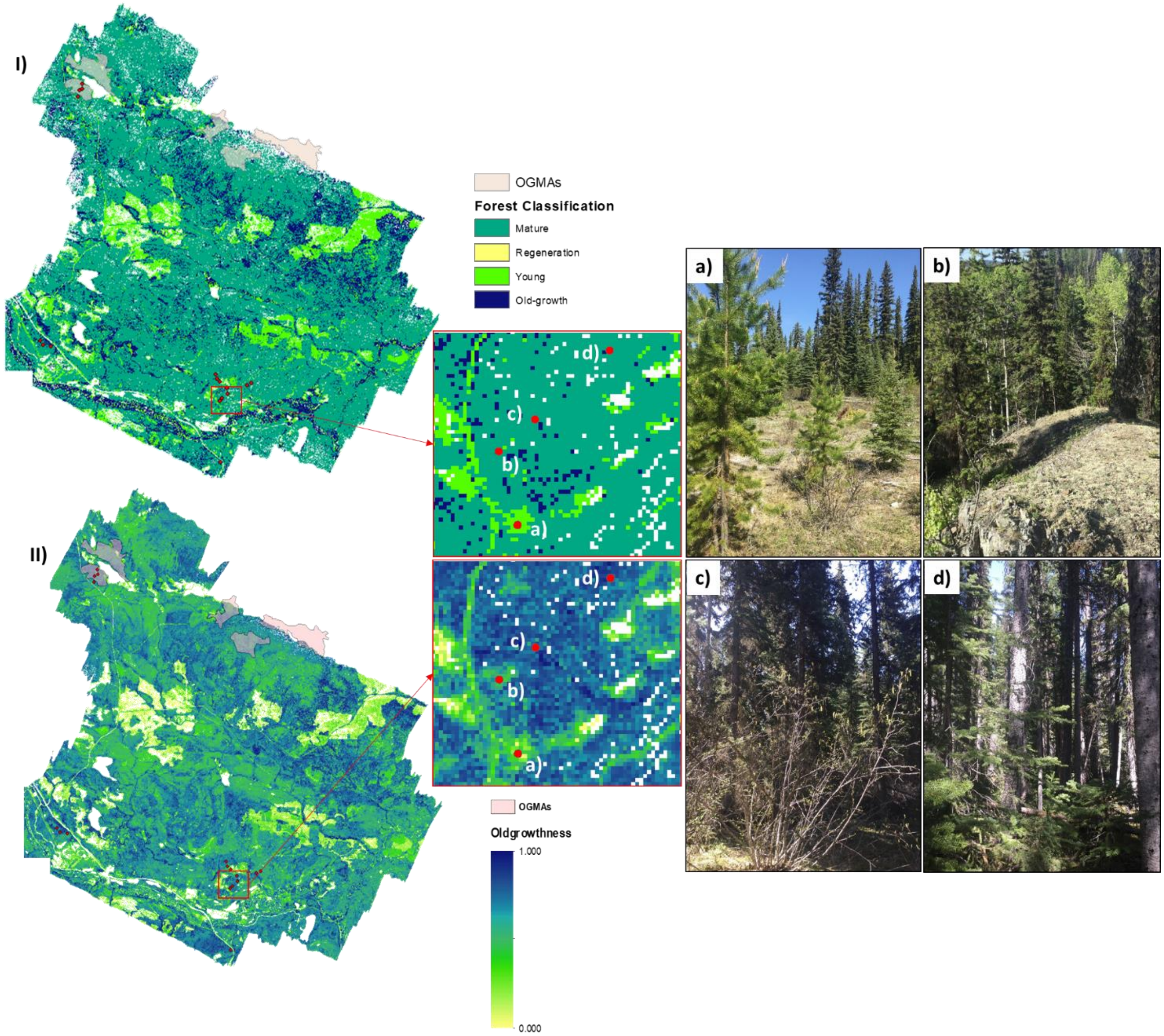

Figure 4 Forest was classified into I) four different forest successions (classification) and II) gradient of the abundance of old-growth attributes (regression). Fourteen locations were visited to evaluate the effectiveness of these two classifications. Four of those sites are depicted here: a) depicts low level of old-growth attributes (young forest), b) bare rock c) intermediate level of old-growth attributes.

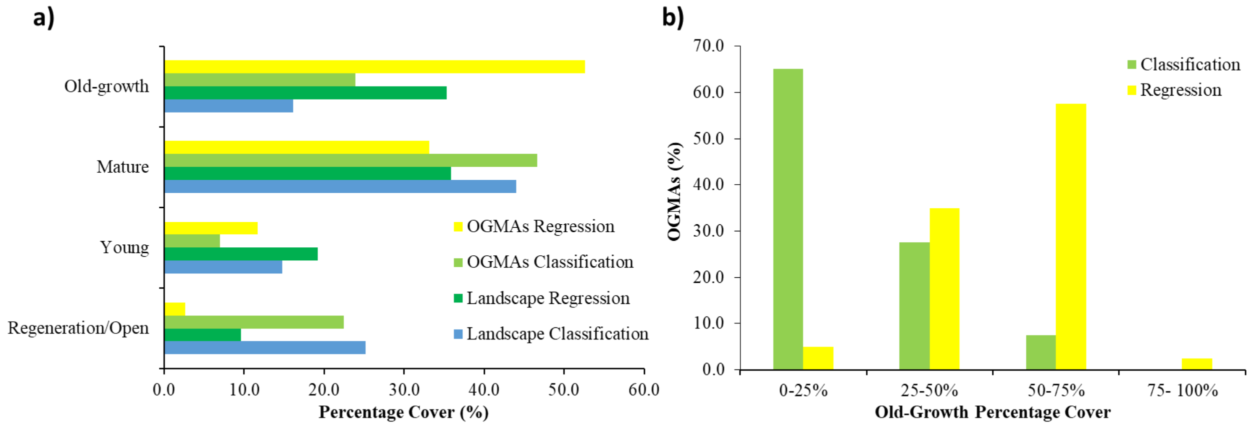

Figure 5 Summary of the forest succession cover obtained from the classification and regression models, where a) displays the percentage cover of each forest succession class for the whole landscape and only for the areas covered by OGMAs, and b) depicts the distribution of OGMAs in terms of percentage of area classified as old-growth forests

4. NEXT STEPS:

- Analyzing empirical data and apply K-mean clustering and PCI statists to classify plots into forest succession and abundance of old-growth attributes;
- Validation of LiDAR metrics;
- Reprocessing of Random forest models with forest succession classification and old-growth index from empirical data;
- Reevaluation of OGMAs based on the percentage of area covered by old-growth forests;
- Selecting OGMAs purely based on old-growth attributes;
- Identifying the trade-offs (e.g. loss of topographic variability representation) between current OGMAs and OGMAs selected purely based old-growth attributes

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