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1 Estimation of forest inventory variables using ALS data and multi-
2 seasonal satellite imagery

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11 variable selection

Abstract

Advanced forest resource inventory (FRI) information is of critical importance for optimizing the forest value chain. Remote sensing offers a cost-effective option for estimating forest inventory and biophysical variables over large areas. The objective of this study was to examine the utility of multi-seasonal multispectral satellite imagery and airborne laser scanning (ALS) data for estimating basal area, species mixture, and stem density for an uneven-aged tolerant hardwood forest in Ontario, Canada. Using random forest (RF) regression as a diagnostic tool, three multispectral sensors were examined: Landsat-5 TM, Sentinel-2A and WorldView-2. The contribution of spectral predictors derived from different sensors as well as ALS height and intensity metrics were evaluated using RF variable importance. As part of a two-step variable selection framework, all the predictor variables were grouped into clusters using a hierarchical variable clustering technique, which revealed the distinctiveness between information contained in spectral predictors, height metrics, and intensity-based metrics. This indicates that ALS intensity data carry unique information complementary to near-infrared bands of multispectral sensors for forest characterization. Compared to single date images, multi-seasonal imagery proved to be more accurate for modelling FRI variables, especially when combined with ALS data. Despite its limited spatial resolution, Sentinel-2A was found to be the most cost-effective image source for enhancing ALS-based inventory models. Using variables determined by the variable selection procedure, best subsets regression outperformed the RF models developed during diagnostic analysis, resulting in a suite of accurate and parsimonious predictive models, with coefficients of determination of 0.73, 0.90 and 0.67, for BA, conifer RBA and SD, respectively.

1. Introduction

Forests are essential resources given that humans rely on them for social, economic, and environmental well-being (Hansen et al., 2013; Falkowski et al., 2009; Bonan, 2008). Over the past few decades, awareness of a changing climate, increasing energy prices, and enhanced concern for environmental issues have resulted in calls for more accurate, comprehensive and cost-effective forest monitoring systems (Puddister et al., 2011; Wulder et al., 2004). Due to the labour-intensive nature of ground-based forest mensuration, numerous efforts have been made to derive spatially explicit forest information using remote sensing. Considering the demand for sustainable forest management, information on forest structure and composition is of critical importance to informed silvicultural decisions and optimization of the forest value chain (Pitt & Pineau, 2009).

Owing to its capability for providing a synoptic view of the earth's surface in a repetitive and economical manner, remote sensing has proven to be a useful technology for forest management (Giri et al., 2011; McRoberts et al., 2010). During the past few decades, research has focused on the extraction of forest biophysical and inventory variables (i.e., forest structural attributes) at various scales with optical remote sensing systems (Song, 2007; Hyypä et al., 2000; Peterson et al., 1988). Despite the availability of numerous advanced image processing techniques with varying levels of reported success, optical remote sensing continues to lack the inherent capability of measuring the vertical structure of the forest (Mora et al., 2013; Ozdemir & Karnieli, 2011; Falkowski et al., 2009), although the increasing availability of high spatial resolution imagery has alleviated this issue to some extent (Xu et al., 2015; Chen et al., 2012; Pasher & King, 2010). However, predictive models based on optical data have yet to gain sufficient accuracy and precision to become operational (Xu et al., 2015). In contrast, airborne laser scanning (ALS)

characterizes forest structure in the form of three-dimensional (3D) point clouds, thus containing unique information on the vertical characteristics of the forest (Lim et al., 2003).

Holmgren et al. (2008) compared high spatial resolution airborne multispectral camera data to discrete return ALS data for species classification in southern Sweden using an individual tree-based approach; the overall accuracy of the multispectral data was found to be slightly lower than that of the ALS data (i.e., 88% and 91% respectively). Erdody and Moskal (2010) estimated canopy height and canopy base height using ALS data and digital image data collected simultaneously. Even though the synergy of both data sources led to the highest accuracy for both canopy fuel attributes being modelled, the goodness-of-fit of the imagery-only model was approximately 50% of the ALS model. Similar results have been reported where multispectral imagery and ALS data were used to model stem volume as well as the volume and biomass of shrub vegetation (Tonolli et al., 2011; Estornell et al., 2012). Given the enhanced accuracy of the synergistic approach, there is a strong incentive for incorporating optical data into existing ALS-based forest inventories (Laurin et al., 2014; Koch, 2010; Dalponte et al., 2008). However, systematic analysis examining the utility of optical data with varying specifications has been scarce in the context of modelling FRI and biophysical variables over large areas. Given the higher acquisition costs of very high spatial resolution imagery compared to freely available datasets (e.g., Landsat TM and Sentinel-2A), the benefits of high spatial resolution data should be well understood relative to what can be achieved with imagery of moderate spatial resolution (i.e., 10 to 30 m). In particular, multitemporal, moderate-resolution remote sensing data has exhibited strong potential for forest type classification, species differentiation and estimation of forest inventory variables (Chrysafis et al., 2017; Zhu & Liu, 2014; Li et al., 2013). However, the utility

of multitemporal optical remote sensing data compared to ALS data has not been examined to any significant degree in the context of FRI.

Given the nature of multitemporal remote sensing and ALS data, a very large number of predictor variables can be derived, many of which exhibit high levels of collinearity (Maltamo & Gobakken, 2014). Due to the lack of statistical assumptions on the predictor variables, non-parametric techniques pose a popular solution to this dilemma (Penner et al., 2013; Breidenbach et al., 2010; Hudak et al., 2008). Nonetheless, non-parametric models are generally less amenable to interpretation, owing to relatively complex model structures. A recent study compared the random forest (RF) regression technique with generalized linear models (GLMs) for modelling vascular plant species richness, and the latter was found to be more parsimonious and accurate (Lopatin et al., 2016). A similar comparison was conducted by Penner et al. (2013) where RF was deemed more suitable for modelling FRI variables than parametric regressions because it does not require model stratification to reach competitive accuracy. However, this study did not make use of a systematic variable selection procedure in the comparison. As a result, the regression models might not have reached optimal accuracy, due to their higher levels of reliance on selected variables (Mutanga et al., 2012; Cohen et al., 2003).

As ALS has matured, more efforts have been made to derive metrics based on intensity data, rather than height data alone (Shang et al., 2017; García et al., 2010; Donoghue et al., 2007). These studies have demonstrated that predictive models taking advantage of ALS height and intensity metrics were more accurate than those based on height data alone. With the advent of multispectral ALS sensors (e.g., Teledyne Optech Titan), height and intensity data are being collected at multiple wavelengths. A recent study utilized Titan multispectral ALS data for species classification at the individual tree level, and the intensity data were found to contribute information complementary

to 3D metrics (Budei et al., 2017). Regarding the acquisition mechanism, ALS intensity data are distinctive from the near-infrared (NIR) channels of multispectral sensors. However, the similarities and differences between these two types of “spectral” data are not well understood, especially considering the difficulties in calibrating ALS intensity data (Korpela et al., 2010).

Given this context, the overall aim of this study is to evaluate the potential of multispectral imagery for enhancing ALS-based estimation of basal area, species mixture, and stem density in an uneven-aged tolerant hardwood forest in the Great Lakes–St. Lawrence Forest Region, Ontario, Canada. The specific objectives are: (i) to examine the utility of multi-seasonal imagery for estimating selected forest inventory variables compared to single-date imagery; (ii) to assess the cost-effectiveness of high spatial resolution data (i.e., WorldView-2) relative to freely available multispectral data (i.e., Landsat-5 TM and Sentinel-2A); (iii) to compare and contrast the information contained in the near-infrared bands of these sensors to ALS intensity data; and (iv) to examine the accuracy of RF relative to linear regression based on variables carefully selected with a two-step variable selection strategy.

2. Material and methods

2.1 Study Area

The Haliburton Forest (HF) (45°17' N, 78°34' W) is located within the Great Lakes - St. Lawrence (GLSL) Forest Region of Ontario, Canada (Figure 1). The average annual temperature and precipitation is approximately 4.9 °C and 1100 mm respectively (Sackett et al., 2012). HF is an actively managed, privately owned forest covering 23,800 ha with 80 percent forest cover (Figure 1). Sugar Maple (*Acer saccharum*) is the dominant tree species, with Balsam Fir (*Abies balsamea*), eastern hemlock (*Tsuga canadensis*), American Beech (*Fagus grandifolia*), and yellow birch (*Betula alleghaniensis*) being co-dominant species (Hossain & Caspersen, 2012). The

implementation of partial harvest silviculture systems for the past 40 years resulted in an uneven-aged landscape in the HF (Arii et al., 2008; Mrosek et al., 2006).

Figure 1 Location of the study area in Ontario, Canada (Source: Google Maps, 2017).

2.2 Field data

During the summers of 2010 and 2011, 97 sampling plots were established in the HF following a stratified random sampling strategy, covering a gradient of ecosite and canopy openness conditions. All plots were circular, with a radius of 28.2 m (i.e., 0.25 ha). For all trees with a DBH ≥ 8 cm in each plot, DBH, tree species, and status (living or dead) were collected. The plot center locations were georeferenced with a Trimble ProXT GPS unit to achieve sub-meter accuracy. A suite of forest inventory variables was derived from the field data, including plot-level basal area (BA), stem density (SD), and the proportion of conifer trees by relative basal area (RBA) as a surrogate for species mixture, such that forest structural and species information is available for decision support in forest management. Summary statistics of these forest inventory variables are provided in Table 1.

Table 1 Descriptive statistics of the forest attributes for Haliburton Forest.

Attribute	Average	Min	Max	Standard deviation
BA (m ² /ha)	28.31	9.75	45.88	7.39
Conifer RBA (%)	0.31	0.00	0.94	0.24
Stem density (Stems/ha)	790.40	400.00	1784.00	334.20

2.3 ALS data

Small-footprint discrete return ALS data (39 flight lines) were collected in 2009 with an ALTM 3100 sensor (Teledyne Optech Inc., Vaughan, Ontario, Canada) mounted in a Cessna Turbo 206 Stationair aircraft (Lim Geomatics Inc., Ottawa, Canada). The instrument was flown at an altitude of approximately 1500 m above ground level, with a scan half angle of 16°, a pulse repetition frequency of 70 kHz, a scan frequency of 36 Hz, and 30% overlap between adjacent flight lines. This resulted in a nominal point density of 1.7 points m⁻². A triangular irregular network (TIN) was created by the vendor based on ALS points classified as ground returns, which was used to normalize the ALS height data.

2.4 Multispectral imagery

The optical dataset used for this study consisted of 6 cloud-free, multi-seasonal images, acquired by three multispectral sensors (i.e., Landsat-5 TM, Sentinel-2A, and WorldView-2). Landsat-5 TM and WorldView-2 were selected due to their distinct spatial and spectral resolutions suitable for natural resources monitoring at different spatial scales. In contrast, Sentinel-2A covers the same spectral channels as Landsat-5 TM, yet provides enhanced spectral and spatial resolution, giving rise to its potential for forest applications. To examine the utility of multi-seasonal multispectral images for estimating FRI variables, two images were acquired for each sensor during leaf-on and leaf-off conditions (Table 2). The Landsat-5 TM scenes were atmospherically corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS)

(Masek et al., 2006). The Sentinel-2 SEN2COR processor implemented in the Sentinel Application Platform (SNAP) (version 5.0.7) was used to convert top of atmosphere to surface reflectance for the Sentinel-2A images (Vuolo et al., 2016). Atmospheric correction for the WorldView-2 images was performed using the FLAASH atmospheric correction module in ENVI 5.4.

Table 2 Multi-seasonal multispectral imagery examined in this study.

Sensor	Resolution (m)	Leaf-on acquisition	Leaf-off acquisition	Channels used
Sentinel-2A	10 & 20	2016-08-15	2017-03-23	2 ~ 8; 8a; 11; 12
WorldView-2	2	2015-07-11	2015-11-17	1 ~ 8
Landsat TM	30	2011-07-03	2011-04-30	1 ~ 5; 7

2.5 Predictor variables

In order to compare the utility of ALS- and imagery-based predictors for estimating FRI variables, we examined two groups of predictor variables from the remotely-sensed data: (1) height- and intensity-based metrics (Woods et al., 2011; Shang et al., 2017); and (2) spectral variables of different spectral and spatial resolutions corresponding to the specifications of Landsat-5 TM, Sentinel-2A, and WorldView-2 imagery (Table 2). Similar to the ALS metrics, where metrics were derived from returns intersecting each 0.25 ha plot, the spectral variables were obtained from pixels intersecting the individual plots. In addition to the plot-level average reflectance values for each band from the three sensors, the coefficient of variation (CV) was calculated as an image texture measure to test for the benefits of high spatial resolution imagery (St-Louis et al., 2009; Culbert et al., 2009; Kuplich et al., 2005). A total of 200 predictor variables were derived (104 ALS metrics and 96 spectral variables). Further, the inclusion of predictor variables from both data sources allows for a direct comparison between ALS intensity-based

metrics and near-infrared data from multispectral instruments with different spectral and spatial resolutions for modelling FRI variables.

2.6 Statistical analysis

To determine the utility of optical imagery and ALS data for modelling FRI variables, a two-step modelling approach was developed (Figure 2). The first step aims to obtain an approximate estimation of the potential of optical imagery for assisting ALS-based predictive models of different forest attributes. In particular, predictor variables derived from the two data sources (ALS and optical imagery) were configured into four categories based on richness of data: leaf-on imagery only, leaf-off imagery only, leaf-on + leaf-off imagery, and leaf-on + leaf-off imagery + ALS. Since we incorporated Landsat-5 TM, Sentinel-2A, and WorldView-2 imagery into our analyses, spectral predictor variables derived from these sensors were examined independently from each other. As a result, we obtained a total of 12 predictor groups (four richness categories $\times$ three sensors).

As a non-parametric technique gaining popularity in the remote sensing community (Belgiu & Drăguț, 2016; Rodriguez-Galiano et al., 2012; Pal, 2005), the RF model is free from assumptions based on data distribution (Breiman, 2001). This feature of RF makes it a suitable tool for diagnostic analysis and establishing goodness-of-fit benchmarks using different groups of predictor variables (i.e., without the need to adjust for collinearity between large groups of predictor variables). After RF was performed on each of the 12 predictor groups for the three selected forest attributes, R^2 values derived from out-of-bag (OOB) data were used as surrogates for goodness-of-fit, since they are generally reported as conservative estimates of model accuracy (Oliveira et al., 2012). For comparison purposes, full RF models utilizing all the 200 predictor variables were developed for each forest inventory variable. Being an ensemble tree-based model,

RF consists of a number of decision tree classifiers, and each tree classifier is trained with a subset of input features using a bootstrap sample of the original calibration data. This allows for the derivation of variable importance measures using OOB data. To determine the predictor variables most sensitive to each forest inventory variable, variable importance scores were obtained from the three full models. Owing to its explicit connection to model accuracy, the average percentage decrease in mean squared error (%IncMSE) was used to represent variable importance.

The R package randomForest (Liaw & Wiener, 2002) was used to calibrate the RF models. Since these models primarily serve the purpose of internal comparisons at the diagnostic stage (i.e., between different predictor groups for different forest attributes), parameter tuning was not conducted. The default parameters were adopted, with the number of regression trees (i.e., ntree) set to 500, the number of predictor variables sampled at each split (i.e., mtry) set to one third of the total number of variables, and a minimum terminal node size (i.e., nodesize) of five. Despite its ease of use and reasonably good predictive power, RF can be difficult to interpret and more computationally demanding compared to regression models. Therefore, we aim to develop more parsimonious and potentially more accurate models in the second step of our modelling framework. After the goodness-of-fit baselines were established for all 12 predictor groups in the first step, those exhibiting good predictive potential were further analyzed in the second step (i.e., variable reduction and final model development) (Figure 2).

Due to the large number of predictor variables within each predictor group, a two-step variable selection strategy was developed to facilitate the development of parsimonious and interpretable models. The primary objectives of common variable selection approaches are to remove predictors with low relevance to the variables of interest (i.e., confounding variables) and reduce the redundancy between remaining variables (Zhu et al., 2015; Galelli & Castelletti, 2013;

222 Chen et al., 2012). We first reduced redundancy within the initial set of predictor variables using
223 a hierarchical variable clustering algorithm (hclustvar) implemented in the R package ClustOfVar
224 (Chavent et al., 2011). This clustering process can be conceptualized and visualized through a
225 dendrogram: using a bottom-up approach, the most correlated predictors identified by the squared
226 Pearson correlation are merged at each step until one cluster remains. To determine the optimal
227 number of variable clusters to retain after partitioning the dendrogram, the adjusted Rand index
228 (Hubert & Arabie, 1985) was calculated. As a result, highly correlated predictor variables were
229 grouped into the same clusters, while relatively independent variables remained in different
230 clusters. Subsequently, synthetic variables equivalent to the first principle component of a PCA
231 applied to the variables in the individual clusters were created to represent these variable clusters,
232 thus eliminating redundant predictor variables. The second step of our variable selection strategy
233 selected variables relevant to the forest attributes of interest. The synthetic variables emerging
234 from the variable clustering phase were evaluated using the variable importance measure
235 (%IncMSE) of RF. To improve the computational efficiency of our model (i.e., directly related to
236 the number of variables in a model) and alleviate the risk of developing a model with high variance,
237 the top 30 synthetic variables with the highest variable importance scores were selected. To make
238 the final models interpretable and easy to apply over large areas, predictor variables with the
239 highest loadings on each of the 30 synthetic variables were used in subsequent analyses. Since the
240 first step of our variable selection strategy only examines the similarity between predictor variables,
241 the reduction of redundancy is independent from the choice of response variables. Therefore,
242 variable clustering based on the initial 200 predictor variables was performed only once. In contrast,
243 the second step was undertaken three times, one for each forest attribute, assuming the varying
244 utilities of the predictor variables for different forest attributes.

After both phases of variable selection, the total number of predictor variables were effectively reduced from 200 to 34 for all the response variables (Table 3). Since these carefully selected predictor variables have low redundancy and high relevancy to the response variables, multiple linear regression models with a significance level of 0.05 were developed using the best subsets technique (Hudak et al., 2006). The Bayesian information criteria (BIC) was used to select the best model for each response variable. To avoid overfitting, the maximum number of predictor variables in each regression model was set to six, even if the lowest BIC value corresponded to a more complex model. During model selection, the variance inflation factors (VIFs) were closely monitored, and regression models suffering from high-collinearity (i.e., containing variables with VIFs of over 10) were discarded. To examine whether the assumptions of linear regression were met by the candidate models, statistical tests were performed using the Shapiro–Wilk Test and the Breusch-Pagon Test for normality of residuals and homoscedasticity respectively (Royston, 1982; Breusch & Pagon, 1979). To assess the robustness of predictive models over a full range of forest conditions, calibration and validation of the regression models was conducted using a 10-fold cross-validation approach, where predictive accuracy was measured by coefficient of determination (R^2) and relative root mean square error (rRMSE).

Figure 2 Workflow diagram of the two-step modelling framework consisting of: (i) diagnostic analysis to determine the predictive potential of different predictor groups and the most influential predictor variables for each forest inventory variables using RF; and (ii) final model development stage where accurate and parsimonious regression models are constructed following a two-step variable selection strategy.

267 **Table 3** Predictor variables selected by the best subsets approach for each forest inventory variable.

Variables	Variable description	BA	Conifer RBA	Stem Density
D1	1 st density metric (Woods et al., 2008)	√	√	
D2	2 nd density metric			√
D3	3 rd density metric	√		
D8	8 th density metric	√		
Elev.MAD.median	Median of the absolute deviations from the overall median			√
Elev.P75	75 th height percentile			√
Elev.P95	95 th height percentile	√		
Int.kurtosis	Intensity kurtosis			√
Int.mean	Intensity mean		√	
Int.P25	25 th height percentile			√
Int.P80	80 th height percentile	√		
Int.P90	90 th height percentile			√
Int.P99	99 th height percentile			√
Int.stddev	Intensity standard deviation			√
Percentage.all.returns.above.mean	Percentage of all returns above the mean height			√
Percentage.first.returns.above.2	Proportion of first returns above 2 m	√	√	
S2A_Aug_B3_cv	Sentinel-2A Leaf on green cv			√
S2A_Aug_B7_mean	Sentinel-2A Leaf on red edge 3 mean	√	√	
S2A_Mar_B11_mean	Sentinel-2A Leaf off SWIR 1 mean	√	√	
S2A_Mar_B12_mean	Sentinel-2A Leaf off SWIR 2 mean	√	√	
S2A_Mar_B2_cv	Sentinel-2A Leaf off blue cv	√		
S2A_Mar_B7_mean	Sentinel-2A Leaf off red edge 3 mean		√	
Wv_Jul_B2_mean	WorldView-2 Leaf on blue mean			√
Wv_Jul_B3_mean	WorldView-2 Leaf on green mean			√
Wv_Jul_B5_mean	WorldView-2 Leaf on red mean			√
Wv_Jul_B6_cv	WorldView-2 Leaf on red edge cv		√	√
Wv_Jul_B8_mean	WorldView-2 Leaf on NIR2 mean	√	√	√
Wv_Nov_B1_cv	WorldView-2 Leaf off coastal cv			√
Wv_Nov_B1_mean	WorldView-2 Leaf off coastal mean			√
Wv_Nov_B5_mean	WorldView-2 Leaf off red mean	√		
Wv_Nov_B6_mean	WorldView-2 Leaf off red edge mean	√	√	
Wv_Nov_B8_cv	WorldView-2 Leaf off NIR2 cv		√	√
Lt5_Apr_B3_mean	Landsat-5 TM leaf off red mean	√		
Lt5_Apr_B4_mean	Landsat-5 TM leaf off NIR mean	√		

3. Results and discussion

3.1 Diagnostic analysis using RF

Single-season spectral predictors exhibited varying predictive power for each of the three forest inventory variables (Figure 3). For BA and conifer RBA, spectral predictors derived from Landsat-5 TM and Sentinel-2A under leaf-off conditions exhibited greater accuracy than those from leaf-on. The leaf-on WorldView-2 image proved to be more useful than the leaf-off acquisition for modelling BA, but the trend is reversed for species mixture (i.e., conifer RBA). This can be attributed to the distinctive spectral signatures for deciduous and conifer trees under leaf-off conditions, when deciduous trees are devoid of foliage. In the context of area-based approach (ABA), the enhanced spectral differences between conifer and deciduous species under leaf-off conditions contributes directly to the estimation of the percentage of conifer trees in each plot. For stem density, similar accuracies were achieved by the leaf-on and leaf-off spectral predictors, with the predictive power of the latter lagging slightly behind. However, when these two groups of predictors were combined, their synergistic predictive power exhibited greater correspondence with stem density (Figure 3). In contrast, the accuracy of the RF models based on multi-seasonal imagery was not significantly improved from the best single season models for BA and conifer RBA. This holds true for all three sensors, with the only exception being the WorldView-2 model for conifer RBA, where the multi-seasonal model outperformed the single season models.

Among the spectral models, Landsat-5 TM exhibited the poorest overall utility for modelling the selected forest inventory variables, due to its relatively coarse spatial and spectral resolution. Spectral predictors derived from Sentinel-2A featured the highest accuracy for modelling BA. Nonetheless, WorldView-2 was found to be the most successful optical sensor for conifer RBA

and stem density. After ALS-based predictors were added to the spectral models, the predictive power of the RF models was greatly improved for BA and stem density. In conjunction with the relatively poor accuracy of the spectral models for these two inventory variables (i.e., $R^2 < 0.5$ regardless of sensor), this indicates the unparalleled utility of ALS data for modelling forest structural characteristics compared to optical sensors. Interestingly, despite the varying predictive power of the spectral models for stem density, their accuracies converged after ALS metrics were added, implying that optical sensors do not contribute complementary information.

When it comes to species mixture, the addition of ALS-based predictors only led to marginal improvement in model accuracy for Landsat-5 TM and Sentinel-2A. For WorldView-2, the combined model (i.e., WorldView-2 + ALS) was outperformed by the multi-seasonal WorldView-2 model. The reason behind this is likely twofold. First, even though RF does not assume predictor variables to be statistically independent, the large number of highly correlated ALS metrics can hinder model performance, thus requiring a variable selection approach to reach optimum accuracy (Chrysafis et al., 2017; Immitzer et al., 2017; Liu et al., 2017; Chan & Paelinckx, 2008). Second, ALS data carry limited information on species, especially at the plot level (White et al., 2016; Breidenbach et al., 2010; Brandtberg, 2007). With the large number of ALS metrics (i.e., 104) added to the multi-seasonal WorldView-2 model (i.e., containing 32 spectral variables), the overall probability of obtaining a useful variable for modelling species mixture is decreased at each split, given the parameter ‘mtry’ is set to one third of the total number of variables, resulting in reduced performance. Similarly, the full BA model did not outperform the more parsimonious model based on multi-seasonal Sentinel-2A predictors and ALS metrics. For the other two inventory variables, the best subsets models reached comparable accuracy as the corresponding full models, indicating

that the combination of only one optical sensor and ALS is sufficient for enhancing ALS-based FRIs.

Figure 3 Predictive accuracies for three forest inventory variables derived from RF OOB data, based on four data richness groups for three optical sensors. Group 1: leaf-on imagery only; Group 2: leaf-off imagery only, Group 3: leaf-on + leaf-off imagery; Group 4: leaf-on + leaf-off imagery + ALS. The accuracies of the full models were also added to the graph as a reference. Because these full models make use of all the available spectral and ALS predictors, dashed lines were used to represent the accuracy of the full models for illustrative purposes.

The variable importance information obtained from the three full models corresponded well with the predictive power exhibited by the different predictor groups shown in Figure 3. For BA, the top 30 most important variables were represented by two general classes of predictor variables. The first class mostly consists of spectral predictors derived from Landsat-5 TM and Sentinel-2A images acquired under leaf-off conditions (Figure 4). This corroborates the stronger predictive power of the multi-seasonal and leaf-off models based on these two sensors compared to those

based on WorldView-2 (Figure 3). Considering the superior spatial and spectral resolution of WorldView-2 relative to that of Landsat-5 TM, it is likely that the SWIR bands available on Sentinel-2A and Landsat-5 TM contribute to the improved predictive power of these two sensors over WorldView-2. For instance, the SWIR band of the leaf-off Landsat-5 TM image ranked the fourth for modelling BA (Figure 4). In addition, the leaf-off WorldView-2 image was acquired in November, while the leaf-off Sentinel-2A and Landsat-5 images were acquired in March and April respectively. Even though all three months represent leaf-off conditions, the lack of model performance associated with the November WorldView-2 image could in part be attributed to the remnant foliage on deciduous trees in November. This may have a negative impact on the relationship between woody materials and multispectral bands of the leaf-off WorldView-2 image, especially in the visible range of the spectrum, considering the most important variables for BA are visible bands from Sentinel-2A and Landsat-5 TM. The second class of predictors that exhibited potent utility for modelling BA is comprised of height percentiles, density metrics, and other ALS metrics that characterize the statistical distribution of ALS height data, which corroborates well with the findings of previous studies which show that ... stands with higher BA have bigger trees that are taller (Penner et al., 2013; Packalén & Maltamo, 2007; Gobakken & Næsset, 2004).

Similar to BA, spectral predictors derived from leaf-off images exhibited the strongest predictive power towards conifer RBA (Figure 4). Leaf-on spectral predictors were also found to carry important information on species mixture, albeit with slightly lower rankings. Considering the distinctive spectral signature between deciduous and conifer trees under leaf-off conditions, this is not surprising. Furthermore, local spectral heterogeneity (i.e., measured by band CVs) was found to be an influential predictor for conifer RBA. Unlike the case with the BA model, where

the most influential spectral predictors represented visible wavelengths, the top predictors for conifer RBA included spectral predictors covering the full range of spectrum (i.e., visible, red edge, NIR, and SWIR). In addition to the significant potential of spectral predictors for modelling species mixture, the domination of one class (i.e., variable cluster 2) of predictors indicates one drawback of the RF algorithm that impacts its variable importance rankings as well as its performance. As can be seen from the top-ranked variables for conifer RBA, several spectral predictors from the same sensor with similar wavelengths were included (e.g., the red edge, NIR1, and NIR2 bands of the leaf-off Worldview-2 image; the red, green, and blue bands of the leaf-off Sentinel-2A image). Upon examining the correlation between these variables, they were found to be highly correlated, with Pearson correlation coefficients greater than 0.9 in both cases. Given that these variables carry almost identical information, it is highly likely that they were used interchangeably, to a large extent, at different splits in the individual regression trees within the RF model. As a result, their variable importance scores are skewed because they are shared between these highly correlated predictor variables. In addition, a variable importance graph inundated with important yet highly correlated variables hinders the interpretation of the contribution of weaker predictors that carry complementary information on the response variable. For instance, the contribution of ALS metrics for modelling species mixture cannot be well understood with only two ALS metrics present in the list of top 30 variables. The presence of highly correlated variables in RF also inflates the probability of these variables being selected at different splits, thus increasing the correlation between individual regression trees. This will increase the variance of the RF model, compromising its predictive performance. Therefore, the use of a variable selection technique in conjunction with RF is highly recommended for not only

predictive purposes, but also interpretation of variable importance (Karlson et al., 2015; Naidoo et al., 2012; Nicodemus et al., 2010).

In comparison to BA and conifer RBA, the RF model for stem density benefited from a wider range of predictor variables, encompassing variables from four out of seven variable clusters (Figure 4). In contrast to the two previous forest attributes, where spectral predictors were the most influential variables, the predictive power of the stem density model can be mostly attributed to ALS metrics, with metrics that characterize the variability of the ALS height and intensity data (e.g., Elev.variance, Elev.stddev, Int.AAD, Int.variance) being the most important predictors. The importance of these metrics for modelling stem density and size class distribution has been described in Shang et al. (2017). In addition to ALS-based predictors, several spectral variables exhibited respectable predictive power towards stem density. In particular, the blue band from the leaf-on WorldView-2 image (i.e., Wv_Jul_B2_mean) ranked fifth in the list of top 30 most important variables. A study conducted by Ozdemir & Karnieli (2011) examined the utility of a spring (i.e., May) WorldView-2 image for modelling forest inventory variables for afforestation and the blue band was identified as the most useful channel for BA, stem volume, and stem diameter diversity. In our RF model, due to the presence of highly correlated variables at the top of the list, the contribution of these spectral variables towards stem density modelling is biased, and likely underrepresented in this instance.

Figure 4 Variable importance scores for the top 30 variables emerging from the full RF models developed using RF with all the 200 predictor variables for each forest inventory variable: (a) BA, (b) Conifer RBA, (c) Stem density. For interpretation purposes, the dendrogram encompassing all 200 variables is partitioned to represent seven clusters, and the variables falling into each cluster are color coded accordingly. The first cluster is represented by a subset of leaf-on WorldView-2 spectral variables, the second by multi-seasonal spectral variables from all three sensors, the third by return proportions and the majority of ALS intensity metrics, the fourth by a variety of ALS height metrics, the fifth by Landsat-based texture variables, the sixth by a subset of texture metrics derived from Sentinel-2A, and the seventh by a subset of intensity metrics.

3.2 Variable selection

Considering the large number of predictor variables (i.e., 200) processed with the variable clustering algorithm, visualization of the corresponding dendrogram can be challenging. To showcase the concept and reveal the relationship between ALS metrics and spectral predictors derived from the three optical sensors, hierarchical clustering was performed on the 34 remaining predictor variables after variable selection (Figure 5). At the bottom of the dendrogram (area to

the left in Figure 5), the most similar variables are grouped into the same clusters, including spectral bands covering similar ranges of the spectrum and adjacent height and intensity percentiles. However, the correlation among these variables have already been greatly reduced compared to the full dendrogram containing all 200 variables. For example, the standard deviation and variance of the intensity data are not simultaneously present in Figure 5 due to the application of the variable selection procedures. Similarly, only the mean reflectance of the leaf-on WorldView-2 NIR2 band remains after variable selection, while the counterparts for the red edge and NIR1 bands have been discarded, due to the high correlation between these channels. When this dendrogram containing 34 variables is cut to represent three functional clusters, the first one is represented by multi-seasonal spectral predictors, the second by ALS intensity-based metrics, and the third by height metrics with a mixture of two spectral predictors from WorldView-2 imagery and one intensity-based metric. This indicates that spectral predictors and structural metrics derived from ALS height and intensity data carry distinctive information for modelling forest inventory variables, even though the ALS instrument operates at the near-infrared wavelength. This could be attributed to the nature of the ALS height and intensity data as three-dimensional measurements of the forest. The intensity values associated with individual ALS returns can be considered indicators of the strength (or power return) of the backscattered energy (Wehr & Lohr, 1999), which is conceptually comparable to uncalibrated DN values from multispectral sensors. However, the spectral measurements obtained by multispectral sensors are primarily influenced by optical properties of the top of the canopy (Schlemmer et al., 2013; Meroni et al., 2004; Goward & Huemmrich, 1992). Even with multiple scattering between canopy layers considered, information contained in multispectral data cannot effectively characterize the vertical distribution of the forest canopy. On the contrary, ALS intensity data are collected at various heights within a forest as the laser pulse

travels through the canopy, thus containing information more relevant to the vertical structure of the forest. For example, the variability of intensity values has been associated with overall canopy density, which facilitated the estimation of stem density for small diameter trees (Shang et al., 2017). Using an individual tree-based approach, Holmgren and Persson (2004) found the standard deviation of ALS intensity data of critical importance to the differentiation between spruce and pine. At the plot scale, intensity percentile metrics also exhibited strong potential for estimating species mixture in plantation forests (Donoghue et al., 2007).

Figure 5 Variable dendrogram obtained by performing variable clustering on the 34 predictor variables selected by the best subsets approach. To reveal the structure of information contained in these variables, this dendrogram is partitioned to represent three variable clusters (highlighted by the colored boxes).

3.3 Predictive performance of the regression models

Compared to the RF models developed in the diagnostic analysis (Figure 3), the linear regression models exhibited consistent improvement in predictive accuracy. As can be seen from

Table 4, the values of the three hybrid BA models all have $R^2 > 0.7$, while the full RF model had a $R^2 = 0.62$. Similarly, the R^2 of the linear conifer RBA models all exceeded 0.8 (i.e., ≥ 0.85 in three out of four cases), significantly higher than the accuracy of the full RF models (i.e., $R^2 = 0.8$). The improvement in predictive accuracy can be attributed to the parsimonious structure of the linear models, which was made possible by the removal of redundant and confounding variables at the variable selection phase. In addition, the presence of strong linear predictors made significant contributions towards enhancing model performance (e.g., multi-seasonal spectral variables for BA and conifer RBA). In comparison, the linear models for stem density only slightly outperformed the corresponding RF models, which can likely be attributed to the lack of strong linear predictors. Since RF can take advantage of a much larger group of predictor variables than linear regression models, it is anticipated that RF coupled with a variable selection strategy would result in a stronger predictive performance for stem density.

As noted earlier (Section 3.1), the combination of ALS and one optical sensor yielded promising predictive accuracy for BA. Therefore, variables representing these predictor groups were used to develop linear models of BA after variable selection. As can be seen from Table 4, leaf-off spectral variables in the visible, red edge, and SWIR regions of the spectrum were the most frequently selected for modelling BA, which corroborates well with the variable importance scores reported in Figure 4. Notably, the red and NIR data derived from the leaf-off Landsat-5 TM image in conjunction with a gap fraction measure (i.e., Percentage of first returns above 2m) yielded a regression model with an R^2 of 0.72 and rRMSE of 13%. In a recent study that examined the utility of Landsat 8 OLI (i.e., Operational Land Imager) imagery for modelling forest variables for a Mediterranean forest, a significant relationship was also observed between field measured BA and the visible and NIR bands of the OLI (Chrysafis et al., 2017). Among all the ALS metrics,

this gap fraction metric has been consistently selected by all three hybrid BA models, due to its moderate positive correlation with BA. The three hybrid BA models featured comparable predictive accuracy, with the one containing ALS and WorldView-2 data performing marginally better than the rest (Figure 6). The slightly more pronounced scattering between the observed and predicted BA at higher ranges is likely a result of under-sampling in our field campaign. Due to the limited number of field plots with high BA values, the statistical relationship between BA and the predictor variables was not well established. Compared to the hybrid models, the ALS-only model had relatively poor predictive accuracy, with a R^2 and rRMSE of 0.40 and 0.20 respectively.

Since spectral predictors derived from Sentinel-2A and WorldView-2 imagery exhibited strong predictive power for conifer RBA in diagnostic analysis, linear regression models were developed to examine whether the addition of ALS metrics could further improve the accuracy of the spectral models. The spectral models based on multi-seasonal Sentinel-2A and WorldView-2 imagery achieved a R^2 of 0.81 and 0.85 respectively for modelling conifer RBA, while the R^2 increased to 0.88 and 0.90 respectively for the corresponding hybrid models (Table 4). For modelling species mixture, the mean reflectance in the SWIR and red edge range of the spectrum proved to be the most useful predictors derived from Sentinel-2A. In comparison, the red edge and NIR bands were the most influential predictors from WorldView-2. It is worth noting that two out of four WorldView-2 predictors measure variability, rather than the average of reflectance at the plot level, giving rise to the strong utility of high spatial resolution imagery for modelling species abundance (Cho et al., 2012; Immitzer et al., 2012; Pu & Landry, 2012). In contrast, all the Sentinel-2A variables selected for modelling conifer RBA represent mean reflectance at the plot level, likely a result of the lack of useful information in the texture variables derived from imagery of relatively coarse spatial resolution (i.e. 10 ~ 20 m). Consequently, more ALS metrics (i.e., 3)

were selected by the hybrid Sentinel-2A model compared to the case with the WorldView-2 hybrid model, containing only one intensity-based metric. Interestingly, this metric (i.e., mean intensity) was also selected by the Sentinel-2A hybrid model. Considering its low correlation with the spectral predictors in both hybrid models (i.e., $VIF < 3$), mean intensity is deemed to carry critical information on species abundance (Heinzel & Koch, 2011; Korpela et al., 2010; Kim et al., 2009), complementary to the contribution of spectral predictors derived from multispectral imagery. In accordance with a R^2 of 0.90 associated with the best model for species mixture, a tight relationship was exhibited in the scatterplot between observed and predicted values (Figure 6). Despite the superior spatial resolution of the WorldView-2 imagery, the two hybrid models featured comparable accuracy, making the multi-seasonal Sentinel-2A imagery a viable option for assisting ALS-based forest inventories, especially considering the relatively high acquisition cost of WorldView-2 imagery.

When it comes to stem density modelling, hybrid models did not lead to significantly higher predictive accuracy than the ALS model (Table 4). In fact, the linear model taking advantage of both WorldView-2 predictors and ALS metrics was outperformed by the ALS model. Owing to the significant predictive power of multi-seasonal WorldView-2 imagery relative to the other two sensors, a linear model was developed using WorldView-2 predictors only, resulting in a moderate R^2 of 0.59. Spectral predictors selected for this model included mean and CV of spectral bands ranging from the visible to NIR regions of the spectrum. The utility of the NIR bands of WorldView-2 imagery for modelling stem density has been reported by Ozdemir & Karnieli (2011). Earlier studies have also applied texture and shadow analysis to high spatial resolution imagery and obtained moderate accuracy for estimating stem density (Kayitakire et al., 2006; Coueron et al., 2005; Lévesque & King, 2003). The ALS model for stem density utilized height

and density metrics as well as three intensity-based metrics, corroborating the high variable importance associated with these two types of ALS metrics for modelling stem density (Figure 4). Figure 6 illustrates increased scatter (i.e., weaker correspondence) between the observed and predicted stem density at larger ranges (i.e., the top quartile), which may be reduced with an improved sampling strategy with greater focus on forest stands in early stand development stages.

521 **Table 4** Multiple linear regression models for BA, conifer RBA, and stem density. The R^2 and
522 rRMSE values of the most accurate model for each response variable were highlighted in bold.

Forest attributes	Predictor group	Selected variables	R^2	rRMSE
BA	LiDAR	Elev.P95, Int.P80, D3, D8	0.40	0.20
	LiDAR + Sentinel-2A	S2A_Aug_B7_mean, Percentage.first.returns.above.2, S2A_Mar_B11_mean, S2A_Mar_B12_mean, S2A_Mar_B2_cv	0.71	0.14
	LiDAR + WorldView-2	Wv_Jul_B8_mean, Wv_Nov_B5_mean, Wv_Nov_B6_mean, Percentage.first.returns.above.2, D1	0.73	0.13
	LiDAR + Landsat-5 TM	Percentage.first.returns.above.2, Lt5_Apr_B3_mean, Lt5_Apr_B4_mean	0.72	0.14
Conifer RBA	Sentinel-2A	S2A_Aug_B7_mean, S2A_Mar_B11_mean, S2A_Mar_B12_mean, S2A_Mar_B7_mean	0.81	0.33
	WorldView-2	Wv_Jul_B6_cv, Wv_Jul_B8_mean, Wv_Nov_B6_mean, Wv_Nov_B8_cv	0.85	0.30
	LiDAR + Sentinel-2A	Int.mean, Percentage.first.returns.above.2, D1, S2A_Aug_B7_mean, S2A_Mar_B11_mean, S2A_Mar_B12_mean	0.88	0.27
	LiDAR + WorldView-2	Int.mean, Wv_Jul_B6_cv, Wv_Jul_B8_mean, Wv_Nov_B6_mean, Wv_Nov_B8_cv	0.90	0.25
Stem density	WorldView-2	Wv_Jul_B3_mean, Wv_Jul_B5_mean, Wv_Jul_B8_mean, Wv_Nov_B1_cv, Wv_Nov_B8_cv, Wv_Jul_B6_cv	0.59	0.27
	LiDAR	Elev.P75, Int.stddev, Int.kurtosis, Int.P90, D2	0.66	0.25
	LiDAR + Sentinel-2A	Elev.MAD.median, Int.P25, Int.kurtosis, Percentage.all.returns.above.mean, S2A_Aug_B3_cv	0.67	0.24
	LiDAR + WorldView-2	Wv_Jul_B2_mean, Wv_Jul_B6_cv, Wv_Nov_B1_mean, Elev.P75, Int.kurtosis, Int.P99	0.65	0.25

Figure 6 Scatterplots of the observed and predicted values derived from the best model for each forest inventory variable based on 10-fold cross-validation.

4. Conclusion

This study assessed the potential of multi-seasonal multispectral imagery for assisting ALS-based forest inventory in an uneven-aged tolerant hardwood forest in Ontario, Canada. For BA, conifer RBA, and stem density, multi-seasonal image data generally exhibited stronger predictive performance than single date images. When multi-seasonal imagery is used in conjunction with ALS data, predictive accuracy was significantly improved for BA and conifer BA, while the accuracy of the stem density model was only marginally enhanced. Among the three sensors selected for comparison, WorldView-2 only slightly outperformed Sentinel-2A, despite its high acquisition cost and higher spatial resolution. Landsat-5 TM, on the other hand, had the overall lowest utility for modelling forest inventory variables, due to its coarser spatial and spectral resolution, as well as the lack of a red-edge feature. According to the variable dendrogram, multispectral imagery, ALS height and intensity data contain distinctive information regarding forest structure. Despite the similar wavelengths, the correlation between ALS mean intensity and average NIR reflectance at the plot level is relatively low, indicating that they provide complementary information for characterizing forest structure. Taking advantage of the two-step

variable selection strategy, linear regression models outperformed RF models in terms of predictive accuracy and ease of interpretation. Overall, the results of this study suggest that freely-available multi-seasonal Sentinel-2A imagery holds great potential for enhancing ALS-based forest inventories, especially after the application of an effective variable selection strategy.

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