How reliable are stand stocking estimates? A comparative analysis on current and new methodologies

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How reliable are stand stocking estimates? A comparative analysis on current and new methodologies*

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EXECUTIVE SUMMARY

Forest inventories created by traditional photo interpretation can be time-intensive to complete, subjective and inconsistent, possibly leading to errors, biases, and outdated inventories. The automated or semi-automated classification of digital remotely sensed imagery offers the potential for greater transparency, consistency, repeatability, and efficiency for inventorying over large areas. In this research, we evaluate the potential of advanced statistical classification models with the digital stereo photography that Ontario already uses to complete its forest inventories (Airborne Digital Sensor ADS40) to provide accurate estimates of three key forest inventory attributes (stand basal area, stocking level, and crown-closure) for the Lakehead Forest Management Unit in Northwestern Ontario.

ADS40 imagery from 2008 and collected at multiple look-angles (i.e., nadir and off-nadir), providing overlapping imagery from which a 3D image point cloud was generated through an automated matching algorithm. From the resultant point cloud, we generated a Digital Surface Model and a Digital Terrain Model, with the latter used to height-normalize the Digital Surface Model.

Linear regression models were created to predict stand basal area and stand stocking using two classes of predictor variables derived from the ADS40 data. The first class of predictor variables are related to individual tree crown (ITC) area and tree density. The second class of predictors are stand-level attributes, based on image texture measures (i.e., measures of canopy smoothness).

Basal area and stocking were estimated by field crews for calibration and validation purposes in 2015 and 2016, respectively. Additionally, experienced photo interpreters used the ADS40 stereo imagery independently within a softcopy environment to manually estimate stand stocking and canopy closure for each of the validation stands following standard photo interpretation methods.

Across all three forest types, at least one of the model types were able to produce stocking values that were not statistically different than those derived from field collected data. Mean differences between field and the best model values for stocking were between 0.03 and 0.06. In comparison, photo-interpretation values for stocking were statically different (lower) than those of field data in all forest types.

Model predictions of basal area were able to accurately approximate field data, showing no statistical difference. While mean differences between the best models and field data were relatively low (0.3 – 1.6 m^2/ha), 95% confidence values exceeded 4m^2/ha.

Both ITC and texture models were able to produce significant predictions, with the relative performance of each model type depending on the cover type, attribute evaluated (stocking or basal area), and the method of evaluation (e.g. r^2, RMSE, 95% confidence interval of difference, etc). The generally strong performance of the texture models highlights the potential for these point-cloud surface attributes to be used in conditions where ITC methods are not able to produce adequate results.

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1. INTRODUCTION

Forest inventories are required for forest management planning and forest operations planning, provide support for environmental assessments and conservation planning, and allow jurisdictions to report on the state of forests over large areas. Field data provide an important role in inventory calibration and validation, but are not feasible as the sole source of data across large and remote areas. Typically, the inventory process involves the manual delineation of forest stands on aerial photographs and the estimation of stand age, height, volume, species composition, and so on, by skilled photo interpreters.

While the process of manual interpretation of aerial photographs has become more efficient in the last decade due to an industry-wide move from hardcopy interpretation to digital / softcopy interpretation, the process remains a lengthy one, and as such, inventories may be poorly maintained and updated infrequently (Morgan et al. 2010, Thompson et al. 2007). Further, photo interpretation can be subjective and inconsistent, leading to errors and biases in the inventory (Morgan and Gergel 2013). The automated or semi-automated classification of multispectral imagery and Light Detection and Ranging (LiDAR) data is increasingly being investigated for forest inventories (e.g., Dalponte et al. 2014, Hilker et al. 2008, Kane et al. 2010, Waser et al. 2011, Woods et al. 2011). Such approaches offer greater transparency, consistency, repeatability, and efficiency for inventorying over large areas (White et al. 2016, Falkowski et al. 2009). Also, as forest management planning becomes more demanding with respect to spatial planning, forest inventories will need to become increasingly accurate to suitably match these demands.

These advanced approaches and newer sources of data are beginning to be adopted in some jurisdictions, however, the costs associated with LiDAR data acquisition and processing remain prohibitive over large areas. Digital stereo photography is more cost-effective to acquire, and in Ontario, the Airborne Digital Sensor ADS40 imagery already forms the basis of provincial forest inventories.

The goal of this research is to develop methods for automatically and objectively estimating several stand-level forest inventory attributes from high spatial resolution digital aerial photography. Specifically, we develop two different algorithms to the ADS40 imagery for an area in Northwestern Ontario to estimate basal area, stocking, and crown closure. These attributes are important for characterizing stand density, volume, and growth and yield, and reliable estimates of these attributes are required for forest planning at both the strategic and operational levels.

Analysis of LiDAR data begins with a three-dimensional “point cloud” – the returns of the laser pulse from the ground and throughout the vegetative canopy. Unlike LiDAR systems, which are known as *active* remote sensing, the ADS40 - and all multispectral imaging sensors - is *passive*. It receives the reflection of electromagnetic radiation from a surface, rather than the returns of a laser beam that penetrates through a canopy. Nonetheless, image data can be used to generate a point cloud similar to that produced with a LiDAR data and have been used to augment forest inventories (Goodbody et al. 2017). The difference is that the image point cloud represents only the single (upper) surface and not

multiple returns from throughout the canopy. The image point cloud can be produced because the ADS40 sensor collects data at multiple look angles (i.e., nadir and off-nadir), providing overlapping imagery. A process of "feature matching" (e.g., Hirschmuller 2005, 2008) is used to identify the same point on multiple overlapping images and determine its 3-D position (White et al. 2013).

Point clouds are typically converted to Digital Surface Models (DSMs), height normalized against a Digital Terrain Model (DTM). Previous studies using image-based point clouds required (pre-existing) LiDAR-derived DTMs for this normalization (White et al. 2013, Pitt et al. 2014, Goodbody et al. 2017). In this study, we test pseudo-ground points from the image-based point clouds (lowest points in the clouds where presumably there was no vegetation) to generate a DTM, thus potentially expanding the applicability and practicality of the approach.

2. BACKGROUND

Basal area at the tree level is the cross-sectional area of a tree stem measured at breast height; at the stand level, it represents the total area of all live trees in that stand and is expressed in square metres per hectare (m^2/ha). Whereas basal area is an absolute measure, stocking represents area occupancy or tree cover relative to a pre-established management norm. Generally, basal area and stocking values increase as the number of trees in a stand increases.

To estimate these variables in the field, technicians determine species, age, and height to ascertain Site Class (site index), then use Plonski's normal yield tables for Ontario (Plonski 1956, 1960, 1974) to get the *normal* basal area estimate. An *actual* basal area is directly estimated in the field by determining the average number of trees in the plot with a wedge prism, and multiplying by a Basal Area Factor. Stocking is then estimated as the ratio of the actual basal area to the normal basal area.

To estimate stocking from aerial photos, interpreters consider species, age and height to ascertain Site Class and the normal basal area, as above. In this case, no actual basal area measurements are available, thus interpreters rely on field calibration sample data and their own local expertise to estimate the number of trees likely to be counted in a prism sweep. Interpreters also recognize that, depending on Site Class, stocking may be equal, less than, or greater than, crown closure values, which are more straightforward to interpret. Crown closure is defined as the percentage of ground area covered by the vertical projection of the tree crowns onto the ground. The maximum value of crown closure is 100%.

3. METHODS

3.1 Study Area

The study is focused within the Lakehead Forest Management Unit (FMU), near the city of Thunder Bay, in Northwestern Ontario (Figure 1). The Lakehead FMU is in a transitional area, containing two forest types as classified by Rowe (1972): the Boreal forest in the northeast, and the Great lakes – St. Lawrence forest in central and western/southwestern areas.

The predominate hardwood species are trembling aspen (*Populus tremuloides*) and white birch (*Betula papyrifera*). Within the hardwood mixed wood stands, the conifer component is mainly white spruce (*Picea glauca*), jack pine (*Pinus banksiana*) and\or balsam fir (*Abies balsamea*). Black spruce (*Picea mariana*) is mainly found within lowland sites as pure stands or in association with tamarack (*Larix laricina*), white cedar (*Thuja occidentalis*) and balsam fir. Red pine (*Pinus resinosa*) and white pine (*P. strobus*) are also present.

The study focused on three forest units in particular: black-spruce lowland (*SbLow*), deep-substrate poplar (*PoDee*), and conifer-dominated mixedwood (*ConMx*). These three types are among the most prevalent in the Lakehead FMU (Table 1). These forest types were also chosen as they represent a large diversity of cover conditions, and thus point cloud characteristics, to test model performance.

Figure 1. Location of Lakehead Forest study area.

Table 1. Lakehead Forest Management Unit Area summary by Forest unit.

Forest Unit Code	Forest Unit Name	Area (ha)	% of Forest
PoDee	Deep-substrate poplar	149,983	25
HrDom	Hardwood dominated	93,089	15
HrdMw	Hardwood mixedwood	76,870	13
ConMx	Conifer-dominated mixedwood	65,287	11
SbLow	Black-spruce lowland	48,599	8
BwDee	Birch dominated upland	47,495	8
SbDee	Black-spruce upland	22,461	4
PjDee	Jack Pine upland	22,414	4
BfMx1	Balsam Fir mixedwood	19,459	3
SbMx1	Black Spruce mixedwood	17,593	3
OCLow	Other conifer - lowland	15,245	3
PjMx1	Jack Pine mixedwoods	8,252	1
OthHd	Tolerant Hardwoods	7,771	1
UplCe	Upland cedar	5,989	1
PrDom	Red Pine dominant	3,962	1
BfPur	Balsam Fir pure	3,177	1

3.2 Remotely sensed Data

ADS40 imagery was collected in the summer of 2008 and was provided to KBM from the Ontario Ministry of Natural Resources and Forestry (MNRF). The ADS40 multispectral sensor captures imagery in the panchromatic, visible (red, green, blue) and near-infrared spectral bands. The panchromatic band has a spatial resolution of 20 cm, while the visible and near-infrared spectral bands have a 40 cm spatial resolution.

The 3-D point cloud, DSM, and DTM were created from the ADS40 data using the “MATCH-T” tool Trimble’s *Inpho* software. The DSM and DTM have a spatial resolution of 40 cm. The DSM was then height-normalized with the DTM using LAStools software (LAStools, 2014) (Figure 2). This DSM is meant to characterize the top of the forest canopy, but is not a true Canopy Height Model because the ADS40 “ground-points” are limited in quantity and accuracy, in turn limiting the derivation of true canopy heights.

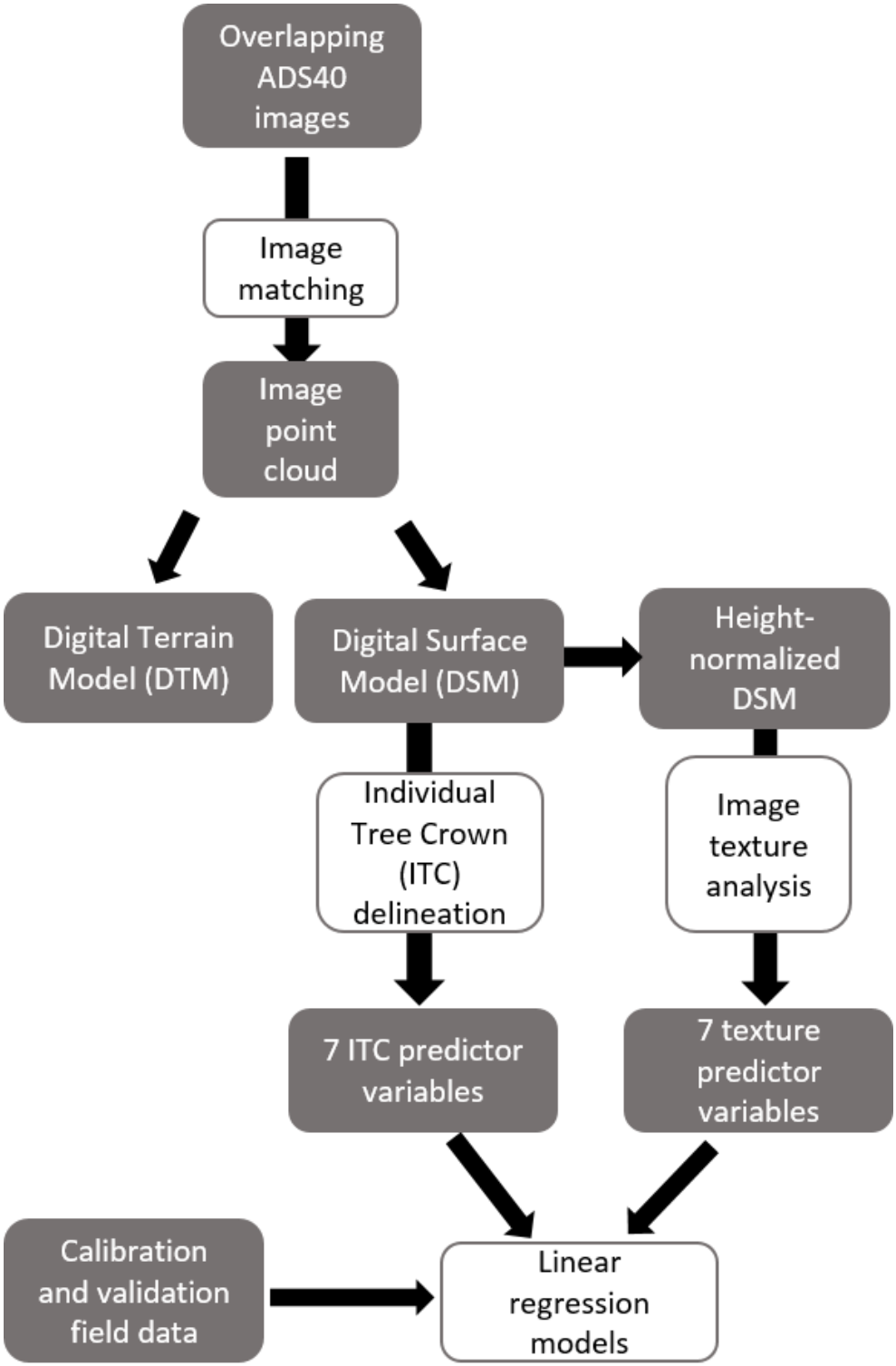

Figure 2. Methodology flow chart

3.3 Field Data

3.3.1. Calibration Field Sampling

Model calibration data was collected between September and November 2015. Forest stands were sampled throughout the Lakehead Forest Management Unit, stratified by the three forest types of interest. Additionally, sample stands met the following criteria: 5 ha to 60 ha in size, at least 40 years in age, moderate to high values of crown closure, reasonably accessible by road, and reasonably regular in shape.

A number of sample plots were delineated within each stand prior to commencing the field work. The following variable sampling intensity approach based on stand size was used: 20 plots in stands between 5 and 10 ha, 25 plots in stands 10 to 40 ha, and 30 plots in stands 40 to 60 ha. The distance between sample points was dependent on the size and shape of the stand. Overall, the average stand size was 10 ha, the average number of plots per stand was 23, overall average plot spacing was 56 m, and average sample intensity was 2.5 plots/ha (Table 2).

Field crews were given a map of these stand and plot locations (Figure 3). At each plot, the crews performed a (BAF 4) prism sweep to generate a tally of all live trees by species. A BAF 4 prism was chosen to allow crews to efficiently cover the entire stand area while collecting a statically acceptable average number of trees (4-16) per plot (Wensel et. al. 1980, Husch et. al. 2003). In order to calculate stand stocking, a minimum of three age and heights of the leading tree species (by basal area) within the stand were measured at representative plots.

Table 2: Calibration sample plot summary statistics by forest unit.

Forest Type	Number of Stands	Average Stand Size (ha)	Average Plot Spacing (m)	Average Plots / Stand	Minimum Plots / Stand	Maximum Plots / Stand	Average Sampling Intensity (plots/ha)
ConMx	31	11	58	23	21	26	2.4
PoDee	32	11	57	23	21	27	2.4
SbLow	32	9	50	23	21	27	2.9

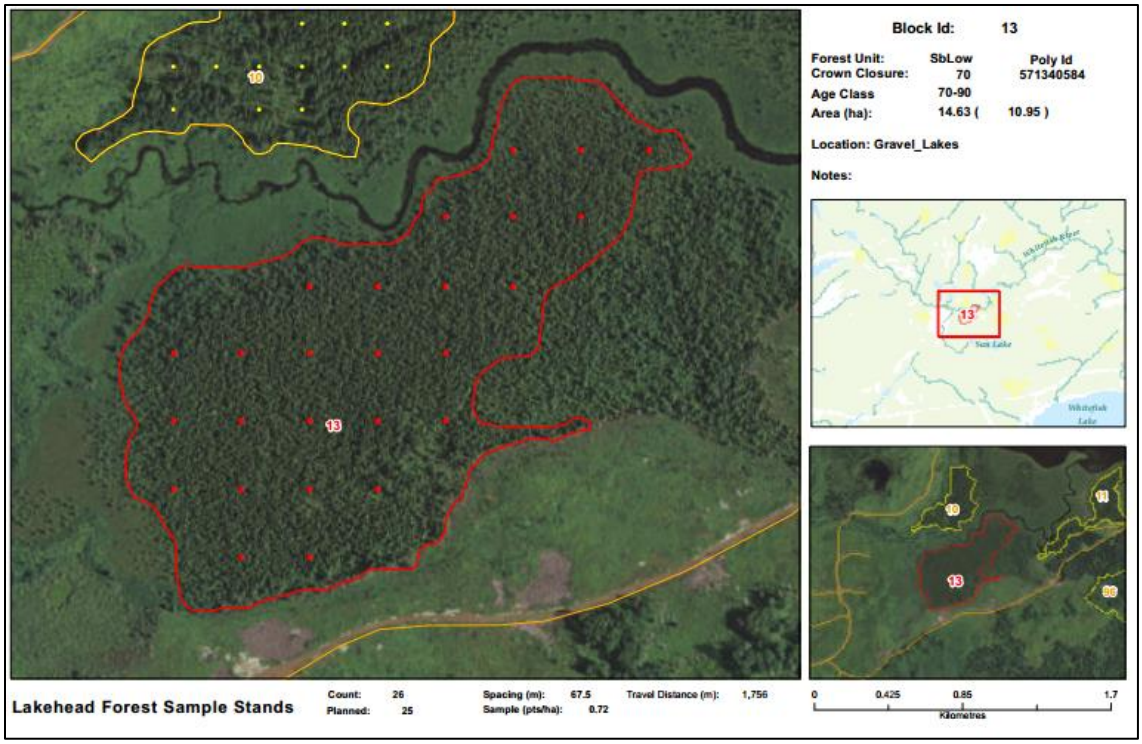

Figure 3. Example of sample plot map supplied to field crews collecting the calibration field data.

3.3.2. Validation Field Sampling

A model validation data set was collected between May and July of 2016. The same methodology for the calibration stand selection described above was used for the selection of the validation sample dataset. To help maintain data consistency, the same lead cruiser from the previous season was used. In total, 96 stands were selected for the validation sample set (Table 3).

Unlike the variable sampling intensity approach based on stand area that was used to select plots for the calibration dataset, in this case sampling intensity was based on stand variability, in order to minimize oversampling and maximize efficiency. An analysis of the calibration data set from 2015 indicated that stand variability was captured with 18 plots or less, more than half (57%) of the time. Stand variability was captured 32% of the time with 12 plots or less. Therefore, crews in 2016 were instructed to measure an initial 12 plots reasonably spread across the stand at marked locations (resulting in approximately 1 plot/ha). Stand variability would be calculated in the field to determine if additional plots were required (with an acceptable error of 20% of average BA (or 4 m^2/ha, whichever was larger) with 80% confidence (i.e. N = (t^2 * variance)/acceptable error)). Crews would continue measuring the remaining marked plots along with additional plots placed at 30 m spacing (based on a logical exit from the stand) until the stand variability had been captured. The total number of measured plots allowed per stand was 30. Overall, the average stand size was 10.5 ha, the average plot spacing was 60 m, and average sample intensity was 2.2 plots/ha (Table 3). As before, at each plot, a prism sweep was

performed to tally count all live in trees by species and three age and height trees were measured within the stand.

Table 3. Validation sample plot summary statistics by forest unit.

Forest Type	Number of Stands	Average Stand Size (ha)	Average Plot Spacing (m)	Average Plots / Stand	Minimum Plots / Stand	Maximum Plots / Stand	Average Sampling Intensity (pts/ha)
ConMx	32	9	56	14	12	26	2.0
PoDee	31	13	70	14	12	24	1.5
SbLow	33	7	47	18	12	34	2.9

3.4 Photo-interpreted estimate of stocking

Experienced photo interpreters used the ADS40 stereo imagery within a softcopy environment (Intergraph's Stereo Analyst for ArcGIS) to manually estimate stand stocking and crown closure for each of the validation stands following standard photo interpretation methods for forest inventory. Four individual photo interpreters completed the exercise, and their results were averaged. To maintain consistency in the interpretation of stand attributes, individuals were given all the other existing FRI values (e.g. height, age, species composition). Basal area is generally not included in Forest Resource Inventory (FRI) databases, and thus was not interpreted here.

3.5 Automated basal area and stocking models

Stand basal area and stand stocking were modelled using linear regression (Figure 2). The regression was conducted in R, using the package "bestglm" with a Gaussian distribution. The AIC (Akaike Information Criterion) and/or the BIC (Bayesian Information Criterion) were used to select the best predictor variables from the complete list (which ranged from seven to fourteen variables, depending on the model).

Two separate groups of predictor variables were developed. The first group of predictors are those relating to individual tree crown (ITC) area and density. The second group of predictors describe the stand as a whole, based on image texture measures (i.e., measures of canopy smoothness). Regression models predicted basal area and stocking individually using a) ITC variables, b) texture variables, and c) a combination of both ITC and texture variables. Separate models were created for each of the three forest types: SbLow, PoDee, and ConMx. Details of each group of predictor variables are provided below.

3.5.1. Individual Tree Crown (ITC) approach to model basal area and stocking

ITCs were automatically delineated from the ADS40 Digital Surface Model (DSM) using the multi-scale tree top detection and watershed image segmentation methods (Hu et al. 2014, Li et al. 2015). Once the ITCs were delineated, seven variables were derived with which to predict stand basal area and stocking (Table 4).

Table 4. List of Individual Tree Crown (ITC) variables included as possible predictors of stand basal area and stocking in regression models.

Name	Meaning
ITC_1	Average ITC area per stand
ITC_2	Standard deviation of the ITC areas per stand
ITC_3	Skewness of the ITC areas per stand
ITC_4	Value of the shape parameter (β) of the Weibull distribution of the ITC areas in the stand
ITC_5	Value of the shape parameter (λ) of Inverse Gaussian distribution of the ITC areas in the stand
ITC_6	Tree density of the stand (total number of ITCs in the stand divided by the stand area)
ITC_7	Canopy cover of the stand (sum of individual tree crown areas divided by the stand area)

3.5.2. Image texture approach to model basal area and stocking

Image texture refers to the local spatial variation of pixel values. When adjacent pixels in an image have similar values, the area appears smooth, whereas an area of pixels with dissimilar values appears rough or coarse. Forest canopy texture, or smoothness, is a visual attribute traditionally used by photo interpreters.

A multitude of approaches may be used to characterize image texture, including first-order statistics (e.g., average, variance, skewness), methods based on geostatistics (e.g., variograms), and those based on co-occurrence matrices (Haralick 1975, Haralick 1979, Carr and De Miranda 1998). We generated image texture measures using both first-order statistics, as well as an approach called MAD (Median Absolute Differences), which is similar to the variogram approach, but was developed specifically for non-stationary and highly variable high spatial resolution topographic data (Trevisani and Rocca 2015). The input layer for deriving all texture measures was the normalized DSM.

Like a variogram, the MAD operator can be thought of as measuring the difference of values between points separated by a particular distance lag (Trevisani and Rocca 2015). We first calculated omnidirectional MAD for distance lags of 1, 2, and 4. Second, a relative roughness index was generated as the ratio of MAD(lag = 1) to MAD(lag = 2). The mean, standard deviation, and skewness of this relative roughness index raster were then derived. Finally, a higher order relative roughness index (the ratio of MAD with lag = 1, and lag = 4) was also derived and its skewness value was the last variable included (Table 5).

Table 5. List of texture variables included as possible predictors of stand basal area and stocking in regression models

Name	Meaning
TEX_1	Mean height of the Digital Surface Model per stand
TEX_2	Standard deviation of the Digital Surface Model per stand
TEX_3	Skewness of the Digital Surface Model per stand
TEX_4	Mean relative roughness index (lag=1, radius = 3, vs. lag=2, radius =3)
TEX_5	Standard deviation of the relative roughness index (lag=1, radius = 3, vs. lag=2, radius =3)
TEX_6	Skewness of the relative roughness index (lag=1, radius = 3, vs. lag=2, radius =3)
TEX_7	Skewness of the relative roughness index (lag=1, radius = 3, vs. lag=4, radius =5)

3.6 Comparison of Methodologies to Field Data

Field measurements of basal area, stocking, and canopy closure were compared to the various models as well as photo-interpretation. Differences in basal area (field vs. models) and stocking (field vs. models and field vs. interpretation) values were tested for statistical significance using paired T-tests for each forest type after assessing the differences for the assumption of normality (Shaprio-Wilk) using SPSS (version 23.0).

4. RESULTS

Stand level basal area and stocking were modelled for each of three forest types, using i) ITC variables, ii) image texture variables, and iii) a combination of the two types of variables. The particular "best" models and variables for regression modelling varied by forest type, and by the attribute being predicted (i.e., basal area or stocking). These results are shown below for each forest type, along with the relationship between the average photo-interpreted canopy closure value and the average tree canopy cover (ITC_7). As all paired differences had normal distributions, (Shaprio-Wilk $p > 0.05$), statistical differences between the field and model and interpreted values were determined for each forest type using paired T-tests.

4.1. Mixed Conifer Stands (ConMx)

The average value of stand basal area estimated in the field for mixed conifer stands was 25.28 m^2/ha, and average stocking estimated in the field for these stands was 0.86.

The best predictions of basal area and stocking in mixed conifer stands were those that used a combination of the texture and the ITC variables (Table 6, Figure 4). In particular, ITC_7, TEX_2, TEX_3, TEX_4, and TEX_7 were key predictor variables. Predictions of basal area resulted in a root mean squared error as low as 6.2 m^2/ha, while the best prediction of stocking had a root mean squared error (RMSE) of 0.25.

Table 6. Comparison of regression models for mixed conifer forests. The best model for each group (that with the lowest RMSE - or the highest Adjusted R^2 if there is little difference in the RMSE) is bolded.

Forest type	Inventory Attribute	Model*	Variables used	Adjusted R^2	RMSE
ConMx	Basal Area	1	ITC_7	0.19	6.75
		2	TEX_1 + TEX_3	0.44	6.55
		3	**ITC_7 + TEX_2 + TEX_3**	**0.51**	**6.49**
	Stocking	1	ITC_3	0.09	0.24
		2	**TEX_2 +TEX_4 + TEX_7**	**0.27**	**0.25**
		3	**TEX_2 +TEX_4 + TEX_7**	**0.27**	**0.25**

*model 1 = ITC variables, model 2 = texture (TEX) variables, model 3 = ITC + texture variables. See tables 4 and 5 for definition of variables.

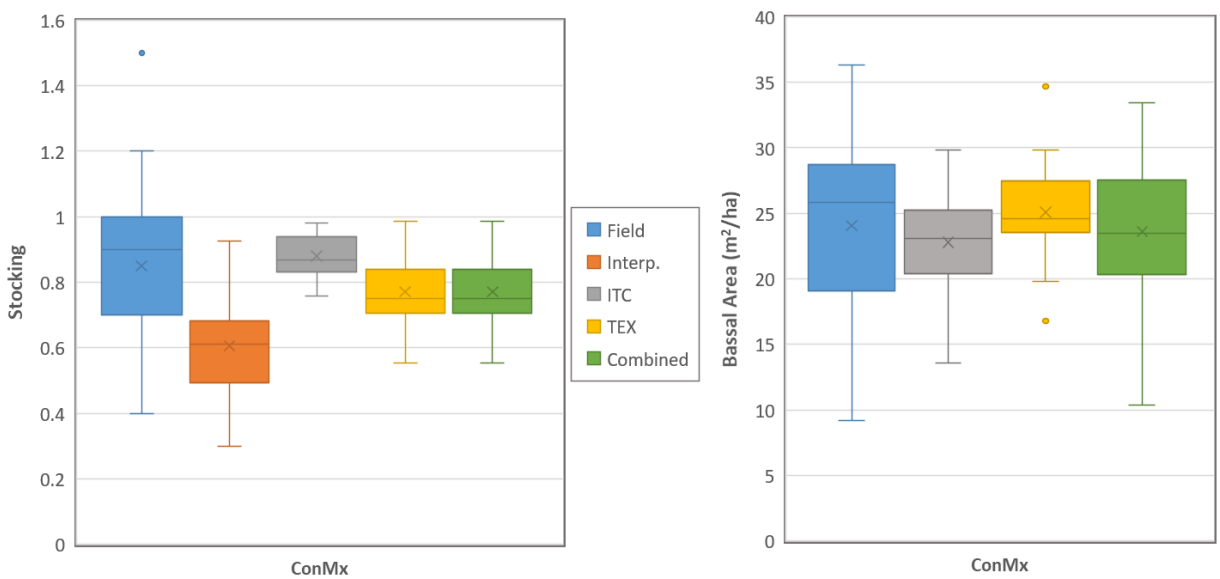

Figure 4. Stand basal area and stocking estimates for different methods in the mixed conifer (ConMx) forest type. The top and bottom of each box represent the 25th (Q1) and 75th (Q3) percentile, respectively, while the centre line represents the median (50th percentile, or Q2) and the 'x' represents the mean. The whiskers extending from each box are Q1 minus 1.5 times the Interquartile Range (the length of the box) and Q3 plus 1.5 times the Interquartile Range. Dots represent outliers.

A key area of interest for the project was to assess whether model results could more consistently and accurately assess stocking compared to photo-interpretation. The best model (model 2 or 3 for ConMx) was able to closely approximate (i.e. within +/- 0.1) field stocking 50% of the time. In comparison, photo-interpretation was able to match field calculated stocking in 37% of the stands and showed a strong bias to under estimating field conditions (Figure 5).

Basal area paired T-test results from the comparison of model estimates to field data illustrated that all models were able to predict stand basal area with no statistical difference ($p > 0.05$) from values

collected in the field. The combined model (Pair 3) had the lowest mean difference (0.5 m^2/ha) and was able to predict field-derived basal area within -2.0 to 2.9 m^2/ha at a 95% confidence interval (Table 7).

Stocking paired T-test results showed that photo interpretation (Pair 1) values were statistically different than values calculated in the field. In comparison, all models were able to predict stocking with no statistical difference ($p > 0.05$) from field data values. The ITC model (Pair 2) had the lowest mean difference (0.03) compared to field data and was able to predict stocking within -0.12 to 0.06 at a 95% confidence interval (Table 8).

The average photo-interpreted canopy closure value was weakly correlated to the canopy closure value derived from the ITC analysis (ITC_7), with a Pearson's correlation coefficient of 0.27 (Figure 6).

Table 7. Basal area paired T-test results in the mixed conifer (ConMx) forest type.

Basal Area		Paired Differences				t	df	Sig. (2-tailed)
		Mean Difference	Std. Error Mean	95% Confidence Interval of the Difference (Lower)	95% Confidence Interval of the Difference (Upper)			
Pair 1	BA (Field) - BA (ITC)	1.277	1.2314	-1.2419	3.7950	1.037	29	0.308
Pair 2	BA (Field) - BA (TEX)	-1.017	1.2021	-3.4753	1.4417	-0.846	29	0.405
Pair 3	BA (Field) - BA (Combined)	0.484	1.2013	-1.9733	2.9405	0.403	29	0.690

Table 8. Stocking paired T-test results in the mixed conifer (ConMx) forest type.

Stocking		Paired Differences				t	df	Sig. (2-tailed)
		Mean Difference	Std. Error Mean	95% Confidence Interval of the Difference (Lower)	95% Confidence Interval of the Difference (Upper)			
Pair 1	STK (Field) - STK (Interp.)	0.243	0.0416	0.1582	0.3285	5.843	29	0.000
Pair 2	STK (Field) - STK (ITC)	-0.030	0.0450	-0.1224	0.0617	-0.674	29	0.505
Pair 3	STK (Field) - STK (TEX)	0.079	0.0435	-0.0104	0.1677	1.805	29	0.081
Pair 4	STK (Field) - STK (Combined)	0.079	0.0435	-0.0104	0.1677	1.805	29	0.081

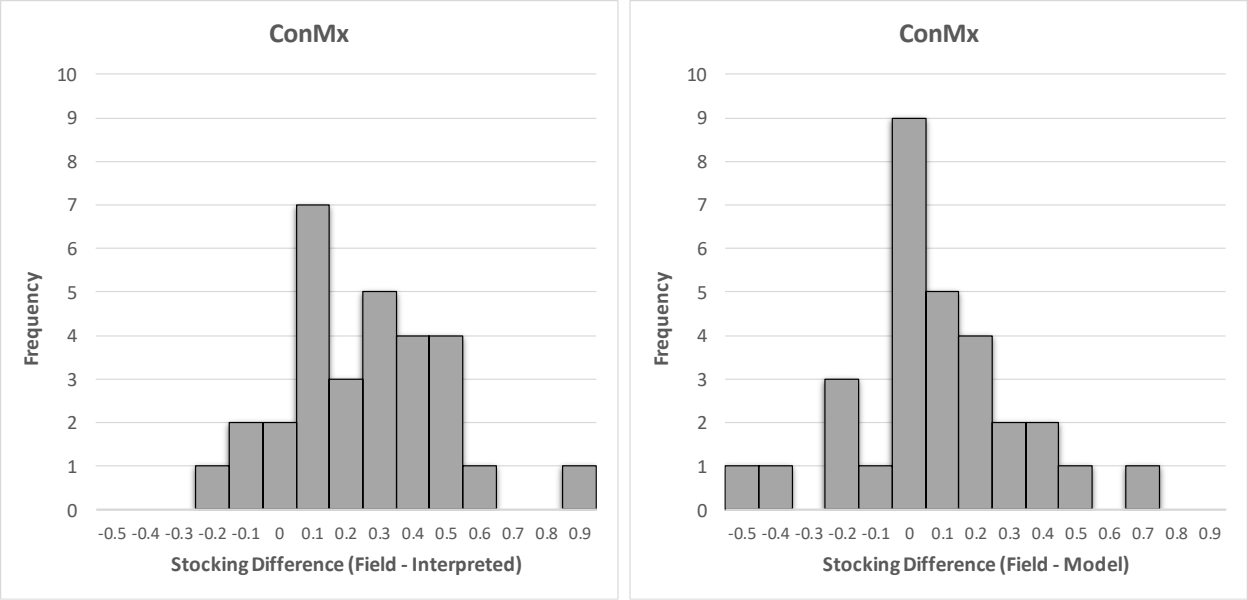

Figure 5. Distribution of difference in stocking values for the mixed conifer forest type: Interpreted vs. field (left) and modelled (model 2) vs. field (right).

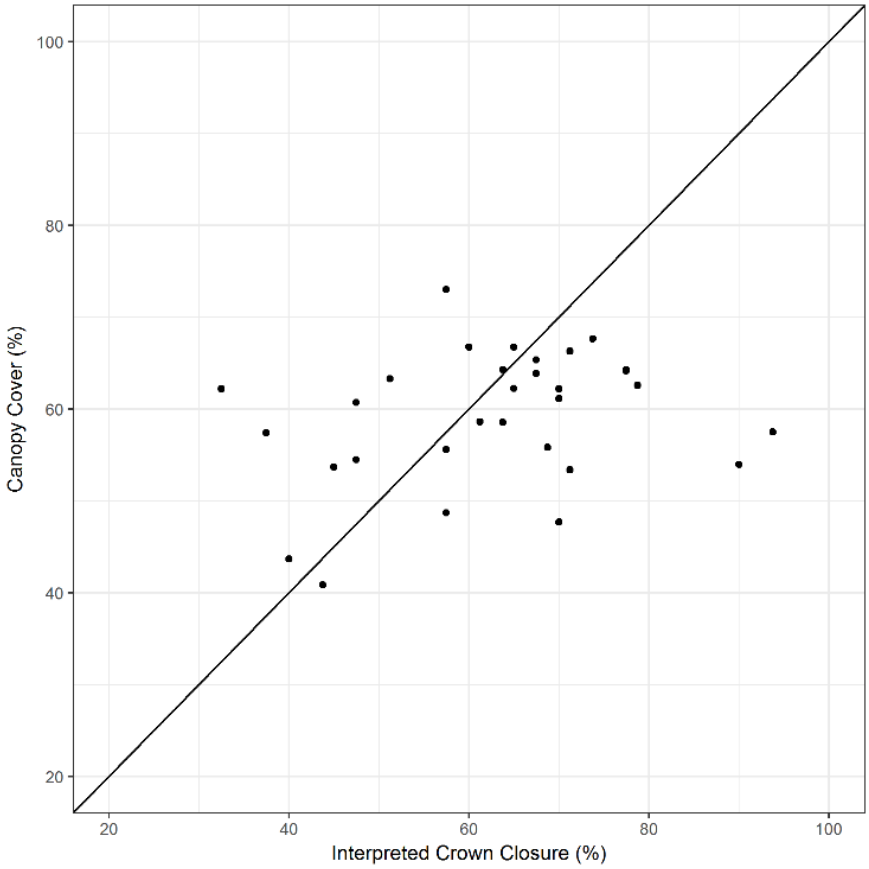

Figure 6. Relationship between standard photo-interpreted crown closure (x-axis) to the estimate of canopy cover derived from the sum of individual tree crown area per stand (ITC_7, on the y-axis), for mixed conifer stands (ConMx).

4.2. Poplar stands (PoDee)

The average value of stand basal area estimated in the field for poplar-dominated stands was 26.10 m^2/ha, and average stocking estimated in the field for these stands was 0.82.

The best predictions of basal area and stocking in poplar stands were those that used the image texture variables, or a combination of the texture and the ITC variables (Table 9, Figure 7). TEX 3 was the key predictor for basal area, and a combination of TEX_3, TEX_5, and TEX_7 enabled the best predictions of stocking. The best model of basal area had a RMSE of ~6.1 m^2/ha, while the best model of stocking resulted in a RMSE of 0.22.

Table 9. Comparison of regression models for poplar forests. The best model for each group (that with the lowest RMSE - or the highest Adjusted R2 if there is little difference in the RMSE) is bolded.

Forest type	Inventory Attribute	Model*	Variables used	Adjusted R^2	RMSE
PoDee	Basal Area	1	ITC_2	0.12	5.94
		2	**TEX_3**	**0.46**	**6.45**
		3	**TEX_3**	**0.46**	**6.45**
	Stocking	1	ITC_1	0.19	0.19
		2	**TEX_3 + TEX_5 + TEX_7**	**0.47**	**0.24**
		3	**TEX_3 + TEX_5 + TEX_7**	**0.47**	**0.24**

*model 1 = ITC variables, model 2 = texture (TEX) variables, model 3 = ITC + texture variables. See tables 4 and 5 for definition of variables.

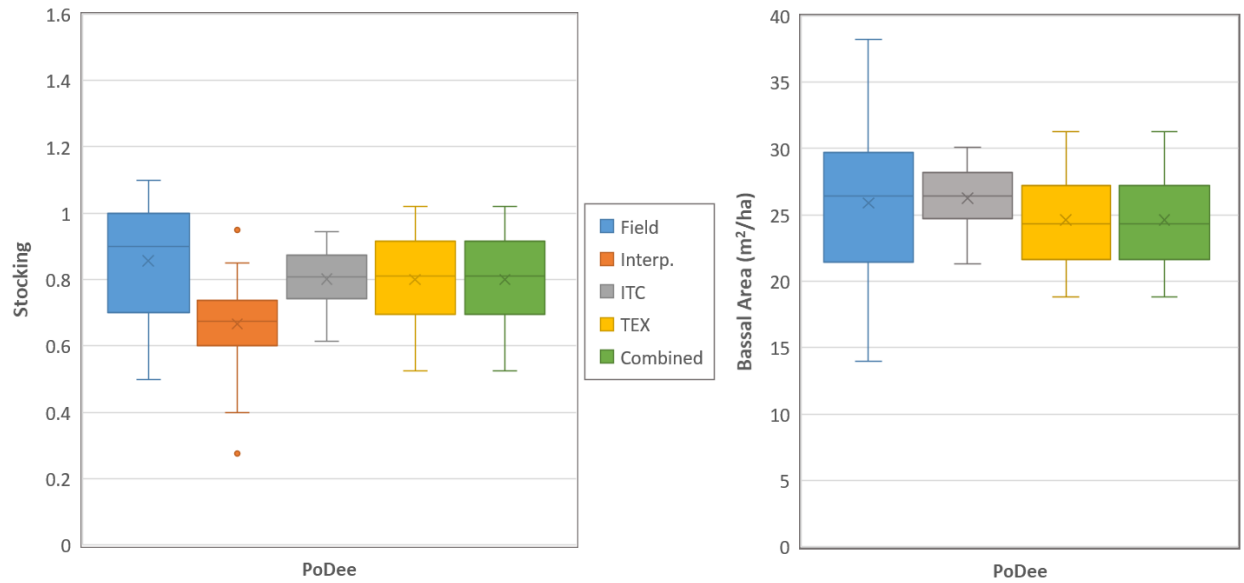

Figure 7. Stand basal area and stocking estimates for different methods in the poplar (PoDee) forest type. The top and bottom of each box represent the 25th (Q1) and 75th (Q3) percentile, respectively, while the centre line represents the median (50th percentile, or Q2) and the 'x' represents the mean. The whiskers extending from each box are Q1 minus 1.5 times the Interquartile Range (the length of the box) and Q3 plus 1.5 times the Interquartile Range. Dots represent outliers.

The best model (model 1) results were able to closely approximate (i.e. within +/- 0.1) field stocking 50% of the time. In comparison, photo-interpretation was able to match field calculated stocking in 30% of the stands and showed a bias towards underestimating field values (Figure 8).

Basal area paired T-test results from the comparison of model estimates to field data illustrated that all models were able to predict stand basal area with no statistical difference ($p > 0.05$) from values collected in the field. The ITC model (Pair 1) had the lowest mean difference (0.3 m^2/ha) and was able to predict field-derived basal area within -2.6 to 1.9 m^2/ha at a 95% confidence interval (Table 10).

Stocking paired T-test results showed that photo interpretation (Pair 1) values were statistically different than values calculated in the field. In comparison, all models were able to predict stocking with no statistical difference ($p > 0.05$) from field data values. The ITC model (Pair 2) had the lowest mean difference compared to field data (0.06) and was able to predict stocking within -0.01 to 0.12 at a 95% confidence interval (Table 11).

The average photo-interpreted canopy closure value was weakly correlated to the canopy closure value derived from the ITC analysis (ITC_7), with a Pearson's correlation coefficient of 0.36 (Figure 9).

Table 10. Basal area paired T-test results in the poplar (PoDee) forest type.

Basal Area		Paired Differences				t	df	Sig. (2-tailed)
		Mean Difference	Std. Error Mean	95% Confidence Interval of the Difference (Lower)	95% Confidence Interval of the Difference (Upper)			
Pair 1	BA (Field) - BA (ITC)	-0.349	1.1005	-2.5995	1.9020	-0.317	29	0.754
Pair 2	BA (Field) - BA (TEX)	1.279	1.1775	-1.1289	3.6875	1.086	29	0.286
Pair 3	BA (Field) - BA (Combined)	1.279	1.1775	-1.1289	3.6875	1.086	29	0.286

Table 11. Stocking paired T-test results in the poplar (PoDee) forest type.

Stocking		Paired Differences				t	df	Sig. (2-tailed)
		Mean Difference	Std. Error Mean	95% Confidence Interval of the Difference (Lower)	95% Confidence Interval of the Difference (Upper)			
Pair 1	STK (Field) - STK (Interp.)	0.191	0.0332	0.1230	0.2587	5.751	29	0.000
Pair 2	STK (Field) - STK (ITC)	0.055	0.0332	-0.0127	0.1232	1.663	29	0.107
Pair 3	STK (Field) - STK (TEX)	0.056	0.0433	-0.0325	0.1444	1.294	29	0.206
Pair 4	STK (Field) - STK (Combined)	0.056	0.0433	-0.0325	0.1444	1.294	29	0.206

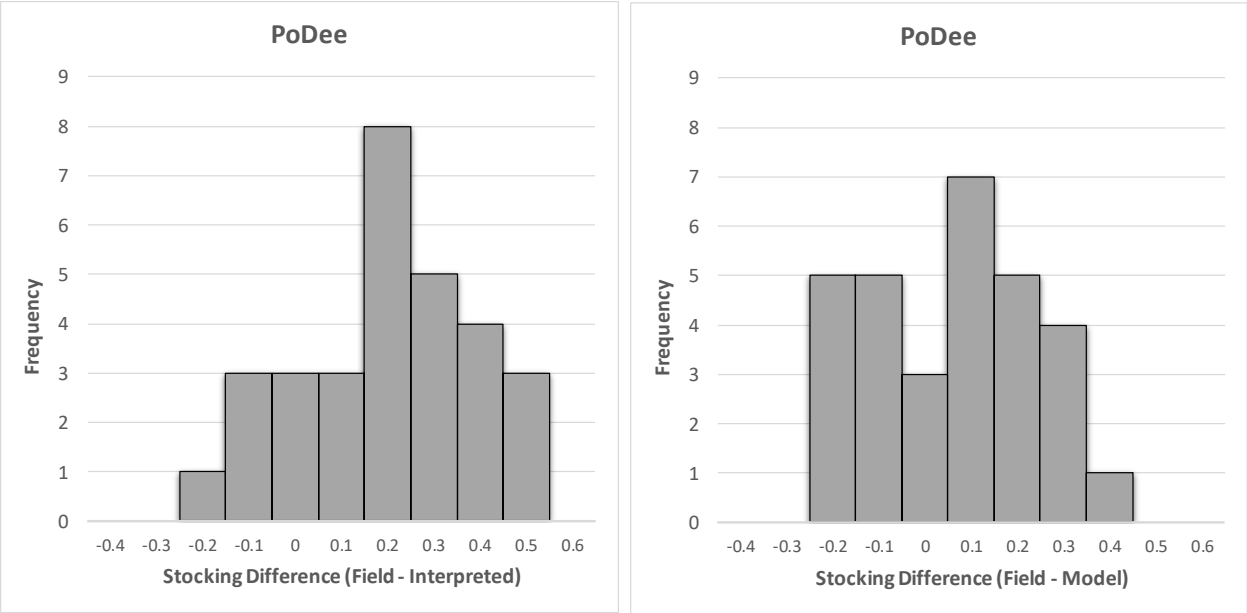

Figure 8. Distribution of difference in stocking values for the poplar forest type: Interpreted vs. field (left) and modelled (model 1) vs. field (right).

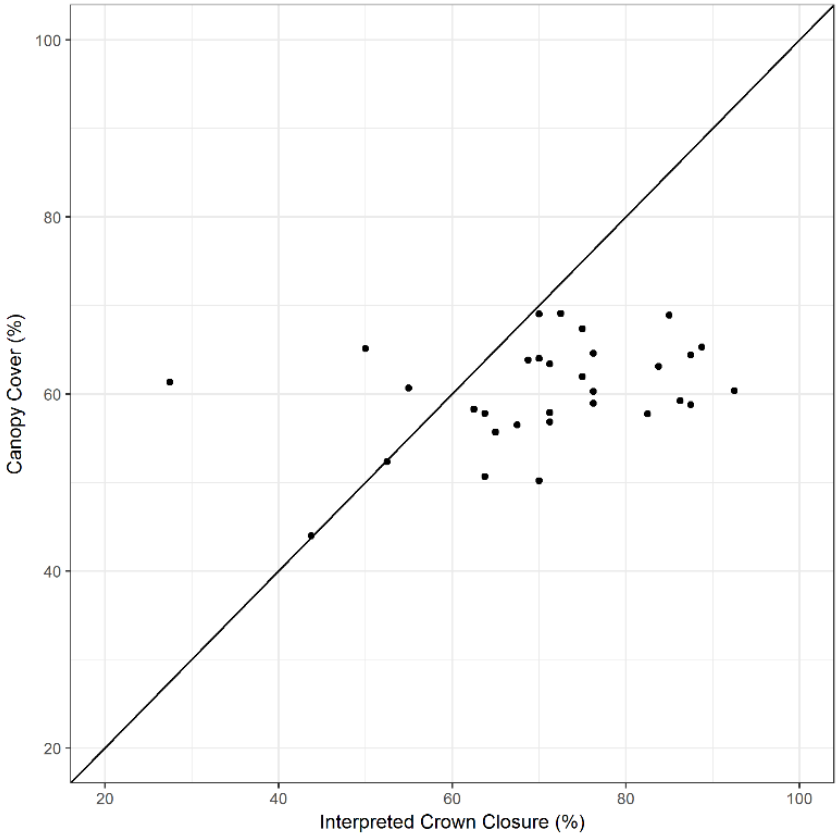

Figure 9. Relationship between standard photo-interpreted crown closure (x-axis) to the estimate of canopy cover derived from the sum of individual tree crown area per stand (ITC_7, on the y-axis), for poplar forests (PoDee).

4.3. Lowland black spruce stands (SbLow)

The average value of stand basal area estimated in the field for black spruce-dominated stands was 27.84 m^2/ha, and average stocking estimated in the field for these stands was 0.85.

The best predictions of basal area and stocking in black spruce stands were those that used the image texture variables (Table 12, Figure 10). TEX 2 and TEX_3 (standard deviation and skewness of the Digital Surface Model, respectively) were the two key predictor variables for both basal area and stocking. Using these two variables, predictions of basal area resulted in a RMSE of 5.8 m^2/ha, while the best prediction of stocking had a RMSE of 0.22.

The average photo-interpreted canopy closure value was weakly correlated to the canopy closure value derived from the ITC analysis (ITC_7), with a Pearson's correlation coefficient of 0.39 (Figure 12).

Table 12. Comparison of regression models for lowland spruce forests. The best model for each group (that with the lowest RMSE - or the highest Adjusted R^2 if there is little difference in the RMSE) is bolded.

Forest type	Inventory Attribute	Model*	Variables used	Adjusted R^2	RMSE
SbLow	Basal Area	1	ITC_1 + ITC_5 + ITC_7	0.30	7.50
		2	**TEX_2 + TEX_3**	**0.51**	**7.20**
		3	ITC_5 + TEX_3 + TEX_5	0.58	8.57
	Stocking	1	ITC_1 + ITC_5 + ITC_6	0.25	0.25
		2	**TEX_2 + TEX_3**	**0.37**	**0.23**
		3	ITC_1 + TEX_5 + TEX_7	0.59	0.28

*model 1 = ITC variables, model 2 = texture (TEX) variables, model 3 = ITC + texture variables. See tables 4 and 5 for definition of variables.

The best model (model 2 for SbLow) results were able to closely approximate (i.e. within +/- 0.1) field stocking 55% of the time. In comparison, photo-interpretation was able to match field calculated stocking in 21% of the stands and showed a strong bias to underestimate field values (Figure 11).

Basal area paired T-test results from the comparison of model estimates to field data illustrated that the ITC and texture models were able to predict stand basal area with no statistical difference ($p > 0.05$) from values collected in the field. The ITC model (Pair 1) had the lowest mean difference (1.6 m^2/ha) and was able to predict field-derived basal area within -4.5 to 1.3 m^2/ha at a 95% confidence interval (Table 13).

Stocking paired T-test results showed that photo interpretation (Pair 1) values were statistically different than values calculated in the field. ITC and the combined models were able to predict stocking with no statistical difference ($p > 0.05$) from field data values. The ITC model (Pair 2) had the lowest mean difference compared to field data (0.05) and was able to predict stocking within -0.14 to 0.04 at a 95% confidence interval (Table 14).

Table 13. Basal area paired T-test results in the lowland spruce (SbLow) forest type.

Basal Area		Paired Differences				t	df	Sig. (2-tailed)
		Mean Difference	Std. Error Mean	95% Confidence Interval of the Difference (Lower)	95% Confidence Interval of the Difference (Upper)			
Pair 1	BA (Field) - BA (ITC)	-1.574	1.4233	-4.4812	1.3323	-1.106	30	0.277
Pair 2	BA (Field) - BA (TEX)	1.837	1.3009	-0.8200	4.4934	1.412	30	0.168
Pair 3	BA (Field) - BA (Combined)	-3.621	1.3921	-6.4638	-0.7779	-2.601	30	0.014

Table 14. Stocking paired T-test results in the lowland spruce (SbLow) forest type.

Stocking		Paired Differences				t	df	Sig. (2-tailed)
		Mean Difference	Std. Error Mean	95% Confidence Interval of the Difference (Lower)	95% Confidence Interval of the Difference (Upper)			
Pair 1	STK (Field) - STK (Interp.)	0.293	0.0394	0.2122	0.3733	7.426	30	0.000
Pair 2	STK (Field) - STK (ITC)	-0.049	0.0440	-0.1387	0.0411	-1.109	30	0.276
Pair 3	STK (Field) - STK (TEX)	0.083	0.0391	0.0035	0.1633	2.132	30	0.041
Pair 4	STK (Field) - STK (Combined)	-0.061	0.0479	-0.1592	0.0362	-1.285	30	0.209

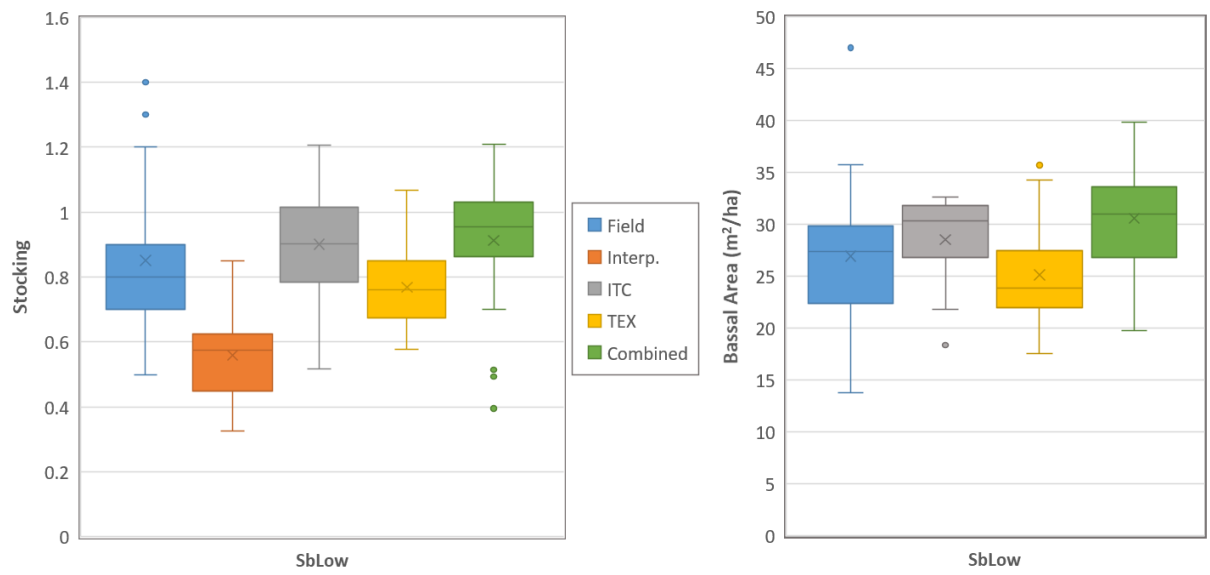

Figure 10. Stand basal area and stocking estimates for different methods in the black spruce (SbLow) forest type. The top and bottom of each box represent the 25th (Q1) and 75th (Q3) percentile, respectively, while the centre line represents the median (50th percentile, or Q2) and the 'x' represents the mean. The whiskers extending from each box are Q1 minus 1.5 times the Interquartile Range (the length of the box) and Q3 plus 1.5 times the Interquartile Range. Dots represent outliers.

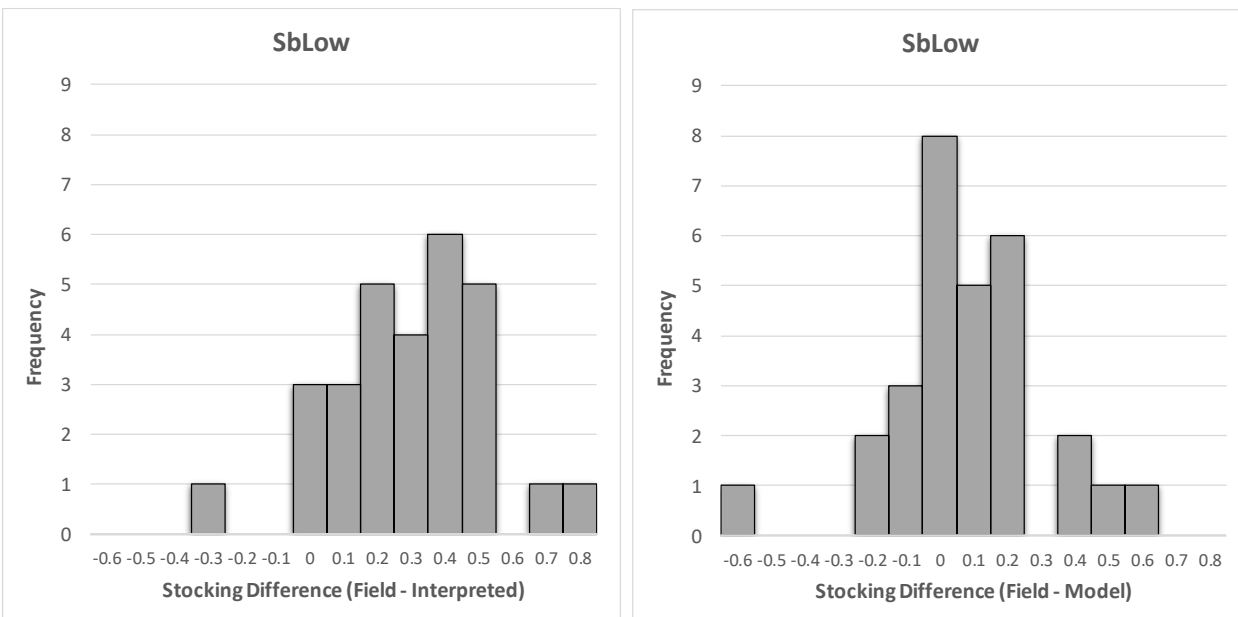

Figure 11. Distribution of difference in stocking values for the lowland black spruce forest type: Interpreted vs. field (left) and modelled (model 2) vs. field (right).

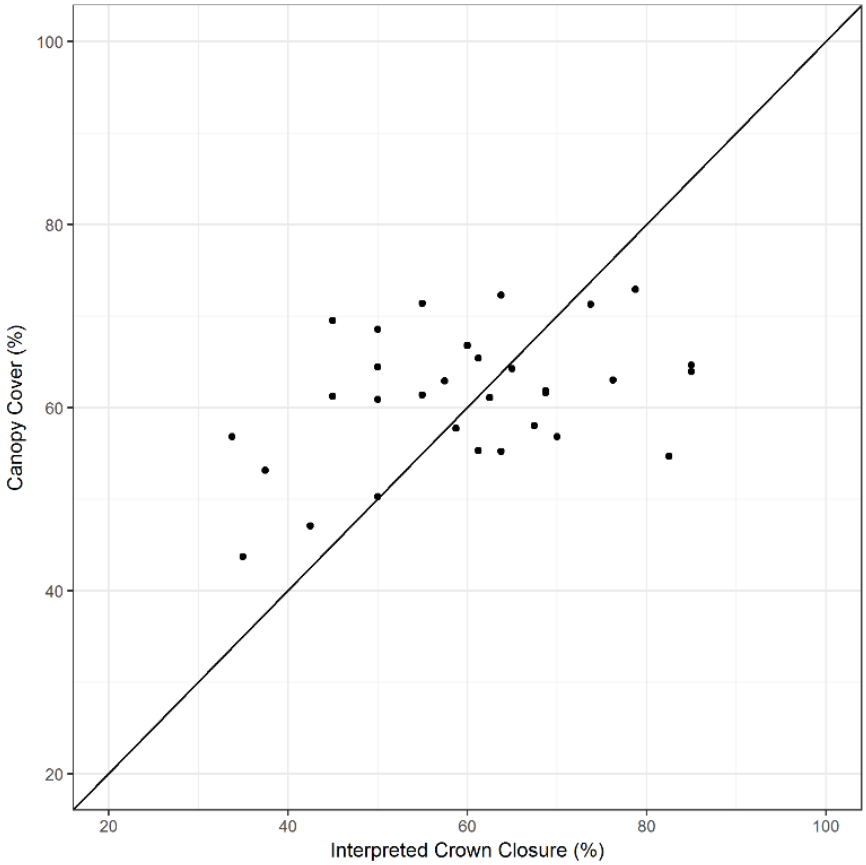

Figure 12. Relationship between standard photo-interpreted crown closure (x-axis) to the estimate of canopy cover derived from the sum of individual tree crown area per stand (ITC_7, on the y-axis), for black-spruce dominated stands (SbLow).

5 DISCUSSION

5.1 Stocking

Across all three forest types, models were able to produce stocking values that were not statistically different than those derived from field collected data. In comparison, photo-interpretation values were statistically different than those of field data in all forest types.

Field and modelled estimates of stand-level stocking were consistently higher than photo-interpreted estimates. This difference is due to the custom of photo-interpreters rarely calling values of stocking greater than 1.0. Discussions with professional photo-interpreters confirmed a reluctance to assign stocking values greater than 1.0 unless field calibration data existed for the stand. To illustrate this point, three FRI datasets for regional FMUs (Dog-River Matawin, Crossroute, and White River Forests) were analyzed with respect to stocking values in the completed FRI and those from their respective FRI calibration lines. Field calibration data for these FMUs reported 8% to 19% of stands had a stocking value greater than 1.0. In contrast, each of these FMUs have less than 1% (0.5 - 0.8%) of the completed FRI forested polygons with a stocking value greater than 1.0 (Table 15). While FRI calibration lines may not be placed in a representative distribution of overall forest-wide stocking conditions, it is clear there

is a discrepancy between true field conditions and delivered FRI values with respect to stocking. For this study in the Lakehead FMU, only one of the four interpreters called stocking values greater than 1.0 for three of the 98 forest stands interpreted; however, 17% of the stands had stocking values greater than 1.0 according to field data. This apparent systematic bias in photo-interpreting stocking highlights one area where automated methods may be able to produce more accurate results.

Table 15. Comparison of FRI calibration line to forest inventory polygons with respect to stocking values.

Forest	Calibration Lines with Stocking > 1.0	FRI Forested* Polygons with Stocking > 1.0
Dog-River Matawin	19% (404/2139 lines)	0.8% (401/51244 polygons)
Crossroute	8% (281/3349 lines)	0.8% (832/100039 polygons)
White River	17% (219/1302 lines)	0.5% (227/44321 polygons)

* Polytype = 'FOR'

Despite relatively poor model performance with respect to R^2 and RMSE values, models still performed with no statistical difference to field data and out performed traditional photo-interpretation with respect to approximating field-derived stocking values. While stocking remains a component of the Ontario FRI system and has a clear calculation while working with field data, it is arguably the most challenging of attributes to discern from remotely sensed imagery. To this end, semi-automated methods to calculate basal area or volume – neither of which are currently directly estimated from photo-interpretation – from image point-clouds may prove to be more accurate and of greater utility to forest managers.

5.2 Basal area

The models generally performed best (highest R^2, lowest RMSE) in the black spruce stands. Across all three forest types, the same one or two image texture variables were key predictors: standard deviation and skewness of the DSM (TEX_2 and TEX_3). For the mixed conifer forest type (ConMx), the ITC canopy cover (ITC_7) was also an important predictor.

The basal area models were able to accurately approximate field data, showing no statistical difference between model values and those from the field. While mean differences between the best models and field data were relatively low (0.3 – 1.6 m^2/ha), 95% confidence values exceeded 4m^2/ha. Possible reasons for this are discussed below and include imagery resolution, lack of an accurate DTM and discrepancies caused by the time-lag of photo acquisition and field data collection. Despite relatively poor performance of the basal area models in this study, the authors believe that the potential to include a model-derived estimate of basal area or volume within the forest inventory is a valuable line of continued investigation. Given that stocking requires several consecutive estimations (i.e. age, height, basal area), and the possible introduction of errors within each, the potential to add a direct basal area estimate to the FRI from imagery characteristics should continue to be pursued.

5.3 Crown Closure

There was a weak positive, linear relationship between photo-interpreted crown closure and the ITC canopy cover (ITC_7). The relationship was strongest for the lowland black spruce stands (SbLow).

The poor predictive capacity of the canopy closure model is likely related to the lack of strength in all ITC variables (i.e. texture models were shown to be better predictors of stocking and basal area). It may be that ITC techniques are of limited effectiveness in this study due to imagery resolution. Also, model canopy closure predictions were only assessed against photo-interpretation calls and were not evaluated against the larger field dataset.

5.4. Limitations and Future Work

Stocking and basal area models created from the image point clouds had limited ability to predict field values; though in the case of stocking, these models were able to perform as well or better than traditional photo-interpretation. Some of the possible reasons for lack of very strong model performance include the time discrepancy between the acquisition of the aerial imagery and the collection of field data, limited image resolution, lack of an accurate DTM, a limited amount of calibration data, and the use of predetermined stand boundaries.

Field data was collected in 2015/16, while the ADS40 imagery was acquired in 2008. Therefore, photo-interpretation and image models were both comparing their estimates against conditions that were captured 7-8 years previous. Changes in canopy closure, basal area and stocking could have occurred over this period as a result of natural stand growth, or small disturbance events (insect, disease, storm events, etc.) that have altered the current stand conditions to have characteristics different than those represented in the imagery.

The resolution of the ADS40 resolution colour imagery (40 cm) may have also limited model performance. Dense point clouds (7-9 points/m^2) produced from higher resolution imagery (e.g. captured by drones) have been shown to produce strong results in predicting forest volume attributes (Goodbody et al. 2017). Point clouds from the imagery used in this study may have lacked the density to allow for accurate delineation of individual crowns, and may be one reason why texture variables performed better those of ITC. The ADS40 point cloud, like all image-based clouds, was also limited in its ability to produce an accurate DTM. A more precise canopy height model would have been produced if the image point cloud had been used in combination with a more accurate DTM (e.g. produced from a LiDAR sensor), and this may have improved model predictive strength.

Models were developed on field data collected from approximately 30 stands per forest cover type. While efforts were made to facilitate field collection (i.e. small stand sizes, ease of access, etc.), the collection of field data represented a significant portion of the study budget. While not necessarily representative of the entire stand condition, use of Ontario FRI calibration plots could be investigated for their utility in creating calibration/verification data for stand point-cloud models. These investigations could include the building and testing of models that use the FRI plots against the characteristics of the entire stand, or the extracting of the point-cloud just in the near proximity of the FRI plots.

The models and their predictive power may be also affected by the FRI stand delineation and species composition estimates. The original species composition and forest unit assignments were kept constant for all stands throughout the analysis. Species composition as determined by field data was not used to change the forest unit call of stands during the photo-interpretation of stocking or in model creation/validation steps in our study. It is possible that a discrepancy exists between the forest unit a stand was given by the original photo-interpreters and what field data would have now determined (e.g. either due to errors in the original estimation of species composition, or due to natural forest succession that occurred over the intervening years between the creation of the FRI and now). Therefore, it is possible that both calibration and validation models may been applied against stands that were in fact in another forest unit in some instances.

The generation of point clouds and surface models within this study was a computationally intensive exercise. If point clouds and surface models were created as part of the larger FRI production process (i.e. either supplied by the vendor or produced by the FRI branch), this would alleviate the time and cost associated with this element of production. It is assumed that this data could then also be leveraged in other forest management activities.

6 CONCLUSION

The goal of this study was to investigate methods for automatically and objectively estimating stand-level stocking, basal area, and canopy closure values for three cover types using characteristics of the ADS40 imagery point-clouds. Specifically, linear regression models were created using individual tree crown area and image texture measures.

Stocking models were able to perform better than traditional photo-interpretation with respect to reasonably approximating field-derived stocking values. Basal area models in all cover types were not able to closely match values calculated from field data in absolute terms, but all cover types had at least one model that was able to predict values that were not statistically difference than field data. Texture variables were generally better than ITC variables in predicting both stocking and basal area in each of the cover types, and highlights the potential for these surface attributes to be used in conditions where ITC methods are not able to produce adequate results. The lack of stronger performance from the ITC models may be a result of image resolution, as studies with high resolution point-clouds have been shown to be successful in predicting forest stand attributes.

The study results provide additional evidence that automated classification of digital remotely sensed imagery offers the potential for greater transparency, consistency, and repeatability, in the creation of forest inventories.

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