Identifying leading species using tree crown metrics derived from very high spatial resolution imagery in a boreal forest environment

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Abstract. Utilizing the spatial information inherent in panchromatic very high spatial resolution (VHSR) imagery, we explored the use of tree crown metrics for identifying leading species over four study sites in the Yukon Territory, Canada. Image segmentation was used to delineate homogeneous forest stands, followed by a tree crown delineation algorithm that identified individual tree crowns within each stand. Leading species in the study area included white spruce, black spruce, lodgepole pine, and trembling aspen. Nonparametric multivariate statistical tests indicated that some tree crown metrics generalized at the stand level have significant utility for discriminating leading species. Based on this result, a classification tree was generated using the crown metrics and independent calibration and validation datasets. The classification tree accurately identified leading species in 72.5% of the stands used for validation ($n = 212$), with the accuracy for individual species ranging from 43.9% to 100.0%. Most errors resulted from confusion between white spruce and the three other, less common, leading species. This study demonstrates the capacity of the spatial information content of panchromatic VHSR imagery to generate a series of crown metrics for discriminating among four common tree species of the Yukon Territory, a location with spatially and temporally limited forest monitoring practices.

Résumé. Au moyen d'images satellitaires à très haute résolution spatiale, nous avons étudié le potentiel d'une série de statistiques calculées à partir de couronnes d'arbres pour identifier l'espèce majoritaire de peuplements forestiers. Les quatre sites d'étude étaient répartis dans le centre et le sud du Territoire du Yukon (Canada). Une segmentation des images a permis la délinéation homogène de peuplements forestiers et fut suivie d'une délinéation des couronnes d'arbres à l'intérieur de chaque peuplement. Les espèces d'arbres présentes sur les sites d'étude étaient l'épinette blanche, l'épinette noire, le pin tordu et le peuplier faux-tremble. Des tests multivariés non paramétriques ont mis en évidence la capacité de discriminer de manière significative les espèces d'arbres à partir de certaines statistiques. Celles-ci ont été calculées à partir des couronnes d'arbres et généralisées à l'échelle du peuplement. En s'appuyant sur ces statistiques, nous avons établi des arbres de classification sur la base de jeux de données d'apprentissage et de validation indépendants. Les arbres de classification ont fourni un taux de classification moyen de 72,5 % avec des taux de classification par espèce variant de 43,9 % à 100,0 %. La plupart des erreurs ont résulté de la confusion entre les peuplements à épinette blanche avec les trois autres espèces, moins nombreuses sur les sites d'étude. Cette étude a montré la capacité d'images panchromatiques à très haute résolution spatiale de générer une série de statistiques à l'échelle de la couronne d'arbre pour la discrimination de quatre espèces forestières dans le territoire du Yukon; un territoire dont les ressources forestières sont historiquement et spatialement peu exploitées.
[Traduit par la Rédaction]

Introduction

Knowledge of the leading species at a forest stand level is often a required inventory attribute and is necessary for estimating stand volume and biomass (Boudewyn et al., 2007; Falkowski et al., 2009). Leading species is commonly defined as the species with the highest percent composition (i.e., by basal area) in a stand. Interpretation of aerial photography is the most common method used to identify leading species (Hall, 2003; Thompson et al., 2007). Automated and semi-automated image classification methods such as maximum likelihood (Rogan and Yool, 2001) and *k*-nearest neighbour (Franco-Lopez et al., 2001; Finley and McRoberts, 2008) have been applied to multispectral remotely sensed data to identify leading species. Over large forest areas, the costs of acquiring and manually interpreting aerial photography can be prohibitive. Moreover, photo-interpretation can be time consuming, labour intensive (Green, 2000), and vulnerable to inconsistency (Morgan et al., 2010).

Canada implements a multiphase, plot-based National Forest Inventory (NFI) for assessment and monitoring of forests. Approximately 1% of Canada's landmass is sampled in the NFI first phase using a systematic network of over 19 000 photoplots located on a 20 km × 20 km grid, with

each plot being 2 km × 2 km in size. Over the plot locations, photo-interpreters manually delineate the stands from aerial photography and characterize the required forest attributes according to established and published NFI standards (Gillis, 2001). In northern regions of Canada, logistical and financial constraints often prevent the acquisition of aerial photography, and the NFI has used a Landsat-based land cover product, namely Earth Observation for Sustainable Development of Forests (EOSD) (Wulder et al., 2008a), to provide a limited number of the required forest inventory attributes (i.e., cover type, density, volume, and biomass) (Gillis et al., 2005). More recently, very high spatial resolution (VHSR; <1 m) remotely sensed satellite imagery has been acquired to fulfill the information needs of the NFI, particularly in northern regions (Falkowski et al., 2009). VHSR images provide spatial and spectral information comparable to that from aerial photography and enable, with limitations, the estimation of forest inventory attributes (Wulder et al., 2008b). Consequently, and as suggested by Falkowski et al. (2009), possible semi-automatic image processing avenues employing VHSR images could be defined to delineate forest stands and determine their forest inventory attributes.

Several studies demonstrated the capacity of VHSR optical images to provide relevant information for tree species identification. Sugumaran et al. (2003) used IKONOS imagery and aerial photography to map trees in an urban area with maximum likelihood and classification tree methods. A spatial resolution of 1 m provided improved classification accuracy compared with 0.25 m and 4 m spatial resolutions. Zhang et al. (2008) combined airborne VHSR optical and light detection and ranging (lidar) imagery to map tree species over a mixed conifer–hardwood forest in Ontario, Canada, at the tree level. Chubey et al. (2006) employed panchromatic and multispectral IKONOS imagery and a classification tree to map pine, spruce, and aspen stands with an overall accuracy of 85% in Alberta, Canada. The classification was implemented using commercial software to segment the IKONOS imagery into objects representing forest stands (Baatz and Schäpe, 2000; Definiens Imaging, 2004). The result of this study demonstrated the utility of using segment-level metrics derived from multispectral high spatial resolution imagery (4 m pixels) for species classification; however, acquiring multispectral VHSR imagery over large spatial extents can be financially prohibitive. By comparison, VHSR panchromatic imagery is less costly, especially when purchased from an archive, and contains information that can be used for tree species identification (Kim and Hong, 2008; Wulder et al., 2008b).

Oliver and Larson (1996) posit that crown shapes are predictable, as each species tends to grow in an expected manner in given environmental conditions. Based on such understanding and practical experience, Sayn-Wittgenstein (1978) developed an airphoto interpretation key for the recognition of the most important Canadian tree species. Interpretation keys were primarily based on tree branch morphology

(e.g., radiating, tapering branches), crown shape characteristics (e.g., perimeter regularity, area), and seasonal variations (via foliage characteristics). Murtha and Sharma (2005) determined five criteria to identify tree species from photo-interpretation: crown boundary (outline), crown topography, crown tone and hue, branching habit, and foliage density.

The spatial resolution of panchromatic VHSR images does not provide sufficient detail to discern branch structure, crown topography, or foliage density; however, crown shape metrics can be derived from individual tree crowns. Kim and Hong (2008) have shown the potential of crown shape metrics and image texture indices based on QuickBird imagery for species identification. Gougeon (1995) developed an individual tree crown (ITC) delineation method based on a valley following logic and approach. The effectiveness of this ITC algorithm has been proven over a range of image types and forest conditions (Leckie et al., 2003; Gougeon and Leckie, 2006); however, at northern latitudes, tree isolation and delineation can be confounded by the complex interactions between sun–sensor–surface geometry and forest structural characteristics (Wulder et al., 2008c). Mora et al. (2010) demonstrated the application of a within-stand, object-based approach for mean stand height estimation.

The main objective of this study was to test the capacity of panchromatic VHSR imagery for identifying stand-level leading species over four study sites in the Yukon Territory, Canada. Given this objective, we first defined a semi-automatic method to delineate forest stands from panchromatic VHSR imagery and then manually interpreted a series of attributes within these stands for calibration and validation purposes. Second, we applied an algorithm that automatically delineated individual tree crown objects, and from these we calculated a number of tree crown metrics. Third, we assessed whether statistics on tree crown metrics, when summarized at the stand level, were useful for discriminating leading species. Lastly, we used the crown metrics as inputs to a classification tree to estimate leading species for the stands in our study sites.

Material and methods

Study area

The study area is composed of four sites located in the southern and central Yukon Territory, Canada (**Figure 1**). The four sites have areas ranging from 625 to 2400 ha and were selected based on road access, the availability of cloud-free QuickBird imagery, and the range of species and structural conditions represented. All of the study sites were located within the Boreal Cordillera ecozone (Ecological Stratification Working Group, 1995), which is characterized by a cold climate with subhumid to semi-arid moisture conditions. Mean annual temperatures range from 1.0 to 5.5 °C, with mean annual precipitation ranging from less than 300 mm in valleys shadowed by coastal mountain ranges to more than 1500 mm at higher elevations. The topography
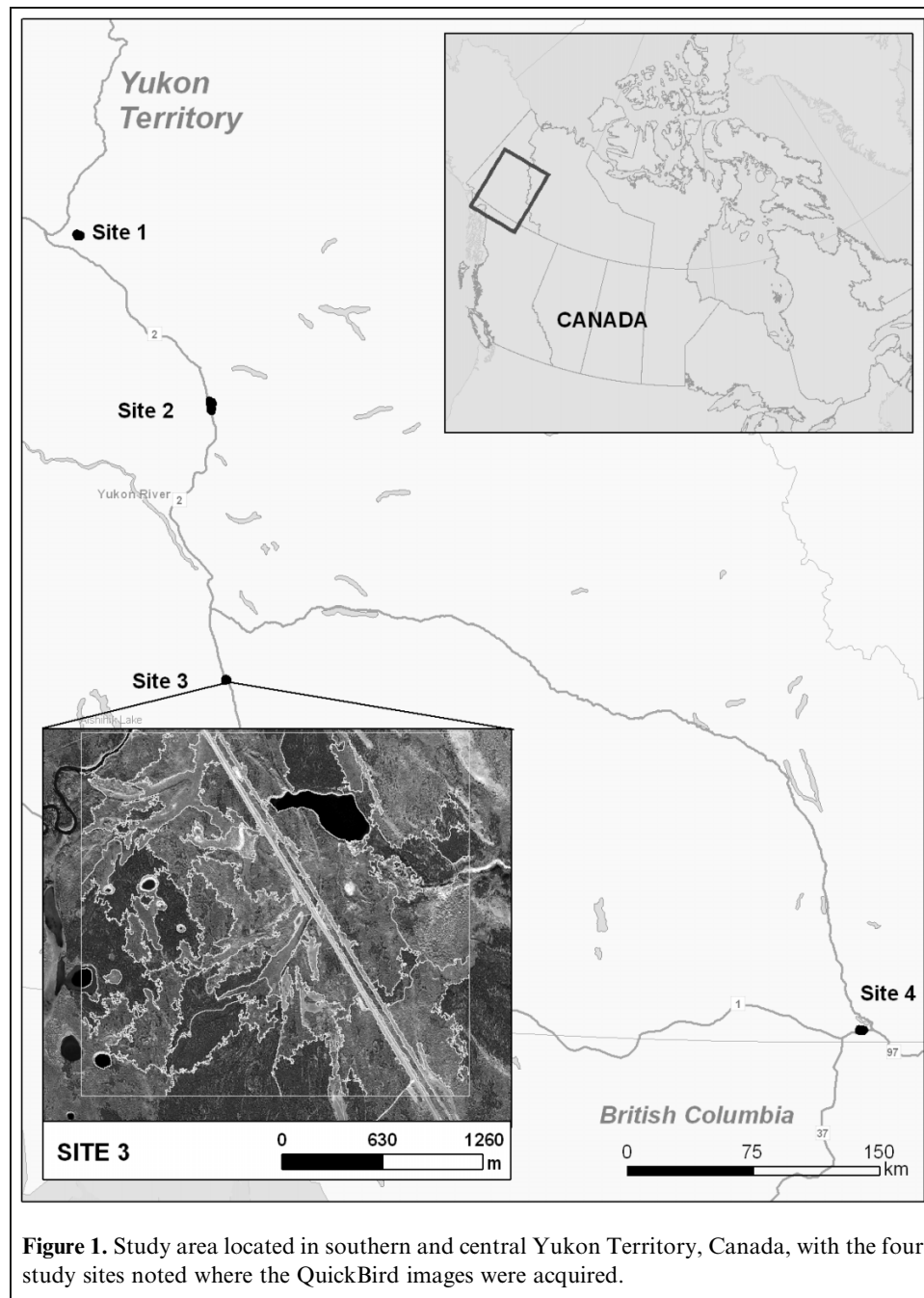
Figure 1. Study area located in southern and central Yukon Territory, Canada, with the four study sites noted where the QuickBird images were acquired.

of the ecozone is characterized by mountains and extensive plateaus, separated by wide valleys and lowlands. The original topography of the area was altered by glaciation, erosion, solifluction, and eolian and volcanic ash deposition, resulting in the current landscapes commonly characterized by glacial drift, colluvium, and outcrops. Permafrost is common in northern areas and higher elevations of this ecozone. The dominant species at these sites were white spruce (*Picea glauca*), black spruce (*Picea mariana*), lodgepole pine (*Pinus contorta*), alpine fir (*Abies lasiocarpa*), trembling aspen (*Populus tremuloides*), balsam poplar (*Populus balsamifera*), and white birch (*Betula papyrifera*). Forest disturbances in the

Yukon Territory are primarily due to wildfire, insects, and, to a lesser extent, forest harvesting.

Data and preprocessing

Figure 2 presents an overview of the methodology implemented in this study. For each study site, an 8 km × 8 km panchromatic (0.45–0.90 μm) QuickBird-2 image with a spatial resolution of 0.60 m was acquired (**Table 1**). Images were delivered in 16-bit unsigned format. We performed a top-of-atmosphere (TOA) radiance conversion according to Krause (2003). The images were orthorectified using a 15 m panchromatic Landsat-7 Enhanced Thematic Mapper Plus

Figure 2. Flow chart of the methodology.
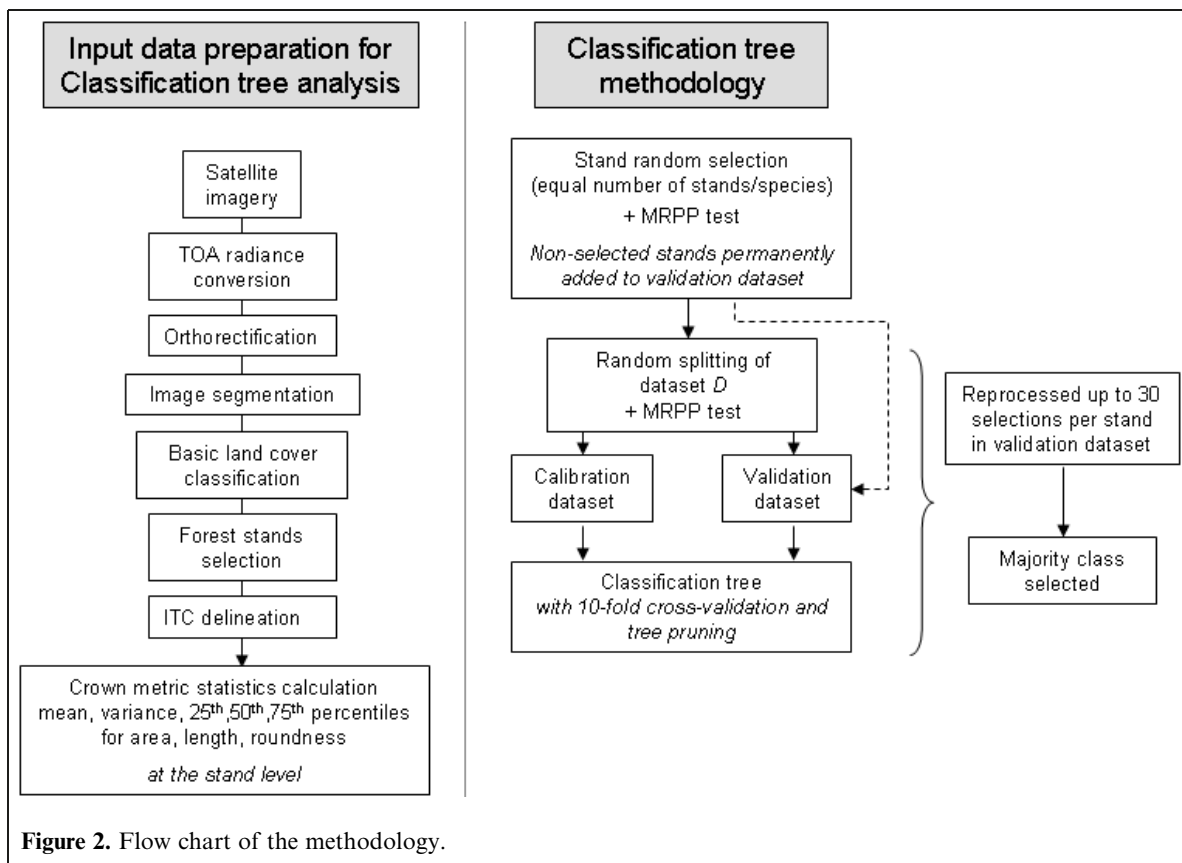
(ETM+) orthoimage (Wulder et al., 2008a), with an average root mean square error (RMSE) of less than 5 m. Note that only the panchromatic imagery was considered in this study to reduce image acquisition costs and enable the extension of the method over large areas.

Image segmentation

A segmentation algorithm implemented through the Definiens Cognition Network Technology software (Definiens Imaging, 2006) was used to delineate homogeneous forest units on the QuickBird images that were analogous to manually interpreted forest stands (Wulder et al., 2008b). To avoid oversegmentation as a result of the spatial resolution of the images (Wang et al., 2004), the segmentation process was applied to a 7×7 or 15×15 pixel median-filtered version of the orthorectified panchromatic image. A median-filtered image is likely to produce more homogeneous image segments and may reduce the amount of convolution in stand boundaries (Falkowski et al., 2009). A protocol for segmentation (Henley et al., 2009) in support of improved characterizations of northern Canadian ecosystems (Falkowski et al., 2009) was used to define an initial set of segmentation parameters: scale = 1200, colour = 0.3, and compactness = 0.9. To account for differences in land cover composition, these parameters and the median-filter window size were adjusted to address the unique characteristics of each image. The final segments were manually reviewed to ensure quality (Wulder et al., 2008b).

Image classification and manual interpretation

The delineated segments from the QuickBird images were classified according to a basic land-cover stratification so that treed segments could be identified and then manually photo-interpreted (**Figure 3**). The fuzzy classifier in Definiens Cognition Network Technology software was used, and the following classes were applied: forest, herb, shrub, bryoid, wetland, exposed land, rock, snow–ice, and water. Class definition was created following NFI and EOSD project standards (Wulder and Nelson, 2003). Segments that were identified as forest were then manually interpreted and attributed in compliance with the NFI Photo Plot standards (Natural Resources Canada, 2004). Treed segments with a crown closure less than 10% were considered nonforest (Wulder and Nelson, 2003; Boudewyn et al., 2007) and were excluded from our analysis (with a label relating the dominant land cover condition, e.g., herb, shrub as appropriate). Photo-interpreters identified the following species over the four study sites: black spruce, white spruce, lodgepole pine, white birch, trembling aspen, and balsam poplar.

Tree crown delineation and metrics calculation

We applied the ITC algorithm by Gougeon (1995) to the treed stands (**Figure 3**). This method, which is based on a valley following principle, requires an upper and lower grey level value threshold to be set to determine whether a pixel represents a portion of a tree crown or the surrounding sha-

Table 1. QuickBird image acquisition parameters.

Site	Size (ha)	Plot centre UTM zone 9N Easting (m)	Northing (m)	Acquisition date[a]	Solar azimuth (°)	Solar elevation (°)	Satellite azimuth (°)	Satellite elevation (°)	Off-nadir view angle (°)	In-track view angle (°)	Cross-track view angle (°)
1	625	45 116	7 133 046	2007-08-28	176.6	35.7	197.3	77.3	11.6	-11.7	-0.2
2	2400	118 968	7 030 079	2007-08-18	174.5	39.9	175.8	84.1	5.3	-5.0	1.8
3	625	130 603	6 866 945	2006-06-12	171.8	51.4	57.2	78.5	10.9	8.1	7.3
4	1375	508 030	6 661 737	2007-06-08	172.9	52.8	173.1	88.3	1.3	-1.3	0.4

Note: UTM, Universal Transverse Mercator.

[a]Dates given as year–month–day.

dow or understorey. For each image the threshold values were manually adjusted according to differences in vegetation structure and distribution.

The crowns delineated by ITC are assessed on a segment (stand) level to compute metrics that described the crown object shapes: area, length, and roundness. Length is defined as the square root of the object area times the length to width ratio derived from a bounding box, and roundness is defined as the difference between the radii of enclosed and enclosing ellipses of a given object (Russ, 2002). As the calculation of length and roundness metrics is unique, these metrics provide complementary information for the characterization of crown shapes.

Comparison of species crown metrics

As indicated by Sayn-Wittgenstein (1978) and Murtha and Sharma (2005), crown shape can be used to discriminate tree species. Sayn-Wittgenstein describes lodgepole pine crowns as being irregularly rounded, and white spruce crowns are described as symmetrical, narrow, and conical. Black spruce crowns are described as narrow and almost cylindrical. As one of the four study sites had a forest fire in 1950, the overall crown distribution statistics for trembling aspen could have been affected (lower variance, percentile values closer to the median).

We conducted a series of statistical tests to demonstrate if a selection of crown metrics (area, length, and roundness), when summarized at the stand level and described by variance, mean, and 25th, 50th, and 75th percentiles, could be used to discriminate leading species.

As leading species were identified and organized by canopy rank during the photo-interpretation process, we implemented a complementary protocol whereby the leading species was identified according to the following steps: species of rank 1 layer (dominant trees) with a canopy cover of at least 50% (by basal area) was selected as the leading species if the leading species in the rank 2 layer (codominant and (or) intermediate trees) was at least the same genus. This protocol ensured the consistency of the dataset for the calibration of the classification tree.

A maximum tree crown size for inclusion in the algorithm was defined (30 m^2) to preclude outliers (reflecting crown conditions not present in the field). As described by Gougeon and Leckie (2006), if the ITC algorithm cannot find any path (via valley following) to properly delineate tree crowns, the algorithm will instead delineate a cluster of trees. These clusters can impact the reliability of crown statistics. By defining a maximum tree crown size, these tree clusters can be excluded from further analysis. Crown metrics were then summarized at the stand level. Stands with metric values that are three or more standard deviations from the mean value were considered as outliers and removed from the dataset.

To determine the utility of the aforementioned crown characteristics for separating stand leading species, we first applied the Jarque–Bera normality test (Jarque and Bera,
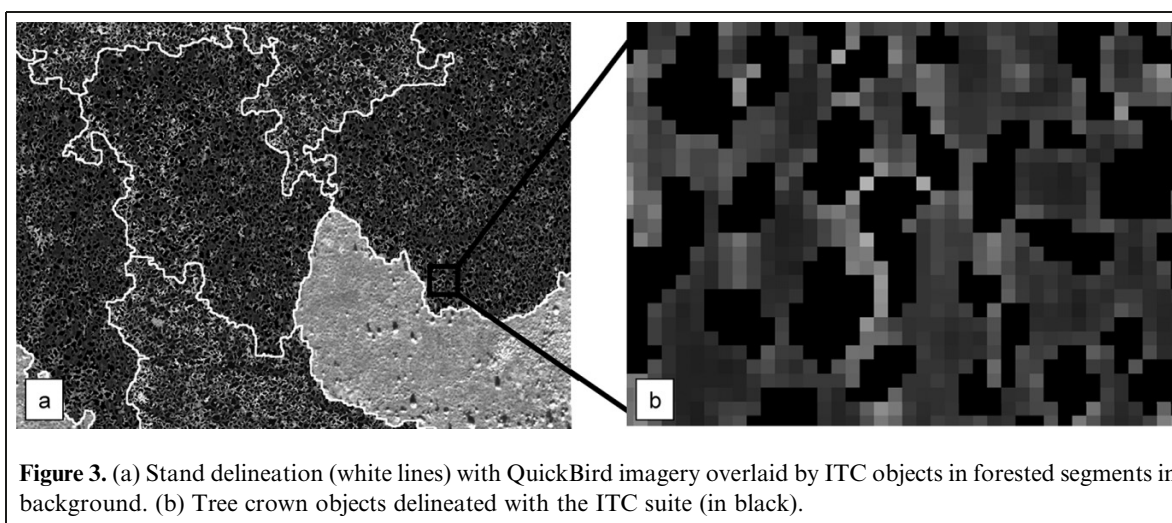
Figure 3. (a) Stand delineation (white lines) with QuickBird imagery overlaid by ITC objects in forested segments in background. (b) Tree crown objects delineated with the ITC suite (in black).

1987) on area, length, and roundness stand value distributions for each species. As a result of non-normal distributions of species metric, nonparametric tests were used to compare variances and means between species. The analysis of variance by ranks (Kruskal and Wallis, 1952) was used to compare the variances, and the Nemenyi test (Nemenyi, 1963) was used to compare the means. To facilitate the Kruskal–Wallis test, which requires samples of equal size, we randomly selected a sample of stands for each species, with the size of the samples constrained to the smallest sample size available (lodgepole pine; $N = 26$). A multiresponse permutation procedure (MRPP) proposed by Mielke and Berry (2001) was performed to ensure that there was no significant difference between the samples selected and the remaining dataset. This nonparametric method tests the hypothesis of no difference between two or more datasets for a range of parameters (i.e., the crown metrics in this study).

Estimation of leading species

Classification trees were used to predict the leading species in each treed stand. A classification tree is a nonparametric method that is capable of handling large datasets composed of heterogeneous variables (numerical and categorical). Therefore, no assumptions are made regarding variable distributions (Breiman et al., 1984). Moreover, classification trees are straightforward to interpret and easy to implement, which is an important operational consideration (Chubey et al., 2006). Another advantage of classification trees is their

ability to select the best variables to discriminate the potential classes of the model (Yu et al., 2006; Laliberte et al., 2007).

To prevent the establishment of a weak classification tree as a result of unbalanced samples sizes (**Table 2**), a new dataset D was created with a stratified random selection of an equal number of stands per species (**Figure 2**). An MRRP test was used to ensure that the random selection was not significantly different from the remaining part of the dataset. Then calibration and validation datasets were created by splitting the dataset D in half using a random procedure. The random division of the dataset D was followed by an MRPP test to ensure the equivalence of the calibration and validation datasets. The p value of the MRPP test had to equal 0.15 or more to accept the dataset partition. A classification tree with a K-fold cross-validation ($K = 10$) was then built with the calibration dataset. Subsequently, the classification tree was pruned and the leading tree species was predicted for each stand of the validation dataset. As each of the three metrics used to characterize the stands was described by five statistics, a total of 15 input variables were used. The sequence of randomly splitting the dataset D, establishing the classification tree, and predicting the leading species was run multiple times to circumvent the effect that a single random splitting could have had on the classification tree establishment and the accuracy of its predictions. More precisely, the sequence was repeated so that each stand of the dataset D was selected at least 30 times in the validation dataset. Lastly, for each stand, the majority class from all of the trials was retained as the predicted class and compared

Table 2. Metric values and number of stands per species with classes from photo-interpretation.

Species	Area (m²)		Length (m)		Roundness (m)		No. of stands
	Mean	Variance	Mean	Variance	Mean	Variance	
Black spruce	5.9	0.07	3.3	0.005	0.25	4×10^{-5}	31
White spruce	7.3	1.00	3.7	0.150	0.30	0.004	163
Lodgepole pine	7.1	0.50	3.7	0.050	0.30	5×10^{-4}	26
Trembling aspen	7.2	0.40	3.6	0.060	0.26	0.001	44

Table 3. Results of the Kruskal–Wallis tests.

	Area	Length	Roundness
χ^2	52.1	43.7	19.7
p	2.8×10^{-11}	1.7×10^{-9}	1.9×10^{-4}

to the leading tree species defined by the photo-interpreter. Thus, we ensured that for each stand the majority class (the leading species) was established on a reliable number of trials. Stands not selected during the first random selection were added to the validation dataset so that the validation data were representative of the stand leading species abundance over the study area. Note that these stands were constantly part of the validation dataset over the course of the trials. The classification tree was implemented using the R software (R Development Core Team, 2005) and the library "rpart."

Results

Image segmentation and interpretation

The segmentation process over the four study sites generated a total of 426 segments, of which 289 were considered treed after the initial stratification following the fuzzy classification and the rule-based refinement of the interpretation process (crown closure > 10%). Lastly, 270 treed stands, with a mean area of 14.5 ha, were selected according to the species homogeneity criterion defined for this study. Note that only one stand had white birch as leading species and only five stands had balsam poplar as leading species; as a result of their small sample sizes, these species and stands were omitted from further analysis.

Tree crown delineation and metrics calculation

Approximately 1.2% of the crown objects produced with the ITC algorithm were identified as large multiple tree clusters and excluded from further analysis. As the average number of crowns per stand was approximately 10 500, the average number of excluded tree clusters (area > 30 m^2) was approximately 130. **Table 2** provides the mean and variance values for each of the three metrics and the distribution size per leading stand species.

Comparison of species crown metrics

When comparing species crown metrics, the distributions of each of the metrics were found to be non-normal

(Jarque–Bera test; $\alpha = 0.05$). Thus, the Kruskal–Wallis test was used to compare variances between species, using a stratified random selection of 26 samples per species. The MRPP test indicated a chance-corrected within-group agreement A of -0.012 and a p value of 0.90. Kruskal–Wallis tests led to the conclusion that there was a significant difference between the species for all three metrics (**Table 3**). The Nemenyi test was then used to compare the means between species for the three metrics. The results of the Nemenyi tests are provided in **Table 4**, in which the values in bold indicate species combinations with a significant difference ($\alpha = 0.05$ and critical value $Q = 3.7$).

Leading stand species classification

The MRPP test was used to ensure the representativeness of the stand selection process, which obtained an equal number of stands per species with a chance-corrected within-group agreement A of 1.5×10^{-3} and a p value of 0.19. For the classification trees trials, 26 stands per species were used. As a result, classification trees were computed with a calibration dataset composed of 13 stands per species (52 stands in total). **Table 5** presents the 10 crown metrics that were selected by the classification trees, by the frequency of their occurrence across the iterations. **Figure 4** presents stands of the entire dataset plotted according to the three most selected metrics. The error matrix is presented in **Table 6**, and the resulting overall accuracy was 72.50%. **Figure 5** presents the percentage of species selection per stand computed over the iterations then averaged per leading stand species. In addition, to characterize the effects of crown closure on species prediction, the accuracies per species were computed according to crown closure (**Figure 6**). **Figure 7** shows the crown closure distribution per species.

Discussion

Stand and crown delineations

Automatic stand delineation provided satisfying results because only 10 stands out of 289 had an area smaller than that of the NFI standards (segment area ≥ 2 ha) and required manual modification. As expected, segment boundaries were more convoluted than those typically obtained from a manual stand delineation (Wulder et al., 2008b). These boundaries can be smoothed if desired; however, we preserved these boundaries because they represented local conditions and the spatial detail of the VHSR imagery used.

Table 4. Statistics q to be compared with the critical value Q for the Nemenyi test.

	BS–WS	BS–LP	BS–TA	WS–LP	WS–TA	LP–TA
Area	**7.7**	**8.0**	**8.9**	0.2	1.1	0.8
Length	**6.9**	**8.8**	**6.2**	1.8	0.7	2.6
Roundness	3.1	**6.1**	1.9	3.0	1.1	**4.1**

Note: Values in bold indicate that species combination is significantly different at $\alpha = 0.05$. BS, black spruce; LP, lodgepole pine; TA, trembling aspen; WS, white spruce.

Table 5. Proportion of statistics selection across classification trees.

Area variance	82%
Roundness variance	73%
Area 50th percentile	64%
Length 50th percentile	22%
Mean area	20%
Length variance	13%
Length 25th percentile	5%
Mean length	4%
Area 75th percentile	4%
Roundness 25th percentile	2%

Stand leading species identification

Kruskal–Wallis tests showed significant differences between species for all crown metrics. Therefore, variance statistics could be employed as potential parameters to discriminate leading species with the classification tree. **Table 5** shows that the variances in the area and roundness metrics were the two most frequently selected input parameters for the classification trees. The 50th percentile of area was the third most frequently selected input parameter. The Nemenyi tests showed that some tree species could also be discriminated using metric mean values.

Black spruce stands could potentially be well discriminated from the other species with the mean area or length metrics (**Table 4**). Mean roundness was pre-identified as a potential crown metric suitable for discriminating black spruce from lodgepole pine; however, mean roundness was not selected by the classification trees. Moreover, despite the fact that the Kruskal–Wallis test showed significant differences between species, the Nemenyi test did not identify any metric as potentially able to discriminate white spruce from either lodgepole pine or trembling aspen. **Figure 4** shows that black spruce clusters could potentially be identified on each two-metric space defined by the most selected statistics. **Figure 5** shows that over the classification trees, black spruce was the most frequently identified species in black spruce stands. The classification trees were able to predict black spruce as the leading species with 100.00% accuracy (**Table 6**).

White spruce stands had the highest mean crown areas. However, the full distribution of white spruce crown area overlapped with the crown area distribution of other species (**Figure 4**), possibly contributing to the resulting accuracy of only 43.90%. The low accuracy observed for white spruce could be explained by the highest variance values observed for the three metrics of the species (**Table 2**). Therefore, the wide range of values induced overlapping metric distributions with the other species (**Figure 4**). **Figure 5** confirms that
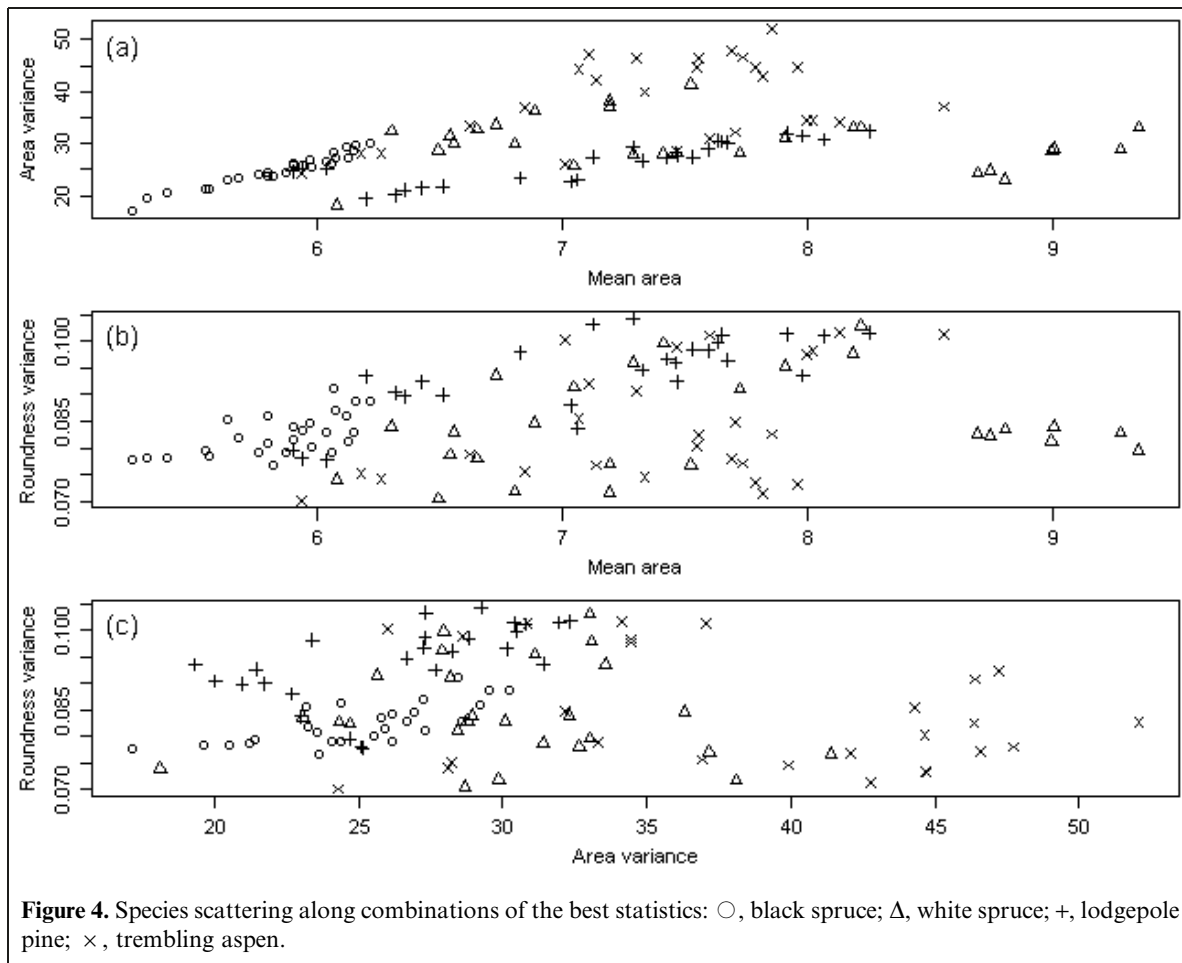

Figure 4. Species scattering along combinations of the best statistics: ○, black spruce; Δ, white spruce; +, lodgepole pine; ×, trembling aspen.

Table 6. Error matrix (%) deduced from the classification trees trials.

Validation	Predicted class			
	Black spruce	White spruce	Lodgepole pine	Trembling aspen
Black spruce	100.00	0	0	0
White spruce	12.90	43.90	25.75	18.40
Lodgepole pine	15.40	3.80	80.75	0
Trembling aspen	13.60	4.50	15.90	65.90

there was confusion among all species for the white spruce stands. The highest degree of overlap occurred with stands dominated by lodgepole pine and trembling aspen (**Table 6**). Confusion in identifying the leading species has likely also occurred during the photo-interpretation process. In addition, recall that for a given stand, leading species was defined as the species of the rank 1 layer (dominant trees) with a canopy cover of at least 50% (by basal area), as long as the leading species in the rank 2 layer (codominant and (or) intermediate trees) was at least the same genus. Therefore, the metrics associated with the leading species could be affected by the other species, especially when the species canopy cover in the rank 1 layer was close to 50%. Moreover, climax white spruce stands, which are widespread across northwestern Canada (Lutz, 1956), often codominate or form a significant part of the vegetation in mixed stands with other tree species. Furthermore, white spruce grows on a wide variety of soils of marine, alluvial, lacustrine, and glacial origin (Eyre, 1980). This variety of suitable soil conditions associated with within-stand species variability may have increased the variance values of the crowns metrics.

Figure 5. Mean species prediction proportions per reference stand species. BS, black spruce; LP, lodgepole pine; TA, trembling aspen; WS, white spruce.

Lodgepole pine stands were identified with an accuracy of 80.75%. However, the smaller sample size of the lodgepole pine dataset may have affected the capacity to assess the reliability of the model for this species. **Figure 4c** shows that the area variance, which is the most frequently selected input parameter, was an efficient statistic to discriminate lodgepole pine from the other species. **Figure 5** shows that over the classifications, the three remaining species were selected as well but in reduced proportions. Most of the confusion between lodgepole pine stands and the other stand types occurred with the other coniferous-dominated stands (i.e., stands dominated by black and white spruce).

Trembling aspen could be well discriminated from the other species by the area variance metric (**Figure 4**), although the variance was similar to that of lodgepole pine (**Table 2**). However, Nemenyi tests showed that mean roundness and length could enable a separation of trembling aspen with lodgepole pine and black spruce, respectively (**Table 4**). Conversely, no statistic was identified as being able to separate trembling aspen and white spruce, and **Figure 4** shows an overlap between trembling aspen and white spruce clusters. **Figure 5** shows that trembling aspen was largely selected across the classifications in trembling aspen stands. The final accuracy of trembling aspen was 65.90%, and most of the confusion occurred with stands dominated by black spruce and lodgepole pine.

Refinement of methodology and future work

The semi-automated approach to the identification of leading species presented herein would be particularly beneficial to Canada's NFI in areas where logistical or financial constraints preclude the acquisition of aerial photography (Falkowski et al., 2009). Furthermore, such an approach would be an improvement on the existing Landsat-based data sources that are currently used in these areas (Wulder et al., 2008a). Opportunities exist to refine the methodology as presented, with the objective of improving the accuracy of the model's species predictions and thereby also improving the estimation of attributes that are dependent on species information, such as volume and biomass.

For example, despite the fact that different species have unique crown metrics, there are other factors besides species that can alter tree crown morphology and impact crown metrics. According to Oliver and Larson (1996), side shade effect, possible phototropism, climatic events such as wind and ice storms, and sudden changes in the tree's hormonal
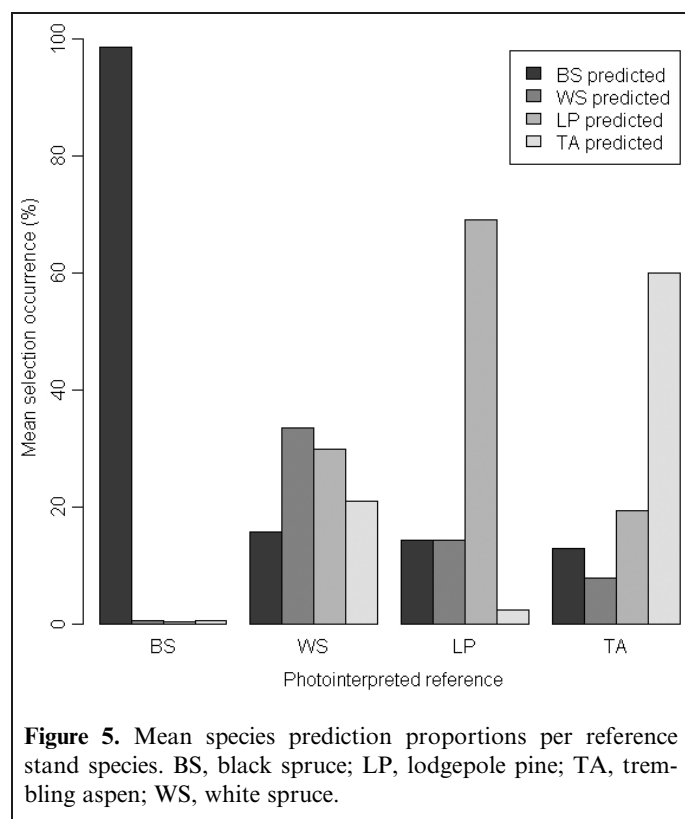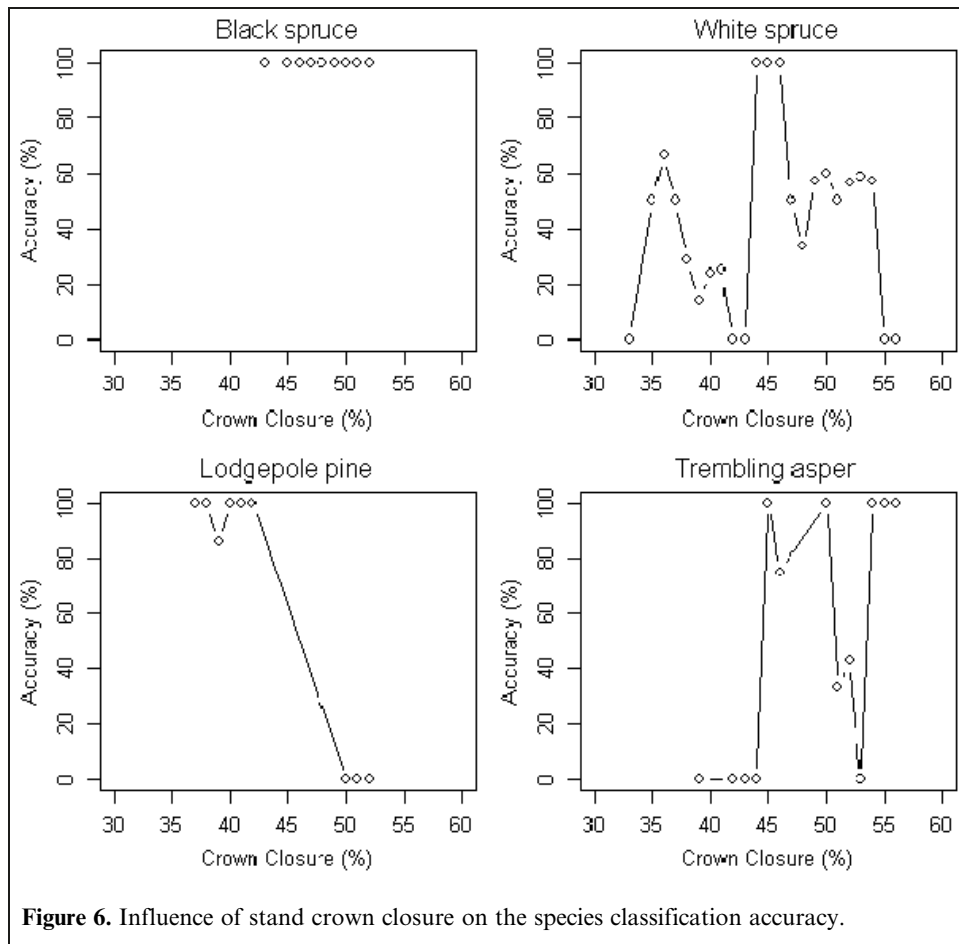
Figure 6. Influence of stand crown closure on the species classification accuracy.
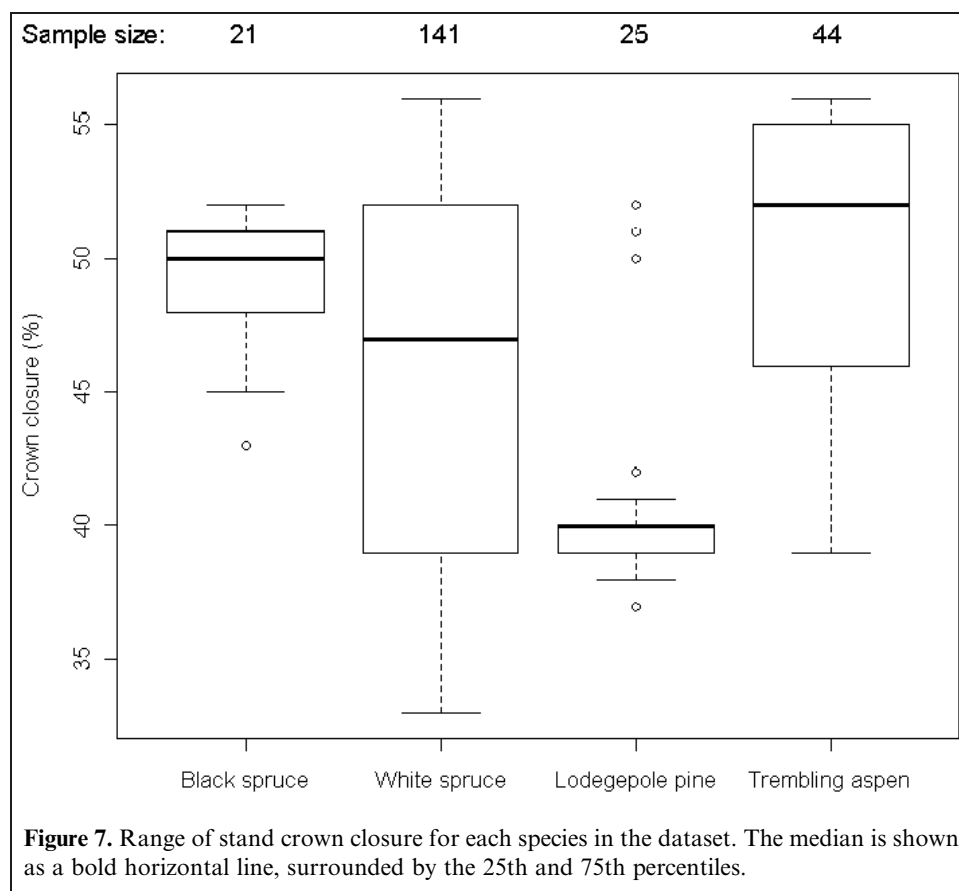
balance are all potential sources of crown shape alteration. One approach to address variability in crown size may be to reduce the size of large crowns identified by ITC based on a predetermined crown size expectation. In this study, we have established a threshold for a maximum crown area of 30 m²; however, a threshold based on the crown size distribution within a stand would consider the specific stand character-istics (species, crown closure, etc.) and may therefore be more effective. Similarly, stratifying by crown closure may also improve estimates of leading species. In this study, we found a linkage between the range of crown closures and the accuracy of leading species predictions (**Figure 6**; **Table 6**).

A protocol was designed to discard outlier tree crown objects and stands during the modeling process; however, stands dominated by white spruce suffered from among-class confusion, particularly with stands dominated by lodgepole pine (**Figure 5**; **Table 6**). The collection of more extensive training data, through additional photo-interpretation or, where possible, field data collection, may help address this. Alternatively, a data-driven classification approach could be followed (i.e., clustering), with the species classification applied to the resulting groups, thereby mitigating any error introduced by faulty calibration data.

Image acquisition parameters (e.g., in-track view angle, satellite azimuth) should also be considered when developing models that are to be extended across large areas or to other areas with similar characteristics. High spatial resolution satellites have nimble sensor heads that can drastically reduce the satellite revisit time to a given location but can also have implications for representations of forest structure (Wulder et al., 2008c). We note in this study that there was some variability in image acquisition parameters (**Table 1**) that may have contributed to some confusion in the clas-sification tree model.

Tree crown parameters such as area and shape change as trees grow and age (Oliver and Larson, 1996). Since an accurate mean stand age is difficult to estimate, particularly from remotely sensed data (Wulder et al. 2004), the potential impact of age on crown metrics was not considered in this study. In our study area, airphoto interpretation indicated that more than two thirds of the forest stands were greater than 100 years old. Therefore, changes in crown size as a result of age are unlikely in our study area; however, in areas with a more heterogeneous distribution of ages, access to ancillary information sources like forest fire history or silvi-cultural records may provide useful information on stand ages in lieu of direct age estimation. Some tree species, such as lodgepole pine, tend to regenerate in relatively homogen-eous stands after a major fire event, and successional pat-terns for other species are known as well (Fortin et al., 1999; Perry and Millington, 2008). Such information, although not always available, may improve species identification.

Figure 7. Range of stand crown closure for each species in the dataset. The median is shown as a bold horizontal line, surrounded by the 25th and 75th percentiles.

Future work should consider additional inputs, such as topographic variables and soil layer information, as some species spatial patterns are driven by such factors (Oliver and Larson, 1996). Furthermore, the method presented herein should be extended to areas with different tree species and to mixed-species stands. The accuracy level and the nature of omission errors related to the stands dominated by white spruce in this area further encourage the creation of generic stand volume and biomass equations by broad cover type (i.e., conifer and deciduous stands). If the accuracy of leading species predictions is considered to be too low, the application of species-specific attribute estimation models for biomass and volume may imply a false precision. In such a scenario, combining regionally appropriate species-specific models with lower precision models based on cover type should be considered. A higher accuracy and likely more parsimonious estimation of cover type may accommodate the lower precision of the subsequent volume and biomass models that are applied.

Conclusion

In this study, we investigated the potential of classification trees to discriminate stand leading species from crown metrics calculated from VHSR satellite images. The four study sites were located in the Yukon Territory, Canada, and were largely represented by four major, regionally important tree species. Preliminary statistical tests identified the potential of some crown statistics summarized at the stand level to discriminate, in a statistically significant fashion, leading species. The most frequently selected input parameters to the classification tree were the variances of crown area and the roundness and mean crown area. An overall accuracy of 72.50% was obtained, with accuracies for individual species ranging from 43.90% to 100.00%. This study demonstrated the potential of crown metrics derived from panchromatic satellite imagery and classification trees to provide information that enables the discrimination of stand leading species in boreal forest stands. Suggestions for the refinement of the methodology presented herein and for future work could potentially lead to an improvement of the model's ability to predict leading species, which in turn could enable more robust estimates of other forest inventory attributes such as stand volume and biomass.

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