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Individual Tree Crown (ITC) Inventory and Analysis of the Petawawa Research Forest:
Stand's Species Composition and ITC-based Volume

François A. Gougeon, Donald G. Leckie, and Murray Woods

Canadian Forest Service
Pacific Forestry Centre

Information Report
BC-X-460

Canada

The Pacific Forestry Centre, Victoria, British Columbia

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2023

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Cat. no. Fo143-2/460E-PDF
ISBN 978-0-660-48647-5
A pdf version of this publication is available through the Canadian Forest Service Publications website: http://cfs.nrcan.gc.ca/publications.

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Abstract

Individual tree inventories promise precision advantages relative to conventional forest inventories and those enhanced by a LIDAR area-based technique. Although this promise has yet to be realized at scale in Canada, advances continue to bring individual tree inventory technologies closer to practical application. This report describes a practical demonstration of the Individual Tree Crown (ITC) approach on the Petawawa Research Forest in Ontario. A typical mosaic of multispectral aerial images (40 cm/pixel) was used to automatically delineate approximately 10 million ITCs, classify these into species and estimate their volumes. To mimic operational situations, the spectral signatures were generated from simple training areas produced using information from two previous forest inventories, with minor on-screen interpretation. Classification accuracy was ascertained for ten common species. Although species classification in this demonstration was generally poor due to some species confusion, the conventional forest inventory benchmark is also known to be poor for challenging situations. Conventional equations were used to establish volumes for 2 000 trees for which species, diameter at breast height (DBH) and height were measured in the field, and simple volume relationships were established for each species plotted as a function of height only ($V = f(HT)$) for application to the ITCs for which we only have species and height (i.e., no DBH). Summarizing at the stand level while compensating for the fact that some of the ITCs are actually tree clusters rather than single trees produced estimates consistent with standard volume assessment of the Petawawa Research Forest.

Résumé

Les inventaires « à l’arbre prêt » nous promettent des précisions supérieures aux inventaires forestiers conventionnels et ceux améliorés par une technique surfacielle au LIDAR. Bien que cette promesse soit encore à être réalisée à grande échelle au Canada, des progrès continuent de rapprocher l’inventaire « à l’arbre prêt » d’une application pratique. Ce rapport décrit une utilisation pratique de l’inventaire « à l’arbre prêt » sur la forêt expérimentale de Petawawa en Ontario. Une mosaïque typique d’images aériennes multispectrales (40 cm/pixel) fut analysée pour isoler approximativement 10 millions d’arbres, classifier leur espèce, et estimer leur volume. Pour imiter une situation opérationnelle, les signatures spectrales furent générées à partir de zones d’entrainement simples produites à partir d’information provenant de deux inventaires forestiers antérieurs et, un peu d’interprétation à l’écran. L’exactitude de la classification fut établie pour les dix espèces les plus communes. Bien que l’exactitude de classification soit généralement faible dû une certaine confusion entre les espèces, l’inventaire forestier conventionnel de référence peut aussi être faible lors de situations complexes. Des équations conventionnelles furent utilisées pour établir le volume de 2 000 arbres pour lesquels l’espèce, le diamètre à hauteur de poitrine (DAP) et la hauteur furent mesuré au sol puis, de simples équations reliant le volume à la hauteur ($V = f(HT)$) furent établies pour chaque espèce pour être utilisées avec les ITCs (arbres individuels) pour lesquels nous n’avons que l’espèce et la hauteur (c.à.d., pas de DAP). Une compilation par peuplements, tout en compensant pour le fait que certains ITCs sont des groupes d’arbres plutôt que des arbres individuels, produisit des estimations de volume comparables à ceux de la méthode conventionnelle pour la forêt expérimentale de Petawawa.

Acknowledgements

We would like to thank Dr. Steen Magnussen (PFC Scientist, retired) and Graham Stinson (PFC, formerly Manager of National Forest Inventory) for their critical review of this work and the manuscript.

1 Introduction

The forest industry is being shaped by a digital transformation that is creating demands for increasingly high precision forest inventory data. Foresters are managing for a multitude of ecosystem goods and services while trying to optimize value from every tree harvested. High precision data are needed for characterizing wood volumes, fibre qualities, wildlife habitat features, harvest residues, carbon, fuel characteristics and more. Individual tree based forest inventories have the potential to help satisfy demand for high precision data and advance sustainable forest management.

The Individual Tree Crown (ITC) approach represents a major shift in paradigm, from mapping relatively homogeneous forest stands and interpreting their structure and composition, to the semi-automatic computer analysis of high spatial resolution (10–100 cm/pixel) multispectral aerial or satellite images producing ITC-based forest inventories (Gougeon and Leckie, 2003). Such forest inventories have the potential to improve predictions of species composition and use allometric volume and biomass equations more directly. Individual tree census could ultimately make stand-level forest inventory and management obsolete. However, current tools and algorithms have not fully matured yet, as many of the isolated objects (isols) identified by ITC technologies are tree clusters rather than individual trees. Still, detailed information at nearly individual tree level offers numerous advantages and, application-specific analyses or regroupings can be done as needed after the initial ITC analysis (e.g. for wildlife management, biodiversity assessment).

Foundational techniques, methods and tools for ITC-based information extraction developed by the Canadian Forest Service are described in detail by (Gougeon and Leckie, 2003; Gougeon, 2010). A large-area ITC study by Leckie et al. (2017) using the same mosaicked multi-spectral imagery at 40 cm pixel resolution covering 228 km^2 overcame key issues associated with scaling up from small study areas with relatively simple forest structure and composition, but Leckie et al.'s solutions were complicated and too challenging to implement operationally. This report describes a more practical demonstration of the ITC approach for the same study area in the Petawawa Research Forest (PRF), Ontario, and introduces new advances achieved over the past two decades of research and development.

2 Background

2.1 Development of the ITC Approach

ITC research and development began three decades ago when prototype multispectral airborne sensors first became capable of acquiring images at close to 1 m pixel resolution and Gougeon and Moore (1989) developed a treetop approach based on finding local maxima to count trees and identify their species. Although equally good at classifying a limited number of hardwood and softwood species, counts of hardwood trees were often overestimated due to the detection of multiple maxima within their crowns, especially as spatial resolutions increased. Treetop techniques became more susceptible to the size of the detection window and/or to the *a priori* smoothing of the images. More adaptable versions were created to tackle the window size issues (Dralle and Rudemo, 1996; Wulder et al., 2000). Another method relied on detecting regions of bigger and smaller trees, followed by adaptable smoothing prior to treetop detection (Gougeon, 1997). Most of these methods were not quite flexible enough to deal with stands with a thorough mixing of species.

Concurrent with additional developments and improvements of multispectral airborne sensors leading to the availability of sub-meter data, Individual Tree Crown (ITC) techniques attempting to detect and delineate crown outlines were also developed. Some were based on first finding local maxima (i.e., treetops) and then finding crown edges spiraling down the crown or by following transects in various cardinal directions until an abrupt change was detected (Pinz, 1991; Pouliot et al., 2002; Koch et al., 2006;); or starting a region-growing segmentation from such a seed point (Uuttera et al., 1998; Erikson, 2003; Lamar et al., 2005). Other approaches were based on scanning the image looking for significant correlations with two-dimensional projections of tree crown models or selected instances of tree crown views (Pollock, 1994; Larsen and Rudemo, 1998). These approaches are very computer intensive since numerous models need to be tested/assessed. Moreover, difficulties making a final decision on the winning model for a given tree arise with a disturbing high frequency. Simpler approaches were based on image grey-level inversions and using well known watershed algorithms (Hyyppä et al., 2001). Generic object detection and analysis packages (Chen et al., 2005) can perform relatively well, especially on plantations. In this study, we used the valley following approach to crown delineation (Gougeon 1995b) which follows valleys of shade that are typically found between trees crowns and use the multispectral data within such crown to recognize their species (Gougeon 1995a), as described later.

Since the majority of crown delineation techniques rely on only one spectral band (or a panchromatic image), they also work well on LiDAR-based Digital Canopy Models (DCM) given sufficient point densities (Leckie et al., 2003; Evans et al., 2006; Zhen et al., 2016). Colour or multispectral information is generally needed for species recognition (McCombs et al., 2003), but the two data types may be difficult to align properly (Dralle and Rudemo, 1997).Here, we are using a LiDAR-based DCM to get individual tree heights for our volume calculations and assessing the importance of such misalignment. Zhen et al. (2016) provides a review of ITC detection and delineation from LiDAR data.

2.2 Forest Volume Assessments

Establishing forest volume at the stand level is traditionally done by connecting plot volumes with a stratification of the forest and then bringing that information back to the stand level. A modern approach uses k–NN to spatialize historical plot volume information to management units via photo-interpreted parameters (Bernier et al., 2010). Establishing forest volume from medium spatial resolution remote sensing (RS) has often followed a similar approach where some RS-extracted parameters are used to spatialize plot volume/biomass information (Beaudoin et al, 2014). However, with the increasing availability of aerial LiDAR data providing dense height information, different approaches are emerging.

In Canada, where coverage of large areas is often compulsory for management and even operational needs, area-based LiDAR techniques have demonstrated lots of potential. They are able to supply substantial quantity of inferred, yet well verified forest information, from top height to merchantable wood volume, and even assignment of logs by sizes to sawmills, at spatial resolutions commensurate (20–30 m) with that of the field plots used as reference (Lim et al., 2003; Woods et al., 2011; White et al., 2013). One study shows the inferred volume to be within 10% of the scaled volume (Woods et al., 2011). Such area-based approaches were also shown to be successful with photogrammetric point clouds extracted from aerial multispectral images with multiple views (Pitt et al., 2014; White et al., 2015), as long as a high-quality digital elevation model of the ground was available. It is beyond the scope of this paper to address all of the potential benefits of using LiDAR in forestry. Wulder provides an overview of the potential role of LiDAR for forest management (Wulder et al., 2008).

Most remote sensing studies of volume at the individual tree level were carried out by analysing LiDAR data, generally at the plot level, and doing crown delineation on the derived DCM. Typically, a single maximum height with/without crown area or diameter is used to calculate volume (Hyyppä et al., 2001; Popescu et al., 2003; Maltamo et al., 2006). In Scandinavia, because such equations exist, crown areas and heights are often used to first infer diameters at breast height (DBH) and then, DBH and height are used in more conventional volume equations. Later works often combine LiDAR data with multispectral or hyperspectral data for species assessments (Popescu et al., 2004; Dalponte and Coomes, 2016); and more recently, given higher return densities, the complete distribution of pulses within a crown are examined as they can also contribute to species recognition (St-Onge et al., 2015; Deng et al., 2016).

2.3 Wider Uses of the ITC Approach

With multispectral satellites capable of 1 m/pixel spatial resolution and better since 2000, ITC techniques became easily applicable to much wider areas and produced relatively good results (CLC-Camint, 2002; Gougeon and Leckie, 2006; Gougeon et al., 2018). However, most ITC-related studies are still done using fairly simple forest settings, address classification of a limited number of species (or species groupings) and are focused on small study sites. On the other hand, in Canada, provinces are still acquiring wall-to-wall aerial imagery (now digital) as part of their forest inventory cycles (~7–15 years) which is still analysed by visual image interpretation in almost the same way as the photo-interpretation of a few decades ago. This digital multispectral data is generally of very good quality and at sub-meter resolutions. It is thus amenable to digital analysis at the individual tree level but is often prepared for human interpretation rather than automated computer analysis. However, access to unaltered data is often possible and mosaicking of radiometrically corrected and balanced imagery is getting more common (Downey, 2010).

As mentioned, one large-area (228 km^2) ITC study (Leckie et al., 2017) using mosaicked multi-spectral flight lines tackled scaling up from the typical small study areas with relatively simple forest structure. However, the procedures used were too complicated to implement operationally. Here, we will use the same dataset in a simpler way to investigate what can be reasonably achieved quickly, check on species composition relative to an existing conventional forest inventory and, examine volume assessments at the individual tree and stand levels. To our knowledge, this is the first ITC-based volume assessment of a large number (8–10 million) of trees.

3 Petawawa Research Forest Data Sets

The study area is the Petawawa Research Forest (PRF) in northeastern Ontario, approximately 160 km northwest of Ottawa, Ontario (77° 27′ 06″ W; 45° 57′ 42″ N). The site contains numerous boreal and temperate species and is thus a very good location to test species recognition. A description of the site is found in (Leckie et al., 2017). PRF forest inventories from 2001 (FoInv01, with volume) and 2007 (FoInv07, without volume) were available.

The imagery was acquired with a Leica ADS80 airborne sensor (Leica Geosystems Ltd. 2016) on September 6, 2009, as part of the Ontario Ministry of Natural Resources and Forestry (OMNRF) on-going program to obtain digital imagery of the whole province, primarily for forest inventory purposes. The sensor head used (SH82) has line imagers with four spectral bands (blue, green, red, and near-infrared) and a panchromatic band, acquired from two different views (backward 16° and nadir). Ground resolution was 28 cm with a cross path view angle of ±32°. The two different views enable human stereographic viewing and analysis, the production of photogrammetric point clouds (PPCs), a corresponding digital canopy model and additional multispectral imagery repositioned to the DCM. The main product used in this study was the orthorectified and radiometrically-corrected (Downey et al. 2010) mosaic of the flight lines over the PRF as provided to OMNRF, with a ground resolution of 40 cm/pixel. The view angle for the data in the mosaic was typically within ±24° of nadir. Also available was a LiDAR dataset acquired August 2012 at approximately 6 pulses/m^2 with a field of view of ±20°. A digital elevation model and digital canopy model were generated by Leading Edge Geomatics at a 50-cm resolution and were resampled to 40 cm/pixel to be more compatible with the rest of the dataset.

A set of 545 field-verified relatively pure test areas were used for some species recognition assessments by comparing their dominant species with that of our ITC classifications. A data base of 10918 field-verified reference trees that had also been delineated on the imagery was used for our ultimate species recognition tests (Leckie et al., 2017). Another independent dataset created mostly for volume assessment was used to build and verify volume inference equations. It provided 2000 field trees (within 223 plots) for which species, DBH and height were ascertained (some heights were inferred, as is often the case in plot assessments). For these 223 plots, dominant and codominant trees average height and the total volume (tvol) within the plot had been estimated.

4 Methodology

4.1 Tree Crown Delineation and Species Classification

The delineation of individual tree crowns (ITCs) over the 228 km^2 area was accomplished using the NRCan ITC-Suite (Gougeon, 2010). To concentrate on the forested area, a non-forest mask was first created using a threshold (<2 m) on the digital canopy height model generated from the LiDAR data. Then, from a smoothed near infra-red (NIR) image, valleys of shade were followed to get an initial separation of tree crowns. Subsequently, a rule-based program attempts to further separate the isolated objects (isols) into individual crowns (Gougeon 1995b). Here, the resulting ITCs, which are the same as used in (Leckie et al., 2017), are considered well separated 77% of the time.

Species classification training areas were created using two previous forest inventories (2001 and 2007) to identify pure stands for each of the study area's common tree species and outlining these on the mosaic image. Some additional image interpretation was used to create training areas for species that rarely appeared as single species stands. Spectral signatures were generated and compared for 10–16 species by automatically extracting the spectral information from the isols within these areas. These signatures were based on the multispectral values of the pixels on the well-lit parts of each tree, amalgamated for each ITC (or isol) and then amalgamated to create the species signatures (Gougeon, 1995a). These MEANLIT species signatures consist essentially of the average ITC (LIT) mean multispectral vectors and the covariance of the ITC means. They were subsequently purified by automatically removing outlier ITCs that are not within two standard deviations of the signature mean and then re-evaluating the signature statistics.

Occasionally, a species requires more than one class to represent biological or stature variations. Here for example, we retained a class of emergent layer white pine (Pwe) as distinct from other, within canopy white pines. Textural and structural signatures were explored for species classification but these were found to be ineffective. Finally, a simple 10 species (12 classes) ITC classification was retained for the further analyses. The classification of each ITC was based on a maximum likelihood decision between these 12 classes with a confidence factor of 0.98, leaving some ITC unclassified.

4.2 Species Assessments

ITC classifications can be verified in various ways, such as using test areas similarly interpreted as the training areas, using test areas assessed in the field, using individual field-verified test trees, or using species composition comparisons with existing forest inventories. For test areas representing a single species and for individual trees, confusion matrices portray the sum of correctly classified items on diagonal cells and the confusion with other classes in the off-diagonal cells. For test areas with multiple species (and approximated species composition) or for existing forest inventory stands, a confusion matrix can be created based solely on the similarity (or not) of the dominant species within that species composition (Gougeon and Leckie, 2011). Both approaches were used here. An additional approach was used to quantify more precisely the differences in species composition between the forest stands of an existing inventory and that created by the classified ITCs within the same polygon. The Euclidian distance in a ten dimensional space (ten species) was measured for each stand and then divide by two because any change in the proportion of one species within a stand should have a doubling effect since the proportion of other species in that stand has to change by the same amount (i.e., species proportions always having to sum to 100%).

4.3 Development of Volume Estimate for Each ITC/ISOL

The methodology to assess ITC-based volume is as follow. Firstly, conventional equations (Honer et al., 1983) were used to establish individual tree volumes for the 2 000 field trees for which species, DBH and height are known (some heights were inferred as is often the case in plot assessments). Then, each species' tree volumes were plotted as a function of only height in order to establish a volume as function of height relationship ($V=f(HT)$) for application to ITCs for which we only know species and height (i.e., no DBH), with a correction factor representing the average difference in LiDAR-based heights and ground measured heights.

Typically some (on the order of 20–30%) of the isolated object (isols) are known not to represent single trees, but are tree clusters (>1 tree per isol) or over-segmented crowns (<1 tree per isol) (Leckie et al., 2016a, b, c). A correction factor based on crown area was introduced to produce volume estimates for these isols. If the crown area of an isol was a multiple of the average crown area for that species, it was assumed to represent more than one tree and its volume was adjusted by the same proportion. For example, if an isol has twice the average crown area of that species the volume assigned to it is doubled. Similarly, if an isol area is a fraction of the average crown area of that species then its volume is taken to be that fraction. Advantages of this approach are two-fold: (a) no need to decide *a priori* which isols represent a single tree and which do not (which is often very difficult (Leckie et al., 2016a, b, c)); (b) the same approach is intuitively reasonable for handling clusters and over-segmented crowns.

4.4 Volume Assessments

Three types of ITC-related volume assessments were done and compared with that of an existing conventional forest inventory (FoInv01) on a stand-by-stand basis. The first one relies on the output of the polygon content description (ITCPCD) program of the ITC Suite. For each species within a polygon, it reports the number of ITCs (i.e., isols) detected and their average height. The species volume equation ($V=f(HT)$) can be applied using this average height, giving the volume of an average tree of that species. The species-related volume for that stand is obtained by multiplying by the number of isols of that species. Combining such results for each species leads to stand volumes (PCD_Vol). The second type of ITC-related volume assessment (ITC-IV) relies on applying the volume equations to each individual entity (isol) with its individual height. The third type of assessment (ITC-IV Adj. Vol.) is similar, but takes into consideration that the entities may be tree clusters rather than single trees, as described above.

An important consideration about ITC-based volume assessments is how heights are derived and fed to the volume ($V = f(HT)$) equations. Generally, heights acquired from a Digital Canopy Model generated from a LiDAR dataset underestimate heights relative to field measured heights (Gaveau and Hill, 2003; Hyyppä et al., 2008). There are two main sources for this underestimation. One is that the creation of a DCM invariably has a smoothing effect on the data, definitively smoothing the highest return. Second, especially in the case of "pointy" conical coniferous tree, the signal has to intercept enough vegetation material to be considered a viable first return. To a lesser extent, this is also true for hardwoods. So a correction factor based on comparing the maximum field measured heights from the plots with that from the DCM for the same plots (1.05, $R^2 = 0.96$) was introduced before DCM heights were used in ITC volume equations.

Another possible consideration relative to the heights used for ITC volume estimation is that crowns derived from aerial flight lines have their positions and shapes affected by off-nadir view angles (Dralle and Rudemo, 1997) while LiDAR-based DCM are less affected due to the better positioning of LiDAR data in 3D space. So, when a maximum from the DCM is picked up within an aerial based ITC to represent its height, it may not be appropriate at large view angles. Two tests were carried out to assess the importance of this factor on the ITC-based volume assessment. The first one uses the aerial data view angles and the DCM heights to reproject the DCM image such that the heights values from this new DCM better fall under the proper image-based ITC. In effect, the new DCM image looks like the corresponding aerial image. In the second test, new ITCs were produced from a more recently obtained PPC-based nIR image for which proper positioning is achieved by stereo disparity autocorrelation. These new ITCs are thus well aligned with the DCM from the LiDAR data and the LiDAR heights gathered from within should be more appropriate. The heights obtained from both methods were compared with that of our standard approach to see if this might be of importance in ITC volume assessments.

5 Results

In this section we examine our ITC classification of the ADS mosaicked imagery into the predominant species of the Petawawa Research Forest: how well they separate spectrally, how well they classify and, how good are the resulting stand species compositions. We also examine various aspects of using the ITC classification to generate species-based volume information at the stand level.

5.1 Spectral Signature Discrimination

The multispectral signatures of fifteen (15) prevalent species in the Petawawa Research Forest are reported in Table 1. Hard maple (Mh) (e.g., Sugar Maple) and soft maple (Ms) (e.g., Red Maple) are fairly distinct spectrally from one another in the NIR channel, with red oak (Or) and white birch (Bw) situated in between. Confusion is to be expected between these species. Poplar is marginally brightest in the NIR, but mostly distinct in the visible bands.

Softwoods are quite distinct from hardwoods in the NIR channel, as expected. White pine (Pw), especially the emergent white pine (Pwe), are situated in between these two groups. A distinct pattern in the other bands distinguishes white Pine from other softwoods and from hardwoods. Within the softwoods, there are more clear distinctions than within the hardwoods. Although quite similar to Jack Pine in the NIR, Black spruce (Sb) should be quite distinct mostly due to the visible bands. White spruce (Sw) can be expected to have problems separating from jack pine (Pj). Red pine (Pr) appears to be quite distinct.

Inbred classification accuracy (i.e., test areas same as training areas) is often used to quickly identify possible species signature confusion. For example, it was found that the introduction of the last three signatures in Table 1 (and of other minority species) created too much confusion and was counterproductive. Finally, a simple 10 species (12 classes) ITC classification was retained (Table 2). Results generally confirm the above observations of signatures and overlaps. As expected, Mh classifies nicely (80%) with little confusion (<10%) with other species. Soft maple (Ms) (42%) has confusion with all the other hardwoods. Red oak (Or) (62%) is only confused with Poplar (Po) (16%) and, white birch (Bw) (63%) with Ms (12%). As anticipated, Poplar is quite distinct (82%). When combining Pw and Pwe, all the softwood accuracies are at greater than 70%, except white spruce (Sw) (43%), which has high confusion (29%) with Jack Pine (Pj). In this test, the number of unclassified trees appears rather high. However, these generally correspond to the isols of the training areas that were filtered out as outliers in the signature generation process.

5.2 Classification Results

The ITC classification is visually consistent with the forest stand polygon outlines (Figure 1) and the species compositions from the 2001 forest inventory. More precise ways to quantify species composition differences are explored in the next section.

Table 3 presents the ITC classification accuracy for ten species relative to field confirmed (but not necessarily single species) test areas, thus only the main species within each area were compared. Only the test areas with a clearly dominant (by 20%) first species were considered (413 of 545 test areas). Since the test areas were generally not single species, some of the confusion visible in Table 3 may not be true confusion. Although the accuracies appear much lower than for the inbred classification (Table 2), the patterns are similar. Most of the softwoods fare relatively well, except white spruce (Sw), and only Mh and Po fare well among the hardwoods.

Table 4 reports the classification accuracy relative to field confirmed single trees. Only the trees with relevant species information were considered ($n = 6421$). More precise species information at ground level was sometimes generalized to match our more generic classes. For example, Balsam Poplar, Largetooth Aspen and Trembling Aspen

Table 1. Multispectral signatures mean (standard deviation) of the twelve classes used in the ITC classification and three additional 'test'-species

Species	Number of ITCs	NearIR	Red	Green	Blue
Mh	87	193 (8)	73 (19)	110.4 (18.4)	61.6 (4.9)
Ms	135	186 (11)	41 (7)	77.6 (11.2)	59.6 (4.3)
Or	283	181 (8.7)	42 (5.7)	74.4 (8.6)	59.8 (3.1)
Bw	33	188.7 (7.3)	44.8 (5.9)	82.5 (9)	60.4 (3.7)
Po	742	193.3 (5.7)	51 (6)	85 (7.3)	64.3 (2.9)
Pw	137	175.6 (11.6)	49 (8)	84.6 (10.8)	62.8 (4.1)
Pj	1002	146.4 (12.2)	43 (6.5)	70.9 (7.7)	55.9 (2.9)
Pr	263	162.6 (11.3)	39.9 (5.5)	69.2 (7.7)	55.2 (2.8)
Sw	180	143.5 (18.5)	44.2 (9.7)	72.7 (12.3)	58.1 (4.7)
Sb	171	146.0 (15)	58.1 (11.8)	88.8 (12.9)	65.0 (5.3)
Pwe	79	181.9 (10.5)	66.9 (12.6)	99.9 (12.1)	69.2 (5.8)
Dead	96	143.4 (19.4)	87.7 (15)	102.2 (13.1)	76.1 (8)
Black Ash (Ab)	196	177.1 (8.8)	58.2 (10.3)	92.8 (11.5)	60.3 (3.8)
Larch (Lt)	219	170.1 (13.4)	56 (10.6)	91.7 (13.3)	64.7 (5.1)
Balsam Fir (Fb)	137	148.5 (18.6)	40.3 (9.9)	70.5 (11.6)	58.7 (4.9)

Table 2. Inbred ITC classification accuracy (i.e., test areas same as training areas) of 10 tree species (12 classes) as ITC percentages. The ITC classes are on the vertical axis, with the unclassified (UN) ITCs percentage reported within each test areas. The number of ITCs involved in each comparison (i.e., each test area) are on the bottom line.

Species	Mh	Ms	Or	Bw	Po	Pw	Pj	Pr	Sw	Sb	Pwe	Dead	
Mh	80.4	3.4	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	1.1	0.0	
Ms	4.1	41.5	5.8	12.2	0.5	0.7	0.0	0.4	0.0	0.0	2.2	0.0	
Or	0.0	13.6	62.0	2.4	6.3	3.4	0.0	2.2	0.0	0.0	0.0	0.0	
Bw	3.1	11.9	3.3	63.4	1.8	2.7	0.0	0.0	0.0	0.0	0.0	0.0	
Po	0.0	9.7	15.7	2.4	81.8	0.7	0.0	1.1	0.0	0.6	1.1	0.0	
Pw	1.0	2.8	0.0	2.4	1.2	66.4	0.0	0.4	8.3	0.0	12.1	0.0	
Pj	0.0	0.0	0.0	0.0	0.0	2.7	77.0	3.9	28.5	0.6	5.5	0.0	
Pr	0.0	2.8	2.5	0.0	0.9	2.1	8.5	81.4	1.0	0.0	4.4	0.0	
Sw	0.0	0.0	0.0	0.0	0.0	1.4	3.7	1.1	43.0	4.6	1.1	0.0	
Sb	0.0	0.0	0.0	0.0	0.0	0.7	0.2	0.0	5.2	80.6	0.0	2.6	
Pwe	0.0	1.1	0.0	0.0	0.1	8.9	0.9	0.7	2.6	1.1	57.1	0.0	
Dead	0.0	0.0	0.0	0.0	0.0	0.7	0.6	1.1	0.5	4.6	2.2	79.5	
UN	11.3	13.1	10.7	17.1	7.3	9.6	9.3	7.5	10.9	8.0	13.2	17.9	
ITCs	**97**	**176**	**121**	**41**	**762**	**146**	**1037**	**279**	**193**	**175**	**91**	**117**	**3235**

were combined into a generic Poplar class before comparing with our classification. For this comparison, ground reference trees (GRED) were manually delineated on the same the imagery and classified using the previous ITC generated spectral signatures. This was done to focus specifically on classification accuracy and avoid any confounding effects from the automated ITC delineation technique. To maximize consistency, a LIT mask was created for these manually delineated trees and applied during the classification process. The classification accuracy of the 6421 field assessed trees into the 10 species was 47.3% on average. The confusion pattern does not differ much from the previous assessment with ITCs (Table 2) and relatively pure test areas (Table 3), except that here we can better track the number of unclassified and dead trees, including the large number of black spruce classified as dead.

5.3 Species Composition Comparisons

For the 2007 forest inventory (FoInv07) stands for which a species composition is assigned, the ITC species composition, with species ranked by their crown closure within a stand, was on average 23% different, with 19% of the stands within 15% difference, 37%

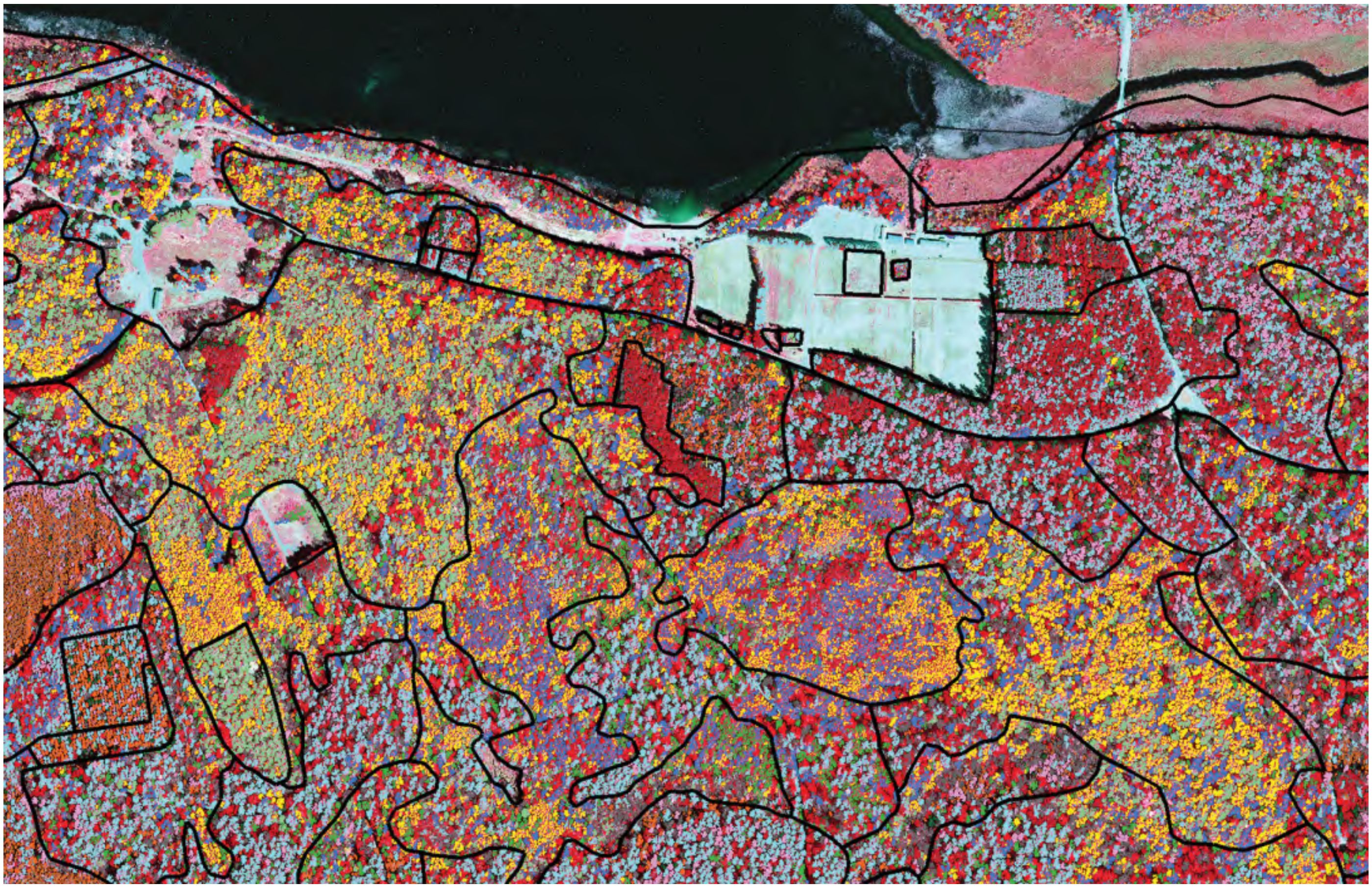

Figure 1. An Individual Tree Crown (ITC) classification with stand boundaries from a previous (2001) conventional forest inventory of a section of the Petawawa Research Forest, Ontario, Canada, overlaid on a colour-IR image. Species are: hard maple (Mh) in green, soft maple (Ms) in light green, red oak (Or) in red, white birch (Bw) in yellow, poplar (Po) in blue, white pines (Pw, Pwe) in cyan, jack pine (Pj) in white, red pine (Pr) in magenta, white spruce (Sw) in orange, black spruce (Sb) in brown, and dead trees in black.

Table 3. ITC Classification accuracy (%) of 10 species relative to field confirmed (but not necessarily single species) test areas: only the main species within the areas were compared. The dominant ITC classes are on the vertical axis. The dominant field species are on the horizontal axis. The number of test areas involved in each comparison are on the bottom line, for a total of 413 test areas. This led to an average Producers' accuracy of 48.2%.

	Mh	Ms	Or	Bw	Po	Pw	Pj	Pr	Sw	Sb	
Mh	58.0	15.6	3.4	11.8	0.8	0.0	0.0	0.0	4.8	0.0	
Ms	4.0	21.9	1.7	2.9	3.4	0.0	0.0	0.0	0.0	0.0	
Or	0.0	0.0	24.1	0.0	2.5	0.0	0.0	0.0	0.0	0.0	
Bw	12.0	18.8	0.0	8.8	0.8	0.0	0.0	0.0	0.0	0.0	
Po	4.0	15.6	53.4	44.1	75.6	3.6	4.5	8.0	4.8	0.0	
Pw	20.0	18.8	10.3	2.9	10.9	89.3	13.6	24.0	19.0	8.3	
Pj	0.0	0.0	0.0	0.0	0.0	0.0	59.1	20.0	4.8	4.2	
Pr	2.0	9.4	6.9	29.4	5.9	0.0	4.5	48.0	0.0	0.0	
Sw	0.0	0.0	0.0	0.0	0.0	0.0	18.2	0.0	9.5	0.0	
Sb	0.0	0.0	0.0	0.0	0.0	7.1	0.0	0.0	57.1	87.5	
Total	**50**	**32**	**58**	**34**	**119**	**28**	**22**	**25**	**21**	**24**	**413**

Table 4. Classification accuracy (%) of manually delineated tree crowns into 10 species classes (using the previous ITC spectral signatures) relative to their field confirmed tree species. The classes are on the vertical axis (Pw and Pwe combined), with the unclassified (UN) and dead percentage reported for each situation. The number of field trees involved in each comparison are on the bottom line. This led to an average Producers' classification accuracy of 47.3%.

	Mh	Ms	Or	Bw	Po	Pw	Pj	Pr	Sw	Sb	
Mh	69.7	17.2	0.2	11.1	0.3	4.0	0.0	0.4	0.0	0.0	
Ms	2.2	27.6	4.2	6.5	3.1	1.3	0.0	0.0	0.1	0.0	
Or	0.0	2.5	22.0	1.9	7.8	0.2	0.6	0.5	0.1	0.0	
Bw	9.6	22.7	5.8	5.6	2.9	0.2	0.3	0.0	0.0	0.0	
Po	1.3	11.7	60.8	37.3	59.2	0.4	0.0	1.6	0.2	0.0	
Pw	11.1	12.9	3.1	10.2	14.4	88.7	8.1	22.0	42.1	0.0	
Pj	0.0	0.0	0.0	0.0	0.2	2.0	53.6	17.6	3.3	0.0	
Pr	0.6	3.7	2.5	21.0	3.2	0.4	6.9	57.3	1.3	0.0	
Sw	0.0	0.6	0.0	0.0	0.2	0.9	29.6	0.5	17.1	0.0	
Sb	0.0	0.0	0.0	0.0	0.0	1.1	0.9	0.0	30.9	71.9	
Dead	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.9	26.8	
UN	4.5	1.2	1.4	6.5	8.7	0.7	0.0	0.1	2.8	1.3	
Total	**314**	**163**	**554**	**324**	**1953**	**452**	**334**	**1279**	**824**	**224**	**6421**

within 20% difference, and 65% within a 25% difference (measured by our Euclidean distance). Also, the main species (or working group species) was exactly the same 43% of the time relative to FoInv07. When the main species is the same, its percentage of crown closure is within 10% of the working group species presence 31% of the time, within 20%, 58% of the time and, within 25%, 67% of the time.

For stands where the main species is judged not to be the same, another 5% of stands are within 10% (by crown closure) of qualifying as having the same main species and, 8% of the stands are within 20% of qualifying. In other words, if we allow ±10% of leeway on the ITC species composition, the working group could be judged the same 48% (43%+5%) of the time; if we allow ±20% of leeway then, the working group could be judged the same 51% (43%+8%) of the time. Of course, this is assuming that interpreters are correct about main species 100% of the time, which is known not to be the case (see discussion section).

5.4 Volume Results

5.4.1 Species volume equations

From a database of 2000 trees for which we have species, height and DBH, standard species-based volume equations (V=f(HT,DBH)), Honer et al. 1983) were used to calculate individual tree volumes. For each species, these volumes were plotted as a function of height alone (e.g., Figures 2 and 2b), leading to relationships of the type V=f(HT), that can be applied to the ITCs for which we only have species and height. Matching the data better, exponential relationship were preferred (Table 5). These inference equations were used to calculate individual tree volumes and aggregated them to stand volumes in our ITC analyses.

To verify the appropriateness of these equations, they were applied to recalculate volume for the field trees they originally came from. Table 6 coveys the average volume (and standard deviation) from the conventional equations and the same statistics for the inferred volumes. In addition, the table gives the average error (in %) and the root mean square error (RMSE) of the fitted models for each species under consideration. The right hand section of the table reports on the slope (and R^2) when the volumes inferred from height alone are compared with Honer's conventional volumes. In general, plotting all the volumes from the newly generated equations (V=f(HT)) versus the volumes generated with the conventional equations (V=f(HT, DBH)) led to a linear relationship (R^2=0.35), where the new equations "generally" underestimated volume by 18% (Figure 3).

5.4.2 Stand volume comparison

Within the ITC Suite, the standard program for reporting information by forest stand (ITCPCD) reports among other things, an ITC (isols) count and an average height for each species. Using our species-based volume equations (V=f(HT)) on that average height and multiplying by the number of ITCs of that species, one can infer the volume of each species within a stand and combine them to get a stand volume (PCD_Vol). The resulting stand volumes were only 24% (R^2=0.60) of the 2001 forest inventory volumes (Figure 4a).

In our second approach, the individual volume (ITC-IV) of each individually detected tree (ITC or isol) was determined from its species and its individual height and then, summarize for each species and each stand. Using this approach, volume is at 39% (R^2=0.627) of the 2001 forest inventory volume (Figure 4b). Thus, doing volume calculations almost tree by tree and using specific heights for each of 6.6 million isols appears better than using species-related ITC counts and their average heights. However, this volume assessment still seriously underestimates relative to the conventional forest inventory assessment.

In our third estimation (ITC-IV Adj. Vol.), we took into consideration that some detected objects (isols) may represent more than one

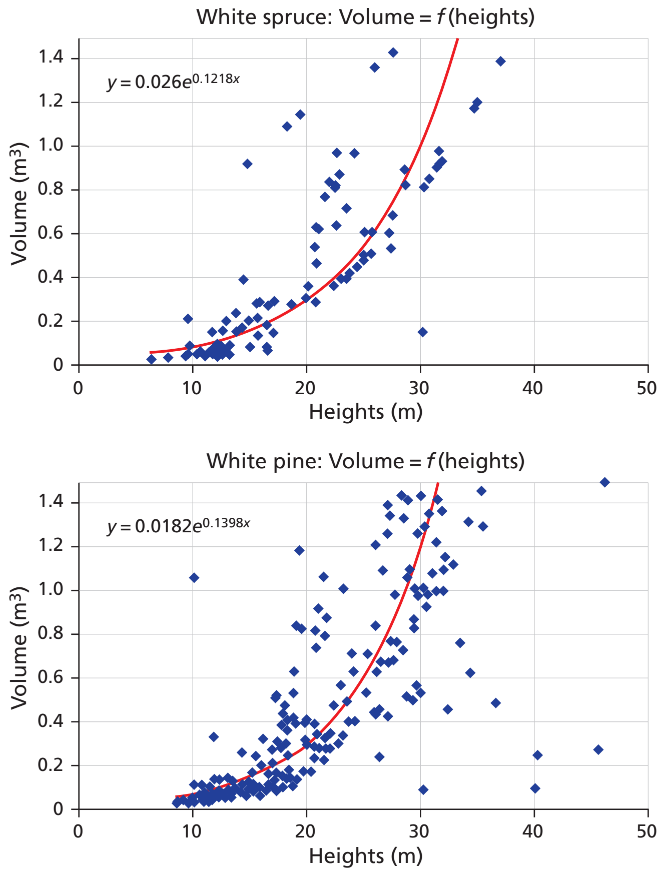

Figure 2. For field measured trees, individual tree volumes were calculated with standard species equations (V = f(HT, DBH)) and then plotted as a function of height alone to get equations of the type V = f(HT). Here as examples, for 93 white spruce trees (a), this led to the inference equation: Volume = 0.026 × Exp (0.12 × height); for 339 white pine trees (b), this led to the inference equation: Volume = 0.018 × Exp (0.14 × height).

Table 5. Equations for volume from heights alone (V = f(HT)) were created (see examples in Figure 2) from a database of field trees for which we have species, heights, and DBHs. This table shows for each species, the number of field trees involved, their average volume and the inference equation for volume as a function of height only.

Species	**No. of trees**	**Honer's av. vol. (m^3)**	**Inference equations V = f(HT)**
Balsam Fir	244	0.104	0.0107 × EXP (0.149 × HT)
Black Spruce	44	0.264	0.0061 × EXP (0.193 × HT)
Jack Pine	301	0.339	0.0693 × EXP (0.072 × HT)
Larch	20	0.241	0.0016 × EXP (0.253 × HT)
Red Oak	38	0.350	0.0108 × EXP (0.124 × HT)
Red Pine	564	1.366	0.0113 × EXP (0.162 × HT)
Soft Maple	123	0.201	0.0083 × EXP (0.154 × HT)
Sugar Maple	69	0.366	0.0033 × EXP (0.208 × HT)
Trembling Aspen	53	0.661	0.0098 × EXP (0.161 × HT)
White Birch	44	0.328	0.0125 × EXP (0.146 × HT)
White Pine	339	1.464	0.0182 × EXP (0.140 × HT)
White Spruce	93	0.506	0.0260 × EXP (0.122 × HT)

physical tree. We used the "crown area based" adjustment factor described above in an attempt to correct this issue. The new stand volumes are now assessed on average at 104% (R^2 = 0.60) of the 2001 forest inventory volumes (Figure 4c).

5.4.3 Possible effects on volume of height measurement mispositioning

Two tests were done to assess the effect of position differences between a LiDAR generated digital canopy model (DCM) and ITCs generated from aerial imagery. In the first test, the trees from the digital canopy model were reprojected to look like that of an aerial

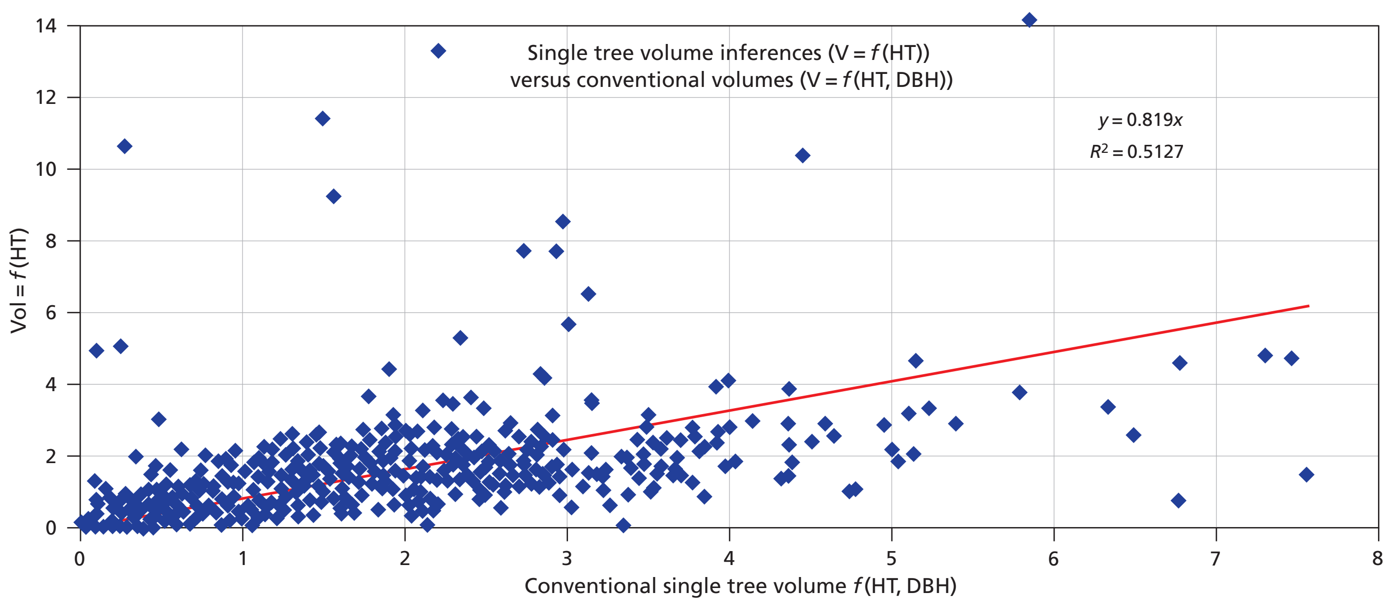

Figure 3. Volume inferences as function of only species and heights (Vol = f(HT)) relative to traditional volumes (Vol = f(HT, DBH)) for 2 000 field trees for which we have species, height and DBH.

Table 6. Using the database of field trees for which we have species, heights and DBHs, we assess the errors of the volumes from the newly generated equations (V = *f*(HT)) versus the volumes generated with the conventional equations (Honer's, V = *f*(HT, DBH)) for each species under consideration. The table reports the number of field trees involved, volumes (and standard deviations) from both equations, the different in percentage and the RMS error. The right hand section reports the slope and R^2 when the volumes inferred from height alone are compared with Honer's volumes.

Species	Number of trees	Honer's average vol. (and std. dev.) (m^3)	Inferred average vol. (and std. dev.) (m^3)	Difference (%)	RMSE (m^3)	Slope	R^2
Balsam Fir	244	0.104 (0.067)	0.099 (0.065)	–4.41	0.060	0.84	0.4
Black Spruce	44	0.264 (0.149)	0.254 (0.139)	–3.80	0.080	0.92	0.65
Jack Pine	301	0.339 (0.166)	0.307 (0.049)	–9.47	0.159	0.75	
Larch	20	0.241 (0.174)	0.220 (0.116)	–7.22	0.113	0.79	0.3
Red Oak	36	0.054 (0.012)	0.053 (0.019)	–1.85	0.054	1.03	0.50
Red Pine	564	1.366 (0.924)	1.249 (0.781)	–8.57	0.800	0.78	0.16
Soft Maple	119	0.153 (0.106)	0.147 (0.079)	–3.92	0.079	0.84	0.31
Sugar Maple	69	0.366 (0.798)	0.417 (1.707)	13.81	1.04	1.79	0.79
Trembling Aspen	53	0.661 (0.548)	0.631 (0.594)	–4.60	0.41	0.89	0.53
White Birch	44	0.328 (0.250)	0.298 (0.224)	–9.09	0.21	0.78	0.28
White Pine	339	1.464 (1.558)	1.414 (2.512)	–3.44	2.25	0.85	0.21
White Spruce	93	0.506 (0.469)	0.496 (0.630)	–1.93	0.39	1.01	0.61

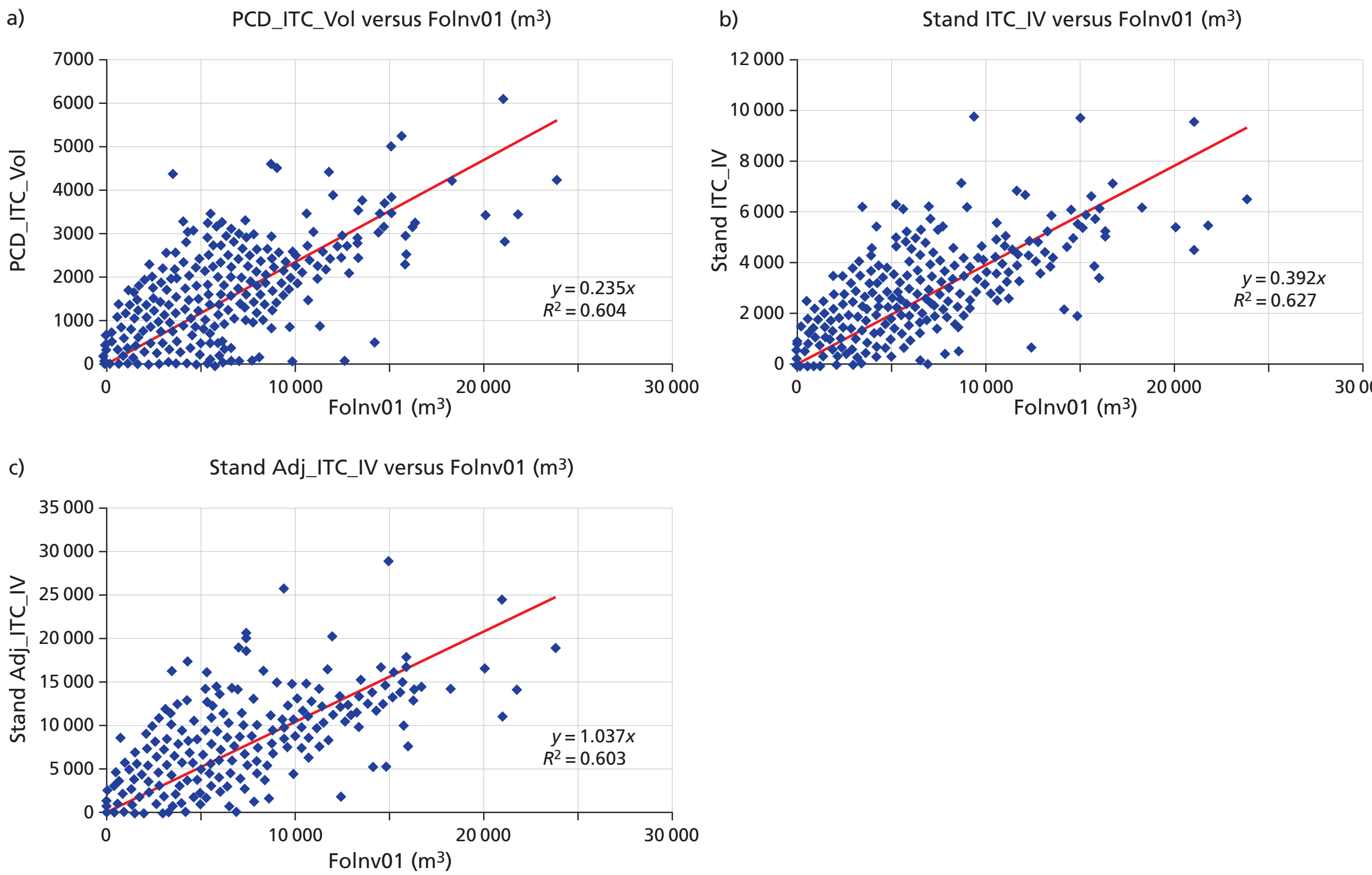

Figure 4. ITC-based volumes relative to 2001 conventional forest inventory volumes (FoInv01) for each stand: (a) ITC-based volume is calculated using our species-based volume equations (V = *f*(HT)) applied to an average species height for that stand and multiplied by the number of ITCs (or isols) for that species within that stand, as provided by the ITCPCD (ITC-Suite's Polygon Content Description) program; (b) ITC-based volume is calculated using classified individual trees (ITCs or isols) and their corresponding species equations (V = *f*(HT)) applied to each individual object (ITCs or isols) top height and summarized by stand; (c) ITC-based volume is calculated using classified individual tree objects (ITCs or isols) and appropriate species equations (V = *f*(HT)) and a crown-area-based multiplicative factor to calculate more appropriate volumes for tree clusters or crown segments, summarized by stand.

image (here, for a single flight line) by taking both DCM heights and aerial view angles into account (Figures 5 and 6). Visual inspection confirmed that the max height positions from this new data set were very close to that of the tree top in the real imagery (Figure 7). Analysis of stand average ITC heights acquired before and after such reprojection led to only a 1% difference, indicating that misalignment of the DCM with the imagery may not have an important effect on volume here, at least at the stand level. Of course such tests are only possible on the original flight lines for which nadir location and thus off-nadir angles are known (i.e., not on a complex mosaic).

In another test, ITCs were delineated on the smoothed near-infrared image generated from the PPC dataset which has good co-location with the Digital Canopy Model generated from the LiDAR data. The heights gathered within these ITCs were compared with the heights from our conventional process, both using the same LiDAR generated DCM (Figure 8). At the stand level, the average ITC heights differed by 2.1% on average. Also, as another point of comparison, the heights from these newest ITCs were at 0.88 of the forest inventory heights, while the heights gathered from the conventional ITCs were at 0.86 of the forest inventory heights, underestimating heights only a bit more. Similarly, when these two LiDAR-generated heights are compared with field measured heights at the plot level, the PPC-ITC heights are 0.821 (R^2=0.61) of the field heights, while the aerial ITC heights are at 0.819 (R^2=0.76). Thus, potential position differences between crowns (ITCs/ISOLs) extracted from aerial imagery and the LiDAR generated DCM does not appear to affect heights significantly (at stand or even plot levels) and should not constitute a large source of error in our volume estimates.

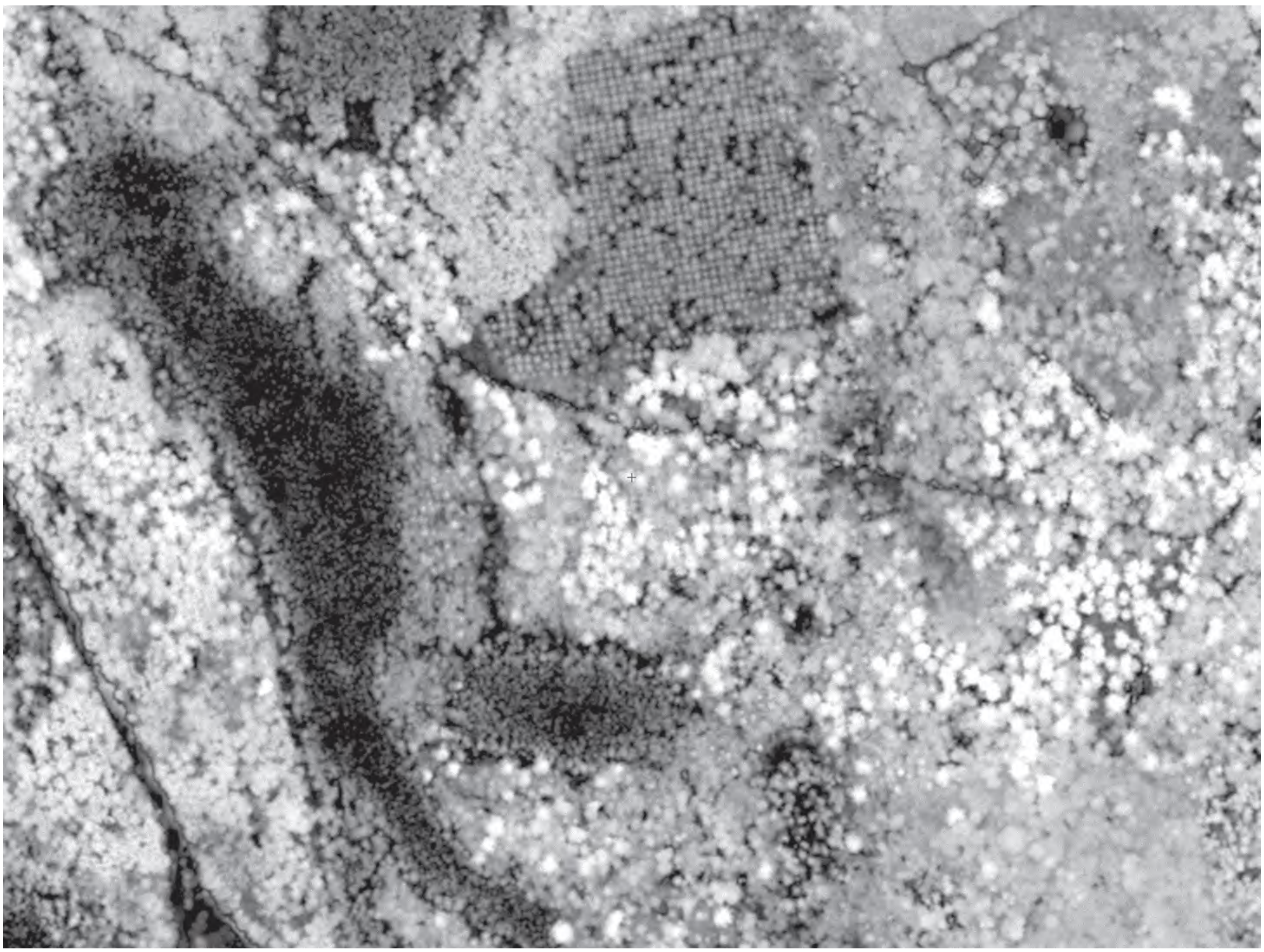

Figure 5. Digital Canopy Model generated at 40 cm/pixel from the 2012 LiDAR first returns.

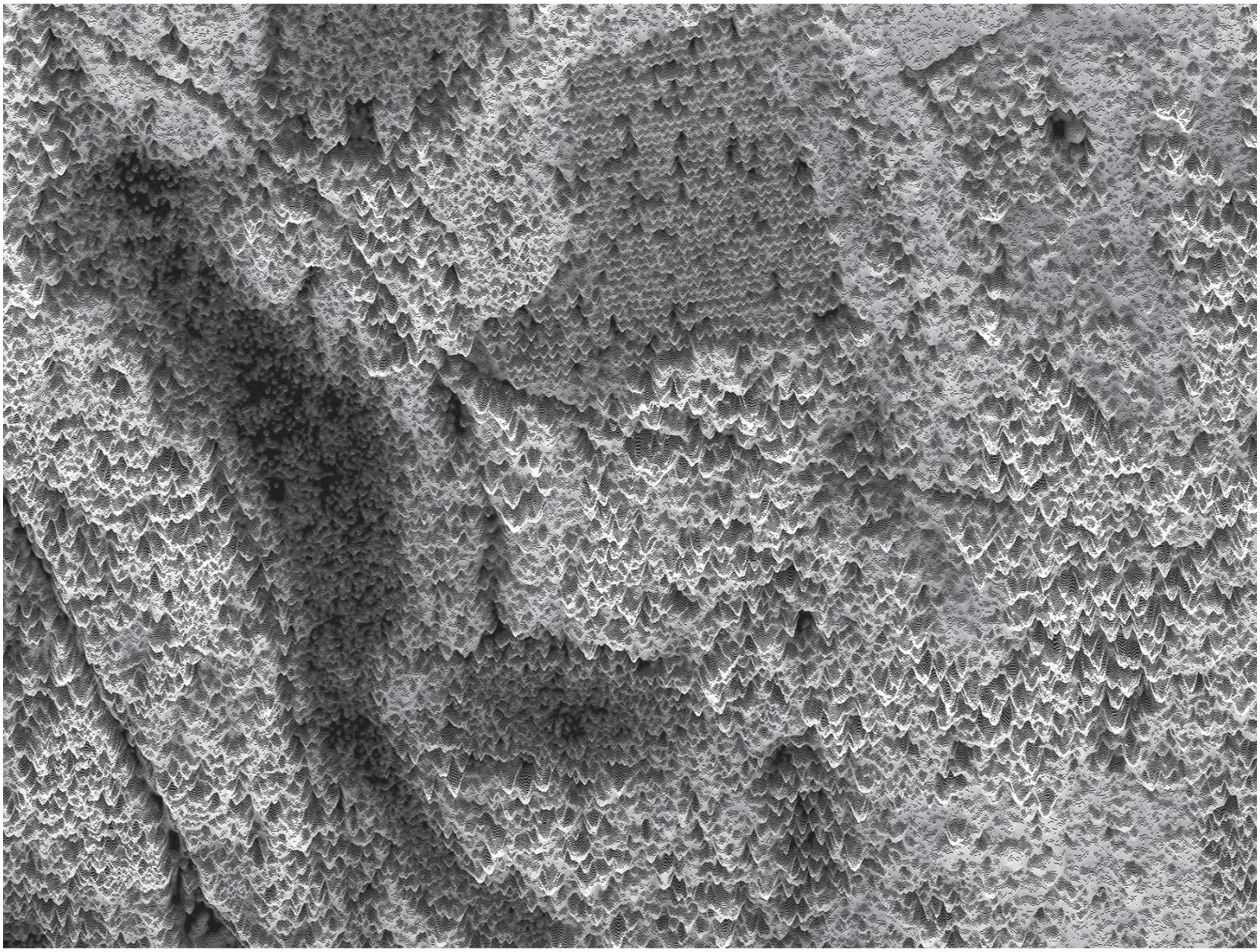

Figure 6. LiDAR-based Digital Canopy Model (from previous figure) reprojected using heights and aerial view angles such that trees have the same look and location as on the aerial flight lines and thus presumably, leading to more meaningful pickup of maximum tree height underneath ITCs from the multispectral aerial data.

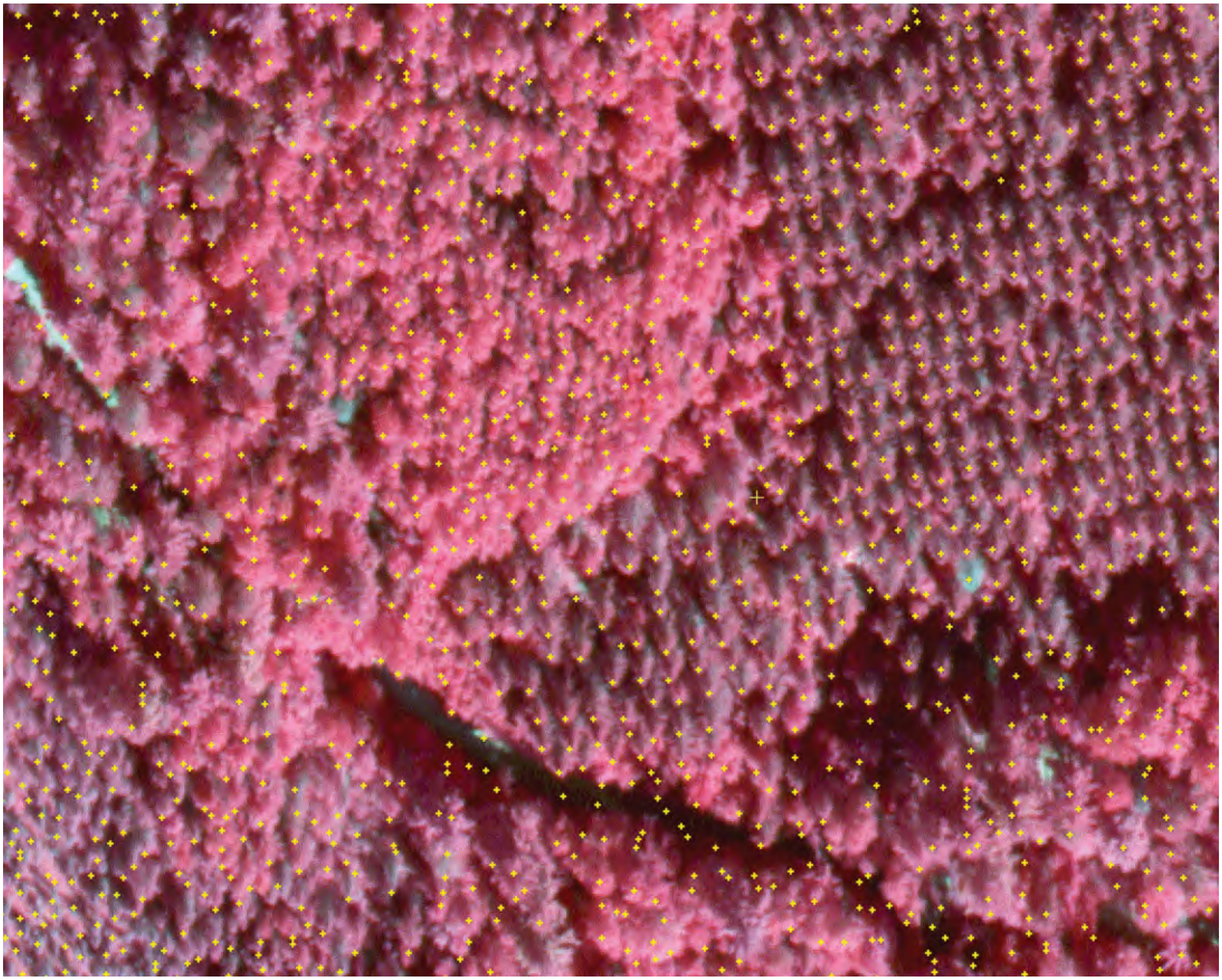

Figure 7. Maximum heights from reprojected LiDAR-based Digital Canopy Model (from previous figure) appears to correspond well with the top of trees in the aerial image and should lead to more precise height acquisitions.

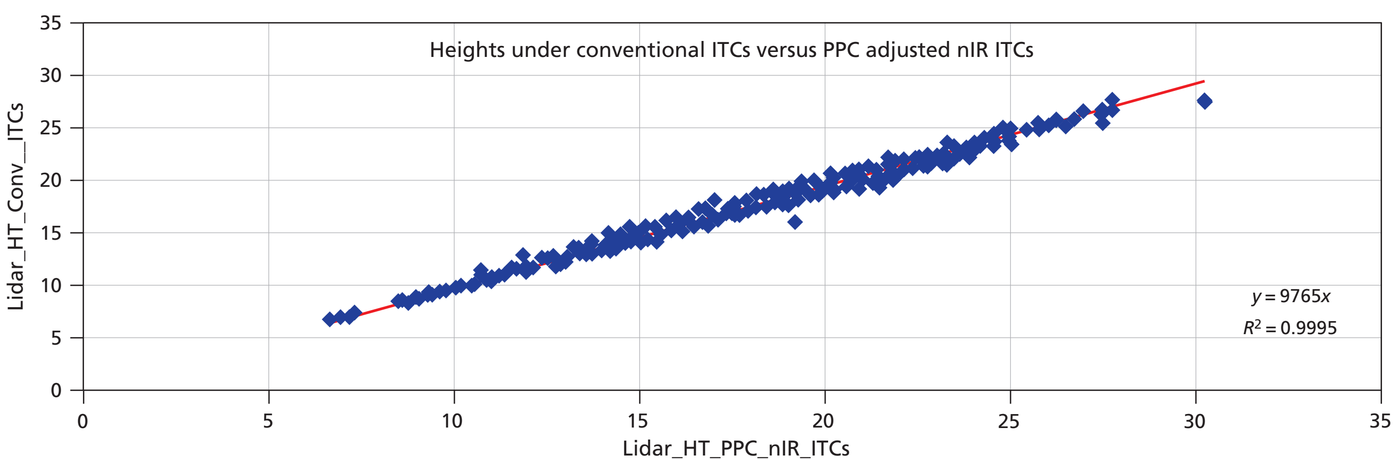

Figure 8. Maximum heights under our conventional ITCs (isols) relative to maximum heights under the ITCs (isols) from the photogrammetric point clouds (PPC) adjusted nIR image, both gathered from the same LiDAR-derived Digital Canopy Model and averaged at the stand level.

6 Discussion

6.1 Species Signature Separation

Although useful in a fast turn-around analysis process to see if a newly added species is somewhat separable, inbred confusion matrices (Table 2) usually convey an overly optimistic view of classification accuracy (here ~75%, for 10 species, Pw and Pwe combined). They can be viewed as an analysis of potential signature separation. It permits the testing of various situations (mature, immature, dense, brightly illuminated, etc.) to see if distinct classes are needed, as seen here with the use of an "emergent white pine" class (Pwe). However, sometimes such additional classes add more confusion to the analysis. After several iterations, we restricted our analyses to the 12 classes (10 species) seen in Table 2, as they appear to offer reasonable spectral separation and constitute most of the dominant species of the PRF. Missing from our analyses due to poor separability are balsam fir, black ash and yellow birch, which cover approximatively 4%, 3%, and 2% of the PRF area, respectively.

6.2 Classification Results

In image analysis, assessing classification accuracy is often done with the delineation on the screen of relatively pure testing areas, generally done using the same process (and at the same time) as the delineation of the training areas. If possible, comparing species classifications with assessments on the ground is usually considered more appropriate. However, assessments using typical small field plots can be problematic because of plot boundary issues and crown (single or aggregations) assignments to such plot area. Comparing with bigger areas on the ground (or stands from an existing forest inventory) can alleviate some of these problems, but since they are not totally pure test areas, one may be forced to compare whether the main species was detected as main species (e.g., Table 3).

Except for white spruce (9.5%), most softwoods classify relatively well, although red pine (48%) had a lot of confusion with both white and jack pine. White spruce is mostly classified as black spruce, to which it is close spectrally, but black spruce has a tighter signature. For the hardwoods, only hard maple and poplar classify well. They are both at the high end of the spectrum in nIR (~193), but quite distinct from each other in the other bands (see Table 1). Soft maple, red oak and white birch are all spectrally close to one another (within one standard deviation), leading to confusion among them. However, trees of these species get mostly classified as poplar due to its overlapping but narrower signature.

Our study site has the luxury of a substantial dataset of tree crowns manually delineated on the image with their species assessed on the ground. Using these could be considered the most appropriate way of testing our classification results (Table 4). However, there are still a few considerations. Compared to using ITCs, recognizing the species of these trees may benefit from the better manual crown delineation carried out. On the other hand, we are classifying manually delineated tree crowns, but the signatures used for the classification were generated from ITCs, which may include a different quantity of shaded pixels at their boundaries. The pattern of strongly and weakly classified species appear the same as for test areas (Table 3), for an average species accuracy of 47.3% for ten (10) species. In both cases, the classification of some species appears extremely poor.

To put these results in perspective, the more precise analysis of the Petawawa Research Forest which used 22 class signatures generated from these "manually delineated field verified trees" and signature refinements using manual outlier removal, achieved 59.3% accuracy when summarized for 14 species and 65.8% accuracy when summarized for 11 species (Table 10 in Leckie et al., 2017). Low classification accuracies were also encountered with several species, notably, red oak, white birch, aspen, and one maple class. Classification of numerous species, even under the best of circumstances, is always challenging.

The similarity of results in Tables 3 and 4 suggests that looking at the main species of simple test areas, relative to using field verified individual trees, can provide a good estimation of species classification accuracies. However, the use of field verified individual trees at the training stage of the classification appear to be important for separating more species with a higher degree of precision and accuracy (Leckie at al., 2017). On the other hand, these improved results were also assisted by the use of additional breakdowns of species into several sub-classes (e.g., bright, normal), where 22 classes were used to analyse 14 species, involving a considerable quantity of work.

Although using field verified individual trees will always be the preferred method of assessing an individual tree classification, using test areas and concentrating on the main species may be sufficient for operational purposes (i.e., similarity of Tables 3 and 4).

6.3 Species Composition Results

The ITC species composition, with ITC species ranked by their crown closure within a stand, was found to be 23% different on average from that of the 2007 forest inventory, with 65% of the stands within 25% overall difference. Also, the main species was the same 43% of the time and if we allow a 20% leeway in possibly considering the 2nd species as main, the main species could be judged the same 51% of the time. This level of accuracy is similar to photo-interpreted inventory accuracy.

In Ontario, a study validating species composition (Pinto et al., 2007) reported a match of the order of 55% relative to field data gathered for 136 stands. Thompson et al. (2007) reported that species composition were considered "incorrect" 64% of the time, with 30% of stands misclassified even at the broader level of softwood, hardwood or mixedwood. Common boreal species like jack pine, black spruce, and trembling aspen were incorrectly recognized half of the time. An audit in British Columbia reveals that "at best" a leading mature species is assess correctly 84% of the time, at worst 32%, with a median result of 51% (Gilbert, 1998). An assessment of the effects of scale in soft-copy interpretation reveals that as scale is changed from 1:15000 to 1:20000 to 1:30000 the probability of correctly identifying the leading species decreases from 0.73 to 0.65 to 0.60 (Penner, 2008). In Quebec, even single species stands were said to be difficult to assess. Pure stands of black spruce, fir, jack pine, and cedar, were correctly identified 76%, 60%, 65%, and 55% of the time, respectively. On the hardwood side, pure stands of maple, yellow birch and poplar were correctly identified 53%, 40%, and 50% of the time. (Commission, 2004). Using a ±20% criterion similar to this study, Cloney and Leckie (1995) found species accuracy in New Brunswick to be around 67%.

Another way to put our results into perspective is to look at the more precise analysis of the Petawawa Research Forest (Leckie et al., 2017) using similar criteria. Using our distance metric, a species composition comparison with the 2007 forest inventory leads to an average distance of 13%, with 69% of stands within a 15% difference and 95% of stands within a 25% difference. This suggests that although our results are similar with results achieved using conventional interpretation, a more sophisticated ITC analysis can get better results. Indirectly, this comparison also gives credence to the 2007 forest inventory itself (our reference dataset), as very similar species compositions were obtained independently in completely different ways.

6.4 Volume Results

6.4.1 Species volume equations

Inferences of volume as a function of height only can frequently produce reasonable results. Indeed, for many species, height is the dominant factor in their volume equation, with DBH explaining a small part of the variance. Generally speaking, this is often the case for conically shaped softwood trees, less often the case for hardwood trees, and even less often the case for open grown trees. As seen in Figure 3, for the 2 000 field trees for which we have calculated volume the conventional way, the relationship with volume based on height alone has an R^2 of 0.51, without any outlier removal. With some outlier removal, the relationship has an R^2 of 0.62. However, the new volume equations still appear to underestimate volume by 18%.

On a species by species basis, most coniferous species appear to convey between 0.75 to 1.01 of the volume compare to the conventional volume equations (slopes in Table 6), with relationship that are more or less solid (varying R^2). However, some R^2 variations depend on the presence of outliers, others on a narrow range of sample trees. For hardwoods, some relationships appear well behaved, for example aspen, white birch and red oak, conveying 0.89, 0.78, and 1.03 of conventional equation volume, while others, sugar maple (1.79), appear to lead to serious departures from the estimates produced by the conventional volume equations. For most species, the new volume equations tend to underestimate. A separate analysis reveals that the volume of some species, like red pine and jack pine, may benefit from equations using crown areas, with or without heights.

6.4.2 Stand volume comparison

In our first comparison (Figure 4a), we used the average height of a given species within a stand to infer the volume of an average tree for that species and multiply by the number of ITCs (isols) of that species within the stand, then summarized for all species in the stand. The resulting volumes were surprising low relative to the reference forest inventory volumes. Our volumes are obviously based on the dominant and codominant trees visible from the air (i.e., not all trees); unclassified trees (~16%) are not considered; and, we know that our equations tend to underestimate volume by 18%. Even so, we did not expect these volumes to be so low (i.e., 0.24 of FoInv01). It appears that simply using average species heights within a stand is not very useful. Presumably, because our volume relationships ($V = f(HT)$) are better fitted by exponential curves, the volume of tall trees get underestimated when averages are used and thus, so does the volume at the stand level.

In our second comparison, individual heights and species were used for each of 6.6 million ITCs (isols) to calculate individual tree volume and accumulate them within a stand. This led to a slightly better assessment of volume at 0.39 of FoInv01 volume (Figure 4b). However, this is still very low. Presumably, not taking into consideration that some isols are tree clusters has an important effect on volume assessment at the stand level.

Finally, taking into consideration that some isols are tree clusters rather than individual trees and applying a crown-area based correction factor to each isol produced stand volumes that are 1.04 times that of the 2001 forest inventory volumes (Figure 4c). This is very close. Possibly, the difference in time (i.e., the tree growth) between the 2001 forest inventory (done with even earlier photos) and the 2012 LiDAR heights could be responsible for a 4% increase in volume. However, it is unlikely to be that simple, especially when we know that our volume equations tend to underestimate the volume (by ~18% as per Figure 3). One possible reason for such ITC-based volume overestimation is that when trees are seen at wider view angles, their crown suffers an apparent stretching, and thus, a volume correction factor based on crown area (meant to compensate for clusters) could overestimate volume. And finally, we do not have an estimate of the error for the 2001 conventional volume assessment, which could easily be in the 10–20% range, nor do we have an estimate for our margin of error.

6.4.3 Possible effects on volume of height measurement mispositioning (LiDAR vs aerial images)

As mentioned, DCMs generated from LiDAR points always present all trees as seen from above, often as a fairly round object, especially in the case of compact coniferous trees. Picking up a max height within such an object has a high probability of corresponding to the true tree top, and relating well to the real tree height (even for hardwood trees). On the other hand, picking a maximum height from a DCM image underneath an ITC created from aerial image analysis may not correspond to the height of that specific tree for large view angles. Here, with flight line overlap, the mosaic is mostly made of data spanning ±24° off-nadir, possibly putting the "apparent" tree top position of a 20 m tree off by 8.9 m, at the extreme. This may place DCM height acquisition off the target tree, as theoretically, it should be pointing more to its base than its top. However, since trees seen off-nadir tend to seriously overlap, that particular height has a high probability of being associated with a neighbourhood tree and is thus, unlikely to return a ground or shrub height. The effect should thus be minimal.

Two tests were carried out to ascertain whether this effect should be an important consideration. The tests reported an overall 1–2% difference in heights when summarized at the stand levels, a change unlikely to have a significant effect on ITC-based volume, specially compare to other effects reported here.

6.4.4 ITC volume – other considerations

When assessing ITC volume at the stand level, an issue when using species-specific volume equations is what to do with the unclassified ITCs, which can constitute up to 10% of all trees. Here, unclassified ITCs represented 8.4% of all detected trees and were not considered in our volume assessment. One could use a generic volume equations (softwood, hardwood) for these, but Tompalski et al. (2014) suggest that using volume equations for the wrong species is better than using a generic one. Of course, one could just force the ITC classification to classify 100% of the trees, specially knowing that misclassified (unclassified) trees will often be classified to a fairly similar species. However, one may not want to do a different classification just for volume assessments.

A related concern is whether dead trees and snags should be considered. Here, dead trees were 3.2% of all classified ITCs. Dead trees are sometimes considered when estimating volume at the stand level. Here, looking at the imagery and our confusion tables (mostly Table 4), it could be that a significant number of dead ITCs are misclassified live black spruce. Again, from a volume assessment point of view, it may be better not to have a dead tree class at all and enforce a 100% classification. However, dead trees are important to consider for many inventory applications, such as habitat assessments, fuel characterization and biomass or carbon estimation.

7 Summary and Conclusion

Individual tree crown based forest inventories aim at improving the precision, accuracy, timeliness, completeness and cost-effectiveness of forest information at the local and regional levels. Here, we presented a simple ITC classification into ten species of a complex forest covering 30×11 km^2 using a mosaic of multispectral aerial data at 40 cm/pixel. The ITC species classification was done using training areas simply acquired by image interpretation, informed by two previous conventional forest inventories. Species accuracies were assessed and stand species compositions compared with that of an existing forest inventory. Individual tree volume inferences based only on height were derived, tested, and applied to the whole area using a LiDAR-based digital canopy model. In our better volume assessment, a heuristic based on crown area was used to compensate for the fact that many of the ITC detected are in fact tree clusters.

The results of our simpler ITC classification were not as good as that of the more sophisticated one where signatures had been generated from field verified trees, with outliers removed and taking special viewing situations (e.g., bright, shaded, etc.) into consideration (Leckie et al., 2017). With our simpler, yet more operational approach, species spectral signature overlaps made it difficult to classify ten species. Nevertheless, the ITC species composition was considered only 23% different on average from that of the 2007 forest inventory, with 65% of the stands within 25% overall difference. We have shown that a relatively decent ITC classification of a simple mosaic is possible with species composition differences with a typical forest inventory that are probably of the same order as between two interpreters.

For our volume assessments, we have verified that the mispositioning of aerial image tree crown relative to the LiDAR DCM was not critical, at least at the forest stand level. This is probably due to the mosaic being built mostly from flight line centres, as it should be. A reasonable comparison was achieved at the stand level, with ITC stand volumes at 1.04 times that of the 2001 forest inventory volumes, but only after a heuristic based on crown area was used to compensate for the fact that many of the ITC delineated are in fact tree clusters. This seems to agree with (Tompalski et al., 2014) and (Vastaranta et al., 2011) who concluded that among all of the factors considered to influence volume prediction accuracy, the tree detection rate remains the most important. Research to improve crown delineation (Leckie et al., 2016a, b, c) may lead to improvements in volume assessments, but there are limits to what can be achieved in that regard. Thus, such “crown area based” heuristic may still be of use in the future. It should be noted that such heuristic could also be applied to individual tree-based biomass and carbon assessments.

For their present forest management inventory cycles, most provinces in Canada are acquiring stereo coverage using high spatial resolution multispectral aerial sensors, but are still relying mostly on an image interpretation process. Given the growing availability of automatic stereo disparity height information from such imagery and given a precise enough digital terrain model (often based on one previous LiDAR data acquisition), precise forest height information can be gathered. In addition, photogrammetric point clouds (PPCs) can be generated and area-based analyses similar to those done with LiDAR data can be run successfully (White et al., 2015; Pitt et al., 2014), providing a slew of forestry information at a spatial resolution typically commensurate with that of plot sizes (e.g. 20×20 m^2). Photogrammetric point clouds can also provide high spatial resolution raster datasets where height and multispectral information are co-located and properly positioned in 3D space. Applying our techniques of semi-automatic computer analysis at the individual tree level to these could lead to species and volume assessments of “properly positioned trees.” This would result in an individual tree forest inventory (i.e., a GIS coverage) where every tree crown would consist of a properly positioned polygon with attributes such as: species, height, crown area, volume, biomass, carbon, etc. providing detailed information closer to what is needed by operational inventories.

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