

Issues in species classification of trees in old growth conifer stands

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Abstract. Old growth temperate conifer forest canopies are composed of assemblages of tree crowns that vary by species, height, size, and intercrown distance. The challenge this complexity presents to species classification is formidable. In this paper we describe the exploration of spectral properties of old growth tree crowns as captured on two independent acquisitions of 0.7 m ground resolution compact airborne spectrographic imager (CASI) airborne multispectral imagery. Underlying spectral separability is examined, and classifications of manually delineated crowns are compared against field-surveyed ground truth. Technical issues and solutions addressing individual tree species classification of old growth conifer stands are discussed. The study site is a western hemlock, amabilis fir, and red cedar dominated old growth area on Vancouver Island on the west coast of Canada. Within-species spectral variability is large because of illumination and view-angle conditions, openness of trees, natural variability, shadowing effects, and a range of crown health. As well, spectral differences between species are not large. An object-oriented illumination and view-angle correction was effective at reducing the effect of view angle on spectral variability. Radiometric normalization between imagery from flight lines of the same site and time period was successful, but normalization with data from other sites and days was not. The use of spectral samples from sunlit areas of the tree crowns (mean-lit signature) produced the best spectral separability and species classification. Because of the wide within-species variability and spectral overlap among species, it was also found useful to create internal subclasses within a species (e.g., normal and bright crowns). It was not feasible to consistently classify species of shaded crowns or stressed trees, and it was necessary to create overall shaded tree and unhealthy classes to prevent these trees from corrupting the final species classification. Classification results also depend on the visibility of trees in the imagery. This was demonstrated by different visibility and shade conditions of trees between the two image dates. This effect is particularly strong in old growth stands because of variations in stem density and spacing and the range of tree heights and sizes. Old growth stands will have shaded, unhealthy, and visually or spectrally unusual trees. Excluding these and considering species classification of manually delineated trees of the normal and bright spectral classes, modest success was achieved, in the order of 78% accuracy. Hemlock and balsam were confused, and cedar classification was mostly confused by the presence of unhealthy trees. If speciation of shaded and unhealthy trees was required, overall species classification was weak. It was shown, however, that shaded and unhealthy trees could be identified well using a classification with shaded and unhealthy classes. Species classification of the remaining trees, including the unusual trees, was 67% for the 1996 imagery and 77% for the 1998 imagery. Despite the difficulties in classifying species in an old growth environment, practical solutions to issues are available and viable spectral classifications are possible. Fully automated species isolation and classification add further complications, however, and new approaches beyond simple spectral techniques need to be explored.

Résumé. Le couvert des vieux peuplements de conifères en zone tempérée se compose d'un assemblage de cimes d'arbres qui varient en espèce, en hauteur, en grosseur et en espacement. Le défi que présente cette complexité pour une classification par espèces est formidable. Dans cet article, nous décrivons l'exploration des propriétés spectrales des cimes d'arbres d'un vieux peuplement tel que captées par deux acquisitions indépendantes d'images multispectrales d'une résolution au sol de 0,7 m du capteur aéroporté CASI (« compact airborne spectrographic imager »). Leur séparabilité spectrale inhérente est examinée et des classifications de cimes délinéées manuellement sont comparées à une vérité acquise lors d'observations sur le terrain. Les enjeux et solutions techniques s'adressant à la classification en espèces d'arbres de vieux peuplements sont discutés. Le site d'étude provient de vieux peuplements sur l'île de Vancouver sur la côte ouest du Canada dominé par la pruche de l'Ouest, le sapin gracieux et le thuya géant. La variabilité spectrale à même chaque espèce est grande dû aux angles d'illumination et de visé, l'ouverture du couvert, la variabilité naturelle, les effets d'ombre et une gamme de mauvaises conditions des cimes. De plus, les différences spectrales entre les espèces sont plutôt faibles. Des corrections par objets pour les angles d'illumination et de visé furent efficaces pour réduire les effets de l'angle de visé sur la variabilité spectrale. Une normalisation radiométrique des images entre les lignes de vol d'un même site prises à la même période fut couronnée du succès, mais la normalisation avec des données provenant d'autres sites ou d'autres journées ne le fut pas. L'utilisation d'échantillons spectrales provenant de la zone éclairée des cimes d'arbres (moyenne du côté éclairé) a

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produit la meilleure séparabilité spectrale et classification par espèces. Dû à une large variabilité spectrale à même chaque espèce et au chevauchement spectral entre les espèces, il s'avéra utile de créer des sous-classes pour chaque espèce (p. ex., cimes normales, cimes brillantes). Il ne fut pas possible de classer avec uniformité les espèces des cimes ombragées ou des arbres stressés. Il fut donc nécessaire de créer des classes génériques d'arbres ombragés et d'arbres stressés pour prévenir une corruption de la classification en espèces par ces arbres. Les résultats de classification dépendent aussi de la visibilité des arbres dans les images. Ceci fut démontré avec des conditions de visibilité et d'ombrage différentes entre les arbres de deux images de dates différentes. Cet effet est particulièrement prononcé avec les vieux peuplements dû aux variations de densité et d'espacement, et à la gamme de hauteur et de grosseur d'arbres. Les vieux peuplements auront toujours des arbres ombragés, malades, et visuellement ou spectralement inusités. En excluant ceux-ci et en considérant seulement une classification par espèce d'arbres délimités manuellement des classes spectrales brillantes et normales, de modestes succès furent obtenus, une exactitude de l'ordre de 78 %. La pruche et le sapin gracieux se confondent, alors que le thuya est principalement confondu par la présence d'arbres malades. Si une séparation en espèces des arbres ombragés et malades est nécessaire, la classification des espèces est faible. Autrement, les arbres ombragés et malades peuvent être bien identifiés lors d'une classification utilisant des classes génériques d'arbres ombragés et malades. La classification en espèces des autres arbres, incluant les arbres inusités, fut de 67 % pour l'image de 1996 et de 77 % pour celle de 1998. Malgré les difficultés à classer les espèces dans un vieil environnement, des solutions pratiques aux enjeux sont disponibles et des classifications spectrales viables sont possibles. Cependant, une approche complètement automatique à l'isolement des cimes et à leur classification en espèces apporte d'autres complications et de nouvelles méthodes dépassant les simples techniques spectrales devront être explorées.
[Traduit par la Rédaction]

Introduction

From an environmental, habitat, and forest management point of view, understanding and quantifying the nature of old growth forests is important. Old growth forests represent an important and often diminishing ecological niche. Remote sensing methods to characterize such stands at an individual tree level would be very useful. Such techniques depend, however, on a good understanding of the spectral characteristics, influencing factors, and species classification capabilities.

In the context of forest inventory and analysis, remotely sensed images are two-dimensional (2D) representations of the interaction of photons with a three-dimensional (3D) canopy (Myneni et al., 1995). Zhang et al. (2002) note that the radiative transfer processes that underlie optical remote sensing data are controlled by the structure and optics of vegetated surfaces. Jaquemoud and Ustin (2001) reviewed the state-of-the-art in leaf optical property research. Although laboratory explorations underlie spectral remote sensing, field experiments are needed to understand the added complexity of a canopy. For example, Knipling (1970) examined general leaf and canopy reflectance and concluded that the levels of visible and infrared reflectance from the canopy are about 40% and 70%, respectively, of the levels from a single leaf. Williams (1991) gives an example comparing needle, branch, and canopy spectral properties. In addition, illumination and sensor geometry affect the spectral response (Kimes et al., 1980; Li and Strahler, 1992; Lobell et al., 2002). An understanding of these structural, optical, and geometric issues for a given scenario permits a better assessment of remote sensing techniques and allows for their modification to improve applications.

The focus of this paper is on individual tree classification using spectral techniques with multispectral imagery. Most individual tree classification studies have used simple spectral approaches like maximum-likelihood classifications (Hughes

et al., 1986; Gougeon, 1995; Gerylo et al., 1998; Key et al., 2001; Leckie et al., 2003). Hyperspectral techniques have been applied to imaging spectrometer data mostly at a canopy level, but also on a single-tree basis (van Aardt and Wynne, 2001). A decision-tree approach was used by Preston et al. (1999) for speciation of eucalypt forest in Australia. Key et al. (2001) used multitemporal imagery to advantage phenological changes in hardwood species. A structure-based approach has been explored with 10 cm imagery (Brandtberg, 1997). These and other studies represent a variety of forest conditions, but few have specifically addressed species classification in old growth conifer stands. The spectral characteristics of complex tree canopies such as old growth are also less well studied.

Old growth stands present particular challenges to tree species classification. Trees may be characterized by spectral and structural idiosyncrasies not common in younger stands. Old growth conifer forests are unique because of tree size, canopy gaps, height–dominance variability, health, and crown morphology differences. Therefore to develop classification techniques for old growth forest, it is useful to examine the basic spectral characteristics of old growth and test classification capability with a simple maximum-likelihood approach. This will provide insight into the underlying issues involved and how well trees can be classified. It will also help in designing different and new classification techniques. This is important, as automated single-tree isolation methods present an opportunity for fully automated single-tree analysis.

This study examines the spectral characteristics of conifer trees within old growth stands and the difficulties they cause for species classification. The spectral separability between species and variability of trees within species are determined. The effect of the added factors of shading and tree health on species classification and spectral variability is also examined. Although an ultimate goal is to develop fully automated techniques with automated tree isolation and then individual tree classification, manually delineated trees were used in this

study. This is to prevent any confusion resulting from errors in automated tree isolations. Various solutions to the difficulties of classifying old growth stands are explored, and the effectiveness of a maximum-likelihood classification is determined. The additional complications in classification and accuracy assessment added by using automated isolation techniques for tree delineation are discussed in a parallel study (Leckie et al., 2004a).

The key issues addressed in the study are as follows: (i) What is the spectral variability of trees of the same species, and how separable are trees of different species? (ii) What are the factors causing variability, and what are the consequences on species classification at the tree level? (iii) How well can the species of well-delineated trees be classified with a simple spectral classifier? Species classification accuracy is analyzed for several cases: (i) trees with spectral characteristics typical of most trees; (ii) trees with uncharacteristic spectral signatures, whether due to illumination conditions, health, or unknown causes; and (iii) including all trees. Case (i) represents the theoretical maximum classification capability if all trees were "well behaved". The accuracy for the true situation including all trees is given by case (iii). Accuracy is assessed and compared for two images acquired several years apart. The robustness of methods and the consequence of different illumination and local view conditions are also examined using the two datasets.

Study site description

The study site is located on central Vancouver Island, British Columbia, Canada (40°50'50" N, 125°27'01" W), southwest of the town of Campbell River. It lies within the montane moist maritime coastal western hemlock biogeoclimatic variant (CWHmm2) and is at moderate elevation (790 m above sea level) in low relief and gently rolling terrain. It was the location of a large interdisciplinary study termed Montane Alternative Silviculture Systems (MASS) that investigated alternative silviculture practices for managing the west coast montane forest of Canada (Arnott and Beese, 1997) and consists of natural old growth forest with experimental treatment areas within the old growth and some areas of clearcutting nearby. There are untreated control areas and adjacent treatments with varying degrees and patterns of partial cutting, from heavy removal in green tree retention, to patch cutting, through to light cutting in shelterwood blocks. Treatments are replicated three times in rectangular 9 ha plots (approximately 360 m × 250 m). This study primarily used the untreated control plots for examining spectral signatures and classification capability, but the spectral characteristics of the old growth trees in the more open treated plots were also examined.

Species composition was dominated by western hemlock (*Tsuga heterophylla* (Raf.) Sarg.), amabilis fir (*Abies amabilis* Dougl. Ex. Loud), and western red cedar (*Thuja plicata* Donn ex D. Don). The amabilis fir is termed balsam, a common name for the species. Also present were mountain hemlock (*Tsuga mertensiana* (Bong.) Carrière) and yellow cedar

(*Chamaecyparis nootkatensis* (D. Don) Spach). Most overstory trees ranged from 200 up to 800 years in age. Typical heights of the old growth trees varied from 26 to 45 m, and diameter at breast height (dbh) ranged from 18 to 190 cm, with a majority between 20 and 70 cm. Crown size for the dominant and codominant trees was from 6 to 10 m in diameter. Stand density for the untreated plots was approximately 360 stems/ha (including suppressed trees), with approximately half consisting of dominant, codominant, and intermediate trees (i.e., trees that might be visible in the imagery). Crown closure estimates for the plots ranged from 65% to 80% as measured in the field using skyward observations in a systematic grid. Stem density for the partial cut treatment plots ranged from 19 to 165 stems/ha, 6 to 50 stems/ha excluding suppressed dominance class trees. Measured crown closure was from 4% to 32%.

Image data, fieldwork, and tree delineation

Compact airborne spectrographic imager (CASI) spectrometer imagery (Anger et al., 1994; Babey et al., 1999) was recorded in cloud-free conditions over the site on 27 September 1996 and 24 September 1998. At this time, ground vegetation, shrubs, and any hardwood trees were green or only slightly senesced. The CASI was operated in spatial mode at high spatial resolution. The specifications of the two CASI images are given in **Table 1**. The 1998 data suffered from a slight defocusing caused by a temporary sensor lens problem, resulting in a lowering of the effective ground resolution to approximately that of the 1996 data. Data were recorded with 12 bit radiometric resolution and were reprocessed to 16 bits for analysis. Each mission consisted of seven adjacent sidelapping flight lines covering the approximately 1.4 km × 6.0 km test site. Data were acquired and processed by Itres Research Ltd. of Calgary, Alberta.

Table 1. CASI imagery specifications.

Date	27 September 1996	24 September 1998
Time (Pacific daylight time)	15:20–16:10	10:45–11:29
No. of bands	8	10
Band centre (nm)	438, 489, 550, 601, 656, 715, 795, 861	484, 550, 588, 613, 643, 668, 701, 742, 782, 862
Band width (nm)	25	14 ^a
Instantaneous field of view (m)	0.7	0.6 (0.7) ^b
Sensor field of view (°)	±18	±18
Swath width (m)	360	310
Solar zenith, azimuth (°)	36, 226	41, 139

^aThe bandwidth was 42 nm for the 484 nm band and 25 nm for the 550 nm band.

^bEffective ground resolution was approximately 0.7 m owing to a lens problem.

The data were radiometrically and geometrically processed as described in Leckie et al. (2004a). No atmospheric correction was applied. The acquisitions were flown using either a 2D gyro (1996) or a 3D motion-detection system (Applanix POS system) with differential global positioning system (GPS) (1998). Data were orthorectified to a digital elevation model (DEM) from the Government of British Columbia digital topographic mapping 1 : 20 000 scale map series (TRIM). With flight-line orientation east–west and sun azimuths of 139° and 226°, bidirectional reflectance effects were quite significant. An empirical object-oriented view-angle correction was applied to correct each band for these bidirectional reflectance effects, and after this correction, an additive normalization was applied, if needed, to make the conifer tree spectral means between the separate flight lines equivalent (Leckie et al. 1999; 2004b). Normalizations were needed for only a few flight lines, and these were small.

Fieldwork was done in October 1996, with a follow-up visit in 1999 after the 1998 data acquisition to check for any changes in the trees. Rectilinear plots were laid out on the ground, and within the plots the coordinates of every stem centre were mapped. For each stem, species, dominance, and diameter breast height were recorded and health problems or unusual features noted. Dominance was assessed in four classes: dominant, codominant, intermediate, and suppressed. In addition, height, crown diameter, and age from increment cores were determined for a sample of approximately 10% of the trees. The characteristics of the understory and ground vegetation were noted. Dominant, codominant, and intermediate trees were also surveyed within a 10 m buffer outside the plot. In total, 11 plots were established and measured for the MASS site. Five were in dense and untreated old growth sites and six were in treatment blocks with varying degrees of cutting. Plots were 40 m × 40 m in the untreated stands and 40 m × 80 m in the cutting treatment areas.

While in the field, the corners of the plots were located on a hard copy of the imagery. As well, distinct trees (e.g., snags or large trees) were also marked on the image print. These positions, along with the stem maps, were used to relate each tree visible in the imagery to the corresponding tree in the tree list of the plot. Additional trees near the plots were mapped, measured, and related to a visible crown in the image. The linking of ground-truth tree points with tree crowns in the imagery was done carefully and checked by independent interpreters. Using the field survey notes, different image enhancements, and on-screen digitization, the crown extent of each visible tree was outlined as a vector (**Figures 1a** and **2a**) and stored as polygons with their associated field records (Leckie et al., 2004a). These tree outlines are referred to as ground reference delineations (greds). Again, the crown delineations were checked by multiple independent interpreters. This formed a complete mapping in the image of the visible crowns within the plots and selected trees adjacent to the plots.

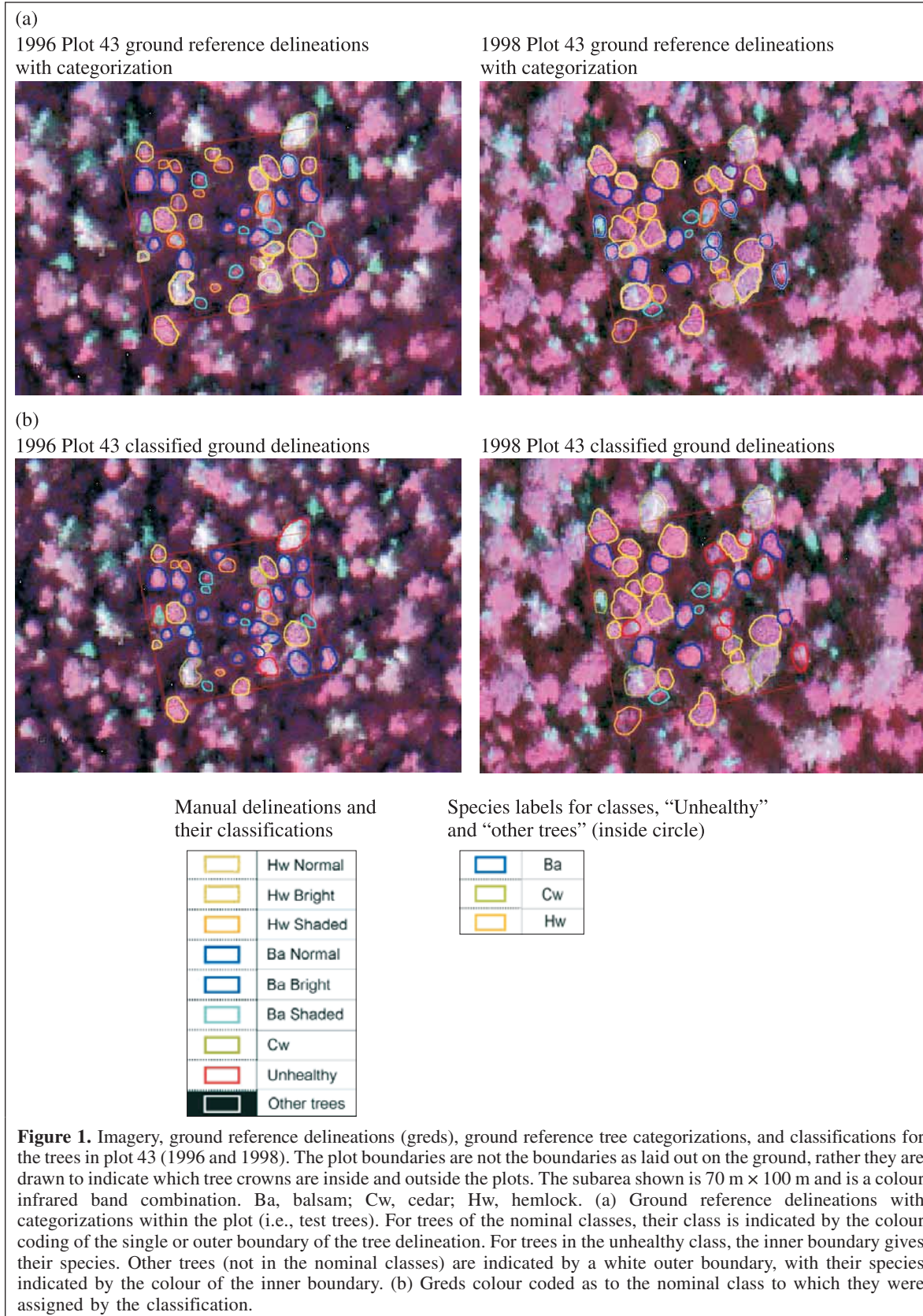
Methods

Spectral signature generation

Spectral signatures were derived for each tree (gred). A single value for each tree (gred) was calculated for each band. Two types of signatures were determined: (i) the spectral value representing the mean of all the pixels within the delineated crown, and (ii) the mean of the pixels representing the sunlit portion of the crown. For the latter case, termed the “mean-lit” signature, the value is calculated as the average of all pixels in the delineation with intensities larger than the mean of the whole delineation. Thus, each tree is represented by one spectral vector, and class signatures are the mean and covariance of the single valued tree vectors in that class. Spectra of each tree were plotted (e.g., **Figure 3**) and characterized, and possible sources of spectral variability were examined by relating spectra to tree characteristics, reviewing the literature, and calling upon examples from other studies.

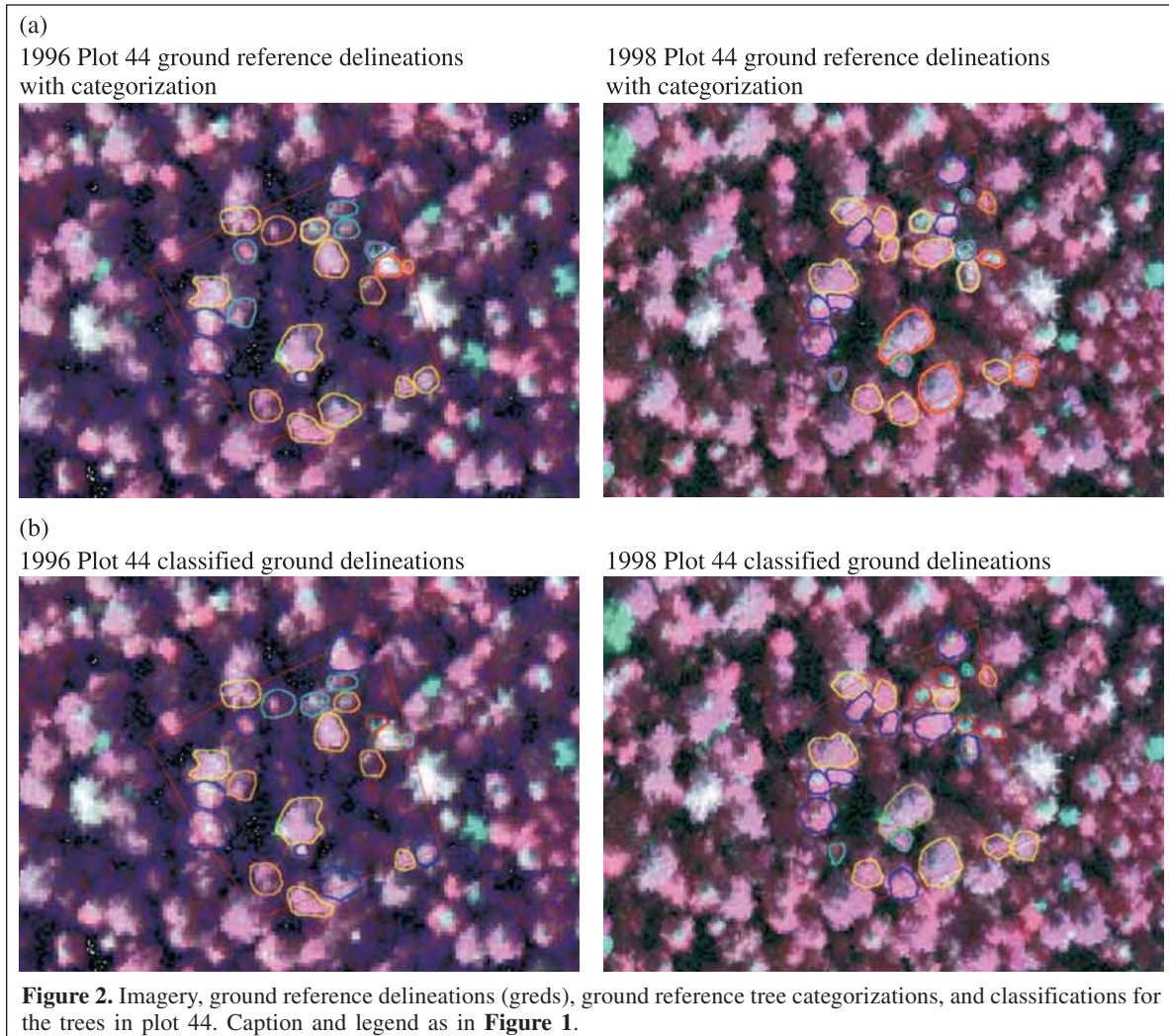
Tree categorization

Trees were categorized based on species, health condition, appearance in the imagery, and spectral characteristics. Trees noted as unhealthy in the field were designated unhealthy. Since it was often difficult to see the tops of the tree crowns from the ground owing to tree height and crown density, trees observed in the imagery to have dead branches, be under stress, or have other health problems were also considered unhealthy. More trees were observed as unhealthy in 1998 than in 1996. Trees in shade in the imagery were assigned a “shaded” code. A number of trees (approximately 10% of the greds in the dense plots), either in the imagery or through examination of the spectra, were considered unusual and were labelled “odd”. These fell into several categories, namely trees that were very bright, visually unusual, or spectrally irregular. Surveyed trees in dense stands outside the plots were reserved for training to derive class signatures. All trees in the five dense plots were designated as test trees for determining classification accuracy. **Figures 1a** and **2a** present the tree delineations and categorizations for two plots. Approximately 120 trees (almost all from outside the plots) were used as training trees for generating the classification signatures. There were 157 trees (greds) within the plots for the 1996 data (**Table 2**) and 163 for the 1998 data, all used as test trees for the classification. It is interesting to note that field counts indicated that there were 154 dominant, codominant, or intermediate trees in the plots and 133 suppressed trees. It must also be noted that because of different view and illumination angles for the 1996 versus 1998 data, the trees visible in the imagery were different (e.g., **Figures 1** and **2**) and thus the training and test sets of trees for the two dates were somewhat different. Overall, 91% of the trees identified in the two images were the same. Of the 157 ground reference test trees for the 1996 data, 129 were labelled as either well-behaved sunlit or shaded hemlock or balsam, sunlit cedar, or sunlit unhealthy (nominal classes) (**Table 2**). Of the remaining 28 greds, 11 were nonshaded mountain hemlock,



shaded cedar, or shaded unhealthy trees, and 17 were designated as odd (nonshaded and not unhealthy). Overall,

there were 50 shaded ground reference trees, and 19 trees were considered unhealthy, four of these being shaded unhealthy.



For the 1998 data, 127 of the 163 ground reference test trees were labeled as belonging to the nominal classes and 14 were odd. Forty-two greds were shaded, and 33 were unhealthy, including eight shaded unhealthy.

Classification and accuracy assessment

Classification was conducted on an individual tree basis (object oriented) as opposed to a pixel-based classification. Each tree was treated as an object represented by one multispectral vector. A supervised maximum-likelihood classifier was used. Signatures representing a class were generated from a set of training trees taken from outside the ground plots. Parallel, but separate classifications and accuracy assessments were conducted on the 1996 and 1998 data.

First, exploratory classifications were done using different class structures, band sets, and signature types. Various band sets and band ratios were tested. Jeffries–Matusita (J–M) distance (Richards, 1993), which gives a measure of the statistical separability between classes, was used to evaluate band combinations and ratios. Both mean-lit and mean signatures were tested. Second, a set of nominal classes was

determined and a standard classification on a standard band set and signature type conducted. Third, to ensure that no bias existed in the particular training and test set chosen, an alternate classification was conducted. The test set of trees and the training trees of the standard classification were pooled and a random selection made, one half going to training and one half to testing. In addition, several special classifications designed to address particular issues were conducted (e.g., classification of species for shaded trees, unhealthy trees, and trees in the open plots).

Classification accuracy was determined on an individual tree crown basis. All delineated trees (greds) within the five dense plots were used as an independent test set. Accuracy was assessed against species but was also analyzed versus other characteristics (e.g., shaded, unhealthy, spectrally or visually odd). **Figures 1 and 2** give examples, for two plots, of the ground reference tree species and class and corresponding classification results for the greds.

Results and discussion

Spectral exploration

The signatures from the manually delineated trees indicated a large spectral variability. The gred mean-lit signatures are discussed here in detail; however, the mean signatures from each gred were also examined and showed similar trends.

Figure 3 gives the signatures of test and training trees of sunlit

hemlock, balsam, and cedar and shows the range of signatures of each species. The main difference within species is the overall intensity of the signature. The variability in reflectance within species can be ascribed to natural variability in factors such as needle reflectance, needle density, branching structure, and crown morphology (e.g., Kimes et al., 1980; Williams, 1991; Rock et al., 1994; Yoder and Pettigrew-Crosby, 1995; Dungan et al., 1996; Blackburn, 2002). Illumination conditions, however, and to some extent view angle were also

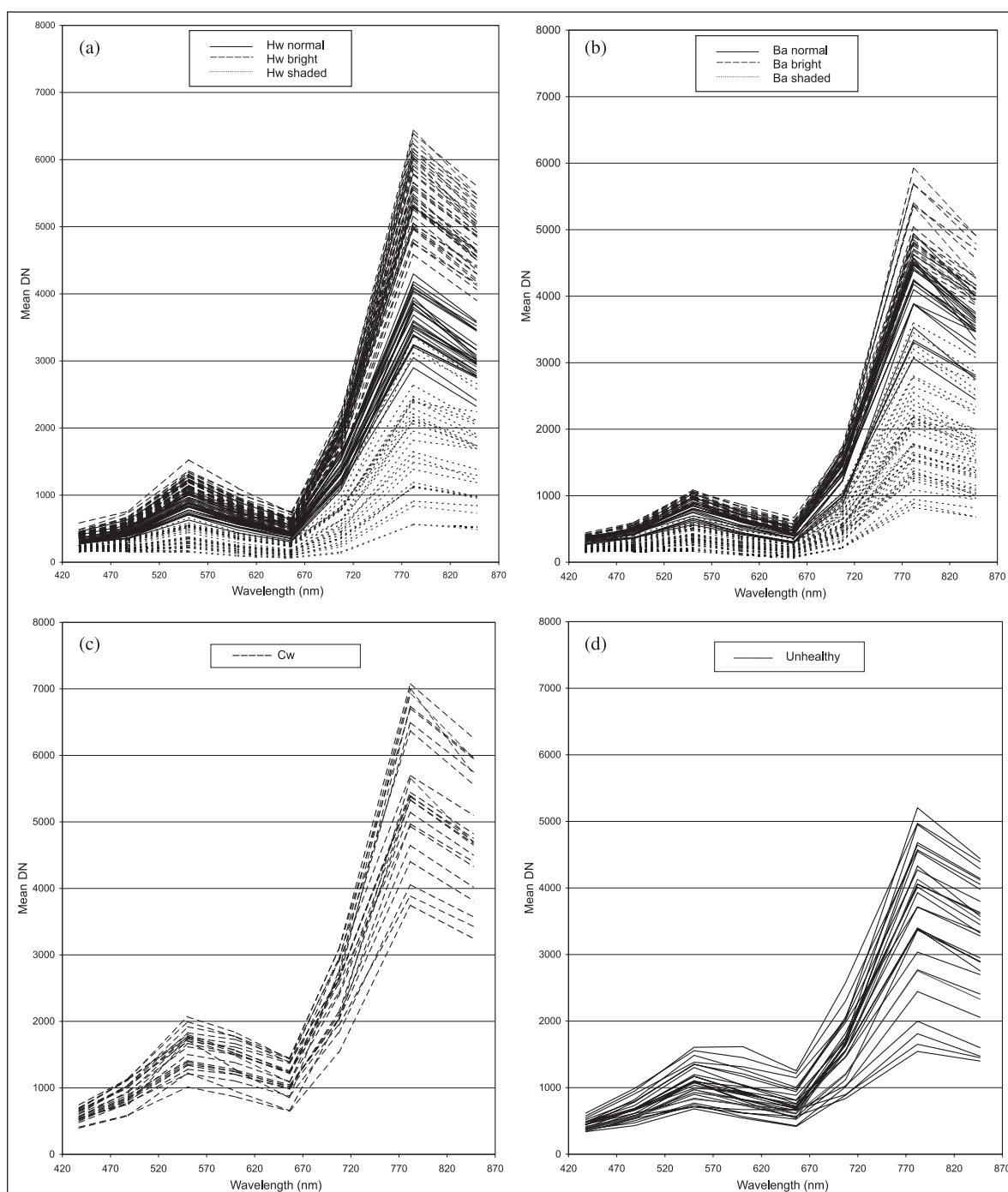


Figure 3. Mean-lit signatures for individual ground reference test and training trees for the nominal classes (1996 data). The range and variability of the signatures within each species are shown: (a) hemlock, (b) balsam, (c) cedar, and (d) unhealthy. DN, digital number.

Table 2. Classified ground reference trees (greds) for 1996.

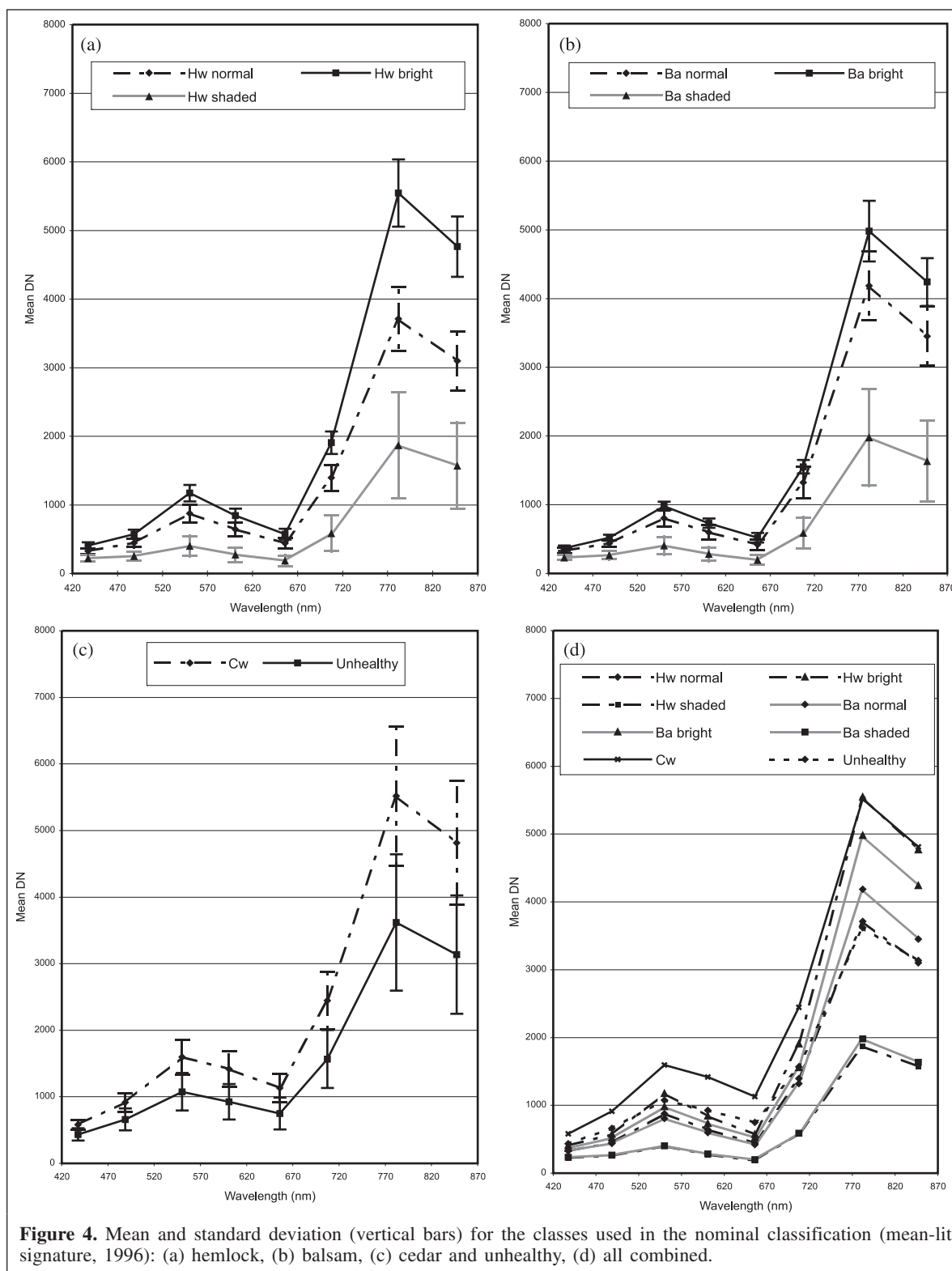
Truth	Hemlock combined (%)	Hemlock shaded (%)	Balsam combined (%)	Balsam shaded (%)	Cedar (%)	Unhealthy (%)	Total no. of trees
Nominal classes							
Hemlock combined	85.4	0	12.2	0	2.4	0	42
Hemlock shaded	10.5	63.2	0	26.3	0	0	19
Balsam combined	10.0	0	90.0	0	0	4.8	21
Balsam shaded	8.0	48.0	4.0	40.0	0	0	25
Cedar	12.5	0	0	0	62.5	25.0	8
Unhealthy	0	0	7.1	0	28.6	64.3	14
Total							129
Other trees							
Mountain hemlock	50.0	0	50.0	0	0	0	4
Hemlock very bright	25.0	0	0	0	75.0	0	4
Hemlock odd	40.0	0	20.0	0	0	40.0	5
Balsam very bright	0	0	0	0	0	0	0
Balsam odd	25.0	0	50.0	0	0	25.0	4
Cedar odd	0	0	0	25.0	0	75.0	4
Cedar shaded	50.0	50.0	0	0	0	0	2
Unhealthy odd	0	0	0	100.0	0	0	1
Snag	0	0	0	0	0	0	0
Shaded odd and unhealthy	25.0	25.0	0	0	0	50.0	4
Total							28
Overall total							157

large factors (Kimes et al., 1980; Li and Strahler, 1992; Deering et al., 1994; Lobell et al., 2002). For example, trees that are taller than the surrounding trees or in more open areas tended to have higher radiance values. This has been observed in other studies (e.g., Gougeon and Leckie, 2003; Leckie et al., 2004b), and trees from the open partial cut areas of this study had characteristically high spectral signatures, in the range of the bright classes and often higher. This was true for both the mean and mean-lit signatures. Crown form of these open trees in the partial cuts was similar to that of the trees in the dense plots, since the partial cutting took place in 1993 and by 1996 the trees had not adjusted their crown form to the more open environment. Therefore, the brighter signature of open trees is likely due to the fuller illumination on the trees.

The overall problem of spectral variability is compounded by the fact that spectral variability also arises from changing illumination conditions due to sun orientation and atmospheric conditions. The data from this study were from several adjacent flight lines taken consecutively. Signatures were compatible, or a simple normalization sufficed to make them comparable. Using data not reported here that were acquired on distant sites at different times did not have compatible signatures, however, and simple normalizations between scenes were insufficient to extend the signatures from one site to another. Different illumination and sun-object-viewer geometry due to slope also cause further differences in spectral signatures. The spectral characteristics of individual trees also depend in part on the bidirectional reflectance. Apart from tree characteristics, this depends on the view and illumination angles. For a given flight line, sun orientation is the same but view angle differs across

the image. An extreme case would be for linear array imagers viewing the sunlit side of the trees on one side of an image and shaded on the other side. The object oriented view-angle correction procedure used in the study was effective at minimizing the effect of bidirectional reflectance. After correction, there was no residual trend of increasing spectral values for trees on the side of the image viewing the sunlit trees and indeed no anomalous trend in species classification across the imagery. The procedure has also proved effective in other studies (Leckie et al., 2003; 2004b).

In addition to the variability within species, there was also large overlap between species (**Figures 3 and 4**). The hemlock signature was higher, on average, than that of balsam, and the higher end of the hemlock range was beyond the range of balsam. Cedar also had a large range, with some overlap with the other species, but was generally higher than the other two species, especially in the visible spectral bands. Spectral curve shape differences between hemlock and balsam were not apparent, but cedar had a slightly higher reflectance in the yellow spectral region relative to the green and red bands. Similar interspecies characteristics were observed for young 25-year-old plantations of cedar, hemlock, and balsam using equivalent 60 cm resolution CASI imagery (Leckie et al., 2003). Western hemlock had higher signatures than balsam (*amabilis* fir), and red cedar was characterized by higher reflectance in the green through red spectral regions. Alternately, spectral reflectance of stacked branches (Goward et al., 1994) indicated western hemlock to have higher reflectance in the green and red parts of the spectrum than red cedar and slightly lower near-infrared reflectance.



The range and overlap of the balsam and hemlock signatures are clearly problematic for classification. Thus, a system of internal subclasses was devised to alleviate some of the problem. Although there is no reason to believe there is not a continuum of signatures between those of the samples

investigated, there appeared to be a set of signatures that was brighter than the norm. For example, **Figure 3** shows that some hemlock trees had signatures higher than those of any of the balsam trees and that a group of balsam trees had signatures lower than those of almost all hemlock. It was hypothesized

that a bright hemlock class would help differentiate at least those hemlock with a signature higher than that of balsam, and the normal balsam will capture the low-signature balsam. Therefore, two subclasses of sunlit hemlock and sunlit balsam were created, a normal class and a bright class. The mean and standard deviations of these and a cedar class are given in **Figure 4**. There will still be much overlap and confusion between classes, but species classification should be improved.

Shadowed and unhealthy trees also had problematic signatures. These types of trees will be more prevalent in old growth stands than in mature or young stands. Shadowed trees have a suppressed signature but grade into normal sunlit signatures depending on the depth and completeness of shading (**Figure 3**). Stress on old growth trees results from a variety of causes, rather than a single or dominant damaging agent. Therefore, the symptoms and resulting signatures often vary and can be gradational into that of healthy trees (**Figures 3 and 4**). Because of the contrast of the shaded and unhealthy trees versus the healthy sunlit trees, it is apparent that a classification with separate classes for shaded and unhealthy trees would be useful.

Classification results

Exploratory classifications

Classifications of the 1998 data were run with different numbers of bands up to 10, and it was determined that classifications using six bands and even fewer produced similar results. A Jeffries–Matusita (J–M) signature separability analysis of different numbers of bands and optimum band combinations confirmed this finding. Standard band combinations (similar bands) for testing species determination for the two dates of imagery were defined. These included six bands (the 489, 550, 601, 656, 715, and 795 nm bands for the 1996 trial and the 484, 550, 613, 643, 701, and 782 nm bands for the 1998 trial). The 438 nm band was not utilized owing to noise. These band sets provided the best spectral matching between the two dates. They also included a band in each of the major spectral zones and eliminated redundancy in the near-infrared spectral region by using only one infrared band. The J–M distance analysis also indicated that the set of six bands used was among the best six-band combinations. It was also determined that the mean-lit signature produced better classification results than the mean of all pixels within the delineation. This is in keeping with the results of other studies (Hughes et al., 1986; Leckie et al., 1992; Gougeon, 1995).

Ratio signatures were also produced and examined, and J–M distances were determined and classifications conducted. The main focus of this analysis was to determine if the ratio bands resolved the problems associated with the variability of the signatures, especially those related to overall brightness of the spectral band signatures (i.e., the normal, bright, and shaded trees). Overall, variability among trees of the same species and overlap between signatures of different species remained a problem. It was therefore decided for this study to use only the spectral bands themselves as input to the classification. The

value of band ratios, relative relationships between bands, and other approaches such as the colour line technique (Gougeon, 1995) needs to be more thoroughly explored.

In addition, a special classification was conducted in which one generic signature was used for the sunlit healthy trees of each species (i.e., combining normal and high reflectance classes). Species classification was poor, confirming the need to have several internal subclasses of healthy species to reduce confusion.

Based on the exploratory classification results, a standard classification scenario was defined and used in subsequent classifications. The scenario included mean-lit signatures based on six bands and eight nominal classes. The eight classes consisted of bright, normal, and shaded hemlock; bright, normal, and shaded balsam; nonshaded cedar; and nonshaded unhealthy. There were insufficient shadowed cedar trees in 1998 to make a class, so a shaded cedar class was not included in the nominal classification for either date.

Standard classification

Nominal classes

Table 3 gives the confusion matrix for the nominal six-band, eight-class classification for the ground reference delineation test trees of both the 1996 and 1998 imagery. As expected, there was confusion between the normal and high signature classes of hemlock and between the two classes of balsam. For the 1998 data, however, the confusion of the two balsam classes was more with hemlock than with the alternate balsam class. The confusion among all four classes (hemlock bright, hemlock normal, balsam bright, and balsam normal) reflects the overlap of the signatures discussed previously. Nevertheless, the important application result is the classification accuracy of the combined species classes of hemlock, balsam, and cedar. These were 85%, 90%, and 63% (average 79%) for hemlock, balsam, and cedar, respectively, for the 1996 data (**Table 2**) and 75%, 78%, and 78% (average 77%), respectively, for the 1998 trial. The main confusion of the hemlock and balsam was with each other (approximately 11% for the 1996 data and 23% for 1998). Cedar was well classified in the 1998 imagery. For the 1996 trial, cedar was confused with the unhealthy class, and vice versa; 29% of unhealthy trees were classed as cedar (**Table 3**). A disproportionate number of the unhealthy trees were indeed cedar, however. The signature of the cedar did have some characteristics similar to those of the stressed trees (**Figure 4**), and confusion might be expected. As well, cedars in old growth stands sometimes grade from healthy to stressed and often have dead, spike-like secondary leaders. The alternate classification with a random division of all trees, half for a training set and half as test trees, produced similar results.

Shaded trees

Shadowed trees had a wide range of signature intensities and variations in relations between bands owing to the range of illumination conditions that may occur for shaded trees. They were not expected to classify well, especially if a sunlit or a

Table 3. Classification results for ground reference test trees of the nominal classes in 1996 and 1998.

	Classification							
Truth	Hemlock normal	Hemlock bright	Hemlock shaded	Balsam normal	Balsam bright	Balsam shaded	Cedar	Unhealthy
1996								
Hemlock normal	90.4	0	0	4.8	4.8	0	0	0
Hemlock bright	5.0	75.0	0	5.0	10.0	0	5	0
Hemlock shaded	10.5	0	63.2	0	0	26.3	0	0
Balsam normal	16.7	0	0	66.6	16.7	0	0	0
Balsam bright	0	0	0	12.5	87.5	0	0	0
Balsam shaded	8.0	0	48.0	4.0	0	40.0	0	0
Cedar	0	12.5	0	0	0	0	62.5	25.0
Unhealthy	0	0	0	0	7.1	0	28.6	64.3
1998								
Hemlock normal	63.2	0	0	26.3	10.5	0	0	0
Hemlock bright	33.3	52.4	0	0	14.3	0	0	0
Hemlock shaded	26.7	0	33.4	13.3	0	13.3	0	13.3
Balsam normal	5.3	5.3	0	89.4	0	0	0	0
Balsam bright	12.5	37.5	0	12.5	37.5	0	0	0
Balsam shaded	0	0	25.0	8.3	0	66.7	0	0
Cedar	0	22.2	0	0	0	0	77.8	0
Unhealthy	15.8	0	5.3	5.3	0	0	15.8	57.8

general combined shaded and sunlit species signature was used to define the species class. A separate shadow class was used for each species, except cedar (recall there were too few shadowed cedar trees in 1998 to make a class). The shadow classes did produce poor species classifications (**Table 3**). It was hoped that cedar might be distinct enough spectrally to classify well, even in shaded situations. A separate classification was run on the 1996 data, which included a shadowed class for all three species. This also showed much confusion among the three shaded species classes, however. Because of the poor expected species classification of shaded trees, the primary operational use of such classes would be to separate the shaded trees from the sunlit trees, for which better results would be expected. Indeed, the shadow classes did successfully prevent most shadowed trees from being classified as one of the sunlit tree classes (**Table 3**). For example, for trees of the nominal hemlock or balsam shaded class, 89% and 67% were classed as one of the two shaded classes in the 1996 and 1998 data, respectively. Commission errors were negligible. If all ground reference trees are considered, including the non-nominal class trees, 82% of shaded trees are classed as shaded for 1996 (**Table 2**), and 61% of shaded trees are classed as shaded for 1998. Again there were low commission errors. One can conclude that shaded classes need to be included in a classification, but they will not reliably provide good species information, despite showing some success at species classification.

Unhealthy trees

Unhealthy trees, owing to the variety of stress symptoms possible in an old growth stand, were also not expected to classify well by species. A special classification was conducted

that included an unhealthy class for each species. The classification did not separate them well into their respective species. A single amalgamated unhealthy class including trees of all species was therefore used in the nominal classification. Very few healthy hemlock or balsam were classified as unhealthy. However, some of the unhealthy trees were classed as the hemlock, balsam, or cedar classes, particularly cedar. Of these trees, 80% (1996) and 63% (1998) were actually classified as the correct species, despite being stressed. Again, the results regarding both the shadowed and the unhealthy classes were similar to those for the second classification trial with randomly selected training and test trees. In general, the species of unhealthy trees cannot be classified, but an unhealthy class is useful to prevent misclassification of stressed trees to the wrong species.

Odd and other trees

The nominal classification and results described previously give the accuracy for test trees properly represented by training trees and classes and an indication of the capabilities of spectral classification and the issues involved but do not tell the whole story. There are a considerable number of ground reference trees that cannot be grouped into a training set or well represented by a class (e.g., very bright or “odd” trees with unusual spectral or visual characteristics, shaded cedar, shaded unhealthy trees, and mountain hemlock). These must also be included in the classification accuracy assessment. For 1996, 28 of the 157 ground reference test trees were considered odd or other (**Table 2**). Similarly, for the 1998 data there were 127 nominal class trees and 36 odd or other trees, for a total of 163 ground reference trees. The nominal classification results

presented earlier therefore give optimistic values in terms of the information the forester wants to describe the stands.

An analysis of all remaining trees in the plots that could be visually detected and delineated on the imagery was conducted (e.g., **Table 2**). For example, a few hemlock trees in the plots had very high intensity signatures. These were generally classified as the bright hemlock class, the class with the highest signature, but in the 1996 data they were often classed as cedar. It must be remembered that trees from plots within dense stands are being analyzed. A secondary analysis was conducted on a suite of sample trees from the more open plots within the stands that had undergone partial cutting treatments. The more open trees commonly had higher intensity signatures, equivalent to those of the bright classes and some higher. Species classification was not as good. Cedar classified reasonably well, but hemlock and balsam tended to be classed as one of the bright classes, especially bright hemlock.

Shaded cedar was not included as a class by itself because there were too few trees. They were classified as hemlock or one of the shaded classes. Snags are a characteristic of old growth stands. The snags had quite distinct signatures with similar values in each band. A problem arises, however, in that, even though snags were mainly classed as unhealthy (67%), 33% were classed as cedar (1998 data). Although in this study there were insufficient numbers of snags within the ground data to make a separate snag class, operationally a separate snag class might help alleviate this situation.

The classification results for the set of spectrally and visually "odd" test trees were also examined. Classification of these trees was poor, but there was some correspondence between their classified species and the correct species class (approximately 40%). There was a tendency to classify these trees as the unhealthy class (approximately 20%–40% of the trees were classed as unhealthy).

Overall classification of all trees

If one examines all the ground reference trees in the plots (nominal, odd, and all others) for the eight-class classification, the percentage of trees classified as the correct species (i.e., sunlit, shaded, or unhealthy) is low. It should be noted, however, that for the unhealthy class there is only one class for all species, and one would not expect good species classification of unhealthy trees. **Table 4** gives the omission and commission accuracies for several cases. These range from how well trees of the particular classes used (e.g., bright and normal) are classified as the correct species, to how well all the trees in the plots are classified as the correct species, regardless of whether they are very bright, odd spectrally, shaded, sick, or a species not included in the classification. Species classification accuracy for the hemlock and balsam was in the order of 58%–68%,² and cedar accuracy was very low (35% for 1996, 44% for 1998²) because the shaded and odd-signature cedars were not classified as cedar (**Table 4**, case 4). There is

no shaded cedar class in the classification, and therefore it is unlikely any shaded cedar will be classified correctly as cedar.

If one assumes that the shaded and unhealthy trees can be separated and one is interested in the species composition of the remaining trees (nominal test trees, very bright, and odd-signature trees), then the accuracies were as follows. The percentage of trees classified as any of the correct species classes (normal, bright or shaded) was 76%, 83%, and 42%, respectively, for hemlock, balsam, and cedar in the 1996 imagery and 72%, 74%, and 64%, respectively, in the 1998 imagery (**Table 4**, case 3). The cedar accuracies increased substantially because the shaded and unhealthy trees, for which there was no class, were not considered. The cedar correspondence is poorer for the 1996 data, mainly because of the odd signature cedar trees being poorly classified (going to unhealthy) and the sunlit normal cedar trees being more confused with unhealthy trees. Equivalent commission accuracies are 79%, 72%, and 39% (for hemlock, balsam, and cedar, respectively) for 1996 and 66%, 59%, and 67% for 1998. For the case of balsam, for example, these numbers represent the percentage of all trees classified as balsam (bright or normal), except the unhealthy trees, which were actually nonshaded healthy balsam.

It is also interesting to compare the overall species composition of the plots as determined for each date. The final classification assigns trees to a species class, a shaded hemlock or shaded balsam class, or the unhealthy class. Combined species composition estimated from stem counts for the five dense plots used was determined (i) from the field stem counts (minus suppressed trees), (ii) based on the true species and categorization of each gred (trees visible in the imagery), and (iii) from the classification of the greds (**Table 5**). For example, excluding the trees categorized as shaded through the visual assessment process, the average plot composition based on the visual categorization of the greds was 47%, 23%, 11%, and 14% for hemlock, balsam, cedar, and unhealthy, respectively, with 4% mountain hemlock (1996 imagery); equivalent classified species composition of the greds was 44%, 27%, 12%, and 17%, with nil for mountain hemlock because there was no mountain hemlock class. Similarly classified species compositions for 1998 data were quite similar (41%, 30%, 11%, 18%, and nil for hemlock, balsam, cedar, unhealthy, and mountain hemlock, respectively), indicating a robustness in the classification. Although perhaps somewhat fortuitous, the species composition as determined from the ground counts, gred ground truth designation, and gred classification with and without the shaded trees was remarkably good (**Table 5**). Remember that there were more trees (greds) considered unhealthy in 1998 than in 1996, as reflected in the categorization of the greds. This indicates that the classification process is reasonably good and that some errors will be compensatory.

²Snag trees were not included in the calculation, and mountain hemlock trees (four for 1996, three for 1998) were considered an error, regardless of how they were classified, even if they were classified as western hemlock.

Table 4. Percent omission (Omiss) and commission (Comm) accuracies of classification of ground reference trees for several analysis cases.

Species	Case 1 ^a			Case 2 ^b			Case 3 ^c			Case 4 ^d		
	1996	Omiss	Comm	1998	Omiss	Comm	1996	Omiss	Comm	1996	Omiss	Comm
Hemlock	85.4	83.3	75.0	66.7	85.4	88.1	75.0	75.5	78.8	72.3	67.5	74.0
Balsam	90.0	72.0	77.8	60.0	90.0	76.0	77.8	83.3	72.2	74.2	62.0	68.4
Cedar	62.5	50.0	77.8	70.0	62.5	50.0	77.8	41.7	38.5	64.3	34.7	38.5
Average	79.3	68.4	76.9	65.6	79.3	71.4	76.9	66.8	63.1	70.3	54.7	60.3

^aSpecies classes of the nominal classification. Omission accuracy: of all ground plot trees that were considered the normal or bright class of a species; how many were actually classed as that species (i.e., either the normal or bright class of that species). Commission accuracy (accuracy when considering commission errors): of all trees considered one of the eight nominal classes that are classified as one of the normal or bright classes of a species; how many actually were a normal or bright tree of that species. For cedar there is just one class (normal).

^bSpecies classes of the nominal classification counting normal or bright trees classified as the shaded class of their species as correct. Omission accuracy: of all ground plot trees that were considered the normal or bright class of a species; how many were actually classed as that species (i.e., either the normal, bright, or shaded class of that species). Commission accuracy: of all trees considered one of the eight nominal classes that are classified as one of the normal or bright classes of a species; how many actually were a normal, bright, or shaded tree of that species. For cedar there is just one class (normal).

^cSpecies classes of all trees not shaded or unhealthy. Omission accuracy: of all the ground plot trees (normal, bright, very bright, unusual, etc.) excluding the shaded, unhealthy, and mountain hemlock trees; how many were actually classed as that species (i.e., either normal or bright classes). Commission accuracy: of all the ground plot trees (normal, bright, very bright, unusual, etc. but excluding the shaded, unhealthy, and mountain hemlock trees) that are classified as one of the normal or bright classes of a species; how many actually were a nonshaded, healthy tree of that species. For cedar there is just one class (normal).

^dSpecies classes for all trees except snags. Omission accuracy: of all the ground plot trees (normal, bright, very bright, unusual, shaded, unhealthy, mountain hemlock, etc.); how many were actually classed as that species (i.e., either normal, bright, or shaded classes). Commission accuracy: of all the ground plot trees (normal, bright, very bright, unusual, shaded, unhealthy, mountain hemlock, etc.) that are classified as one of the normal or bright classes of a species; how many were actually non-snag trees of that species. For cedar there is just one class (normal).

Accuracies are lower than or equivalent to those of other studies examining individual tree multispectral classification of conifer species. Most studies, however, have not addressed stands as complex as old growth forests and generally have few unhealthy or odd trees, or results including these trees are not reported. Some studies examine only automatically isolated trees. Leckie et al. (2003) used similar CASI imagery for healthy young stands of red cedar, western hemlock, balsam (amabilis fir), grand fir (*Abies grandis* Dougl. ex Loud.), and Douglas-fir (*Pseudotsuga menziesii* Mirb.). Accuracy was much higher than in this study (on average, 92% at the stand level), perhaps reflecting more uniform stands in terms of age, crown form, dominance, tree openness, height, and health, leading to less spectral variability and better species classification. Gerylo et al. (1998) classified tree species, also at the stand level, using 30 cm multispectral video camera imagery. Accuracies were 80% and 84% for lodgepole pine (*Pinus contorta* Lamb.) and white spruce (*Picea glauca* (Moench) Voss), respectively, in simple stands in an area of predominantly aspen (*Populus tremuloides* Michx.), lodgepole pine, and white spruce. Differentiation of manually identified slash pine (*Pinus palustris* Mill.) and loblolly pine (*Pinus taeda* L.) trees was examined on 76 cm resolution multispectral imagery (Hughes et al., 1986) using three spectral bands and signatures generated from the brightest pixel within the crown; classification accuracy was 80% for slash pine and 64% for loblolly pine. Research into single-tree classification of manually delineated trees of boreal and northern forest species using 36 cm five-band multispectral imagery from a multidetector electro-optical imaging sensor (MEIS) indicated classification accuracies varied depending on the species present (Gougeon, 1995; Leckie and Gougeon, 1999). Accuracies varied from 52% to 88% for five conifer species (Gougeon, 1995). For eight conifer species (Leckie and Gougeon, 1999), accuracy was 35%–72%, with most in the range 60%–70%. These accuracies were 15% less, on average, than those achieved by expert photointerpreters using the same imagery and trees.

Summary and conclusions

In summary, for the classification of manually delineated tree crowns, the 1996 and 1998 data show the same issues to be important. The class signatures and relationships among them for each date show similarities. Average species classification accuracies for the nominal sunlit hemlock, balsam, and cedar trees were comparable (79% and 77% for 1996 and 1998 data, respectively), but the error structures by class were quite different (Table 3). Thus the accuracies for the sunlit healthy trees, represented by a class within the classification, were generally good for both years. Even when including the sunlit trees with uncharacteristic signatures and appearance in the imagery (e.g., very bright or odd signatures), accuracy was reasonable. If all trees (i.e., shaded, odd, very bright, and unhealthy) were included, then species classification accuracy was lower, in the order of 55% for both years (Table 4).

Table 5. Percentage by species of ground-surveyed trees (except suppressed), ground reference delineations (test trees), and classified greds.

	Hemlock		Balsam		Cedar		Unhealthy		Other	
Field counts: ^a	48.7		33.1		7.8		7.8		2.6	
Image data year:	1996	1998	1996	1998	1996	1998	1996	1998	1996	1998
Classified greds (nominal only)	<i>52.0</i>	<i>44.3</i>	<i>31.5</i>	<i>36.9</i>	<i>7.9</i>	<i>8.2</i>	<i>8.6</i>	<i>10.6</i>	—	—
Greds (with shaded trees)	44.6	39.9	31.9	28.5	8.9	9.5	12.1	20.2	2.5	1.9
Classified greds (with shaded trees)	<i>49.8</i>	<i>41.1</i>	<i>30.3</i>	<i>34.8</i>	<i>8.4</i>	<i>9.5</i>	<i>12.3</i>	<i>14.6</i>	—	—
Greds (without shaded trees)	47.4	40.2	23.4	26.5	11.2	11.1	14.0	19.6	3.7	2.6
Classified greds (without shaded trees)	<i>44.3</i>	<i>40.8</i>	<i>27.4</i>	<i>30.0</i>	<i>11.5</i>	<i>11.5</i>	<i>16.8</i>	<i>17.7</i>	—	—

Note: Three cases are considered: (i) from the field stem counts (minus suppressed trees), (ii) based on the true species and categorization of each gred (trees visible in the imagery), and (iii) from the classification of the greds. Compositions calculated from the classification results are given in italics.

^aField counts were done in October 1996, with a follow-up visit in 1999.

However, average species accuracies were 67% for 1996 and 70% for 1998 (**Table 4**) if the shaded and unhealthy trees were excluded (i.e., assuming these are classified as such and removed from the calculation of species percentage for a stand). Therefore, accuracy depends on the nature of the stand, trees, and particular illumination and view conditions of the imagery. There are inevitably a certain percentage of trees that for a variety of reasons can be considered odd. These are likely to be more common in old growth stands. In this study about 10% of the trees were considered anomalous. Some trees will be shaded and some will be unhealthy; there will be trees of uncommon species that cannot be represented by a class. An old growth stand with more conifer species than cedar, hemlock, and balsam can be expected to have poorer species classification. In addition, as demonstrated with the two datasets, not all trees are visible, and the trees that are visible in the imagery change with sun and view angle. Therefore, classification of the visible trees, even if perfect, would not necessarily represent the true species composition of the stand or be the same between two acquisitions.

Overall, species classification in old growth stands based on spectral properties is difficult. There is tremendous variability and overlap in the spectral signature of trees in old growth stands, which make species classification problematic. This variability increases when considering open trees and stands, sites on slopes, and data that have been acquired under different illumination conditions. Therefore, there can be even more variability in signatures than indicated in this study. An object-oriented (tree based) empirical view-angle correction procedure sufficed in compensating for the effects of bidirectional reflectance within flight lines. A simple normalization was effective at making imagery and signatures compatible for flight lines within a block of adjacent lines acquired consecutively. The mean-lit signature reduced variability of tree signatures by excluding the shaded portion of sunlit crowns and was more useful for classifying species than the mean of pixels within the tree crown. Six bands or fewer did better than or as well as 10 bands or ratio bands at differentiating species.

It was necessary to make judicious use of classes to obtain useful results. Multiple classes within species were needed to reduce the effect of the signature overlap among species. Tree

health and shadowing are major problems. Unhealthy and shaded classes separated these cases from the normal species classification scheme to prevent them from causing severe species classification errors. These trees, however, do not end up with any species designation. With the overlap present among classes and the multiple class per species approach used to mitigate the signature overlap problem, it is inevitable that there will be some instability in the classification. The nature of the instability will depend on the dividing point chosen between classes and the training trees selected to represent the multiple classes (in this case the bright and normal signatures). It will also depend on the characteristics of the shaded and unhealthy class. For example, there may be trees that are only slightly stressed or shaded.

The effectiveness of the overall approach, however, was demonstrated by achieving useful results for both dates and for alternate classifications using a random selection of trees as training and testing. These results, being obtained with manually delineated trees, also form a baseline target for methods involving automated tree isolation that suffer from errors and inconsistencies in tree delineation (Leckie et al., 2004a). Use of object-oriented bidirectional reflectance correction, internal classes, and separation of shaded and healthy trees all helped mitigate some of the issues identified for species classification. Issues remain, however, and additional approaches need to be explored, perhaps using spectral relationships between bands, texture within trees, mathematical expressions of branching structure, shape of the crown shadow zone, crown outline shape, and context.

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