Comparison of Possible Multispectral Classification Schemes for Tree Crowns Individually Delineated on High Spatial Resolution MEIS Images

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Abstract

In the computer analysis of high spatial resolution multispectral aerial images for forest inventory purposes, it may be more useful to deal with individual tree crowns as the "objects" of our analysis than with forest stands or individual pixels. Starting from this tenet, it becomes important to be able to spectrally define these tree crowns as succinctly as possible. This paper proposes, describes, and compares seven different ways that tree crowns in high spatial resolution aerial images can be spectrally defined for species classification.

In testing these seven types of multispectral signatures , it was found that five led to relatively similar classification accuracies (72 ± 3%) in differentiating five coniferous species. Additional classification accuracy improvements (to 76%) were possible with some of the signatures by using Canonical Analysis prior to classification. The "tree colour line"-based signatures, a newly introduced approach, gave comparable results to simpler signatures such as those based on the mean multispectral value of tree crowns. Red pine (*Pinus resinosa* Ait) crowns were consistently hard to separate spectrally from other species, whereas black spruce (*Picea mariana* (Mill.) B.S.P.) crowns were consistently easy to distinguish.

Résumé

Lors de l'analyse par ordinateur d'images aériennes multispectrales de haute définition ayant pour but l'inventaire forestier, il pourrait être plus pratique d'utiliser les cimes d'arbre comme objets de notre analyse plutôt que les peuplements forestiers ou les simples pixels. En partant de cette proposition, il devient important d'être capable de définir spectralement ces cimes le plus succinctement possible. Cet article propose, décrit et compare sept manières différentes de définir spectralement des cimes d'arbre provenant d'images aériennes de haute résolution spatiale dans le but d'identifier leurs espèces forestières.

Parmis les sept types de signatures spectrales testés, cinq menèrent à des exactitudes de classification du même ordre (72 ± 3%) en différentiant cinq espèces de conifères. Une amélioration de l'exactitude de classification (jusqu'à 76%) fut rendu possible pour certainnes signatures en utilisant une procédure d'analyse canonique avant la classification. Les signatures basées sur la "ligne de couleur des arbres", une approche nouvelle, ont donnés des résultats comparable aux signatures plus simples telles que celles basées sur la valeur multispectrale moyenne des cimes d'arbres. Les cimes de pin rouge (*Pinus resinosa* Ait) furent uniformément difficile à séparer spectrallement des autres espèces, alors que celles d'épinette noire (*Picea mariana* (Mill.) B.S.P.) furent uniformément facile.

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Introduction

The availability of high quality georeferenced digital aerial images such as those produced by the Multi-detector Electro-optical Imaging Scanner (MEIS) (McColl *et al.*, 1983) presents an opportunity to reevaluate the use of digital remote sensing in forestry. Indeed, when subjected to standardized enhancements and used in the context of computer-assisted on-screen image interpretation, such images are likely to permanently change the ways in which forest inventories are done (Leckie, 1990). The easy integration of these images and their georeferenced interpretations with the Geographic Information Systems on which most modern inventories now reside should provide substantial productivity gains over the conventional ways of interpreting aerial photographs. However, the full potential of digital aerial images will only be realized when most of the analysis can be done by computers.

Although forest damage assessments (e.g., spruce budworm damage) are most likely to be carried out with MEIS images having spatial resolutions of about 5-10 m/pixel, it is expected that forest management inventories will be done at the high spatial resolution of about 30-70 cm/pixel (Strome et al., 1989). At that resolution, it becomes conceivable to think in terms of automatically isolating individual tree crowns and, then, of distinguishing species by various semi-automatic classification approaches (Gougeon ,1993). For some situations, such as intensively managed, special purpose, and small privately owned forests, the individual tree inventory may be the desired final product. However, for the naturally mixed large Canadian forests, the crowns would later be regrouped to form the familiar forest stands prevalent in Canadian inventories (Eldridge and Edwards, 1993). It is likely that semi-automatic inventories of sufficient precision can only be achieved using such high resolution data and these intermediate steps of crown isolation and species identification on an individual tree basis.

The "traditional" classifiers found in the digital remote sensing field (i.e., those available in most commercial remote sensing image analysis packages) and most subsequent improvements were developed essentially to analyse low resolution satellite images (10-80 m/pixel). They typically use a pixel-based approach to image classification that is not very useful for classifying higher spatial resolution data (Trietz et al., 1985; Marceau 1991). Their basic assumptions of pixel independence and signatures based on normal distributions of pixel multispectral values break down at higher spatial resolutions (Crane et al., 1972). This paper addresses the need for new multispectral classification approaches where individual tree crowns, rather than pixels, are the objects to parameterise and classify. Following the same philosophy, some classification approaches based explicitly on texture, structure, and context (Woodham and Pollack, pers. comm.), and others using these criteria only implicitly in Artificial Neural Networks (Pinz and Bischof,1990; Zaremba et al., 1993) are being planned or developed . All of this work could possibly lead to a knowledge-based system that would identify the species of individual tree crowns by accumulating evidence from all of these domains (Gougeon, 1993; Pinz et al., 1993; Murtha 1993).

Individual Tree Data

The automatic isolation of individual tree crowns in high resolution aerial images, including digitized aerial photographs, is already at a point where the availability of data packets (or records) containing only the multispectral image data from the crown of single trees is possible (Pinz, 1991;

Gougeon, 1993). However, in order to avoid the introduction of possible bias to our results, this work uses individual tree crowns delineated by hand from two radiometrically corrected high resolution MEIS image strips. These two long strips (16 and 30 thousand lines, 1024 pixels/line) of MEIS-II data were acquired from an altitude of 1700 feet (520 metres) on August 16, 1988, over an area of the Petawawa National Forestry Institute near Chalk River, Ontario (46°0′ North, 77°25′ West). These 36 cm per pixel images were captured in six spectral bands (centred at 449, 548, 640, 675, 873, and 1017 nm), but the sixth band was not used due to poor quality. View angle effects were alleviated using an empirical process in which sample areas are used to produce a correction curve as described in Leckie (1987). A section of one of the strips is shown in Figure 1.

From these data, the crowns of 50 trees of each of five coniferous species, black spruce (*Picea mariana* (Mill.) B.S.P.), jack pine (*Pinus banksiana* Lamb.), red pine (*Pinus resinosa* Ait.), white pine (*Pinus strobus* L.), and white spruce (*Picea glauca* (Moench) Voss) were manually delineated on the screen. The multispectral values of the pixel contained in each crown were made available to generate various types of signatures (see next section) for classification purposes. The tree species were ascertained both in aerial photographs acquired simultaneously with the digital data and on the ground. Very detailed information is available on each tree because the same data set was also used for a study assessing on-screen interpretation capabilities (Leckie 1993). Two typical tree crowns and their manually delineated contours are shown in Figure 2. Also typical, is the fact that a significant part of the red pine crown is in the shade. This usually complicates matters for most classification processes. Figure 1 and 2, and the tree crown dimensions found in Table 1 may be sufficient to give the reader a sense of the spatial scale in which the various classification approaches will have to perform.

Multispectral Signature Types

When using individual tree crowns as objects to be spectrally classified for species identification, it is important to find significant crown-based multispectral parameters to use as signatures. In this context, it should be kept in mind that in practice classifiers can exhibit poorer results when too many parameters or dimensions are considered and that, in such cases, more samples are needed to get statistically significant signatures. Considering the limited amount of data (pixels) available for some tree crowns (see Table 1), it is imperative to find parsimonious indices with sufficient discriminating power.

The first three such indices (signatures) examined in this paper are: the mean multispectral value (a vector of size "n", for n bands) of all pixels contained in a tree crown (labelled: ave_sign), the mean multispectral value of pixels found only on the well lit parts of a tree crown (lit_sign), and the multispectral value of the most brilliant pixel of the tree crown, often corresponding to the tree top for conifers (tt_sign). Used in maximum likelihood classifiers, these signatures have been moderately successful for species recognition on medium resolution (1.2m/pixel) MEIS images (Gougeon and Moore, 1989) and for single tree defoliation assessments (Leckie *et al.,* 1992). Using the overall mean of a tree crown intuitively makes sense as it simulates the integration process that goes on when lower spatial resolution data are used, with the added benefit of ensuring that areas outside of a tree crown are not corrupting its signature. However, since whole crown multispectral distributions may exhibit bimodal tendencies related to their lit and shaded parts, such means can be strongly influenced by the proportions of pixels in each category. Using the mean vector from only the well lit parts of the crown should alleviate this problem and bring further improvements. Here, the lit parts are empirically defined as all the pixels with values in the near infrared band above the mean value of that band, a simple yet conservative approach. Finally, because some shading causing variabilities is usually present even within the lit parts of tree crowns, the use of only the most brilliant pixel of each tree crown is intuitively appealing. This pixel may be less prone to this sort of noise and hence may be more representative of the species' multispectral characteristics. Here, this pixel is defined as the one with the highest value in the near infrared channel.

In an effort to find other simple indices to parameterize tree crowns without being penalized by the relative proportions of lit to shaded areas, a technique has evolved which will be referred to as the "tree colour line" approach. This technique stemmed from viewing plots of all of the pixels comprising a tree crown in a multidimensional (mD) spectral space. In three dimensions (the highest dimensional space easily viewed), such a set of pixels typically takes on a cigar-shaped distribution. In multiple two dimensional views (see Figure 3), the patterns look like elongated ellipses. Such ellipses, or the multidimensional hyperellipse, can be represented at the simplest level of abstraction by a line. Each tree crown can thus be represented by its own "tree colour line" and, if we assume that species are recognizable by their inherent colours (i.e., specific light reflection and absorption characteristics, bidirectional reflectance distribution function), such tree colour lines could be representative of their respective species.

The first tests of this approach were done using tree crown signatures consisting of the slopes and intercepts of the various colour lines generated when crown pixel values in each spectral band are plotted against that of the near infrared band (si_sign). This is referred to as the multiple 2D tree colour line approach where, for n dimensions, each signature consists of n-1 slope and intercept values (see Figure 3). The next tests were done with the multidimensional tree colour lines as parameterized by the first eigenvector of the data found in each tree crown, anchored in multidimensional space by the mean value of that data (mpc1_sign). The eigenvector, or first principal component, gives only the main direction of spread of the data in mD space. To define a particular line in multidimensional space, this general direction needs to be situated precisely in space. The colour line could be defined by this direction and its intersection with n-1 axes, but it is more convenient, and mathematically equivalent, to use the mean vector to situate it precisely in space. Further tests were done by adding a way to parameterize the spread of data around that mD line (mpc1ev_sign). This was accomplished by adding the eigenvalues found for each of the principal directions to the previously defined signature. The first eigenvalue, proportional to the variance in the direction of the first principal component, is somehow representative of the tree colour line length. The other eigenvalues are proportional to the variances found in the direction of the other components, and are thus, by definition, orthogonal to each other. They quantify the other dimensions of the hyperellipse formed by the data. A more conventional way to parameterize the spread of data in mD space is to use its mean value and its covariance matrix. However, because even at the high spatial resolution used (36 cm / pixel) there is only a limited number of pixels available for each tree (approx. 21-155 pixels/tree), we run the risk of underspecifying the covariance matrix. For this reason, only three spectral channels were used to generate these signatures (mcov_sign).

Classification Results

Seven rounds of classifications were carried out, one for each of the seven types of signatures described above (summarized in Table 2). In each round, the signatures were computed for each of the 250 manually delineated tree crowns and, then, 10 classifications were run. For each classification, the tree crowns forming the training and the testing sets were selected at random with equal probability of belonging to one set or the other. This implies that on average, for each classification, there were about 25 tree crowns of each species to train the classifier and about 25 to test the resulting classification. This approach was used in order to remove any selection bias. However, because any two such classifications could lead to significantly different results, their overall accuracies sometimes varying by up to 22%, the confusion matrices resulting from averaging the results of 10 classifications from each round are presented. This reduces any selection effect and should lead to a good comparison and a satisfactory overall impression of the relative merits of each type of signatures.

The mean confusion matrices (or contingency tables) resulting from these seven rounds of classifications are shown in Tables 3 to 9. The non-diagonal elements correspond to the mean number of test tree crowns involved in errors of omission and commission. The diagonal elements correspond to the mean number of test tree crowns that were classified properly. They are divided by the average number of test trees of each species to get the average accuracy for each class. The mean total number of test trees is also given. The value in the bottom right corner corresponds to the mean average accuracy (~~AA~~) and the value labelled ~~OA~~ to the mean overall accuracy, with the range of overall accuracies just below. Here, the average accuracy of a classification is defined as the average of the species-specific accuracies, while the overall accuracy is defined as the ratio of correctly classified test tree crowns on the number of test tree crowns used to verify that classification. Looking from Table 3 to 9, it is apparent that the classifications were rather well behaved, in that the matrices are essentially diagonal.

The mean confusion matrix from the first round of classifications which corresponds to the signatures based on the tree crown's mean spectral values is shown in Table 3. Least correctly classified is red pine (50.8%) with a value significantly less than other species, which have between 70% and 90% correct classification. The poor differentiation of red pine brings the mean overall classification accuracy down to 73.6% from what would otherwise be in the realm of 80%. Red pine is mostly confused with jack pine, to the point that about 35% (9.1/25.9) of the red pine is classified as jack pine. Conversely, about 15% (3.7/23.8) of the jack pine is labelled red pine. Other confusions in the range of 10-15% occur between white pine and white spruce, and some white spruce (11.7%) is classified as black spruce. Other species confusions are all below 10%, and some species (e.g., black spruce or jack pine with white pine) are never confused. This pattern of species separation seems to repeat itself, with minor variations, for all the other classification rounds (Tables 4-9) independent of the type of signatures being used.

Table 4, depicting results from the round of classifications using the mean spectral values from the well lit parts of crowns, follows essentially the above pattern. It differs only in that there is an increased amount of confusion between white spruce and red pine crowns (of the order of 11% compared to 6% in Table 3). It leads to a mean overall classification accuracy of 73.7%, with a range of 69.7 to 79.7% over 10 classifications. There is apparently no significant difference between classifying the whole tree crown mean or the lit parts mean for the recognition of these species. In both cases, adding a vector containing the standard deviation of each channel to the mean spectral vector did not lead to any significant changes (results not shown here).

Table 5, representing results from classifications with the "tree top" signatures, exhibits poor species accuracies for red pine, white pine, and white spruce, for a mean overall accuracy of only 64.2%. This poor result is mainly attributed to the significant mutual confusion between red pine and white pine and also to a noticeable number of white spruce trees being judged as jack pine. Weaknesses present with the two previous signature types were also manifest with this type of signature. Hence, this type of signature, one of the easiest to implement on conventional systems designed for satellite image analysis, leads to significantly poorer results than the previous two.

Table 6 gives the results of the first of the "tree colour line" approaches. It displays a better performance (71.7%) than the "tree top" approach, but one that is no better than the two first signature types. Confusions of the order of 25% and 15% are noticeable between red pine and jack pine, and, white pine and white spruce, respectively. Red pine, which has been consistently the most difficult species to recognize so far, seems to have improved its accuracy by about 12 to 23 percentage points (pp[1]), although there are more errors of commission of other species to red pine (double that of the first two approaches). The white pine and jack pine mean species accuracies (72.3 and 64.6 , respectively) are significantly lower than with the first two types of signatures, by 9 and 14 pp respectively. Also, the range of overall accuracies obtained by the 10 classifications in this round increased from about 10 pp in the first two rounds to about 16 pp.

Footnote 1: Percentage points, abreviated "pp", are use here to remove some confusion when comparing classification results. For example, a classification accuracy improvement from 72% to 76% is not an improvement of 4% as is often casually said, but one of 4 pp. It actually is an improvement of 5.6% ((76 - 72) × 100 / 72). Using pourcentage points allow the reader to more readily verify the classification results and comparisons discussed here.

Table 7, representing the simplest multidimensional implementation of the "tree colour line" approach, shows accuracies quite close to the better of the more conventional signature types (i.e., ave_sign and lit_sign). Although its mean overall accuracy is a comparable (72.8% *vs.* 73.6% and 73.7%), this approach is the least consistent, as illustrated by the big range of classification accuracies obtained (64.0 to 86.2, a range of about 22 pp). Compared to the previous signature type, which was a cruder implementation of the "tree colour line" approach, the apparent gain in red pine recognition experienced there disappeared, but so have the errors of commission to red pine. In general, red pine recognition is as poor as with most of the other signature types and the overall species confusion patterns are the same.

Table 8 gives the results of applying signatures based on the multidimensional tree colour line when the variance around the line is also taken into account. It shows a slightly weaker mean overall accuracy (69.3%) than with the previous less defined colour line approach. This is attributed to the fact that even though the red pine accuracy is a bit higher (and somehow compensated by a decline in white spruce accuracy), white pine accuracy is lower by about 10 pp. There is in fact a noticeable confusion increase between red and white pine, implying that the addition of eigenvalues may be detrimental to their separability. Also, for the first time (except maybe with the weaker tree top signatures), jack pine seems to get significantly confused with white spruce (about 11%). On the other hand, the addition of the eigenvalues seems to make classification results more stable than the previous approach, as implied by the much narrower range of classification accuracy variations (about 11 pp).

Table 9, which represents the use of a more conventional method (mean vector and covariance matrix) of parametrizing the spread of data in multidimensional space, exhibits patterns similar to the confusion matrices obtained with all the other signatures, except for red pine. In this case, that species is confused with jack pine and white pine to the point where wrong classifications exceed correct ones. The recognition of the other four species is comparable to that of the other signatures, with black spruce recognition being slightly lower than average and jack pine slightly higher. The possible poor classification results due to sparsely populated covariance matrices (even with only three spectral bands) did not materialise, at least not in an obvious way. They should have been more prevalent with black spruce and white spruce crowns, which on average are made of only 21 and 27 pixels, respectively.

Discussion

The comparison of seven types of multispectral signatures for species classification of individual tree crowns delineated on high spatial resolution aerial images shows that:

a) there is a good selection of possible multispectral parameters (see Table 2) that can be extracted from tree crowns when these become the "objects" of interest in new classification schemes (i.e., not pixel-based);

b) various multispectral signatures produced more or less the same results (see Table 10), with mean overall accuracies around 72 ± 3% (except for the "tt" and "mcov" signatures), while attempting to differentiate among the tree crowns of five conifer species;

c) the "tree top" signature approach, that worked well on medium resolution images (Gougeon and Moore, 1989) and is the easiest to implement as a procedure with existing commercial image analysis system, gave the poorest results with high spatial resolution images (64.2%);

d) red pine crowns seem to be consistently hard to separate spectrally from other species (with an average mean species accuracy of 48.2%), especially from jack pine crowns;

e) black spruce crowns are consistently well separated from the other four coniferous species with an average mean species accuracy of 88.9%;

f) some types of signatures bring significant confusion between red pine and white pine crowns;

g) there is always 10-15% of confusion between white pine and white spruce crowns,

h) for most signature types, the confusion between jack pine and white pine or white spruce crowns is minimal (< 10%); and finally,

i) if one was to dispense red pine crowns from the classification process the overall accuracies with most of these classification schemes could be of the order of 75-80% for four conifer species.

In general, the results for signatures based on the "tree colour line" approach were not significantly different, at least not in differentiating the five coniferous species used here. Simple signatures, such as the mean multispectral value of a tree crown (ave_sign), appear to fare just as well. The logical progression from using just the crown mean, to using the mean plus the eigenvector parametrizing the colour line direction, to using the mean and the eigenvector plus eigenvalues parametrizing the spread around the colour line, did not lead to increased classification accuracies. On the other hand, parameterising the spread of tree crown pixels in multidimensional space with the tree colour line approach is significantly better than using a more conventional covariance matrix.

An interesting aspect of the present comparative study, and one that is rarely found in the remote sensing literature, is repeatability. Redoing every classification 10 times with different training and testing sets demonstrates that rather large variations in overall accuracies, up to 22 pp, are possible, making any non-replicated comparison of classification scheme performances dubious.

Canonical Analysis

A feature compression scheme based on Canonical Analysis (CA) (Jenson and Waltz, 1979) was used to further investigate two aspects of the classification scheme comparison: a) the lack of reflection in the results of the increasing definition of the tree crown multispectral characteristics available from some of the signatures and, b) the possibly of alleviating the higher spread of classification accuracy results found with the more complex signatures. Because in practice classifiers often produce poorer results in high dimensionality spaces, a dimension reduction scheme such as CA may be beneficial to both aspects.

Canonical analysis leads to the same dimensionality reduction properties as the better known principal component transformation, but it takes into consideration inter- and intra-class distances before creating a better lower dimension separating space. In addition, CA components do not have to be orthogonal to each other like principal components. The canonical analysis is performed on the training data set and the resulting space reduction transformation is applied to the testing data set before its classification. Here, four CA components were used because the addition of a fifth component made little or no difference.

Using the same randomized selection of training and testing samples, another set of 70 classifications (ten for each of the seven signature types) were run with CA. Only the summary of the results is shown here (see Table 11). As expected, reducing the dimensionality of the signatures by canonical analysis did not significantly change the classification results with the simpler signatures, such as "ave", "lit", or "tt". However, it brought classification improvements to the signatures with higher dimensionality such as "si", "mpc1", "mpc1ev", and "mcov". On average, for the latter, classification results improved by 4.25 pp, although only the improvement with the "mpc1ev" signature is statistically significant. In addition, classification repeatability also improved as seen in the diminishing classification accuracy ranges. Species-specific differentiating aspects, however, remained essentially the same as in classifications without a priori canonical analysis.

Conclusions

In testing seven types of multispectral signatures for tree crown species identification in high spatial resolution MEIS images, it was found that five led to relatively similar results (72 ± 3%) while differentiating five coniferous species. Improved classification accuracy (to 76%) was shown to be possible with some of the signatures by using canonical analysis prior to classification. "Tree top" signatures, previously found to work well with medium resolution aerial images (1.2m/pixel) and the easiest to implement with existing commercial image analysis software, performed significantly worse (64%) than any of the others at this higher spatial resolution (36 cm/pixel). The "tree colour line"-based signatures, a newly introduced approach, did not bring significant improvement over simpler signatures such as those based on the mean multispectral value of tree crowns (76% *vs* 74%). Red pine crowns were consistently difficult to separate spectrally from other species (21- 67%), whereas black spruce was consistently the most successfully classified species (84 - 96%). Without red pine crowns, the overall accuracies with most of these classification schemes could be of the order of 75-80% for four coniferous species. It is hoped that the addition of textural (structural) parameters will alleviate the red pine crown identification problem. The experiment should also be done with other MEIS images and other tree species. The testing of "tree colour line"-based signatures with hardwoods and the streamlining of automatic tree crown delineation with species recognition will be future concerns.

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Table 1
Tree crown average dimensions for 50 trees of each species.

Species	Code	Pixels / tree	Estimated crown area (m^2)	Estimated crown diameter (m)
Black spruce	BS	21	2.7	1.9
Jack pine	JP	54	7.0	3.0
Red pine	RP	120	15.6	4.5
White pine	WP	155	20.1	5.1
White spruce	WS	27	3.5	2.1

Table 2
Types of multispectral signatures

Tree Average (ave_sign):
The mean multispectral value of all pixels contained in a tree crown, a vector of size "n", for n spectral bands (here, n = 5).

Average of Lit Parts (lit_sign):
The mean multispectral value of pixels found in the better lit parts of a tree crown. Here, the better lit parts of the crown are defined empirically as all pixels with values in the near-infrared band above the mean value of that band, a simple yet conservative approach.

Tree Top (tt_sign):
The multispectral value of the most brilliant pixel of the tree crown in the near infrared channel, often corresponding to an area near the tree top for conifers.

Slope & Intercept (si_sign):
Based on the "Tree Colour Line" approach, these signatures consist of the slopes and intercepts of the tree crown colour line as all the bands are compared with the near infrared band one by one (sometimes referred to as the "multiple 2D tree colour line approach").

Mean vector & first principal component (mpc1_sign):
The "Tree Colour Line" approach in multiple dimensions - the distribution of pixels for each tree crown is represented by its first eigenvector (its colour line direction) and its mean vector (to anchor the line in multidimensional space).

Mean vector & first principal component & eigenvalues (mpc1ev_sign):
As above, but eigenvalues are added to describe the spread of the distribution in the various directions.

Mean and covariance matrix (mcov_sign):
The mean and covariance matrix of the distribution of pixels in multispectral space for each tree crown.

Table 3

Mean results of 10 classifications with "Crown Average" signatures

Species	BS*	JP	RP	WP	WS	
BS	21.7	1.0	0.3	0.0	3.0	
JP	0.6	18.7	9.1	0.0	0.1	
RP	0.1	3.7	13.0	1.9	1.1	
WP	0.0	0.0	1.9	19.5	3.5	
WS	1.6	0.4	1.6	2.7	18.0	
Mean no. of trees	24.0	23.8	25.9	24.1	25.7	123.5
Mean species accuracies	90.4	78.6	50.2	80.9	70.0	$\overline{AA}$ = 74.1

$\overline{OA}$ = 73.6%
(68.3 - 77.6)

* See Table 1 for the meaning of species code

Table 4

Mean results of 10 classifications with "Crown Lit Parts Average" signatures

Species	BS	JP	RP	WP	WS	
BS	23.4	1.5	0.0	0.0	1.9	
JP	1.5	21.4	8.7	0.4	0.5	
RP	0.0	2.2	14.0	1.2	2.7	
WP	0.0	0.1	1.3	20.8	3.2	
WS	1.6	1.3	2.9	3.1	16.1	
Mean no. of trees	26.5	26.5	26.9	25.5	24.4	129.8
Mean species accuracies	88.3	80.8	52.0	81.6	66.0	$\overline{AA}$ = 73.7

$\overline{OA}$ = 73.7 %
(69.7 - 79.7)

Table 5
Mean results of 10 classifications with "Tree Top" signatures

Species	BS	JP	RP	WP	WS	
BS	23.2	1.0	0..2	0.0	1.9	
JP	0.5	19.0	6.8	1.2	2.5	
RP	0.0	3.0	10.8	4.9	2.2	
WP	0.0	0.0	5.9	15.2	5.2	
WS	1.5	1.6	2.6	4.2	13.0	
Mean no. of trees	25.2	24.6	26.3	25.5	24.8	126.4
Mean species accuracies	92.1	77.2	41.1	59.6	52.4	$\overline{AA}$ = 64.5

$\overline{\text{OA}}$ = 64.2%
(53.9 - 70.3)

Table 6
Mean results of 10 classifications with "Tree Colour Lines (Slope & Intercept)" signatures

Species	BS	JP	RP	WP	WS	
BS	20.3	1.9	0.0	0.0	1.2	
JP	0.8	17.3	6.3	0.1	0.5	
RP	0.0	6.6	16.4	3.1	2.6	
WP	0.0	0.3	0.8	17.5	2.8	
WS	2.1	0.7	2.1	3.5	18.2	
Mean no. of trees	23.2	26.8	25.6	24.2	25.3	125.1
Mean species accuracies	87.5	64.6	64.1	72.3	71.9	$\overline{AA}$ = 72.1

$\overline{\text{OA}}$ = 71.7 %
(61.5 - 77.6)

Table 7

Mean results of 10 classifications with "Tree Colour Line (PC1 and Mean)" signatures

Species	BS	JP	RP	WP	WS	
BS	23.4	1.6	0.1	0.4	1.3	
JP	0.3	16.1	7.6	0.3	0.3	
RP	0.1	4.9	13.0	2.4	2.3	
WP	0.2	0.6	1.2	16.9	2.3	
WS	1.8	0.9	2.7	2.3	20.0	
Mean # of tress	25.8	24.1	24.6	22.3	26.2	123.0
Mean species accuracies	90.7	66.8	52.8	75.8	73.3	$\overline{AA}$ = 71.9

$\overline{OA}$ = 72.8 %
(64.0 - 86.2)

Table 8

Mean results of 10 classifications with "Crown Mean, First PC & Eigenvalues" signatures

Species	BS	JP	RP	WP	WS	
BS	24.1	2.2	0.1	0.0	1.4	
JP	1.1	16.7	4.2	1.3	2.5	
RP	0.3	3.1	14.7	5.3	1.7	
WP	0.0	0.5	4.8	16.1	1.8	
WS	1.5	2.9	2.7	1.9	16.6	
Mean # of trees	27.0	25.4	26.5	24.6	24.0	127.5
Mean species accuracies	89.3	65.75	55.5	65.5	69.2	$\overline{AA}$ = 69.1

$\overline{OA}$ = 69.3 %
(63.6 - 74.1)

Table 9

Mean results of 10 classifications with "Crown Mean and Covariance Matrix (3D)" signatures

Species	BS	JP	RP	WP	WS	
BS	21.7	1.2	0.1	0.0	1.9	
JP	0.9	19.2	8.5	1.3	2.2	
RP	0.0	3.2	5.0	4.2	1.9	
WP	0.3	0.6	6.3	18.5	2.1	
WS	2.8	1.2	3.7	1.8	18.3	
Mean # of trees	25.7	25.4	23.6	25.8	26.4	126.9
Mean species accuracies	84.4	75.6	21.2	71.7	69.3	$\overline{AA}$ = 64.4

$\overline{OA}$ = 65.3 %
(60.2 - 69.4)

Table 10

Comparison of various multispectral classification schemes for tree crowns individually delineated on high resolution (36 cm) MEIS images (with 50 trees / species, 5 species, 10 classification runs / scheme).

Signature Types	Mean Species Accuracies (MSA) BS	JP	RP	WP	WS	Mean Overall Accuracy (range)
ave_sign	90.4	78.6	50.2	80.9	70.0	73.6 (68.3 - 77.6)
lit_sign	88.3	80.8	52.0	81.6	66.0	73.7 (69.7 - 79.7)
tt_sign	92.1	77.2	41.1	59.6	52.4	64.2 (53.9 - 70.3)
si_sign	87.5	64.6	64.1	72.3	71.9	71.7 (61.5 - 77.6)
mpc1_sign	90.7	66.8	52.8	75.8	73.3	72.8 (64.0 - 86.2)
mpc1ev_sign	89.3	65.8	55.5	65.5	69.2	69.3 (63.6 - 74.1)
mcov_sign	84.4	75.6	21.2	71.7	69.3	65.3 (60.2 - 69.4)
Average MSA	88.9	72.9	48.1	72.5	67.4	70.1

Table 11

Classification comparison of multispectral signatures (after a canonical transformation) for tree crowns individually delineated on high resolution (36 cm) MEIS images (with 50 trees / species, 5 species, 10 classification runs / signature type).

Signature Types	Mean Species Accuracies (MSA) BS	JP	RP	WP	WS	Mean Overall Accuracy (range)
ave_sign	90.6	74.4	54.9	69.3	68.1	71.9 (66.7 - 75.4)
lit_sign	89.8	68.2	66.9	83.7	62.6	74.3 (70.7 - 78.0)
tt_sign	89.5	74.5	59.1	61.7	55.1	67.7 (56.9 - 74.8)
si_sign	85.8	71.3	65.7	80.0	63.4	73.3 (68.3 - 79.1)
mpc1_sign	93.8	71.5	57.9	83.5	72.0	76.4 (72.1 - 80.5)
mpc1ev_sign	95.7	70.0	64.3	80.0	70.3	76.2 (71.2 - 79.2)
mcov_sign	89.4	74.1	45.9	71.5	70.3	70.2 (65.1 - 78.1)
Average MSA	90.7	72.0	59.2	75.7	66.0	72.8

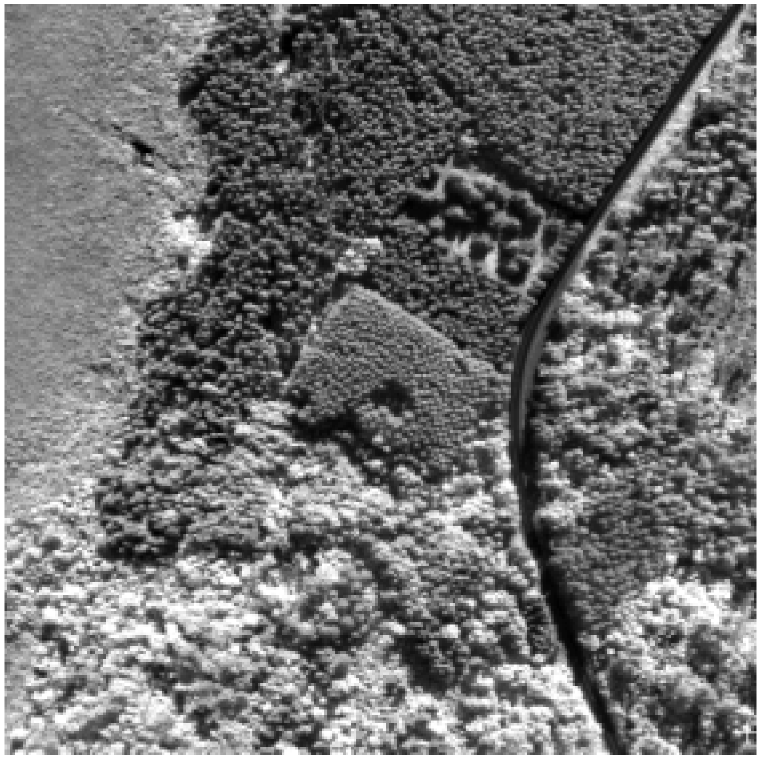

Figure 1 - Representative section of one of the 36cm/pixel MEIS-II image strips acquired on August 16, 1988, over the Petawawa National Forestry Institute's experimental forest.

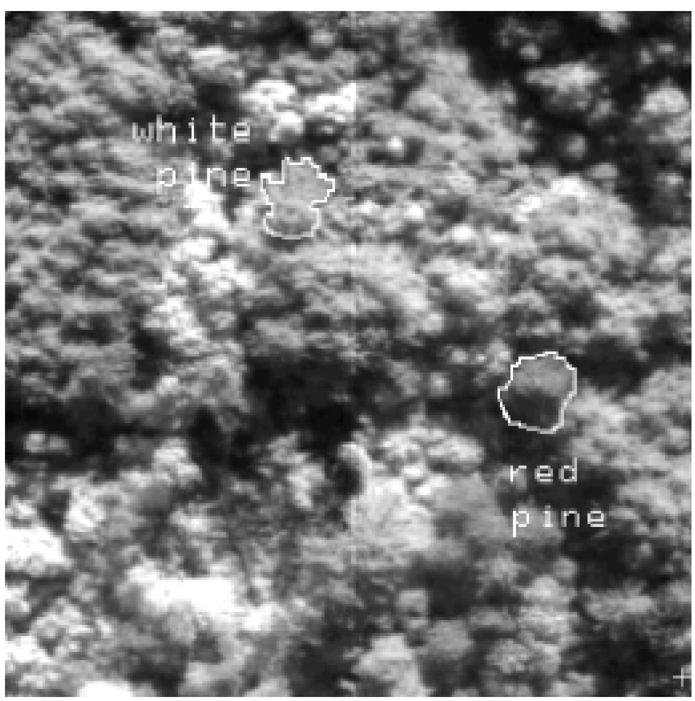

Figure 2 - Two examples of the manually delineated crowns used to train and test the various classification schemes.

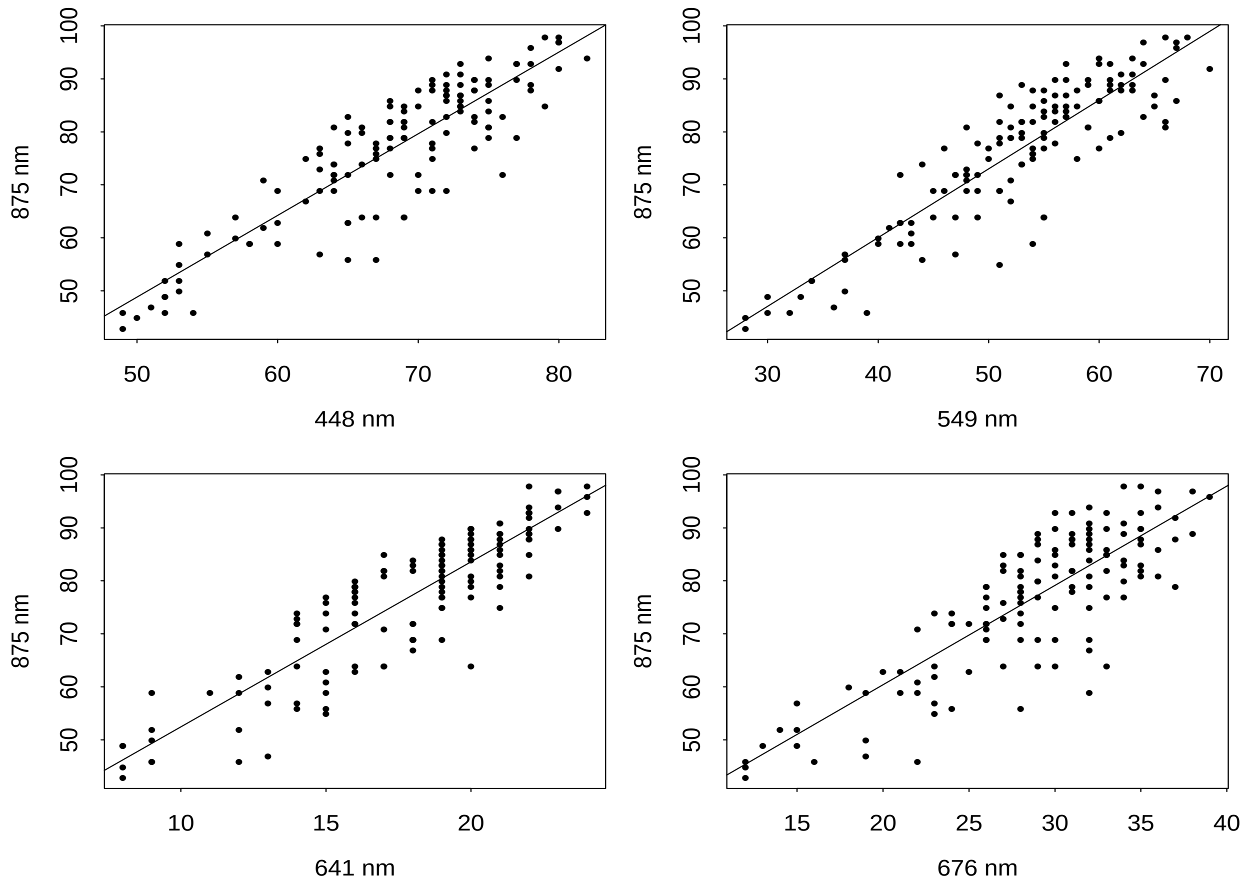

Figure 3 - The four 2-D tree colour lines obtained by fitting least squares lines to the crown's pixel data in scattergrams of each spectral band versus the near infrared band (here, for a white pine).

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