CLASSIFYING AND MAPPING FOREST COVER TYPES USING IKONOS IMAGERY IN THE NORTHEASTERN UNITED STATES

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ABSTRACT

Accurately mapping forest cover types in the northeast using remotely sensed data has proven problematic. High species diversity and spatial variability make creating training areas of spectrally "pure" classes of forest cover types difficult. The advancement of higher spatial resolution satellite sensors have historically allowed for increases in the accuracies of mapping forest cover types. These accuracies have been further increased by image processing techniques such as hybrid forms of the supervised and unsupervised classification methods. However, since the launch of very high resolution (VHR) sensors (≤4m) such as IKONOS, traditional *per-pixel* automated classification has not always worked well. While increases in spatial resolution create increased amounts of informational detail, this also creates higher within class spectral variability, potentially causing lower classification accuracies when solely using *per-pixel* classification techniques based upon spectral comparisons. By incorporating other image processing techniques such as texture into automated classification, the increased within class spectral variability inherent to very high resolution images may increase our ability to discern relatively homogeneous clusters of pixels. Segmenting images into clusters of unique texture followed by classifying those clusters based on their spectral response patterns is a potential method for both: 1) increasing the accuracy of utilizing very high resolution images for classification, and 2) increasing the accuracy of mapping forest cover types in the northeast. Preliminary results considered in the context of an index indicate that the *per-segment* approach to forest cover type classification yields a significantly better accuracy compared to the *per-pixel* approach.

INTRODUCTION

The history of satellite sensor engineering for purposes of collecting remotely sensed imagery has shown a trend in developing higher spatial resolution sensors. Beginning in the 1970's with the Landsat program, satellite sensors have developed from pixels having a spatial resolution of 80 meters, to today's orbital sensors discerning pixels at sub-meter resolutions. While it is likely the demand for this level of spatial resolution has multiple origins, its demand from forestry professionals stems from their need to represent their managed lands at scales appropriate to make decisions regarding tree inventories.

Natural resource managers employ cover type maps for a wide variety of purposes regarding the planning and assessment of the lands over which they steward. The level of informational detail, or specificity of the classification system, and accuracy of these maps will directly translate into the effectiveness of management decisions based upon them. This creates a demand for cost efficient, accurate, and updated cover type maps detailing practical information that land managers can confidently rely upon to make decisions. The interpretation of large scale aerial photography has been and remains an important tool for identifying the extent of forest cover types. However, these techniques are at a disadvantage when compared to automated classifications, their application for large areas can be prohibitively time and money consuming, and their repeatability has shown inconsistent results between different human analysts.

However, many forestland managers throughout the 1980's were slow in adopting automated classifications as a form of inventorying due to unacceptably low classification accuracies (Skidmore and Turner 1988, Moore and Bauer 1990, Bolstad and Lillesand 1992). Landsat Thematic Mapper (TM) overall classification accuracies for mapping the forest cover types of the northeastern United States have varied widely between 45% through 95% based on combinations of Anderson level 2 and 3 classification schemes (Anderson *et al*. 1976, Bolstad and Lillesand 1992). Federal, state, and private forest managers typically require an inventory that can identify species to an overall accuracy of at least 80% (Bolstad and Lillesand 1992), and classify Anderson level 2 information to an overall accuracy of 90% (Salajanu and Olson 2001). Until remote sensing classifications can consistently achieve these accuracies at the scales needed by the forest management community, northeastern forest cover type classifications generated from automated image processing techniques will largely remain an academic pursuit.

The evolution of sensor technology and image processing techniques have brought ever increasing abilities to accurately map forest cover types in the northeast, every advance made brings automated image classification closer to becoming a practical solution for use by forest managers in inventory. The success of the original Landsat MSS for forest cover type classification has varied considerably depending on the classification scheme used and the image processing techniques applied, but this sensor has generally been unsuccessful mapping forest cover types in the northeast because of its coarse spatial, spectral, and radiometric resolutions (Hopkins *et al.* 1988, Moore and Bauer 1990). The advancements of the Landsat program with the launch of the Thematic Mapper brought increases in spatial, spectral and radiometric resolutions resulting in the increased abilities of researchers to accurately classify forest cover types in the northeast (Hopkins *et al.* 1988, Moore and Bauer 1990). Although the discriminatory abilities for mapping forest cover types were increased in TM, the spatial resolution of this sensor limits its minimum mapping unit for classification to several acres rather than individual trees (Schriever and Congalton 1995). Also, the successes of the TM sensor for forest classification in the northeast have been largely attributed to the increase in spectral resolution, especially the addition of the middle infrared bands, with only slight benefits gained by the higher spatial resolution (Hopkins *et al.* 1988, Moore and Bauer 1990, Wolter *et al.* 1995). Salajanu and Olson (2001) determined that when all other sensor characteristics are relatively equal, namely spectral resolution, increases in spatial resolution increase classification accuracies at Anderson levels 1, 2, and 3. They concluded that the SPOT sensor, with multispectral spatial resolutions of 20m, was able to map forest cover types more accurately than the equivalent multispectral bands of Landsat TM. However, many other authors determined that increases in spatial resolution negatively effect the accuracy of *per-pixel* based maximum likelihood classifiers because of the increased within class spectral variability, illustrating a need to develop novel image processing techniques in order to fully exploit the informational content of higher resolution images (Irons *et al.* 1985, Cushnie 1987, Johnson 1994, Marceau *et al.* 1994, Lobo 1997, Franklin 2001). Carleer and Wolff (2004) used IKONOS data to map tree species in Belgium. Their effort utilized a mean filter in a 3x3 moving window to reduce the intraclass variance of the data. This technique improved their classification's overall accuracy to 85%, but effectively degraded the spatial resolution of the image. The mean filtering also created a higher proportion of mixed pixels. Irons *et al.* (1985) noted that while increases in spatial resolution increase the informational content of an image, thereby increasing within class spectral variability, increased spatial resolution also decreases the amount of "mixed" pixels relative to "pure" pixels, counteracting any detrimental effects caused by increased spectral variability. Carleer and Wolff (2004) pointed to a need for classification methods adopting regional techniques (image segmentation) in order to fully capitalize on the potential of very high resolution images for forest classification.

While the effects of increased spatial resolution on the accuracy of automated classification of remotely sensed images is debated in the literature, the need to develop novel classification approaches to increase the accuracy of automated classification seems clear. Chuvieco and Congalton (1988) identified three successive steps in the classification of digital imagery; an initial training phase where seed statistics are generated to identify and represent the project's informational categories, followed by the assignment of the undefined pixels to informational categories (those pixels not used in the training process), and completed by an accuracy assessment. They stressed that the selection of training statistics is critical to achieve the highest possible classification accuracy. This is because training areas need to be spectrally indicative of that particular cover type exclusively, otherwise assignment of the undefined pixels to informational categories will be unsatisfactory. Supervised and unsupervised classifications have inherent advantages and disadvantages when trying to define training areas for image classification (Fleming *et al.* 1975, Chuvieco and Congalton 1988, Bauer *et al.* 1994, Jensen 1996). Supervised classifications have a subjectivity associated with them because the analyst assigns informational labels to classes which may exhibit more or less spectral variation than the analyst can account for. This is because spectral reflectance patterns are the result of a combination of soil type and moisture content, herbaceous and understory vegetation, and overstory vegetation, all of which are effected by slope, aspect, elevation, and atmospheric effects which vary from site to site. Unsupervised classifications group spectrally homogeneous areas of pixels, but these groupings may have unclear informational correspondence. Remote sensing classification projects have seen increased accuracy results by combining the techniques of both supervised and unsupervised classifications (Fleming *et al.* 1975, Chuvieco and Congalton 1988, Bauer *et al.* 1994, Jensen 1996). This approach, referred to as a hybrid classification, is at an advantage compared to the singular application either of its component classifications because it capitalizes on each of the techniques' benefits while minimizing their drawbacks. Many variations of the hybrid technique have been developed over time. Fleming *et al.* (1975) presented a "modified clustering" approach for Landsat MSS data. This technique applied an unsupervised classification on several image subsets, labeled the spectral groups to classes, and then combined these groups to account for within class spectral variation. These combined classes were then used as training statistics to classify the image with a supervised technique. Chuvieco & Congalton (1988) presented a technique in which training statistics from both supervised and unsupervised methods are clustered via complete linkage and squared Euclidean distance into a dendrogram to interpret classes with both meaningful information and spectral representation. This is followed by testing the appropriateness of each training cluster using discriminant analysis, reclassifying the image using these new training statistics, and then performing an accuracy assessment. Bauer et al. (1994) presented guided clustering, a technique that isolates each image class in order to perform an unsupervised classification to capture the within class spectral variation. Once each class has individually been classified into subclasses, all of the subclasses are used as training statistics to reclassify the entire image via supervised classification. The resulting image clusters are then recoded to represent the individual informational classes. Jensen (1996) presented a technique termed "cluster busting", which begins with an unsupervised classification using an ISODATA algorithm. All of the pixel groups with clear informational correspondence are masked out of the image, and successive unsupervised classifications followed by masks are applied until the classification is satisfactory.

The increased within-class spectral variability of very high spatial resolution images dictates a need for an approach to automated classification alternative to those based solely upon spectral comparisons of pixels. Regional approaches have shown potential. Regional approaches, also referred to as image segmentation, cluster pixels sharing a common attribute into a region, followed by classifying all of the pixels within the region to the same class. Two general techniques have been widely used to segment images into regions. Segmenting an image based on GIS data such as land use, soils, property boundaries, etc., or segmenting an image based upon its own data properties, such as the spatial distribution of texture. Aplin *et al* (1999) and Kayitakire *et al* (2002) both demonstrated higher classification accuracies when using GIS based image segmentation when compared to pixel based classifications. Aplin *et al* (1999) used a decision model for the classification of image segments based on the composition of each region's pixels, previously classified via a per-pixel supervised maximum likelihood technique. However, often times ancillary data in GIS format for many regions is not available (Mladenoff and Host 1994) and segmenting digital images into discrete objects needs to be accomplished via methods to the original images themselves.

By incorporating other image interpretation techniques to automated classification such as some measure of texture, the increased within class spectral variability inherent to very high resolution images may allow for discerning relatively homogeneous clusters of pixels based on autocorrelation of texture. Segmenting images into regions of unique texture (or other interpretation elements) followed by classifying those clusters based on their spectral response patterns could potentially yield higher classification accuracies. The success of this technique depends on the spatial and spectral resolution of a sensor. Giakoumakis *et al.* (2002) used *object oriented classification* in order to analyze Landsat TM and IKONOS data to map forest fuel types in the Mediterranean. The results indicated that while the spectral resolution of TM is superior to that of IKONOS, and therefore better able to recognize major land cover classes, the spatial resolution is coarse to a degree where no information is obtainable for individual objects smaller than 30 meters. IKONOS was able to recognize individual objects, and detect texture differences and anomalies within the study area, but for the classes under consideration neither shape nor texture was enough for satisfactory discrimination of cover types, indicating a need for increased spectral resolution (Giakoumakis *et al.* 2002).

METHODS

Study Area

The study area utilized for this research has been chosen for its indicative properties which are characteristic of northeastern forest types. In addition, this area has been the focus of forest cover type mapping research, conducted using a variety of image processing techniques applied to Landsat TM data (Schriever and Congalton 1995, Pugh and Congalton 2001, Plourde and Congalton 2003).

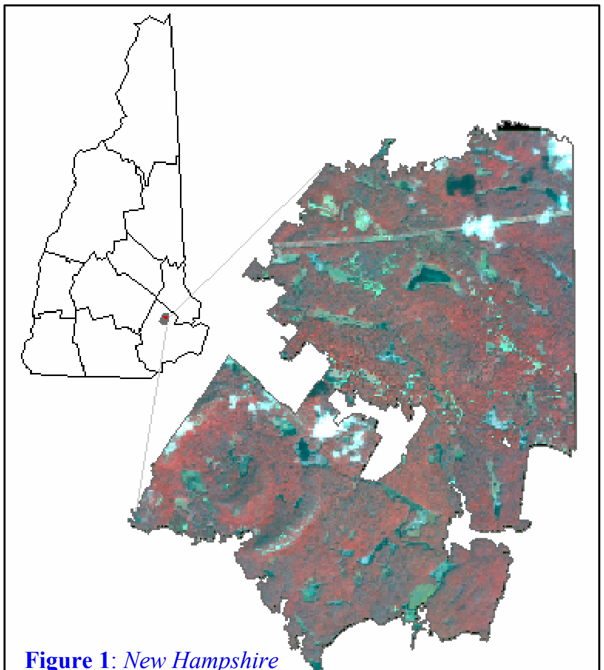

Figure 1: *New Hampshire counties and study area location.*

The study area is completely contained within Rockingham County in southeastern New Hampshire (Figure 1), part of the New England Seaboard physiographic province. The study area also falls within the political boundaries of the towns of Deerfield and Nottingham. The study area is comprised of two study sites, one site of 4,146 acres (1,678 hectares) is found on public land occupying approximately 75% of Pawtuckaway State Park, and the other site of 4,621 acres (1,870 hectares) is within privately owned land northeast of the public site, falling adjacent to the public site in some areas. The privately owned study site is characterized by having rural and industrial forest land uses. 25% of the private site is owned by a single lumber company and is considered industrial forest, and the remaining 75% of the private site is rural forest. Irland (1982) defined rural forests as forested areas in which the dominate land ownership belongs to farmers and rural residents, and that the land provides a wide range of hunting, fishing, watershed protection, and aesthetic benefits. Industrial forests are characterized as being actively managed to provide timber and wood fuel. The public study site is dominated by wild forest, defined by Irland (1982) as being lands designated as wilderness areas, watershed protection areas, and/or the land holdings of nonprofit organizations.

The topography of the public lands study area ranges from 250 feet (above mean sea level) to 1000 feet. In contrast, the private study site's elevation begins at 250 feet and plateaus at 500 feet. The climate of this area can be characterized as having an annual mean minimum temperature of 35.6°F, a mean maximum temperature of 58.5°F, a mean annual precipitation of 44.42 inches, and a mean annual snowfall of 56.2 inches (Garoogian 2000; Epping, NH weather station).

Data

A single IKONOS scene was purchased from Space Imaging LLC covering the full extent of the greater Pawtuckaway study area. This scene was acquired in on September 1st, 2001 at 3:44 pm. The overall scene includes some cloud cover. IKONOS data has an 11 bit radiometric resolution and 4 multispectral bands (1 blue, 2 green, 3 red, and 4 near infrared) each having 4 meter spatial resolution. There is an additional panchromatic band of one meter spatial resolution. The best visual composite for the purposes of discriminating forest cover types is a false color composite using bands 4, 3, and 2 as the respective RGB image. This was further enhanced by merging the 1 and 4 meter resolution data into a 1 meter fused image, used for field work and heads-up image interpretation.

The data delivered by Space Imaging was registered to the New Hampshire State Plane (FIPS zone 2800), NAD 83, feet. The positional error of the "Reference" product is published as having a 11.8 meter Root Mean Square Error (RMSE). The initial processing of the IKONOS data was to reduce the amount of data needing to be processed, and to avoid spectral confusion of land covers outside of the study areas. This was done by clipping the study area out of the full scene, in addition to clipping out clouds and non-applicable areas such as utility easements composed of young vegetation easily confused with other forest types.

The reference data for use in assessing the accuracy of this classification were collected by Pugh (Pugh and Congalton 2001) in between 1994 and 1995. Although there is a time gap of seven years between the reference data collection and the image acquisition, actual forest cover type change should be insignificant, especially in the conservation areas within Pawtuckaway State Park. The reference data set guidelines for the definitions of the forest cover type classes were used in the classification, adopted from the Society of American Foresters (SAF) classification scheme (Eyre 1980, see appendix "Classification System Guidelines and Forest Cover Type Definitions"). The reference data were collected with a minimum mapping unit (MMU) of two acres.

Derivative Bands

In addition to the raw IKONOS bands 1 through 4, derivative bands were generated through indices, band ratios, and principal component analysis. This included a NDVI band (Normalized Difference Vegetation Index), a TNDVI band (Transformed Normalized Difference Vegetation Index), a Vegetation Index (VI), a 4/3 ratio band (IR/R), and the first principal components band for both all of the visual bands (1, 2, and 3) and all of the raw bands. After these derivative bands were calculated they were rescaled to more appropriately match the average dynamic ranges of their component bands, thus avoiding over influence during the classification stage.

Training Statistics

Potential training areas were delineated by interpreting the IKONOS one meter fused false color composite image in combination with an enlarged National High-Altitude Photography (NHAP) color infrared photo. Forest cover type stands were delineated and determined based on criteria offered by Hershey and Befort (1995). Centroid coordinates, or the mean geometric center of a polygon, were generated for use in locating these stands in the field for the purposes of verifying their forest cover type. Centroids were located with the aid of Global Positioning Systems (GPS).

Representative training areas identified from field sampling were then compiled into a spectral library for use as supervised classification statistics. Congalton and Chuvieco (1988) suggest training statistics be collected from digital imagery via a "seed" technique. "Seed" is a region growing technique which creates training areas based on an input pixel. The analyst sets a spectral Euclidean distance from which to accept neighboring pixels to add as training data in addition to the original "seed" pixel. The pixels that are accepted are within the set Euclidean distance from the mean of the seed. This technique proved to be ineffective for establishing training areas of forest cover types with high spatial resolution imagery. Its results created training areas that were not indicative of the classes of interest. Instead, spectral training data were collected by manually digitizing the extent of each training area.

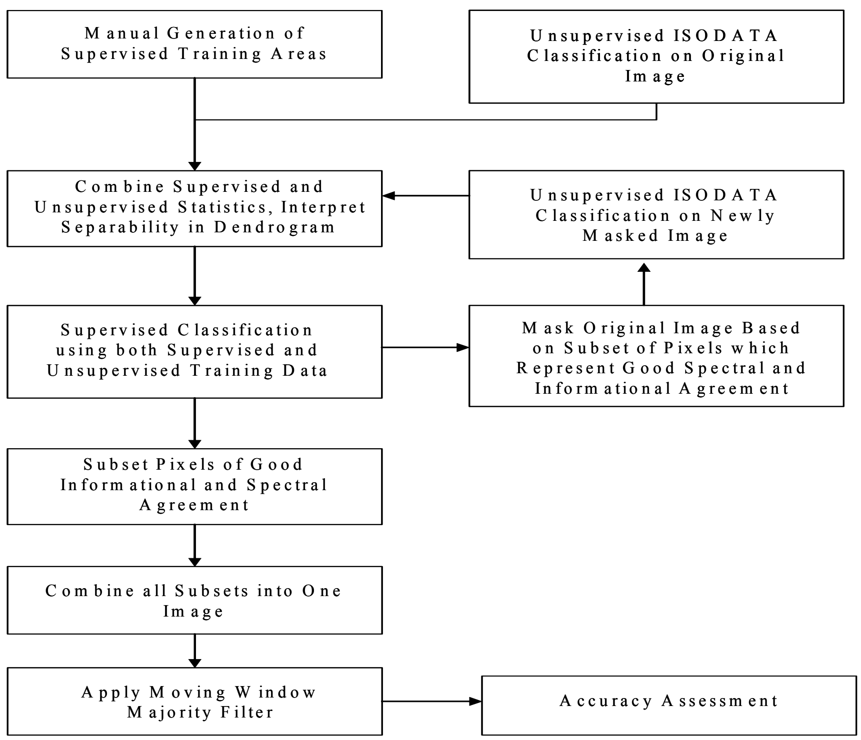

Figure 2: *Schematic detailing per-pixel classification technique.*

Several measures of separability were used for determining the optimum bands for use in the classification. These included spectral pattern analysis, bi-spectral plots, and the distance measures Jefferies-Matusita and Transformed-Divergence. After assessing all of these measures of separability, the 6 best bands for classification were the blue, green, red, near infrared, NDVI, and IR/R bands.

Per-Pixel Classification

The per-pixel classification strategy utilized the forest cover types of both non-mixed and mixed species compositions as training areas. The classification technique used a combination of hybrid methods (Figure 2). The study area was initially classified with a 100 cluster unsupervised maximum likelihood classifier. These statistics were then combined with the original supervised training data and assessed in a dendrogram illustrating distances between classes based upon squared Euclidean distance and complete linkage. Where supervised data of consistent informational content grouped with unsupervised clusters, those clusters were assigned to that informational category and used for a subsequent supervised classification. Where supervised data of inconsistent informational content grouped together, minority training areas of SAF hardwood/softwood level information were discarded, along with all unsupervised clusters within that group. Groups showing no informational cohesiveness were entirely discarded. Once some clear informational groups were established in the dendrogram, a supervised classification was performed on the data. Classified pixels established from training areas which showed clear informational grouping were then masked from the original data, and the process was repeated iteratively for three iterations. The final image was then assembled from the classified pixels that shared spectral and informational groupings from the three iterations. Finally, a neighborhood filter was applied in a 3x3 moving window using a majority rule.

Per-Segment Classification

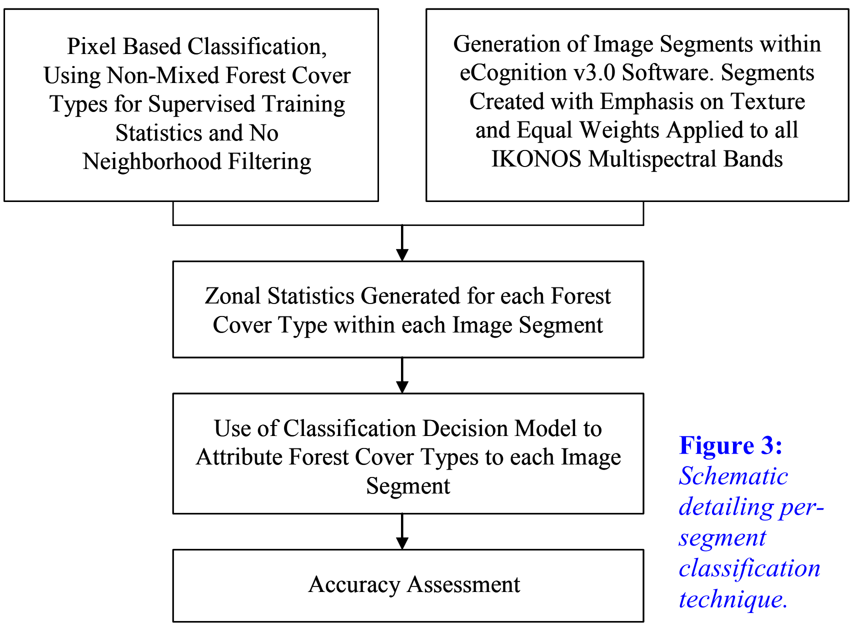

Figure 3: *Schematic detailing per-segment classification technique.*

The per-segment classification strategy consisted of three phases: the first was a per-pixel classification approach using the aforementioned technique except using only non-mixed forest cover types as supervised training areas, the second was generating image regions using eCognition v3.0 software, and the final phase classified each of the image segments according to each segment's classified pixel composition (Figure 3). Generation of image segment's in eCognition was primarily dependent on the texture of the image, the technique considered all 4 multispectral IKONOS bands and weighted them evenly. The scale parameter in eCognition was also set relatively high in order to generate satisfactory image regions coinciding to forest stand boundaries. Classes were assigned to image segments based upon a classification decision model (see appendix "Decision Model for Classification of Image Segments to Forest Cover Types") which used an ordered set of queries defined such that they met the authors' interpretation of the classification system guidelines defined by the source of the ground reference data, which had been adopted from the Society of American Foresters (Eyre 1980).

RESULTS

Accuracy Assessment

The accuracy assessment for both per-pixel and per-segment techniques used a stratified random sampling strategy. IKONOS Imagery, rectified to Space Imaging's "Reference" product level, has a published RMSE of 11.8 meters, dictating a need to choose pixels for use in the accuracy assessment occurring within a 5x5 window of completely homogeneous land cover. This was done in an effort to avoid the positional errors that may occur when comparing two datasets, especially when a sample point falls on or close to the edge of a classified region or polygon. Random points were created using the Accuracy Assessment module in ERDAS Imagine, point classes for both classified and reference data were extracted via a pixels to ASCII subset, and error matrices were generated using pivot tables in Microsoft Excel. Results from the accuracy assessment are reported in error matrices (Tables 1 and 2) and Kappa statistics (Tables 3 and 4).

						Reference							
		1	2	3	4	5	6	7	8	9	10	Total	User's Accurarcy (%)
Classified	1 White Pine	7	5	0	0	0	0	3	0	0	10	25	28
	2 White Pine / Hemlock	5	1	0	0	4	4	5	0	0	7	26	3.8
	3 Hemlock	5	2	0	0	4	7	0	0	0	0	18	0
	4 Other Conifer	5	11	1	1	10	4	5	1	1	4	43	2.3
	5 Mixed	3	4	2	0	11	4	1	2	0	7	34	32.3
	6 Red Maple	4	5	1	0	17	2	7	1	3	0	40	5
	7 Oak	1	3	1	0	8	4	10	9	2	3	41	24.3
	8 Beech	2	4	0	0	7	2	0	0	1	8	24	0
	9 Other	2	6	0	0	3	1	1	2	3	0	18	16.6
	10 Non Forest	4	4	1	0	2	0	1	0	1	17	30	56.6
	Total	38	45	6	1	66	28	33	15	11	56	299	
	Producer's Accuracy (%)	18.4	2.2	0	100	16.6	7.1	30.3	0	27.2	30.3		Overall Accuracy = 17.39

Table 1: Similarity of Per-Pixel based classification technique to previously collected reference data.

						Reference							
		1	2	3	4	5	6	7	8	9	10	Total	User's Accurarcy (%)
Classified	1 White Pine	21	0	0	0	0	0	0	0	0	0	21	100
	2 White Pine / Hemlock	7	4	0	0	4	2	3	0	0	1	21	19
	3 Hemlock	0	0	0	0	0	0	0	0	0	21	21	0
	4 Other Conifer	4	3	0	3	3	1	0	0	0	7	21	14.2
	5 Mixed	2	6	1	0	4	1	4	2	0	1	21	19
	6 Red Maple	0	0	0	0	11	7	0	2	1	0	21	33.3
	7 Oak	1	2	0	0	2	2	8	3	3	0	21	38
	8 Beech	0	1	0	0	2	0	10	1	0	7	21	4.7
	9 Other	2	1	0	0	8	0	6	4	0	0	21	0
	10 Non Forest	1	0	0	0	2	0	0	0	0	18	21	85.7
	Total	38	17	1	3	36	13	31	12	4	55	210	
	Producer's Accuracy (%)	55.2	23.5	0	100	11.1	53.8	25.8	8.3	0	32.7		Overall Accuracy = 31.4

Table 2: Similarity of Per-Segment based classification technique to previously collected reference data.

Technique	KHAT	Variance	Z Score
Per-Segment	0.2380952	0.0011935	6.8918048
Per-Pixel	0.0788525	0.0006184	3.1708099

Table 3: Summary Statistics of pixel and segment based techniques

Pairwise Comparison	Z Score
Segments vs Pixels	3.7409731

Table 4: Pairwise Comparison

CONCLUSIONS

Several factors may account for the low accuracies obtained in these results: challenges in extracting training area statistics, the classification decision model, spectral limitations of the IKONOS sensor, accuracy assessment constraints, and the reference data itself. A forest cover type is a descriptive classification of forestland based on the occupancy of an area by a dominant or defined mixture of tree species (Eyre 1980), so identifying a forest cover type as a training area for image classification includes sampling of multiple trees. The amount of pixels needed to represent a forest cover type training area with Landsat TM data would be far less than the same area with an IKONOS image. It was noted in the Training Statistics section that using the *Seed* tool with VHR imagery did not produce areas representative of forest cover types. This is because if the origin pixel was set within a tree's canopy, the Euclidean distance would have to be set extremely high in order to grow a region that would expand past that tree's canopy and into other trees' canopies across bare ground, shadows, etc. It would also produce statistics with very high variability. Identifying training areas by manually creating polygons overcomes that limitation, but creates training statistics which may not be spectrally indicative of the forest cover type, especially when trying to conduct per-pixel comparisons. The per-segment approach avoids the creation of training areas which include mixed tree species, but assigns a forest cover type to each segment based on a classification decision model. The model used here is an interpretation of the forest cover type definitions that were used to generate the reference data. While those guidelines have some numeric definition, the decision model's effectiveness may be enhanced by creating a more representative model.

Data exploration identified potential difficulties in trying to separate forest cover types to SAF species level classes. Bi-spectral plots, dendrogram analyses, and spectral pattern analysis all indicated a good potential to separate the classes into their respective hardwood and softwood categories, but species groups within those categories seemed inseparable based on spectra alone. Separating vegetation to the species level has been historically difficult with multispectral scanners with bands analogous to IKONOS, the addition of a middle infrared band could aid in the separation of forest cover types at SAF species level detail.

Class	Original	3x3	5x5	7x7
White Pine	169373	126160	93405	76598
White Pine / Hemlock	18140	1947	109	9
Hemlock	27790	4192	380	34
Other Conifer	433184	564446	637212	668854
Mixed	219998	149641	98064	68251
Red Maple	436587	543816	601918	627120
Oak	316152	344323	341371	332858
Beech	84527	25133	5918	1644
Other	99608	28887	5472	1039
Non Forest	321962	338776	343472	350914

Table 5: Effect of Neighborhood filter on pixel counts per class.

Ideally, an accuracy assessment would meet several criteria; it would collect 50 random samples per class, multiple samples would not occur within the same land cover polygon, and the reference data would be collected at the same minimum mapping unit as the classified data were generated (Congalton and Green 1999). The results of the per-pixel classification generated small and fragmented areas of classified pixels for some classes, and subsequent neighborhood filtering increased some class's pixel counts while severely decreasing other class's pixels (see table 5). This made selecting pixels to be used in the accuracy assessment which met the 5x5 homogeneous criteria impossible for some classes, so a 5x5 majority rule was used instead. This also made finding 50 samples per class in the per-pixel classification impossible, so the sampling strove to collect at least 20 samples per class instead. While these constraints were not an issue with the per-segment approach, the sampling strategy was mimicked for comparison purposes. Another assumption which had been violated was that the minimum mapping units were dissimilar between the classified and reference data sets. The reference data collected by Pugh (Pugh and Congalton 2001) were based on a two acre minimum mapping unit, and comparing these data to the classified IKONOS imagery resulted in a large discrepancy (A 3x3 filtered IKONOS image has a MMU 31 times smaller than the two acre MMU of the reference data). The reference data were also collected ten years ago. While different dates of creation may result in seemingly minimal differences, especially for the purposes of forestry reference data, it notably raised discrepancies in areas which have been logged and now have an entirely different species composition resulting in a different forest cover type.

Due to those previously listed discrepancies, it could be useful to refer to this assessment as a "similarity assessment" instead of an accuracy assessment. Preliminary results of the overall accuracies were very low for both methods, 17% for the per-pixel approach and 31% for the per-segment approach, but considering this method of assessment in the context of an index, the results indicate that the per-segment approach is more appropriate for forest cover type classification of very high spatial resolution imagery. This is further illustrated by the pairwise comparison Z Score of 3.74, indicating that the two methods are significantly different at the 95% confidence interval. Even though both KHAT statistics represent a better than random classification, they both fall into an area of very poor agreement with the reference data, although it is worth noting the per-segment approach is much higher than the per-pixel technique.

Future research should be conducted gathering spatially precise training areas and emphasizing a more rigorous accuracy assessment. Training areas verified in the field should be recorded with a spatial precision such that the imagery analyst can extract spectral information regarding the canopy of only a few trees, minimizing variability but ensuring the collection of a known tree type in an otherwise undistinguishable contiguous canopy. Alternative classification decision models should be experimented with to more closely match the procedures for identifying forest cover types on the ground. Finally, current reference data should be collected at a scale matching that of the IKONOS classified image.

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APPENDICES

CLASSIFICATION SYSTEM GUIDELINES AND FOREST COVER TYPE DEFINITIONS

Coniferous

WP – Eastern white pine comprises a majority of the stocking (>70%) and characteristically occurs in pure stands. Its associates include red pine, pitch pine, quaking and big-tooth aspen, red maple, pin cherry, and white oak on lighter textured soil. On heavier soils, associates are birches (paper, sweet, yellow, and gray), black cherry, white ash, northern red oak, sugar maple, basswood, hemlock, red spruce, balsam fir, white spruce, and northern white cedar.

WH – Eastern white pine and eastern hemlock, in combination, comprise the largest proportion of the stocking, but neither species alone represents more than half of the total. The combination rarely exists without associates, and red maple is a very common one. Other common associates include paper birch, northern red oak, beech, sugar maple, yellow birch, gray birch, red spruce, white ash, and balsam fir.

HE – Eastern hemlock is pure or provides a majority of the stocking (>70%). Common associates are eastern white pine, balsam fir, red spruce, sugar maple, beech, yellow birch, northern red oak, white oak, yellow poplar, basswood, black cherry, red maple, and white ash.

OC – Other conifer species besides those previously listed comprise at least a majority of the stocking (>70%).

Mixed

MX (white pine, red oak, red maple) – Eastern white pine and northern red oak are the most important species in this forest cover type, although red maple is always present. Each contributes at least 20% of the stocking. White ash is often a major associate. Other trees commonly found are eastern hemlock, birches (paper, yellow, and sweet), black cherry, basswood, sugar maple, and beech. Minor species may include eastern hophornbeam and striped maple.

Deciduous

RM – Red maple comprises a majority of the stocking (>50%). Most of the common associates include red spruce, balsam fir, white pine, sugar maple, beech, yellow birch, eastern hemlock, paper birch, aspen, black ash, pin cherry, northern red oak, and black cherry.

OAK – White, black, and or northern red oak comprise at least a majority of the stocking (>50%). One or more species of hickory are consistent components but seldom comprise over 10% of the basal area. Other associates may include sugar and red maple, white and green ash, American and red elm, basswood, black cherry, American beech, and eastern hemlock.

BH – American beech must comprise at least 25% of the stocking and may be associated with any of the previously listed hardwood species. If American beech comprises at least 25% of the stocking, then this classification takes precedence over any other forest class.

Other

OTHER – Any other highly distinct forest cover type not already listed (e.g., ash, sugar maple, aspen).

Non-forested

NF – Non-forested cover types include any cover type which consists of less than 25% tree crown closure and includes cover types like agricultural land, urban, industrial, residential, brush, wetlands (swamps, areas with significant standing water; bog, wet area without standing water) and open water.

DECISION MODEL FOR CLASSIFICATION OF IMAGE SEGMENTS TO FOREST COVER TYPES

Considering all segment pixels:

- If polygon is composed of >=75% Non-Forested (NF) pixels, then
    - **Polygon = NF**, else,

Considering all forested segment pixels:

- If polygon is composed of >=25% Beech (BH) pixels, then
    - **Polygon = BH**, else,

- If polygon is composed of >70% White Pine (WP) pixels, then
    - **Polygon = WP**, else,

- If polygon is composed of >70% HE pixels, then
    - **Polygon = HE**, else,

- If polygon is composed of >70% Other Conifer (OC) pixels, then
    - **Polygon = OC**, else,

- If polygon is composed of >50% Red Maple (RM) pixels, then
    - **Polygon = RM**, else,

- If polygon is composed of >50% Oak (OAK) pixels, then
    - **Polygon = OAK**, else,

- If polygon is composed of >=20% WP **AND** >=20% OAK **AND** >0% RM pixels, then
    - **Polygon = MX** (Mixed), else,

- If polygon is composed of <=50% and >0% WP **AND** <=50% and >0% Hemlock (HE) **AND** WP pixels + HE pixels > Any other forest type, then
    - **Polygon = WH** (White Pine / Hemlock mix), else,

- If polygon is composed of >70% WP + HE + OC, then
    - **Polygon = OCmix** (Other Conifer Mix), else,

- If polygon does not classify to any of the previously listed forest types, then
    - **Polygon = Other**