INVESTIGATING NEW ADVANCES IN FOREST SPECIES CLASSIFICATION

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ABSTRACT

Detailed forest classification provides critical information for forest managers. The potential for species level classification from remotely sensed data has been challenging in the past because of limitations of both available image data and traditional classification techniques. Such limitations may be reduced by the increased availability of higher spatial resolution imagery as well as detailed digital elevation models e.g. derived from lidar collections. This project is a multi-year effort aimed at evaluating the benefits of combining traditional image classification techniques with derivatives of active remote sensing sources such as lidar for species level forest classification. The project plans to evaluate the relative benefits of different classification schemes, considering accuracy, efficiency, and effectiveness.

The project focuses on the classification of imagery for the area in and around the Heiberg Memorial Forest in Tully, New York, utilizing existing forest inventory information for ground reference. The project aims at evaluating the applicability of different classification methodologies. Traditional approaches—such as supervised classification—provided a means to generate baseline classifications of satellite imagery (Landsat). This paper focuses on the classification of high spatial resolution QuickBird satellite imagery, with a goal of generating species level classification. Input to the classification includes a number of datasets derived from the imagery, as well as simple topographic characteristics derived from a digital elevation model. Incorporating such layers requires alternative methods of classification such as rule-based classifiers or neural networks. This project considers an object-oriented approach to rule-based classification. The analysis showed promising results for the separation of coniferous forest species. However, further research is needed to understand the benefits of different ancillary data layers as well as the derived data layers.

INTRODUCTION AND OBJECTIVES

Overview

Land cover classification provides valuable information to forest managers. Historically, remote sensing approaches to such classification have focused on generalized forest classes. As higher spatial resolution data sources become more widely available, the potential for species level classification has increased significantly. While lower spatial resolution imagery provides an averaged response over a region, individual trees are visible in some high resolution imagery. This provides an opportunity to evaluate the composition of the mixed-species stands that are common in northeastern forests. However, a challenge to effectively utilizing high spatial resolution imagery is that the spectral response of an individual tree is influenced by variations in canopy illumination and topographic effects. New techniques, especially those involving fusing supplemental data sources, appear necessary to fully utilize high spatial resolution imagery.

Recent literature has shown the utility of active remote sensing modalities, such as radar and lidar, for image classification over a variety of ground cover types. Radar sensors have been used for forest classification with some success; however, these systems typically provide lower spatial resolution than that attained from lidar systems. Lidar systems generate both intensity and range information from which parameters such as land cover classes and topography may be derived. Lidar data is expected to provide complementary information to traditional multispectral imagery to improve species level forest classification. However, lidar acquisitions involve high cost, and the benefit of using lidar data has not been established. Prior analysis (Quackenbush *et al*., 2006) focused on establishing a baseline by classifying moderate resolution Landsat 7 Enhanced Thematic Mapper Plus (ETM+) satellite imagery. This paper reports the results of the classification of high spatial resolution QuickBird imagery. An understanding of the potential benefit of including topographic information in the classification was explored using United States Geological Survey (USGS) 10 m digital elevation models (DEMS). Later research will incorporate higher resolution lidar DEMs in the classification.

Recent research projects at the State University of New York College of Environmental Science and Forestry (SUNY-ESF) have acquired extensive ground reference information throughout the northeastern United States. This includes precise forest inventory plot locations, as well as detailed tree level information including size, location, and species. This data provides a unique opportunity to support new remote sensing analyses for forest classifications.

Objectives

As discussed above, this project reports the results of classifying high spatial resolution imagery (QuickBird) with 10 m USGS DEMs for the purpose of generating species level information for the area in and around the Heiberg Memorial Forest in Tully, New York. This classification was performed in two stages: an initial classification was performed to delineate forested regions; a secondary classification divided the forested regions into deciduous areas and further separated softwood areas into four species grouping.

BACKGROUND

Species Level Classification

Classifications using remotely sensed imagery provide a convenient way to catalog large areas, providing inventories to support forest management decisions. Up-to-date inventory data is essential for forest management and having species level data provides a valuable tool to aid in this process. Attempts at classification of individual tree species have primarily utilized the spectral content of an image (Leckie *et al*., 2003). The success of such classifications has largely been restricted to simple stand conditions, and in many cases, to classification of western forests in the United States. The conditions within northeastern forests have frequently proved challenging for image classification, since many of the indicators utilized in the west—for example, elevation and soil moisture—do not apply (Szymanski, 2002). Additionally, northeastern forests are frequently a complex mixture of species and structures (Zhu, 2003).

Numerous authors have reported attempts at performing species level classification using a range of techniques and data layers. Pugh (2005) and Michelson *et al*. (1998) considered the advantages of using multi-temporal approaches to gain species level classification results. Rignot *et al*. (1994) used Synthetic Aperture Radar (SAR) imagery to classify vegetation based on dominant species in Alaska and attained similar results using SAR data as compared to traditional multispectral analysis. However, the majority of the stands analyzed contained greater than 90% of a single species. Pugh (2005) not only considered multi-temporal data but also combined Landsat ETM+ and SAR imagery in attempting to define individual softwood species in a study area in upstate New York. Puzzolo *et al*. (2003) used moderate resolution imagery (SPOT – 20 m ground sample distance) to delineate species groupings in a mountainous region in the Italian Alps. They found forest composition in the region to be a function of elevation, slope, aspect, and soil conditions. The authors were able to delineate fundamental coniferous groupings—e.g., spruce/fir vs. pine—using a multidate analysis. However, they were not able to break down deciduous groupings. Volden *et al*. (1998) compared the utility of radar and hyperspectral data for image classification. Like many researchers, they found that combining microwave and optical data improved the classification. Similar to research previously discussed, the stands classified by Volden *et al*. (1998) were dominated by a single species.

Classifying High Spatial Resolution Imagery

High spatial resolution imagery is increasingly being used for generating detailed land cover classifications. This imagery provides unique advantages and challenges for performing such classifications because of the level of variability within a scene (Quackenbush *et al.*, 2000). Whereas lower-resolution imagery—such as Landsat ETM+—provides an averaged response within a 30 m pixel, newer commercial sensors—such as that used from an aerial platform by Emerge, or from a satellite platform by Digital Globe—can produce imagery with a ground sampled distance (GSD) below 1 meter. However, the additional detail associated with high resolution imagery comes with a level of complexity that makes the data less straightforward to utilize (Myeong *et al*., 2001).

When using a medium resolution image such as Landsat ETM+, the spectral characteristic of a forested region is recorded as a generalized response, averaging multiple trees and potentially the ground cover between them. When working with such high spatial resolution imagery, substantially more detail is available within the same forested region, and individual tree crowns are often identifiable. A significant challenge in working with high resolution imagery is that the variation in illumination across an individual feature—such as a tree crown—can lead to differences in spectral response (Riordan, 2003). Riordan (2003) describes some of the approaches considered to mitigate the shading challenge frequently observed in high spatial resolution imagery. One approach to shadow mitigation is the incorporation of some measure of spatial structure. Examples of such approaches include the use of data from active sensors such as radar and lidar.

Active Remote Sensing

A significant portion of commercially available remote sensing data is acquired using passive sensors. The sensors used by Emerge and Digital Globe fall into this category. These sensors rely on energy from the sun interacting with an object of interest and then being reflected back to the sensor. Passive sensors are often restricted by clouds or low light conditions (Zhu, 2003). As an alternative, active sensors supply their own energy source. The information attained from active and passive sensors is quite different, and is frequently very complementary.

When compared to traditional digital elevation models, lidar technology provides highly detailed topographic information. Most applications of lidar in forestry generally use lidar data in cooperation with other data types. Researchers have discovered that information from lidar provides great utility by incorporating spatial structure for land cover classification. Hodgson *et al*. (2003) found that including lidar information improved image classification by reducing confusion within shadowed areas in high resolution imagery. Dowling and Accad (2003) used lidar data to classify vegetation within riparian zones. They found that height information generated from lidar provided an important structural characteristic that was particularly useful in classifying vegetation types. Dowling and Accad (2003) used height information to cluster vegetation into groups, then visually assigned species grouping.

The primary application of lidar collection in the forestry industry has revolved around range information and height generation (Leckie *et al*., 2003). Early sensors provided first return data only, that is, an image was created based on the signal that was returned from the first object encountered. In a forested region, this may be the peak of a tree crown. However, the lidar signal may also transmit through the crown, bouncing off layers within the canopy and eventually bouncing off the ground. The most distant object, usually the ground, generates the response that is termed the last return. Lidar sensors are now frequently able to record first and last return as well as the variation in the intensity of the returned signal. Research has shown that the intensity response from lidar systems has also proved useful as input into image classification. Riordan (2003) found that height and intensity from lidar data individually improved classification, but the greatest improvement in classification accuracy was when utilizing both data components. Leckie *et al*. (2003) found that the combination of lidar and multispectral data provided unique possibilities in terms of individual tree level inventory. They found that incorporating lidar data reduced confusion caused by sunlit ground vegetation. The research presented by Leckie *et al*. (2003) focused on even aged stands of a single species with variable density.

Classification Algorithms

Many algorithms have been utilized to perform land cover classification. These include supervised and unsupervised methods, pixel- and segment-based techniques, and parametric and non-parametric approaches. The decision to use any particular algorithm depends in part on the data under analysis. While traditional approaches such as an unsupervised ISODATA algorithm or supervised maximum likelihood classifier have shown some success in generalized classification of image data, they are limited in terms of the inclusion of ancillary data layers (Aicher and Stiteler, 2004). Combining data with varying statistical characteristics is frequently problematic. This complicates the incorporation of disparate data sets in an image classification. Rule based approaches provide an alternative that allows direct inclusion of supplementary data layers. Researchers have utilized a range of rule-based software including Cubist (Aicher and Stiteler, 2004) and See5 (Hodgson *et al*., 2003). Rule based classifiers and supervised classification techniques both require input reference data to allow the computer to develop patterns that describe the data. Other methods reported to combine disparate data types include the use of neural networks (e.g. Pugh, 2005).

This project has utilized several different classification methodologies. The maximum likelihood (ML) algorithm provides a means to classify multispectral imagery using multivariate spectral statistics. This supervised approach was used to provide a baseline classification of medium resolution ETM+ imagery (Quackenbush *et al*., 2006). Such a fundamental technique provides a structured foundation necessary to produce results that are comparable with other analyses. The later stages of the project aimed to incorporate ancillary layers such as derivates of the imagery as well as of lidar data. However, the utility of incorporating derived data layers using traditional methods of classification is limited. The analysis reported in this paper utilized eCognition software (http://www.definiens.com) to delineate image objects and relied on the rule-based classifier in the See5 software (http://www.rulequest.com/see5-info.html). See5 is a data mining tool used to characterize patterns, create classifiers, and generate predictions.

STUDY AREA AND DATA

Description of Study Site

The Heiberg Memorial Forest is a 9637 ha property, approximately 33 km south of Syracuse in upstate New York (42.75° N, 76.08° W). Elevation on the property varies between 382 m and 625 m AMSL. This property was acquired by SUNY-ESF in 1948, and was converted from agricultural land to forest. Vegetation at Heiberg has been managed to produce a diverse representation of forest ecosystems in the northeastern United States. The property is bordered to the east by state forest land that is also monitored by researchers at SUNY-ESF. This diversity allows for a unique opportunity to study a variety of different forest covers within a relatively small study area. Deciduous trees on the property consist predominantly of mixtures of red maple, sugar maple, red oak, beech, and birch. Conifer species include red pine, white pine, Norway spruce, Scotch pine, hemlock, northern white cedar, and tamarack (larch). The distribution of these species throughout the property is very uneven.

Image data

The early stages of this project, reported in Quackenbush *et al.* (2006), utilized multi-season Landsat ETM+ image data. The analysis reported in this paper utilized QuickBird imagery acquired on 9 August, 2004. The four-band multispectral QuickBird imagery used for the classification had 2.44 m GSD. The spectral range of the four bands is: blue (450 – 520 nm), green (520 – 600 nm), red (630 – 690 nm), and near-infrared (760 – 900 nm). The imagery over the study area had an 11° off-nadir look angle. The imagery contained some cloud cover; however, Digital Globe characterized the atmosphere as being relatively clear. Digital Globe supplied the imagery with radiometric, sensor and geometric corrections. Experimentation performed at SUNY-ESF verified that the image registration was within a single pixel, hence further geometric processing was not applied.

Lidar data over the study area has been obtained by the New York State Department of Environmental Conservation (NYS DEC). However, this data was not available at the time of performing the research for this paper. To explore the benefit of including elevation data in the classification, 10 m digital elevation models from the USGS National Elevation Dataset (http://ned.usgs.gov/) were downloaded. Later experimentation will focus on using the high resolution lidar dataset, which includes first and last return and intensity layers. In addition to the image and DEM layers used for classification, normal color aerial imagery with 60 cm ground sampled distance acquired by Emerge on 11 October, 2001 was available. The Emerge imagery provided additional visual verification for the ground reference data.

Ground Reference Information

This project took advantage of information obtained from previous forest inventories in the study area. These inventories provide periodic information on status and trends of a variety of parameters describing forests and forest use. The most recent inventory work in the Heiberg study area was carried out as part of the NASA funded Forest Organization Remote Sensing Technology Project (http://forest.esf.edu). There are 222 plots in Heiberg and more than 270 plots in the neighboring state forest that were visited during the period of 2001 – 2004. Data is collected at each plot location on a regular cycle, for some at a ten year interval, for others, annually or semi-annually. Each plot includes a detailed description of all trees within a 15 m radius of the plot center. Plot locations have been determined using survey grade global positioning system units. Compartment level information of Heiberg, monitored by SUNY-ESF, provides additional information. A third source of ground information was supplied through field visitations performed by Pugh (2005). Figure 1 shows the plot locations throughout Heiberg and the adjacent state forest as yellow points overlaid on the QuickBird imagery. The coverage of the Heiberg property is revealed through the boundaries of the yellow compartment polygons. Some plots were obscured by cloud and cloud shadow in the QuickBird imagery.

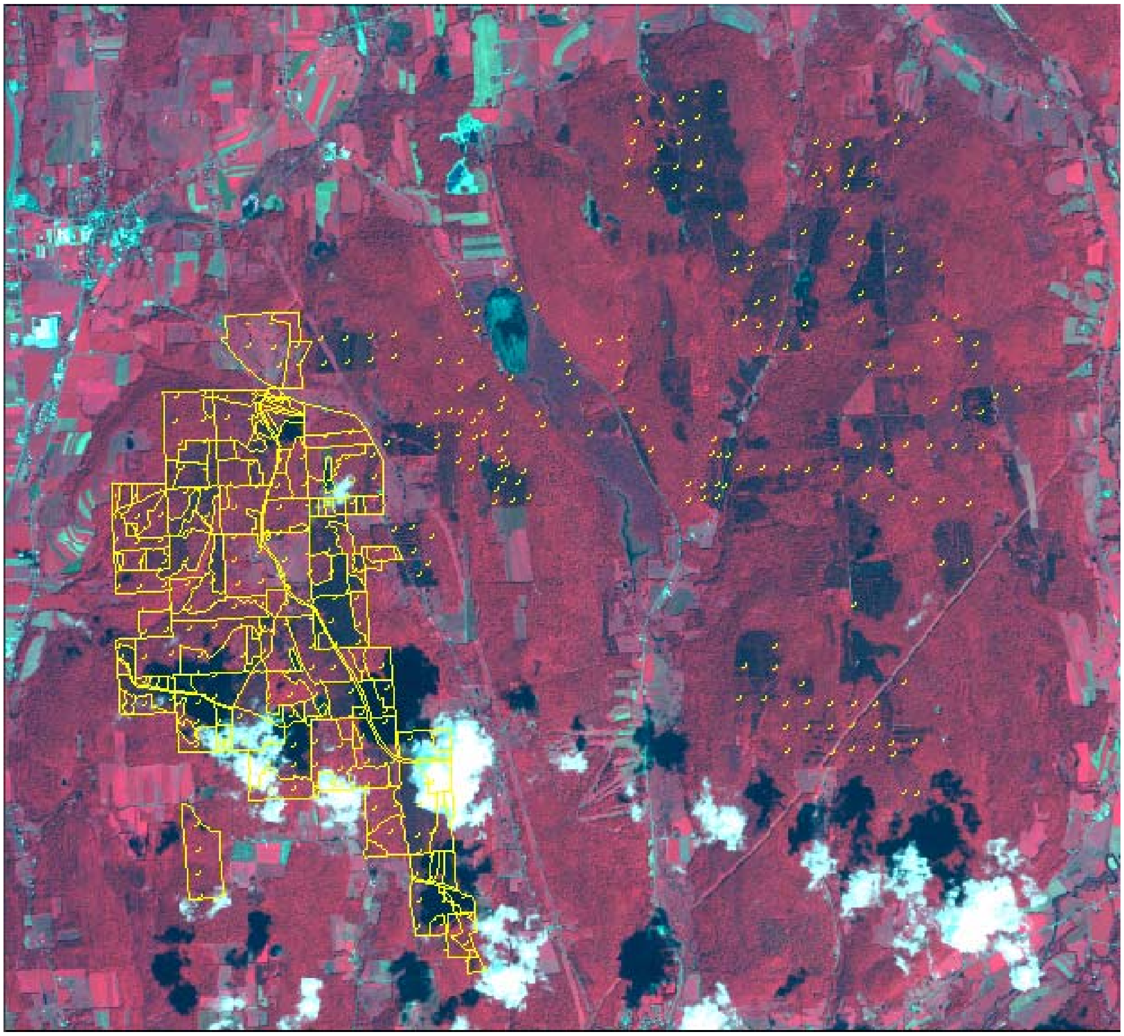


Figure 1. Plot locations in Heiberg and neighboring state forest over QuickBird imagery: Heiberg compartments are shown as yellow polygons.

METHODS

Overview

The classification of forests within the QuickBird imagery was performed in two stages. The goal of the preliminary classification was to separate forest from the other cover types present in the area: impervious areas, water, agriculture, and open land. This classification is essentially an Anderson Level I classification (Anderson *et al*., 1976). The secondary classification then divided forested regions into hardwood and softwood, with further separation of softwoods into four species groupings: Norway spruce, pine, hemlock, and larch. This classification essentially combines both Anderson Level II and Level III. For convenience, the remainder of this paper will use the terms Level I and Level II/III to indicate the primary and secondary classifications, respectively.

Object Delineation

Prior to performing the Level I and Level II/III classifications, eCognition was used to identify image objects with spectral similarity. This software is designed for object-oriented image analysis (http://www.definiens.com/). The algorithm used for image segmentation within eCognition is based on the Fractal Net Evolution Approach (FNEA) (Yu *et al.*, 2006). FNEA is a multiresolution segmentation algorithm that starts with single-pixel objects. Small adjacent objects are merged into bigger ones based on the smallest

spectral and spatial differences within the object. Image objects of varying size were generated using multiple levels of segmentation.
Figure 2 shows two levels:
Figure 2a shows the largest objects used to remove cloud and cloud shadow from the study area;

Figure 2b shows the smaller objects aimed at isolating forest from other land cover types. The clouds were removed from the analysis by considering thresholds on the objects means for blue, red, and NDVI values. The cloud shadows were removed by considering thresholds on the objects means for red, near-infrared, and NDVI values.

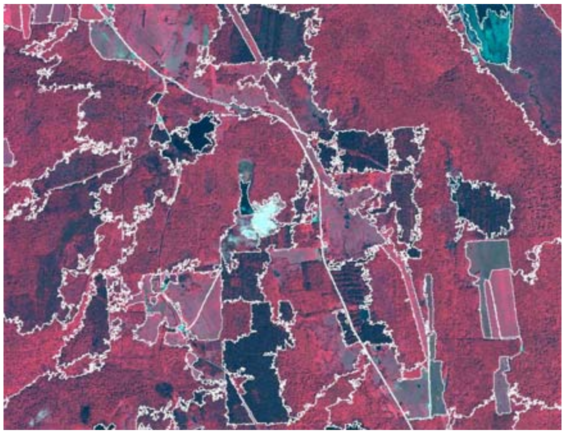
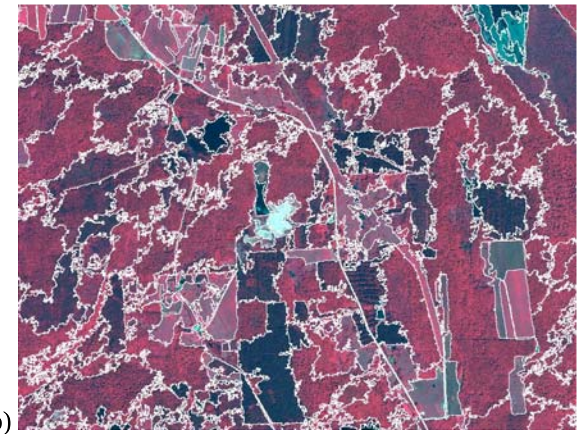
(a)  (b) 

Figure 2. Segmentation comparison: (a) Large objects used to define cloud and cloud shadow (b) Smaller objects used to delineate Level I classes.

Image Classification

There are a range of algorithms used for performing image classification. This research utilized a decision tree approach for the following reasons: (i) it is a non-parametric classifier, therefore it requires no assumptions of specific statistical distribution; (ii) it can handle large set of records of training data; and (iii) it can incorporate ancillary data sets. The decision trees were built using the See5 software package (http://www.rulequest.com/) and incorporated the adaptive boosting algorithm presented by Schapire (2003). The boosting algorithm used generates a combination of classification trees. Votes assigned to each tree helped to determine the final class given to a set of records (Schapire, 2003).

For the Level I classification, impervious, water, agriculture, and open land classes were visually identified, since the distinction between these categories in the high spatial resolution imagery was apparent. Forest objects were selected based on the available forest inventory information. A total of 711 objects were used in the Level I classification. This included 48 impervious objects; 412 forest objects, 80 open objects; 50 objects in water; and 121 in agriculture. The uneven distribution in the classes represented the uneven distribution of the presence of these cover types on the ground. Approximately one third of the plots were randomly selected for use in accuracy assessment.

Only the 412 forest objects were considered in the Level II/III classification. Based on the available reference data, plots dominated by Norway spruce, hemlock, and tamarack (larch) were selected. There were not enough plots containing red and white pine separately, so pine was considered as a species grouping. The predominant deciduous species present included red maple, sugar maple, and red oak; in order to generate a sufficient size sample, these species were considered together.

Ten data layers were utilized in the See5 classification: four QuickBird multispectral bands, three topographic layers—elevation, slope, and aspect—and three layers derived from the imagery—NDVI, intensity, and hue. Although the input layers had different GSD, eCognition automatically resamples layers to the smallest pixel size, in this case 2.44 m. Traditional classifiers typically rely on spectral data, potentially with the addition of a minimum number of ancillary data layers. One of the advantages of working with decision tree software such as See5 is that a large number of attributes can be considered. A total of 53 attributes were generated by eCognition for each image object: (i) mean and standard deviation for each of the ten input layers; (ii) the ratio of the mean value in each of the four multispectral bands and the hue band to the sum of the mean values for all bands; (iii) 22 texture features including Grey Level Co-occurrence Matrix (GLCM) and Grey-Level Difference Vector (GLDV) metrics for red and near-infrared bands; and (iv) six geometric features based on the object shape and size (Definiens, 2004).

RESULTS

Level I Classification

The Level I classification aimed to separate forested areas from all other cover types. For every object delineated by eCognition, 53 different attributes were considered in developing the classification tree. In performing classifications, See5 winnows the available attributes to remove those that do not contribute to the solution. Of the 53 attributes input into the classification, nine had an estimated importance of more than 1%; these are shown in Table 1.

Table 1. Estimated importance of attributes used in Level II classification (only attributes with importance > 1% are shown)

Importance	Object Attribute
47%	Mean of NDVI
34%	Mean of hue
31%	Grey level difference vector entropy
11%	Mean of NIR band
10%	Ratio of blue band to sum of all spectral layers
9%	Grey level co-occurrence matrix homogeneity in red band
7%	Grey level difference vector angular second moment for NIR band
6%	Standard deviation of NDVI
4%	Object length/width ratio

Table 2 provides the confusion matrix that summarizes the Level II classification results for the QuickBird imagery. This assessment used approximately one-third of the available training data that had been set aside during classification. In a confusion matrix, user's accuracy measures the probability that an area classified as a particular cover type on the map is actually that cover type on the ground; producer's accuracy measures the probability that an area on the ground will be correctly classified on the map (Stehman, 1997). Both measures provide a means to evaluate the uncertainty within an individual class. The overall accuracy for the classification was 88%, which showed there was some confusion. However, the primary goal of the classification was delineating forested areas. Both the user's and producer's accuracy for the forest class was high.

Table 2. Results of Level II classification on QuickBird imagery acquired

	Reference Data					
Classified Data	Imper.	Forest	Open	Water	Agric.	**User's Accuracy**
Impervious	62	0	0	0	4	**0.94**
Forest	1	163	2	4	4	**0.94**
Open	11	0	22	0	4	**0.61**
Water	0	0	1	26	0	**0.96**
Agriculture	6	0	5	0	37	**0.77**
Producer's Accuracy	**0.78**	**1.00**	**0.73**	**0.87**	**0.76**	**Overall: 0.88**

Level II/III Classification

The second component of the classification involved investigation of the potential for species level distinction using the QuickBird imagery. This process focused on classification of the regions identified as Forest in the Level I classification. Based on the reference data available and the portions of the QuickBird imagery obscured by cloud and cloud shadows, there was not sufficient data to separate out types of deciduous forest. Hence, the Level II/III classification focused on types of softwood. Table 3 illustrates the attributes that had an importance of greater than 1% in the See5 classification.

Table 3. Estimated importance of attributes used in Level II/III forest classification (only attributes with importance > 1% are shown)

Importance	Attribute
39 %	Grey level difference vector angular second moment in NIR band
35 %	Mean NDVI
10 %	Mean elevation
4 %	Grey level co-occurrence matrix homogeneity in NIR band
4 %	Mean slope
3 %	Grey level co-occurrence matrix dissimilarity
3 %	Grey level co-occurrence matrix entropy
3 %	Standard deviation of elevation

Because the total number of samples within some of the forest classes was small, the Level II/III classification accuracy was analyzed using a ten-fold cross-validation method. This method is able to provide a more reliable estimate of predictive accuracy given a small number of evaluation data (RuleQuest, 2007). As shown in Table 4, the classification tree provided generally good results with an overall accuracy of 76%. Most of the user's accuracy statistics were also reasonable, varying between 67% and 83%. However, producer's accuracy for some species grouping, larch in particular, showed poor separability.

Table 4. Results of Level II/III forest classification on QuickBird imagery acquired

	Reference Data					
Classified Data	Nor. S.	Pine	Heml.	Larch	Decid.	**User's Accuracy**
Norway Spruce	64	15	2	5	6	**0.70**
Pine	7	35	1	1	3	**0.74**
Hemlock	2	2	75	2	9	**0.83**
Larch	0	0	1	6	3	**0.60**
Deciduous	10	8	12	10	124	**0.76**
Producer's Accuracy	**0.77**	**0.58**	**0.82**	**0.25**	**0.86**	**Overall: 0.75**

DISCUSSION

The results reported in Table 2 demonstrate that the object approach to classification performed well at separating forested regions from other cover types based on QuickBird imagery and elevation data layers. The species level classification results shown in Table 4 indicate that there is some variability in the accuracy level attained based on the class under study. It is possible to use the class indicators to understand what type of misclassification is occurring, and possibly develop techniques to reduce those errors. It should be noted that since the accuracy assessment was based on a random selection of the available plot data, the distribution between species was not even. This can lead to issues in the accuracy assessment, since successful classification of a predominant cover type. For example, in the Level II/III classification, the large proportion of the total objects that were deciduous may provide a false measure of user's accuracy for that category. The low user accuracy for pine (58%) indicates the confusion between spruce and pine. the low accuracy for larch (27%) might be related to the small sample size (24 samples).

For the decision tree classification, 53 features generated in eCognition were used to build rulesets. More research is needed into the feature selection, since experimentation has shown different combinations of features result in different classification accuracy. Table 1 and Table 3 illustrate the attributes used for the Level I and Level II/III classifications, respectively. There are few attributes in common between the two classification levels.

Various texture attributes appear in both tables; however, while the Level I classification relied heavily on the statistics from the input spectral bands and their derivatives—e.g. mean NIR, mean hue, standard deviation of NDVI—the Level II/III classification relied heavily on the input elevation data and derivatives of that. It is yet to be determined if increasing the number of features included further improves classification results or causes issues related to information redundancy.

Understanding the usefulness of ancillary data layers will require additional study. These results suggest that elevation data is important for the species level classification. Future research will assess the utility of improving on the resolution of the elevation through the inclusion of lidar based elevation models. Soil data is an important factor in tree growth and should also be evaluated for incorporated into the classification.

CONCLUSION

Forest species classification and individual tree parameters can provide important information for forest managers. In this project, a decision tree classifier was applied to high spatial resolution multispectral QuickBird imagery to delineate forested regions, and then classify these regions into five forest species groupings. This research employed the object-based image analysis in eCognition to derive segmentations of the forest area. The characteristics of these image segments were used as classification units rather than individual pixels. The Level I classification successfully separated forested regions from other cover types. The use of the two stage classification allowed the classification tree to consider different attributes for each of the levels considered. In the Level I classification, attributes based on the image data were critical, while in the Level II/III classification the derivatives of the elevation data were important. Decision tree analysis using See5 showed an overall accuracy of 76% for the Level II/III classification. This work shows that the potential of high spatial resolution image for detailed forest mapping is promising, and that elevation data can play a key role in this process. The accuracy was found to be highly influenced by the sample size and classification protocol, which will be the focus of further research.

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