FOREST SPECIES CLASSIFICATION AND TREE CROWN DELINEATION USING QUICKBIRD IMAGERY

Yinghai Ke, Graduate Student
Lindi J. Quackenbush, Assistant Professor
Environmental Resources and Forest Engineering
State University of New York College of Environmental Science and Forestry
Syracuse, New York 13210
yke@syr.edu, ljquack@esf.edu

ABSTRACT

Efficient forest management requires detailed knowledge of forest stands, including species information and individual tree parameters. Remote sensing data are increasingly being used to investigate forest classification at both coarse and fine levels. In this paper, we first examined the capability of QuickBird multispectral imagery for species level forest classification using eCognition software and a rule-based classification with the assistance of ancillary topographic data. We then applied a local maximum filter and watershed segmentation algorithm to perform tree identification and tree crown delineation using the QuickBird panchromatic band. The QuickBird imagery used in the study was acquired over Heiberg Memorial Forest in Tully, New York on 9 August 2004.

For the species classification, image objects were extracted as classification units with a multi-resolution segmentation algorithm in the eCognition software. Fifty-three features including spectral metrics, texture, elevation features, and geometric features were calculated for each image object. Existing ground reference records were used for training and evaluation using the See5 data mining tool. Classification trees were built and results were evaluated using a cross-validation approach. The overall accuracy of the results was 76%, while the lowest producer's accuracy (27%) suggested confusions exist.

Forest species classification was followed by individual tree delineation. We examined the performance of an existing algorithm by visually comparing results in three different scenarios: Emerge aerial imagery for a coniferous-dominant area, and QuickBird satellite panchromatic images over a coniferous-dominant area and over a deciduous forest stand. Preliminary results showed the tree identification and tree crown delineation algorithms were most applicable for coniferous trees in the Emerge image. Tree-top identification performance was a critical factor that influenced the accuracy of tree crown delineation.

INTRODUCTION

Overview

Remote sensing has been a valuable source of information over the course of past few decades in mapping and monitoring forest. It provides a cost-effective tool to help forest managers better understand forest characteristics, such as forest area, locations, and species, even down to the level of characterizing individual trees. The application of remote sensing in forest management began with manual interpretation of aerial photographs, but is increasingly reliant on new data and methods (Franklin, 2001). Medium spatial resolution satellites such as Landsat (pixel size of 15 to 30 m) and SPOT (10 to 20 m) have proved to have capability for obtaining regional-scale forest variables (Wulder et al., 2004). As higher spatial resolution satellite imagery—e.g. QuickBird (0.6 to 2.8 m^2), IKONOS (1 to 4 m^2)—become more available, there is an increasing potential to provide more detailed information. Unlike medium resolution satellite imagery, which provide an aggregated response over a region, individual trees are visible in high resolution imagery. This provides opportunities to differentiate species and individual trees. However, high spatial resolution imagery poses a new challenge because the spectral response of an individual tree is influenced by variation in canopy illumination and topographic effects, thus accuracy is reduced for conventional pixel-based classifications (Quackenbush et al., 2000).

As a solution to this high resolution problem, object-oriented classification was introduced. In contrast to traditional image processing methods, the basic processing units of object-oriented processing are image objects or segments. Traditional image classifications focus on the differentiation of spectral values for each pixel. Because objects are groups of pixels, statistical values such as mean or standard deviation can be derived, which provides additional information. In addition to spectral metrics, texture and geometric characteristics of the objects can also be used for classification.

Objectives

This project has two fundamental objectives: species level classification and individual tree crown identification. The first objective involves making use of the rich set of object-based information to classify forest area to a species level. ECognition software (www.definiens.com) was used to generate image objects based on its multiresolution segmentation algorithm, and extract features within each objects. See5, a rule-based classification tree software, was used to perform the classification. The second objective of this paper is to illustrate the potential for individual tree identification and tree crown delineation using QuickBird panchromatic imagery with 0.6 m ground sampled distance (GSD). Such high resolution enables visual identification of trees, especially coniferous trees. However, for efficient forest management, computer-based automated identification is required. Several algorithms have been presented for automatic individual tree recognition for aerial images. They include valley-following algorithms (Gougeon, 1995), crown-modeling and template-matching based methods (Pollock, 1998), concentric-circle searching algorithms (Pinz, 1991) and 3D crown surface reconstruction algorithms (Sheng et al., 2003). Wang et al. (2004) presented a marker controlled watershed segmentation algorithm and attained 75% accuracy. The study areas of Wang's research were coniferous forest stand with medium density, and there are no detailed descriptions about the performances of these methods used for deciduous trees. This paper basically followed Wang's watershed algorithm to examine the performance of the method in different scenarios: QuickBird satellite panchromatic imagery (0.6 m GSD) over both deciduous and coniferous stands, and Emerge aerial image (0.6 m GSD) over a coniferous stand.

DATA COLLECTION

Study Area

The study was undertaken in and around Heiberg Memorial Forest, a 9637 ha property owned by the State University of New York – College of Environmental Science and Forestry (SUNY-ESF). Heiberg is approximately 33 km south of Syracuse in upstate New York (42.75° N, 76.08° W). Elevation in the area varies between 382m and 625 m AMSL. Vegetation at Heiberg has been managed to produce a diverse representation of forest ecosystems in the northeastern United States. Deciduous trees on the property consist predominantly of mixtures of red maple, sugar maple, red oak, beech, and birch. Conifer species include red and white pine, Norway spruce, hemlock, northern white cedar, and tamarack (larch).

Image Acquisition and Data Preparation

High spatial resolution multispectral imagery was acquired over the study area by the QuickBird sensor on 9 August 2004. The QuickBird data set was composed of a single panchromatic image (450 – 900 nm) with a GSD of 0.6 m, and 4-band multispectral imagery with 2.44 m GSD. The four bands include: blue (450 – 520 nm), green (520 – 600 nm), red (630 – 690 nm), and near-infrared (760 – 900 nm). The imagery over the study area contained 1% cloud cover, with a relatively clear atmosphere and an 11° off-nadir look angle. Digital Globe supplied the imagery with radiometric, sensor and geometric corrections. Experimentation performed at ESF verified that the image registration was within a single pixel, hence further geometric processing was not applied. High resolution imagery was also acquired by the Emerge airborne sensor on 11 October 2001. This set of imagery was true color with 0.6 m pixel size, and was been georeferenced to UTM Zone 18N, WGS84.

Ancillary data for this study included layers generated from the imagery as well as topographic information in the form of a USGS 10 m digital elevation model (DEM). Slope and aspect were derived from elevation data. An IHS transformation and normalized difference vegetation index (NDVI) calculation were performed on the QuickBird multispectral bands in order to include intensity, hue and NDVI as additional data layers.

Ground Reference Data

This project takes advantage of the information obtained from continuous forest inventories (CFIs) taken within the study area. The most recent CFI work in the study area at Heiberg 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, some at a ten year interval, others annually or semi-annually.

General plot measurements include plot location determined using survey grade global positioning system units, forest type designation, count of total number of small trees, and estimates of the mix of species for smaller trees. Each plot also includes a detailed description of all large trees within a 15 m radius of the plot center. These measurements include tree species, position within the plot (distance and direction from plot center), crown position, vigor, diameter at breast height (DBH), and tree height (Van Siclen et al., 2002). Compartment level information for Heiberg, monitored by SUNY-ESF, provides additional information. Figure 1 shows the plot locations through Heiberg and the state forest as yellow points overlaid on QuickBird imagery. The coverage of the Heiberg property is revealed through the boundaries of the yellow compartment polygons. Another source of ground information was supplied through field visitations performed by Pugh (2005).

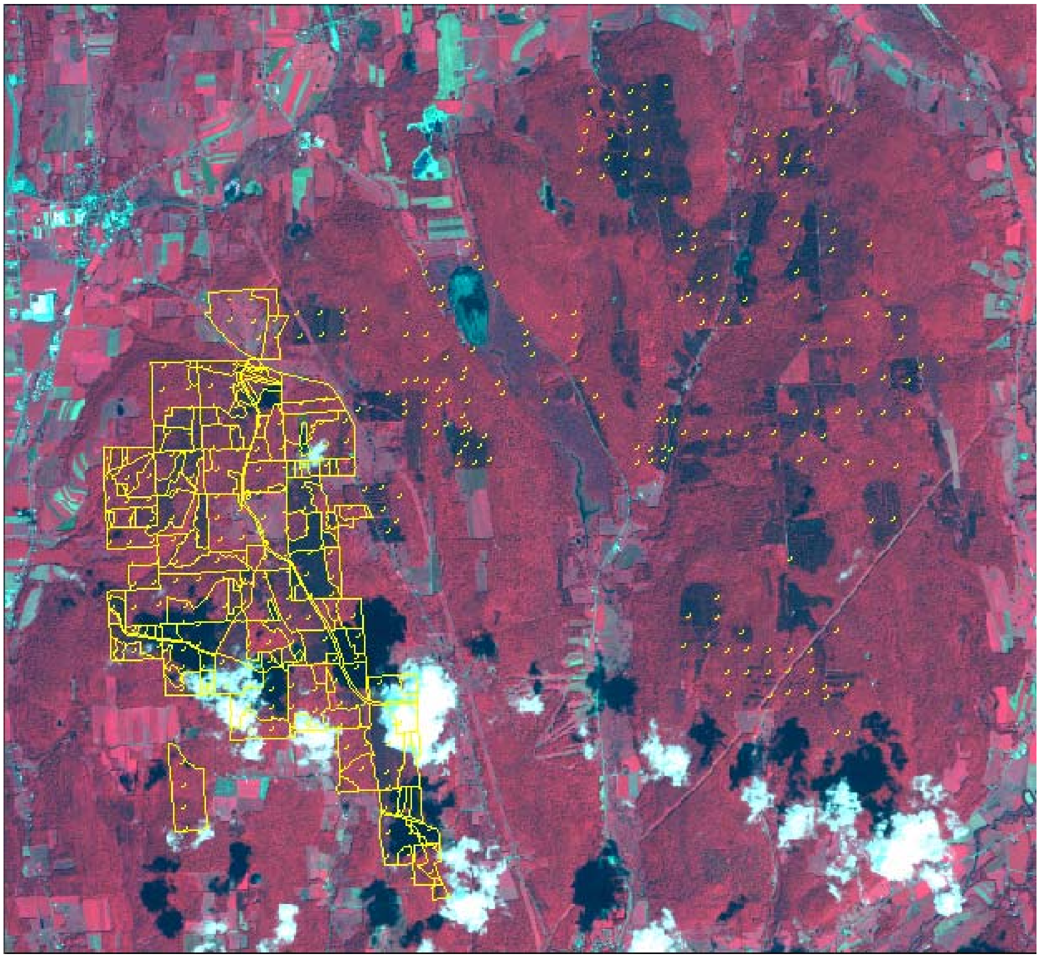


Figure 1. Plot locations (yellow dots) in Heiberg and neighboring state forest over QuickBird multispectral imagery acquired on August 2004. Compartments within Heiberg are shown as yellow polygons.

FOREST SPECIES CLASSIFICATION

Image Object Segmentation

The first objective of this project was to perform a species level forest classification. This section outlines the classification process and results attained, additional detail is provided by Quackenbush and Ke (2007). Ten data layers were imported into eCognition to perform the classification. This included 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 resampled these layers to the highest resolution, that is, the topographic layers with 10 m pixel size were resampled to 2.44 m. ECognition is a commercial software package for object-oriented image analysis. 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 growth of heterogeneity, which is defined through both spectral and spatial differences within the object. The merging process stops when the smallest growth exceeds user-defined parameters. The *scale parameter* defines the maximum allowed heterogeneity for the resulting image objects; *color* determines the percentage contribution of the spectral values to the homogeneity criterion, as opposed to the percentage of the shape homogeneity defined by the *shape* parameter. *Smoothness* is used to get smooth borders of objects, and *compactness* is used to optimize objects with regard to compactness (Definiens, 2004).

The image objects were generated using three levels of segmentation based on different values of the scale parameter. The first level was used to delineate the cloud and cloud shadow, setting the scale parameter as 500. The second level aimed at isolating forest from other land cover types, and used a scale parameter set as 250. The third level attempted to perform species classification, and the scale parameter was set as 120. The other eCognition parameter settings included color as 0.8, shape as 0.2, and smoothness and compactness were both 0.5. Figure 2 shows the comparison of first two levels of segmentation in the same sample area.

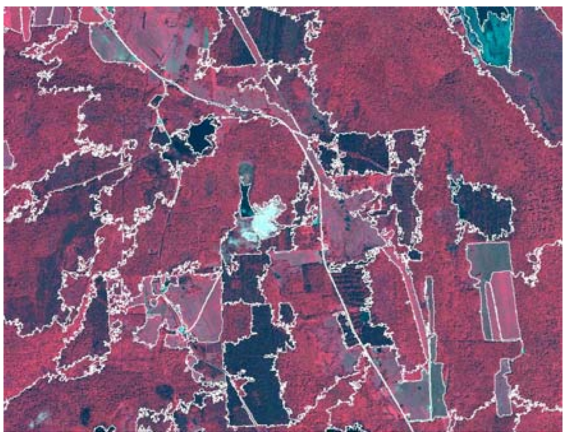
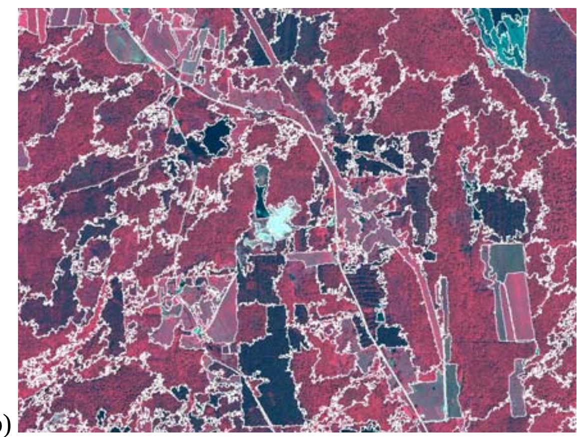
(a)  (b) 

Figure 2. Segmentation comparison: (a) Scale parameter = 500, (b) Scale parameter = 250

For each object, eCognition calculates features from the ten input layers. A total of 53 features were generated including: (i) mean and standard deviation for each of the ten input layers (ii) ratio of each of the mean value in the four multispectral bands and hue band to the sum of the mean values for all spectral 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 object shape and dimension (Definiens, 2004).

Decision Tree Classification Procedure

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 (www.rulequest.com) and incorporated the adaptive boosting algorithm presented by Schapire (2003). Based on the training data sets, several decision trees were generated rather than just one. Votes assigned to each classifier helped to determine the final class given to a set of records.

In this study, there were 401 training cases generated from the previously acquired ground reference data (Quackenbush et al., 2006). Each of the training cases was assigned to the third-level object that contained the point location and the 53 characteristics—e.g. statistical and texture metrics—were determined for the object. The forest species in the region were grouped into pine, spruce, hemlock, larch, and deciduous.

Classification Results

The classification tree generated by See5 was expressed as a ruleset, an example of which is shown in Figure 3. The boosting algorithm used generates a combination of classification trees (Schapire, 2003); hence, Figure 3 is not a precise representation of the classification rule. See5 determined the thirteen most important features to perform the classification. These were ranked as follows: GLDV angular second moment in near-infrared band, NDVI mean value, mean elevation, GLCM homogeneity in near-infrared band, mean slope, GLCM dissimilarity in red band, GLCM entropy in red band, standard deviation of elevation, standard deviation in red band, compactness, GLDV mean in red band, ratio of near-infrared band, and standard deviation of NDVI. Definiens (2004) provides an explanation of the derivation of these features.

```
Rule 4/1: (28.8/4.4, lift 3.9)
        GLDVMEANAR > 3.26
        GLDVMEANAR <= 3.65
        GLCMHOMONI <= 0.26
        STDDEVNDV > 10.79
        MEANSLP <= 18.3
        ->  class 2  [0.824]

Rule 4/2: (5.7/0.7, lift 3.7)
        GLCMHOMONI <= 0.27
        MEANNDV <= 236.71
        STDDEVNDV <= 5.83
        MEANSLP > 6.94
        MEANSLP <= 18.3
        ->  class 2  [0.775]

Rule 4/3: (1.9, lift 3.5)
        STDDEVRED <= 8.07
        GLCMHOMONI > 0.27
        ->  class 2  [0.746]

Rule 4/4: (19.5/5.7, lift 3.3)
        GLDVANGNNI <= 0.01
         STDDEVNDV > 8.74
        MEANELE <= 602.93
        MEANSLP > 6.94
        MEANSLP <= 18.3
        ->  class 2  [0.689]

  ……
```

Figure 3. Example rulesets for species classification.

Classification accuracy was analyzed using a ten-fold cross-validation method, which was able to provide a more reliable estimate of predictive accuracy given a small number of evaluation data (RuleQuest, 2007). As shown in Table 1, 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 1. Results of classification on QuickBird multispectral imagery

	Reference Data					
Classified Data	Spruce	Pine	Hemlock	Larch	Deciduous	**User's Accuracy**
Spruce	64	15	2	3	6	**0.71**
Pine	7	35	1	1	3	**0.75**
Hemlock	2	2	75	2	9	**0.83**
Larch	0	0	1	6	3	**0.67**
Deciduous	10	8	12	10	124	**0.76**
Producer's Accuracy	**0.77**	**0.58**	**0.84**	**0.27**	**0.86**	**Overall: 0.76**

INDIVIDUAL TREE CROWN DELINEATION

Sample Images

Individual tree delineation was the second objective of this project. At the current stage of the project, we examined existing algorithms and attempted to evaluate the capability of QuickBird satellite imagery for tree crown delineation. Three images were used for this purpose: Emerge aerial digital image over a coniferous dominant area;

and QuickBird panchromatic images over a coniferous area and a deciduous area. All three images (shown in Figure 4) have a ground sampled distance of 0.60 m.

Individual Tree Identification

Local maximum filtering was used for tree identification (Wulder et al., 2000). The algorithm assumes that a tree apex has a local maximum image brightness value, and that the crown boundary has local minimum brightness values. The filtering is conducted by assessing brightness values using a moving window. The center pixel is considered to indicate a tree-top if it has the greatest value within the window. Wulder et al. (2000) showed that window size strongly influences commission and omission errors. In this study, a 3×3 window was used to detect coniferous tree top, and a 7×7 window for deciduous trees.

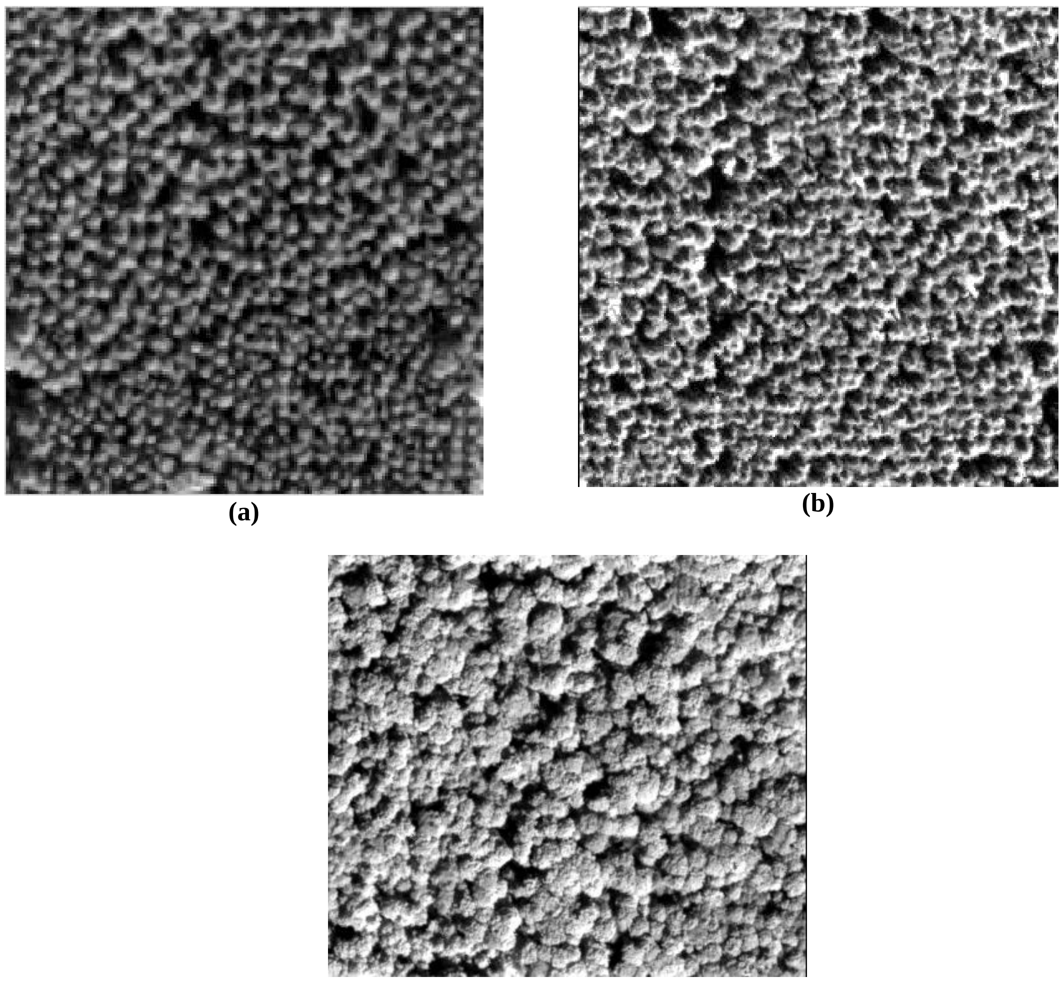


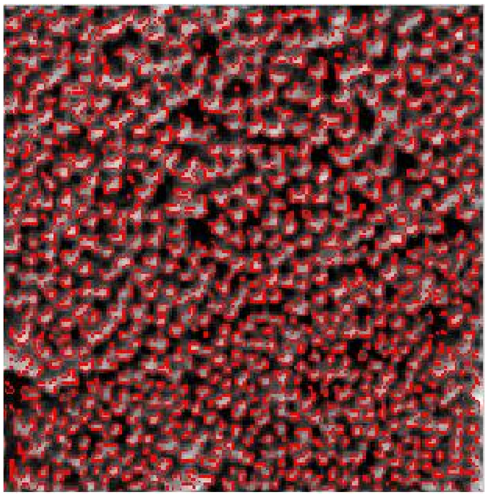
Figure 4. Sample images (a) coniferous forest in Emerge red band; (b) coniferous forest in QuickBird panchromatic band; (c) deciduous forest in QuickBird panchromatic band.

Tree Crown Delineation

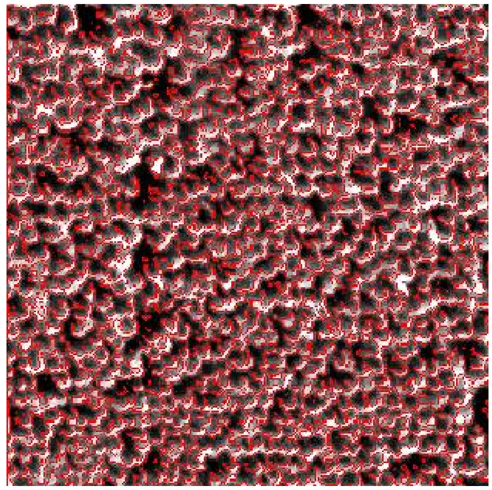
A Laplacian of Gaussian (LOG) operator (3×3) was first applied to each image to reduce the intensity variation within a tree crown. Then, a watershed segmentation was applied to the smoothed images (Wang et al., 2003). The watershed algorithm treats the inversion of the gray-scale image as an elevation model. Objects were treated as catchment basins separated by watershed lines. The algorithm has been widely used in image analysis (Soille, 1999). In this project, local maxima were used as a marker and marker-controlled watershed segmentation was conducted in the sample images (Pesaresi and Benediktsson, 2001).

Results

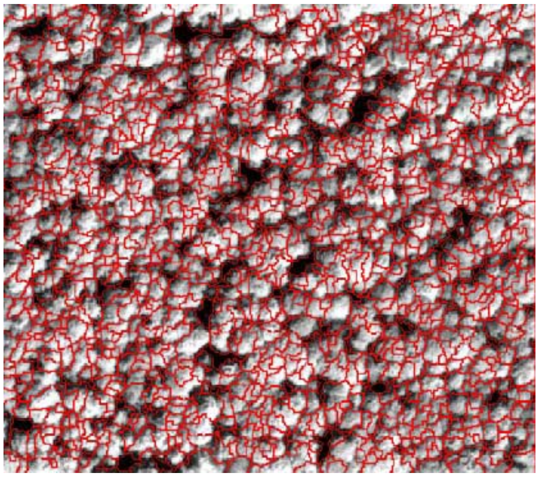
Figure 5 shows the crown boundaries delineated by the watershed algorithm. Visual examination of the results indicated that for coniferous trees, tree crowns were isolated well, regardless of the image source, while large over-segmentation errors were shown in the deciduous tree crown delineation.



(a)



(b)



(c)

Figure 5. Tree crown delineation results for (a) coniferous forest in Emerge red band; (b) coniferous forest in QuickBird panchromatic band; (c) deciduous forest in QuickBird panchromatic band.

DISCUSSION

Species Classification

The results in Table 1 suggest that QuickBird multispectral imagery and ancillary data have the ability to separate coniferous forest species. Not surprisingly, the highest user's accuracy was for the deciduous class due to its distinction with all the coniferous species. The low user accuracy for pine (58%) indicates the confusion between spruce and pine. While low accuracy for larch (27%) might be due to the small sample size (22 samples). It should be noted that in the study area, some plots are composed of a mixture of species, especially in the non-managed forest areas. It would seem that rather than classifying forest into individual species, a more reasonable approach may be to work with forest types that are comprised of species groupings. However, our attempts to work with forest types found that the overall accuracy is very poor due to the lack of samples for each forest type.

For the decision tree classification method, we used 53 features generated in eCognition to build rulesets. More research is needed into the feature selection, since experimentation has shown different combinations of features result in different classification accuracy. It is yet to be determined if increasing the number of features included further improves classification results or causes issues with information redundancy. Soil data is an important factor in tree growth and should be acquired for incorporation into the classification.

Individual Tree Delineation

Visual examination of the tree crown delineation results shows the Emerge aerial image obtained the best results. The main reasons can be explained as: (i) the cone-shaped coniferous tree crown are more easily to be modeled; (ii) the Emerge image was acquired with near nadir view angle so that the tree crown delineated is more consistent with the actual tree crown; (iii) the forest area covered by Emerge image are with less dense tree distribution, such that individual trees can be better isolated. In the QuickBird image over the coniferous area, some adjacent trees were segmented as one tree. Part of the reason is that shape was not considered as a factor in the watershed segmentation, which only used the digital number in the image for delineation. Since the partitioning of the forest in the QuickBird image is denser than the forest in the Emerge image and tree crowns are subject to overlap, the grey-scale boundaries were not necessarily the actual tree crown boundary. Severe over-segmentation was derived in the QuickBird image of the deciduous trees. Experimentation showed the error was mainly caused by large commission error of tree identification. Due to the irregular shape of deciduous tree crown, multiple maxima were detected over one tree. Since each maxima corresponds to one object in the watershed segmentation, this commission generates multiple segments for an individual tree crown.

Future research will involve refinement of the tree identification and segmentation results; comparison and analysis of various algorithms over the same area; development of new algorithms for automated identification of trees in mixed forest area, and procedures for accurate tree crown delineation.

CONCLUSION

Forest species classification and individual tree parameters can provide important information for forest managers. In this project, high spatial resolution multispectral QuickBird imagery was used to classify five forest species groupings. This research employed the object-based image analysis in eCognition to derive segmentations of the forest area. These characteristics of these image segments were used as classification units rather than individual pixels. Decision tree analysis using See5 showed an overall accuracy of 76%. This work shows the potential of high spatial resolution image for detailed forest mapping is promising. The accuracy was found to be highly influenced by the sample size and classification protocol, which requires further research for improvement.

The project also examined the utility of satellite and aerial imagery to delineate individual tree crowns. Analysis was performed to compare the results of watershed segmentation for tree crown delineation on Emerge aerial image over a coniferous area, and QuickBird images over both coniferous and deciduous areas. The results showed that accurate tree identification is a critical factor that affects the results of crown delineation. Large commission error for deciduous trees introduced severe over-segmentation. Consideration of density of forest area, species of trees, sun angle, and view angle should be included in our further research.

REFERENCES

Definiens, 2004. *eCognition User Guide*. 72 p.

Franklin, S. E., 2001. *Remote Sensing for Sustainable Forest Management*. CRC, Boca Raton, 424 p.

Gougeon, F. A., 1995. A crown-following approach to the automatic delineation of individual tree crowns in high-spatial resolution aerial images. *Canadian Journal Remote Sensing*, 21(3): 274-284.

Pesaresi, M., J. A. Benediktsson, 2001. A new approach for the morphological segmentation of high-resolution satellite imagery. *IEEE transactions on Geoscience and Remote Sensing*, 39(2):309-320.

Pinz, A., 1991. A Computer Vision System for the Recognition of Trees in Aerial Photographs, In Tilton J., editor, *Multisource Data Integration in Remote Sensing*, NASA. pp. 111-124.

Pollock, R., 1998. Individual tree recognition based on a synthetic tree crown image model. In D. A. Hill, D. G. Leckie (Eds), *Proceedings of the International Forum on Automated Interpretation of High Spatial*

Resolution Digital Imagery for Forestry. Victoria, BC: Canadian Forest Service, Pacific Forestry Center. pp. 25-34.
Pugh, M.L., 2005. Forest Terrain Feature Characterization using multi-sensor neural image fusion and feature extraction methods. Ph.D. Dissertation, State University of New York College of Environmental Science and Forestry. 215 p.
Quackenbush, L. J., P. F. Hopkins, and G. J. Kinn, 2000. Developing forestry products from high resolution digital aerial imagery. *Photogrammetric Engineering and Remote Sensing*, 66(11): 1337-1346.
Quackenbush, L. J., Y. Ke and C. N. Kroll, 2006. Investigating New Advances in Forest Species Classification: Establishing a Baseline. *Proceedings of 2006 ASPRS Annual Conference*, May 1-5, 2006, Reno, Nevada (American Society of Photogrammetry and Remote Sensing, Bethesda, Maryland), unpaginated CD-ROM.
Quackenbush, L. J. and Y. Ke, 2007. Investigating New Advances in Forest Species Classification *Proceedings of 2007 ASPRS Annual Conference*, May 7-11, Tampa, Florida (American Society of Photogrammetry and Remote Sensing, Bethesda, Maryland), unpaginated CD-ROM.
RuleQuest, 2007. See5 Tutorial, (http://www.rulequest.com/see5-win.html), date last accessed 14 February 2007.
Schapire, R. E., 2003. The boosting approach to machine learning: An overview. *Nonlinear Estimation and Classification*. Springer-Verlag, New York, NY, 171p.
Soille, P., 1999. *Morphological Image Analysis: Principles and Applications*, Springer, Berlin: New York, 319p.
Sheng, Y., P. Gong, G. S. Biging, 2003. Model-Based Conifer Canopy Surface Reconstruction from Photographic Imagery: Overcoming the Occlusion, Foreshortening, and Edge Effects. *Photogrammetric Engineering and Remote Sensing*. 69(3): 249-258.
Van Siclen, K., W. M. Stiteler, IV, and P. F. Hopkins, 2002. Ground reference for assessment of forestry applications in remote sensing. *Proceedings of the XXII FIG International Congress, ACSM-ASPRS Conference and Technology Exhibition.* Bethesda: ASPRS.
Wang, L., P. Gong, and G. S. Biging, 2004. Individual Tree-Crown Delineation and Treetop Detection in High-Spatial Resolution Aerial Imagery. *Photogrammetric Engineering and Remote Sensing*, 70(3): 351-357.
Wulder, M., K. O. Niemann, D. G. Goodenough, 2000. Local Maximum Filtering for the Extraction of Tree Locations and Basal Area from High Spatial Resolution Imagery. Remote Sensing of Environment, 73: 103-114.
Wulder, M.A., R.J. Hall, N.C. Coops, and S.E. Franklin, 2004. High spatial resolution remotely sensed data for ecosystem characterization, *Bioscience*, 54(6): 511-521.
Yu, Q., P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schironkauer, 2006. Object-based Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery. *Photogrammetric Engineering and Remote Sensing*, 72(7): 799-812.