Tree species identification in an urban environment using a data fusion approach

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TREE SPECIES IDENTIFICATION IN AN URBAN ENVIRONMENT USING A DATA FUSION APPROACH

An Abstract of a Thesis

Submitted

in Partial Fulfillment

of the Requirements for the Degree

Master of Arts

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May 2007

ABSTRACT

This thesis explores a data fusion approach combining hyperspectral, LiDAR, and multispectral data to classify tree species in an urban environment. The study area is the campus of the University of Northern Iowa.

In order to use the data fusion approach, a wide variety of data was incorporated into the classification. These data include: a four-band Quickbird image from April 2003 with 0.6m spatial resolution, a 24-band AISA hyperspectral image from July 2004 with 2m spatial resolution, a 63-band AISA Eagle hyperspectral image from October 2006 with 1m spatial resolution, a high resolution, multiple return LiDAR data set from April 2006 with sub-meter posting density, spectrometer data gathered in the field, and a database containing the location and type of every tree in the study area.

The elevation data provided by the LiDAR was fused with the imagery in eCognition Professional. The LiDAR data was used to refine class rules by defining trees as objects with elevation greater than 3 meters. Classes included honey locust, white pine, crab apple, sugar maple, white spruce, American basswood, pin oak and ash.

Results indicate fusing LiDAR data with these imageries showed an increase in overall classification accuracy for all datasets. Overall classification accuracy with the October 2006 hyperspectral data and

LiDAR was 93%. Increases in overall accuracy ranged from 12 to 24% over classifications based on spectral imagery alone. Further, in this study, hyperspectral data with higher spatial resolution provided increased classification accuracy.

The limitations of the study included a LiDAR data set that was acquired slightly before the leaves had matured. This affected the shape and extent of these trees based on their LiDAR returns. The July 2004 hyperspectral data set was difficult to georectify with its 2m resolution. This may have resulted in some minor issues of alignment between the LiDAR and the July 2004 hyperspectral data.

Future directions of the study include developing a classification scheme using a Classification And Regression Tree, utilizing all of the LiDAR returns in a classification instead of just the first and fourth returns, and examining an additional LiDAR-derived data set with estimated tree locations.

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This Study by Matthew Voss

Entitled:

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using a data fusion approach

has been approved as meeting the thesis requirement for the

Degree of

03/22/07

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ACKNOWLEDGMENTS

I would like to thank Dr. Ramanathan Sugumaran for his assistance in acquiring the data, conducting the research and in writing this thesis. His help was invaluable.

I would also like to thank the other members of my thesis committee, Dr. Thomas Fogarty and Dr. Dave May, for their assistance in the writing of this thesis.

The faculty of the Geography Department have all been encouraging and helpful in my stay here, and I would like to thank all of them for their assistance throughout the years.

My fellow graduate students have been of great help. In particular, Nathan Green assisted in gathering the spectrometer data over several hot August days.

I would also like to thank former Geography Department head Dr. Suckling. The help and guidance he provided in my return to college is very much appreciated.

The Iowa Space Grant Consortium provided funding for much of the data used in this research. Without their support, none of this would have been possible.

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CHAPTER 1

INTRODUCTION

Land cover maps are of great importance to natural resources managers. These maps are used in both planning and assessment of large areas of land. The level of information as well as the accuracy provided by these maps can have a large influence on the effectiveness of land management decisions (Lennartz & Congalton, 2004). Tree species maps are a type of land-cover map that have garnered increasing attention from researchers.

Municipal governments use land cover maps for maintenance, management and conservation (Sugumaran, Pavuluri & Zerr, 2003; Jim & Lui, 2001). As cities grow rapidly, urban forests can be displaced by infrastructure. Cities frequently use land cover products to limit the issuance of building permits near areas of protected trees. In addition, as populations of major metropolitan areas continues to grow, population planners must balance increasing demand for trees for recreational areas and urban greenbelts with space for commercial and residential construction (Jim & Liu, 2001). County and local officials also utilize land cover maps to monitor bird habitats. Some birds prefer certain types of trees (W. Newton, personal communication, February 20, 2007). As such, there is demand for accurate and up-to-date land cover maps.

The U.S. Forest service is responsible for national forests and grasslands that cover 193 million acres of land (U.S. Forest Service, 2005). Traditional methods for developing a map of tree species involved a forestry worker going out into the field, examining each tree and identifying it by its unique characteristics. This method can be time consuming and consequently expensive at such a scale. Thus, there is a need by professional foresters for time-effective and cost-effective methods for tree species identification.

Recent developments in imaging technology have made remote sensing technologies a viable option in forest management. During the history of modern remote sensing, more and more platforms have been developed to facilitate vegetation classification. Early Landsat imagery included an infrared band, which has been widely shown to highlight vegetation. This multispectral imagery was the standard in remote sensing for many years. Recently, many studies have utilized multispectral imagery purchased from private remote sensing companies. IKONOS and QuickBird imagery provides very high resolution satellite-based multispectral imagery. Because this imagery is widely available and provides 1 meter spatial resolution, it has been popular with researchers.

When remote sensing data is use to identify tree species, there are several factors that affect outcome. These include spectral and spatial resolution, seasonal effects, classification algorithm and additional data such as soil maps or elevation information.

Spectral resolution refers to the number of bands that an image has. Multispectral scanners typically collect three to seven bands that cover the range from visible light to near infrared. Hyperspectral scanners can have 30 to more than 200 bands for this same range of wavelengths. Higher spectral resolution, or more bands, can provide more spectral detail and make it easier to differentiate objects based on spectral signatures.

Spatial resolution can have a significant influence on overall accuracy. This form of resolution is a measure of how much ground is captured by each pixel. Spatial resolution varies greatly. The MODIS satellite provides products with 250m to 1,000m spatial resolution. The QuickBird satellite provides spatial resolution of 60cm. The level of spatial resolution desired depends on the application. In a study at the individual tree level, finer spatial resolution is desirable, while coarser resolution would be preferred if the study involves identifying groups of trees in a forest.

Seasonal variations in leaf chlorophyll content can be influential depending on the species and the location of the study. If imagery is collected at the proper time, researchers may take advantage of the reduced chlorophyll production and leaf senescence as fall sets in.

Certain trees change at different rates, so this can help in the identification of species.

Classification algorithms have a heavy influence on classification accuracy, and there is a great deal of variation among them. Traditional classification schemes generally involved statistical analysis of individual pixels. Non-traditional schemes include Classification And Regression Tree (CART), subpixel classification and object-oriented classification. Object-oriented classification places pixels into groups which are called segments. These are used as the basis for the classification, and it allows many more classification rules to be established, such as distance from other objects.

Additional data can also improve classification accuracy. These data can include elevation and soil maps. Soil maps can be used to identify areas where certain species of trees are more likely to grow, for example.

In recent years, a range of sensors providing hyperspectral data have become popular with researchers who are trying to determine what sorts of minerals or particular types of vegetation are on the ground. These sensors use many contiguous bands to create very detailed spectral profiles. Researchers have found that the increased detail has led to increased accuracy in terms of classification. Sensors capable of creating hyperspectral imagery are still comparatively rare and the data is not as readily available as Landsat imagery, and thus hyperspectral imagery is underrepresented in research of this type. Hyperspectral imagery also consumes greater amounts of storage space than do multispectral sensors because of greater spectral resolution. This greater spectral resolution comes at the expense of spatial resolution. Scanners such as NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor typically provide imagery with 30 meter spatial resolution and 224 spectral bands, although lower altitude flights can generate 4 m resolution imagery. Hyperion is a space borne hyperspectral sensor. It collects 220 bands at 30-meter resolution. As can be seen, there are tradeoffs with remote sensing data. If high spatial resolution is desired, then spectral resolution must be sacrificed, as is the case with IKONOS and QuickBird data. However, if spectral detail is required, then it comes at the cost of spatial resolution.

Additional data such as digital elevation models, soil maps or geological information can improve classification accuracy. For example, the most recent development in remote sensing is Light Distance and Ranging (LiDAR). This is an example of an active sensor, meaning that it is not dependent on reflected sunlight as are the multispectral and hyperspectral sensors. These sensors provide their own source of energy to be reflected. The airborne sensor scans the ground with a laser collecting the reflected light. This is translated into highly accurate elevation data that is also collected at high horizontal resolution.

Researchers have used this data for three major applications: topographic applications, measuring vegetation canopy structure including crown height, crown width and estimations of trunk diameter and prediction of forest stand structure, such as overall biomass (Lefsky, Cohen, Parker & Harding, 2002).

Numerous studies have utilized multispectral imagery to develop tree species maps, and there are increasing numbers of studies utilizing hyperspectral imagery, although comparatively rare, particularly at the individual tree level. Generally, these studies incorporate AVIRIS hyperspectral imagery at a 30 meter resolution. This resolution allows researchers to identify large areas of a single species of tree, but not individual trees. QuickBird multispectral scanners can provide sub-meter resolution which allows researchers to single out particular trees, but they lack the higher spectral detail of hyperspectral scanners, and thus classification accuracy suffers.

Further, the bulk of studies extant incorporate the more traditional classification schemes that function only at the pixel level. Studies using object-oriented classification are rare, particularly those that use hyperspectral imagery. Finally, the vast majority of studies examine imagery collected at one date. Very few studies take advantage of the phenological leaf changes trees experience every season.

This study was focused to consider spectral and spatial resolution, seasonal variations, classification algorithms and additional data sources for the identification of tree species. The goal of this study is to develop a methodology that could be applied to large study areas which would allow for the classification of tree at the individual species level. If a method can be developed that meets the 80% accuracy typically required by forest managers, it would provide an alternative to traditional methods that is cost effective and considerably faster (Lennartz & Congalton, 2004).

Questions that this study will answer include: What accuracy can hyperspectral imagery in combination with object-oriented classification provide when classifying trees at the species level? What benefits are gained, in terms of classification accuracy, by incorporating multiple images collected at different times of the year? What contributions to overall accuracy can elevation data, such as LiDAR, provide? And finally, can individual tree species be accurately mapped using remotely sensed imagery?

The next section provides a brief literature review of studies utilizing a range of data types and classification algorithms to identify trees at a species level.

CHAPTER 2

LITERATURE REVIEW

There is considerable literature regarding the classification of tree species utilizing airborne or spaceborne imagery using numerous classification methods. As the variety of literature may suggest, no consensus has been reached as to what methodology or type of imagery is superior.

Studies can vary in terms of spatial resolution, spectral resolution, the season in which the data are collected, classification algorithm and additional data such as elevation provided by a three-dimensional sensor.

This review of literature will first examine multispectral studies beginning with basic Landsat studies and concluding with the high-resolution satellite-based platforms like QuickBird and IKONOS. Then hyperspectral studies will be reviewed. The effects of seasonal variations on classification will be examined, as will some of the classification schemes used to improve overall accuracy. Following this, the review will turn to LiDAR applications in tree species identification. Finally, integrated approaches, which incorporate a wide array of applications, will be examined.

With the exception of LiDAR, all of these methods rely on the variations among each tree's spectral signature. Variations in these signatures are caused by a number of factors. The basic components affecting a tree's signature are the stem (branches), leaf and litter of the trees. An additional factor is the structure of the canopy itself. Among trees, it is generally found that there is less reflectance in the visible portion of the spectrum and greater reflectance in the near infrared (Asner, 1998). Further, variation among species of trees is greatest in the short wave infrared, which spans 1500-1900 nanometers, while these differences are less noticeable in the visible spectrum (Asner, 1998).

The stable reflective properties of leaves are "due to biochemical characteristics resulting from the presence of biologically active pigments" (Asner, 1998, p. 240). These reflective properties result in distinctive features, which most tree species share. There are absorption features at 450 and 680 nm, which are the result of chlorophyll. The jumps in reflectance and transmittance in the near infrared are caused by increased photon scattering at the air-cell interface with spongy mesophyll (Asner, 1998).

Another factor in determining reflectance is the Leaf Area Index (LAI). In general, canopy LAI is responsible for changes in the Near Infrared (NIR) and small variations in the visible spectrum. Leaf angle also causes a shift in the green peak and the 695-700 nm red edge (Asner, 1998). Decreased leaf angle also led to increased NIR reflectance.

The next portion of the review will present examples of multispectral data used in tree species identification.

Multispectral

Multispectral data refers to a remotely sensed image that typically contains four bands – blue, green, red and infrared. It is important to realize that this data is non-contiguous, meaning that there are portions of the spectrum that are not represented in the spectral profile. These portions of the spectral profile may contain absorption features or peaks, such as those mentioned in the preceding section. However, among the different types of data represented in this literature review, this type of data generally has the highest spatial resolution.

Meyer, Staenz and Itten (1996) were among the early researchers in remote sensing tree species identification. They used color infrared film to image two areas of the Swiss Plateau. Their system was more hands-on than current methods. After scanning the film into three bands, tree crowns were manually digitized in ESRI ARC/INFO. They created five classes for four tree species (pine, spruce, fir and beech). There were two classes for pine trees – one for healthy pines and one for diseased pines. These were classified using a parellepiped method. They found they were able to classify trees with 80% accuracy.

Huguenin, Karaska, Van Blaricom and Jensen (1997) studied two different tree species in Georgia and South Carolina. Cypress and Tupelo trees were studied utilizing LandSat TM (Thematic Mapper) imagery in an effort to develop a method of locating wetland areas for more effective land management.

Because of the large pixel size and questionable results obtained with traditional classification methods, the researchers used subpixel classification. This method provided 91% accuracy classifying Tupelo trees and 89% accuracy with cypress trees. Additionally, when field work was done to verify the classification, it was found that the trees were identified correctly if they were in stands alone or if they were in mixed stands. The best traditional classifier, minimum distance, was 18% less accurate for cypress and 6% less accurate for tupelo. Additionally, the subpixel classifier was able to identify cypress trees when they were heavily mixed with other species. The traditional classifiers were unable to do this.

Carleer and Wolff (2004) attempted an analysis of tree species in a Belgian forest using a high resolution IKONOS image. Their classification of the image was broken down into 10 groups (7 tree classes and 3 miscellaneous classes). Their results were quite good with an overall accuracy of 86%. There was some confusion between some classes, oak and old beech, for example. This was attributed to the similarity of the spectra. Conifers also remained troubling even though researchers isolated them and performed an unsupervised classification on them.

The layers utilized in this classification were the blue, green, red and near infrared IKONOS layers, PCA layers and a Normalized Difference Vegetation Index (NDVI) layer. A three-pixel by three-pixel mean filter was applied to all of these layers. This filter smoothed the image, but also "increased the separability of the classes by introducing variability" (Carleer & Wolff, 2004). While this was effective in reducing variability which is a source of classification error, it introduced mixed pixels, which can also lead to error. The solution suggested by Carleer and Wolff is to apply the mean filter by region. Despite the error introduced by the filter, results were still superior compared to the non-filter outcome. Without the filter, the accuracy fell from 86% to 79%.

The pixel averaging filter would seem to be an important component of species analysis. Variation among trees in a species or even within portions of a tree is a serious concern. Variation within a species was a concern of Okina, Roberts, Murray and Okin (2001) as well.

The results obtained by Kristof, Csato and Ritter (2002) support the use of a filter although one was not applied in their research. They used 1 meter panchromatic and 4 meter multispectral IKONOS imagery of a forest in Hungary. These were resolution merged into a 1 meter multispectral image. Their initial results were not particularly strong.

"It is also important to note that high spatial resolution doesn't facilitate spectral-based classification. Medium-resolution satellite images, such as SPOT HRVIR or Landsat TM, have the advantage of 'self-calculating' mean spectral values" (Kristof et al., 2002, p. 5). Larger pixel size means that a pixel may represent an entire tree which eliminates variations among branches. Additionally, they mention how high resolution imagery may present bright and dark sides of tree crowns and confuse most classifiers. A solution they found was the segmentation of their imagery. Traditional classifiers yield 31% accuracy while an object-oriented approach boosted that accuracy to 74% (Kristof et al., 2002).

More studies indicate that high spatial resolution does not lead to successful species classification. Much of the innovation with this research lies in grouping pixels that represent a single object.

"Simple pixel-based analyses are no longer applicable because of the difficulty of classifying high-resolution data where each pixel is related not to the character of an object or an area as a whole, but to components of it" (Ehlers, Gahler & Janowsky, 2003, p. 316).

Ehlers et al. (2003) incorporated Geographic Information Systems technology into their research. This German group was attempting to classify species and land cover using 3-D aerial imagery with 15 cm resolution. The multispectral data actually lacked a red band because the sensor was originally designed for another mission so one was interpolated from neighboring bands. This shortcoming was offset by the 3-D data. This allowed them to separate shrubs from trees by classifying some data by height. Data were separated into vegetative, non-vegetative and shadows. Within the vegetation class, there were short and tall vegetation. The objects in the image were classified within these groups. GIS was then used to recombine these layers into a single land cover map based on some simple rules. The results from this classification were very good. The goal of this research was to produce new land cover maps for an area around the Elbe River. Previous land cover maps were simple man-made maps with comparatively little detail. The land cover maps created contained much more detail than previous maps. Land cover classes were classified with 95% accuracy (Ehlers et al., 2003).

Lennartz and Congalton (2004) used high spatial resolution imagery (QuickBird multispectral) to identify tree species in forests in the northeast. Their subject area was two large forest reserves in southeastern New Hampshire, one privately owned and one part of a public reserve. Data consisted of the four bands of a QuickBird image from September 2001. In addition to these four bands, several additional layers of data were derived from this data including several NDVI indices, principal component analyses, and other vegetation indices that were not specifically detailed.

Classifications were performed using per-pixel and per-object methods using eCognition™. Using per-pixel classification, accuracy was calculated to be 17%. Using per-object classification, the accuracy was listed at 31%.

Explanations listed for these disappointing results were basically that it was difficult to find a training area that contained an example of a particular tree species. More frequently, the species were intermingled. Future research in the project includes "gathering spatially precise training areas and emphasizing a more rigorous accuracy assessment" (Lennartz & Congalton, 2004).

Kosaka, Akiyama, Tsai and Kojima (2005) attempted to classify tree species using high resolution data. This data consisted of QuickBird imagery of Norikura Mountains in the Japan Alps. This data includes the 60cm panchromatic and 2.4m multispectral images. Prior to classification the data was radiometrically corrected to eliminate the topographic effect. This was done by averaging a 13 by 13 pixel area and normalizing the rest of the data to that reference area.

Hajek (2005) performed research on a mountainous area in the Czech Republic. Using eCognition™, he conducted an object-oriented classification on a QuickBird satellite image. Among the unique methods he incorporated, Hajek expanded his feature space, meaning that he derived more bands of data from the existing data. A principal component was derived as well as several averages both in 3x3 and 5x5 kernel sizes to remove variations in single trees as Kristof et al. (2002) found. Haralick texture measures were also derived as were Intensity-Hue-Saturation transforms and edge detection transforms.

Hajek conducted several segmentations before obtaining his finished product. The first segmentation simply divided the like pixels into groups. This was then used in a segmentation-based classification, which resulted in a basic land cover map. This map was then re-imported as a thematic vector layer. A finer segmentation was conducted again at a much finer scale on the Forest segments. This segmentation was utilized for the finer work of his research.

Hajek (2005) used a hierarchy of three levels. The first level was basic – forest, field and urban. The second level divided the forest level into dense, sparse and clear cut. The final level specified trees by the four species of the area - *Fagus, Picea, Larix* and *Betula* (Hajek, 2005). Classification was conducted using fuzzy logic to derive rules which were used to define the classification. They included shape, mean layer values, relative border to neighbor objects and relative area of sub-objects (Hajek, 2005).

Results of this study were mixed. The classification of the pinea and larix conifers had accuracy greater than 90%. The fagus class attained approximately 70% accuracy. There were difficulties that arose from the confusion between the picea class and shadows. Likewise there was confusion between betula and a class of trees with sparse leaf cover. One of the benefits of this particular method of classification was that the classification rules can be easily converted for use on other datasets. (Hajek, 2005).

Hyperspectral

Hyperspectral data contains much more information per unit of area than does a more traditional multispectral scanner. This is achieved by dividing the visible and near infrared portions of the spectrum into more bands that cover smaller sections of the spectrum. With multispectral imagery, the spectral profile of an object is a line created by three or four points. With hyperspectral imagery, the line is defined by between 30 points with an AISA sensor to more than 200 with an AVIRIS or Hyperion sensor. This creates a spectral signature with more detail, and these details can be used to distinguish one object from another.

Thenkabial, Enclona, Ashton, Legg and De Dieu (2004) compared three satellite-based sensors – the Hyperion hyperspectral scanner, IKONOS, LandSat ETM plus - and ALI, a multispectral scanner. This study was conducted in an African rainforest. The motivation for this study was to determine how to best utilize these new developments in remote sensing. They would determine this by attempting to develop a method of estimating forest biomass and classify the forest.

An additional goal of this research was to determine the optimal hyperspectral bands for tree species identification and biomass estimation. The researchers felt optimizing bands would reduce the dimensionality and volume of the data sets, which would allow them to apply traditional methods of classification (Thenkabial et al., 2004).

The researchers felt they had a good sampling of the available sensors. IKONOS represents hyperspatial data as it provides 1-4 m spatial resolution in four bands while Hyperion provides hyperspectral data in 220 discrete bands with 30m resolution.

The research areas were divided into 30m x 30m plots (the resolution of three of the four sensors). Each plot was divided into an area with homogenous features. In all, there were 102 areas from which samples were gathered. Of these, 65 were common to images from all the sensors. The remaining plots were either outside of one of the boundaries of an image, obscured by clouds or part of another land use/land cover (LULC) class. In each plot, the six most common species of trees and shrubs were recorded as was the percent of the area covered by canopy and the LULC classification. The three major LULC classes were primary forest, secondary forest and fallow.

Four IKONOS, nine ALI and six non-thermal ETM+ and 157 Hyperion bands were used for classification. Bands in the range of 427.55 nm to 925.85 nm from the visible and near-infrared (VNIR) sensors; and 932.72

nm to 2395.53 nm from the SWIR sensors were found to be unique and relatively noise-free.

Ultimately, it was determined that the Hyperion was better suited to determining both biomass and classifying the land cover. It was 45-52% more accurate across individual classes than multispectral data in classification, and it explained 36-83% of the variability in biomass.

Okin et al. (2001) discussed the practical limitations of hyperspectral data and its classification. Their research focused on classifying vegetation and soil types in arid and semi-arid regions. Classification was performed on an AVIRIS image of the California desert utilizing spectral libraries. The classification method utilized was Multiple Endmember Spectral Mixture Analysis.

Among the conclusions they reached was the importance of spectrally determinate and indeterminate vegetation. Spectrally determinate was defined as any vegetation with high spectral contrast. A green lawn is spectrally determinate because it has a strong red edge and deep absorption bands (Okin et al. 2001). Conversely, spectrally indeterminate vegetation does not have high contrast. This is particularly true of plants that are native to arid regions.

Their research also seems to indicate that the use of spectral libraries may not be ideally suited to the classification of vegetation species. In particular, plants of arid regions tend to vary in terms of spectral signature a great deal from plant to plant. The phenology of the plants changes rapidly in response to a small amount of water, so a single type of vegetation may have a comparatively wide range of spectra. This led them to conclude that their vegetation type results were not reliable without a detailed knowledge of the location and type of each plant which defeats the purpose of remote sensing. Their results for species type identification were not strong. A small degree of uncertainty in vegetation type endmembers led to 30% error in modeling. The researchers were much more comfortable with results obtained for vegetation cover. Much stronger results were also obtained for soil type analysis.

"We have found that the vegetation signature is by and large too faint amid a dominant, bright soil background to yield reliable and useful information" (Okin et al., 2001, p. 224).

Cochrane's (2000) research on species identification in the Brazilian rainforest deals with the concerns raised by species variability. Previous research had indicated that there could be considerable variation caused by pollution, position in the tree and age of the leaf, for example. In his research Cochrane collected multiple samples within a species of tree, some from different parts of the same tree, others from different trees. Using a hand held spectrometer, he measured the spectral responses of each leaf.

His research indicated that there was indeed variation among trees of the same species within a forest of a couple hundred hectares. Additionally, he noted samples in which the spectra exhibited "extreme variation" (Cochrane, 2000). These variations were caused by a fairly small number of factors including leaf angle and crown structure.

This study may have been more applicable had it dealt with average spectral response of the entire tree. However, his results do seem to indicate that a tree of the same species may vary in spectra according to factors associated with location. Cochrane believes that classification of trees is possible with hyperspectral data, but it will require either further analysis following the classification or spectral shape filtering.

le Maire, Francios and Dufrene (2004) researched methodologies for differentiating tree species. In particular, they review various ratios and band combinations that have been implemented by other researchers. This was done by creating a database of 53 leaves that had been randomly sampled. Using this database, they compared all leaf chlorophyll indices published from 1973-2000 (le Maire et al.). They compared the results of each of these indices against actual chlorophyll values and plotted the results based on their accuracy. The final results of this research were that a simple difference ratio provided the most accurate chlorophyll estimates. Several of these indices may be applicable to this research such as NDVI and greenness ratios as well as traditional chlorophyll ratios.

Many hyperspectral scanners do not provide high resolution data. Conversely, high spatial resolution data provides at most three bands of information and, in some cases, only one. As Greiwe and Ehlers (2004) mention, fewer bands of data often result in classification errors. While hyperspectral data can improve classification accuracy, it does not provide the spatial accuracy required for certain applications (in their case, urban land use mapping).

Greiwe and Ehlers (2004) used the same high resolution sensor that Ehlers et al. used in combination with 128 bands of HyMap data to classify the city of Osnabrueck in Germany. The high resolution data came from the High Resolution Stereo Camera airborne sensor. These provided 0.125m resolution. This image was segmented and then these segments were applied to the hyperspectral data. Additionally, prior to final classification, Spectral Angle Mapper (SAM) tools were used to determine the most appropriate pixels for each class. The SAM tools allowed them to select pixels that were representative of their entire class and this accounted for a 20% increase in accuracy. Using this methodology, they achieved 73% overall accuracy.

Boyd, Foody and Ripple (2002) explored different vegetation indices in their attempts to classify coniferous species in Oregon. For this project, an AVHRR data set of a region in the Cascade Mountains was used. There are five major coniferous species of trees prevalent in this area.

The researchers explored three basic means of classification – vegetation indices, multiple regression, and neural networks. Vegetation indices included six common ratios selected on the basis of their ability to use all of the data that AVHRR provides. The regressions were conducted in an attempt to determine correlations between the bands and the land cover. Three different types of neural networks were used to classify this data - the multi-layer perceptron, radial basis function, and generalized regression neural networks. It was this method that the researchers preferred. It allowed them to analyze data without making assumptions about it (Boyd et al., 2002).

Xiao, Ustin and McPherson (2004) used hyperspectral AVIRIS data to identify tree types for urban mapping. Their study area was the city of Modesto, California. Spectral reflectance is affected by pigment, internal leaf structure, water composition and tree architecture (Xiao et al., 2004). Their data indicated that conifers tend to have lower reflectance values than do broadleaf deciduous trees. They further found that spectra tend to vary not only in magnitude but also in profile. In general, they found that the data provided by the AVIRIS sensor was suitable for tree species mapping.

Clark, Roberts and Clark (2005) used HYperspectral Digital Collection Experiment (HYDICE) data as well as laboratory spectrometer samples to study trees in Costa Rica. The laboratory spectrometer data allowed them to classify species with 100% accuracy. Classification of the airborne hyperspectral data ranged from 88 to 92% using maximum likelihood classification.

Bunting, P. and Lucas, R. (2006) used hyperspectral data in an object-oriented classification scheme to outline tree crowns in a diverse forest structure with trees of varying ages and sizes. This data would serve as a beginning step for further analysis.

Zhang, Rivard, Sanchez-Azofeifa, and Castro-Esau (2006) used HYDICE data to study variations among tree species and within tree crowns in Costa Rica. Although they were able to separate several species of trees, they found that it may be impractical to attempt to identify large numbers of tree species using hyperspectral data alone due to some overlap in spectral signatures. They suggest that the addition of LiDAR data may increase overall classification accuracy. Additionally, they suggest that knowledge of tree phenology may be helpful in improving classification accuracy.

Seasonal Variations

Researchers have taken advantage of the differences in the rate at which trees blossom or their leaves senesce. In the fall, it is often easy to notice that leaves of certain types of trees change before others, or that some trees have leaves that simply turn brown while other turn to bright shades of red.

Sugumaran et al. (2003) conducted a study in which imagery collected in April, August, September, and November was utilized in the classification of trees in Columbia, Missouri. Classifications were performed using each image and a traditional maximum likelihood classifier and CART. The results obtained from the September image were the most useful in classifying trees. Key, Warner, McGraw and Fajvan (2001) found that images collected during the fall provided the best overall results in their study. They found that spring images collected immediately after leaf out was second best. Results obtained by Birky (2001) agree with this finding. It was found that trees are generally less productive during periods of extreme heat or moisture stress. They further found that productivity, as measured by the normalized difference vegetation index, remains high through the fall. Variations are less likely to occur among plants if they are stressed during the summer months. Spanner, Pierce, Running, and Peterson (1990) also attributed some of these variations to the changes in overall image makeup as well as solar zenith angle.

Classification Algorithms

Classification is largely a matter of statistical analysis. There are many, many ways to perform this analysis. As remote sensing imaging technology has advanced, the methods for analyzing that data have advanced as well. The vast majority of classification schemes perform there analysis on each pixel without regard for neighboring pixels. A recent development in classification technology called object oriented classification groups pixels together in an effort to mimic the way the human mind identifies objects. These groups can be classified in relation to neighboring groups.

Sugmaran et al. (2003) compared the maximum likelihood and CART methods for identifying trees. Hajek (2005) used object-oriented classification of trees in a mountainous region of the Czech Republic. Accuracies obtained for the coniferous classes exceeded 90%. However, other classes in the classification were approximately 70%. Lennartz and Congalton (2004) used object-oriented classification to classify trees in the northeastern United States with QuickBird data after obtaining poor results with traditional per-pixel classifications. Overall classification accuracy with traditional methods was 17%. Using object-oriented classification, accuracy increased to 31%. Ehlers et al. (2003) used geographic information systems to incorporate elevation data into a classification of land cover in Germany. Accuracy for several classes exceeded 90%. Kristof et al. (2002) used object-oriented classification after obtaining poor results using traditional classification. Overall accuracy rose from 31% using traditional classifiers to 74% using object oriented. Kristof et al. (2002) concluded that high resolution imagery provides too much detail for traditional classifiers. Huguenin et al. (1997) used subpixel classification because they were using imagery with 15m spatial resolution. Using this method, they improved their accuracy by 18% in one class and 6% in the other.

LiDAR

Light Detection and Ranging is a relatively new technology. It is also commonly called an airborne laser scanner or a laser altimeter. It involves the laser pulses emitted from an airborne platform. The time it takes for the pulse to return to the platform is used to compute the distance the beam has traveled. This is then used to create a high-vertical accuracy map of the terrain. Uses of LiDAR data for vegetation analysis include calculating above ground biomass, stem counts and crown widths (Van Aardt & Wynne, 2004) and it can also be used to complement the spectral data in a classification.

Haala and Brenner (1999) used laser altimeter data to extract features in an urban environment. They first created a Digital Surface Model (DSM). A DSM differs from a Digital Terrain Model in that the surface includes buildings and trees, whereas the terrain simply refers to the surface of the earth. In extracting building and tree forms, the DSM is preferred. This was complemented with high resolution color infrared imagery to extract buildings, trees and streets. This is a common application of LiDAR data. Sohn and Dowman (2007) developed an automated methodology for extracting building footprints from LiDAR and IKONOS multispectral imagery.

Van Aardt and Wynne (2004) used Lidar and hyperspectral AISA data to classify tree species in Virginia. In this case, the AISA data were collected in 16 bands at 1 meter resolution. In particular, they investigated the segmentation process in eCognition™ quite thoroughly. They found that classification using the 720nm band and LIDAR to perform the multiresolution segmentation was the best. This was achieved by comparing variances within each segment to variations from segment to segment. They found that this method could provide accurate results. One of the benefits of creating the hierarchical classification rules using the eCognition™ software is that these rules can then be applied to larger parcels of forest (Van Aardt & Wynne, 2004).

Holmgren and Persson (2004) developed a method of identifying spruce and pine trees using a LiDAR dataset. Using data collected over a Norwegian forest, they were able to correctly classify spruce and pine trees with 95% accuracy. The researchers generally found that spruce trees were more conical in shape than pine trees. Pine trees were more often mis-classified, however they felt this may have been influenced by the neighboring trees and the competition for sunlight.

Collins, Parker and Evans (2004) used LiDAR and very high resolution multispectral imagery to map tree species in a wildlife refuge in Mississippi. Classification was performed in eCognition™ utilizing training samples as well as the hierarchical classification tools provided by eCognition™. Four tree species classes were identified with a 72% accuracy rate.

Chen, Vierling, Rowell and DeFelice (2004) used LiDAR and mutlispectral IKONOS imagery to estimate pine tree coverage in a forest. One of the principal discoveries of their study was that LiDAR may be an effective method of estimating Leaf Area Index. This was one of Asner's (1998) primary influences on vegetation reflectance. Chen et al. (2004) reasoned this is logical because leaf area index and LiDAR are dependent on the amount of light that passes through the canopy.

Much of the current research with LiDAR explores its usefulness in estimating physical characteristics of trees. Næsset and Gobakken (2005) estimated heights, basal areas and volumes of spruce and pine trees; Roberts et al. (2005) used LiDAR to estimate leaf area index in loblolly pines; Solberg, Naesset and Bolandasa (2006) developed a methodology to segment individual trees and used these segments to estimate heights and crown diameters; Bortolot (2006) used LiDAR to define tree clusters and used these clusters (rather than individual tree segments) to estimate density and biomass, and Rowell, Seielstad, Vierling, Queen and Sheppherd (2006) segmented LiDAR canopy data to determine tree stem locations.

While multispectral imagery provides high spatial resolution, it does not appear to provide spectacular results. Hajek (2005) was able to obtain very good results in some classes, while obtaining poor results in others. Huguenin et al. (1997) were able to successfully classify only two species. Hyperspectral imagery, however, provides more spectral detail that can be used to separate many more species. Xiao et al. (2004) used AVIRIS hyperspectral imagery to identify a wide variety of species in an urban setting. LiDAR can also be used to improve classification accuracy. Collins et al. (2004) used LiDAR and high resolution imagery to classify tree species, as did Van Aardt and Wynne (2004). Further, when dealing with high resolution imagery, non-traditional classification schemes (such as object oriented) are the preferred tools (Lennartz & Congalton, 2004; Kristof et al., 2002).

CHAPTER 3

METHODOLOGY

Study Area

The University of Northern Iowa campus was selected as a study area. The campus covers approximately 120 acres and is located in Cedar Falls, Iowa. This study area was chosen for several reasons. First, the researchers have good knowledge of the area, which removes the possibility of confusing portions of the study area. Second, the campus has a wide variety of trees. The dominant deciduous species are oak and maple and the dominant evergreen species are pine and spruce. Additionally, many of these trees are separated from each other by grassy areas. This makes it easier to distinguish them from nearby trees, which could be difficult in a more natural environment. Third, the university's Facilities Services office has information about each of the trees on the campus, which saves researchers the time it would take to identify them. Fourth, it is a manageable size for developing training sets for both classification and accuracy assessment.

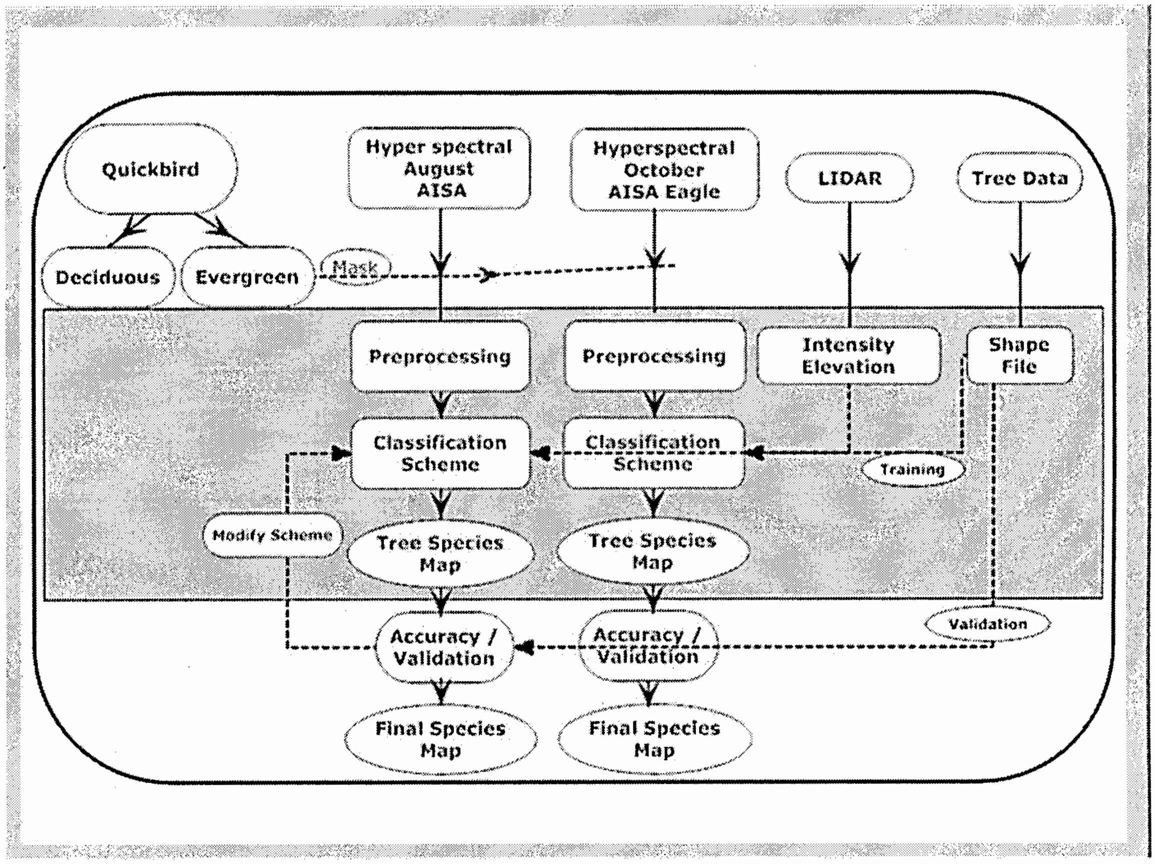

Figure 1. Overall project workflow

Data Used

A wide variety of data types were utilized in this research. These data include a shapefile, spectrometer data collected in the field and an assortment of airborne multispectral and hyperspectral imagery. The data are summarized in Table 1.

Table 1.

Data types

Collection date	Data type	Spatial resolution	Spectral resolution
April 2003	Multispectral	0.6m panchromatic, 2.4 multispectral	4 bands
July 2004	Hyperspectral	2m	23 bands
August 2004	Field spectrometer	NA	750 bands
April 2006	LiDAR	1m	Discrete multi-return
October 2006	hyperspectral	1m	63 bands
July 2006	shapefile	NA	NA

Chronologically, the first data set is a multispectral image collected in April 2003 by the QuickBird satellite (Figure 2). It provides two products: the first is a 0.6m spatial resolution panchromatic (black and white) image and a 2.4m spatial resolution four-band image. The panchromatic image represents reflectance from 445 to 900 nm. The multispectral image divides that same region into four bands: blue from 450-520nm, green from 520-600nm, red from 630-690nm and near-infrared from 760-900nm.

Figure 2. April 2003 QuickBird image

The second piece of data is a hyperspectral image (Figure 3). It was collected in July 2004 with the Airborne Imaging Spectroradiometer for Applications by the Center for Advanced Land Management Information Technology (CALMIT) at the University of Nebraska – Lincoln. The image has 24 bands with 2-meter spatial resolution. These bands cover the spectral range from 430 to 900 nanometers. The near infrared spectrum begins at 750 nm so this image incorporates the visible spectrum and the beginning of the infrared.

Figure 3. July 2004 hyperspectral imagery

Ground-based spectrometer samples were also collected August 6 and 9, 2004. These were gathered using an ASD Hand Held field spectrometer. The device measures reflectance from 325nm to 1,075nm. The device was set to collect 25 samples and average the results. It was attached to a 1m bar which allowed the spectrometer to be held in the branches of the tree. Samples were collected and reviewed before moving to the next tree. Ninety-two spectra were collected over the two-day period. The majority of the samples were of trees in the study area, but other objects such as grass, roads and sidewalks were collected as well for reference data.

The fourth piece of data for the project was a LiDAR dataset acquired in the spring of 2006 by The Sanborn Mapping Company Inc. Figure 4 is an oblique representation of a portion of the LiDAR dataset. The sensor used was a Leica ALS50 with a sampling rate of 83kHz. The data was provided in the form of nine one-square-kilometer tiles that cover all of UNI campus and a good portion of the surrounding area. One of the tiles (Area 1 Tile 5) was sufficient to cover central campus. This is a discrete multiple return LiDAR data set. Each laser pulse emitted by the sensor is recorded as three or four return pulses. This allows for the analysis of more understory vegetation. The spatial resolution of this data is 1m. Two products come from LiDAR data. First is the elevation for each point. The second is the intensity of the reflected laser beam. This data is not as frequently used as the elevation data in most analysis; however, it can be useful. The intensity data is similar to traditional remote sensing imagery. Objects such as sidewalks reflect a greater amount of the infrared radiation emitted by the laser scanner than do trees.

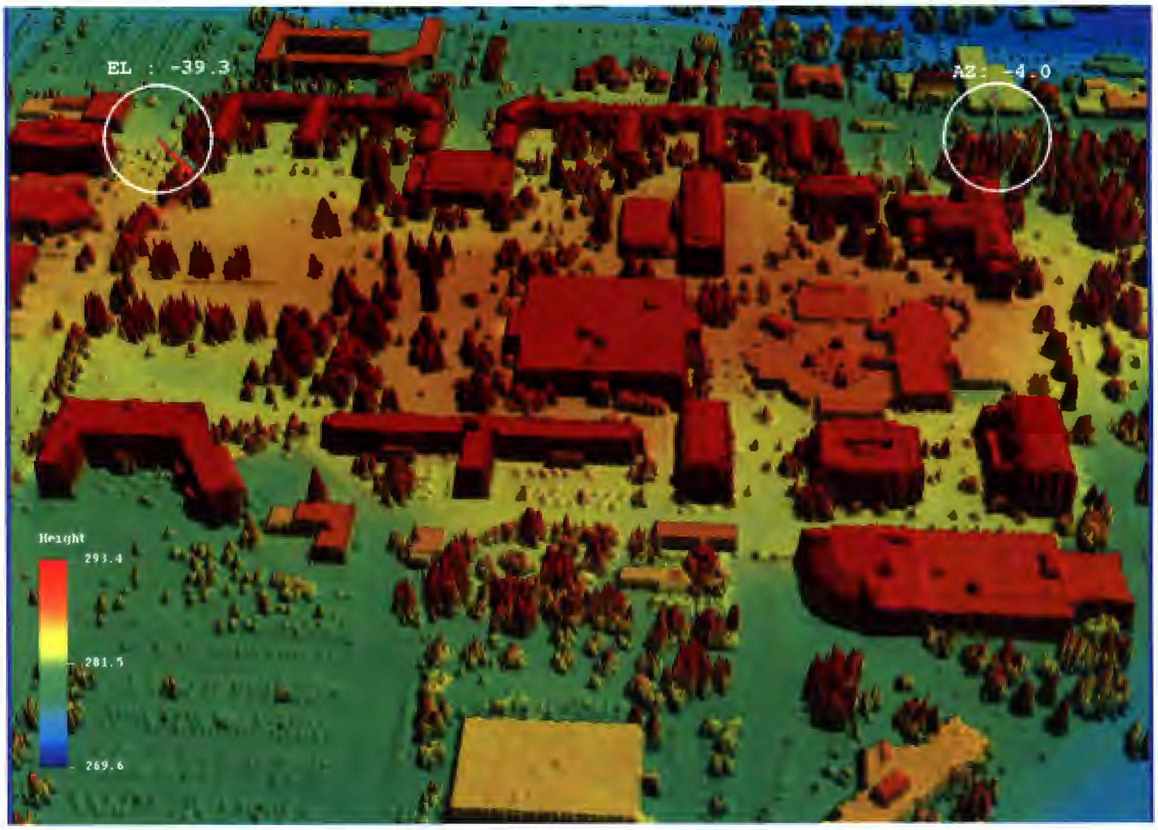

Figure 4. LiDAR data collected in April 2006

Additionally, LiDAR is an active remote sensing platform so objects on the ground do not possess shadows. This is of great benefit in some data analysis processes.

The last piece of remote sensing data was a hyperspectral image gathered in October 2006 (Figure 5). This image was also gathered by CALMIT at the University of Nebraska - Lincoln using the AISA Eagle sensor. This data set consists of three strips that run east-west. It has 1m spatial resolution and 63 bands covering the range between 400 and 980nm. This image is of higher resolution that the previous hyperspectral image. It was acquired to take advantage of the fall leaf changes.

Figure 5. Hyperspectral imagery collected October 2006

A final, but critical, piece of data was a database produced by the UNI Facilities Services department. Figure 6 was created using the tree database and several byproducts of the LiDAR dataset processing. The shapefile contains every tree and shrub on the UNI campus as well as much of the infrastructure. It provides information about the trees on campus including the scientific and common names, some basic information about the condition of the tree and maintenance-related information such as when it was last pruned. This file was used as a reference for the project.

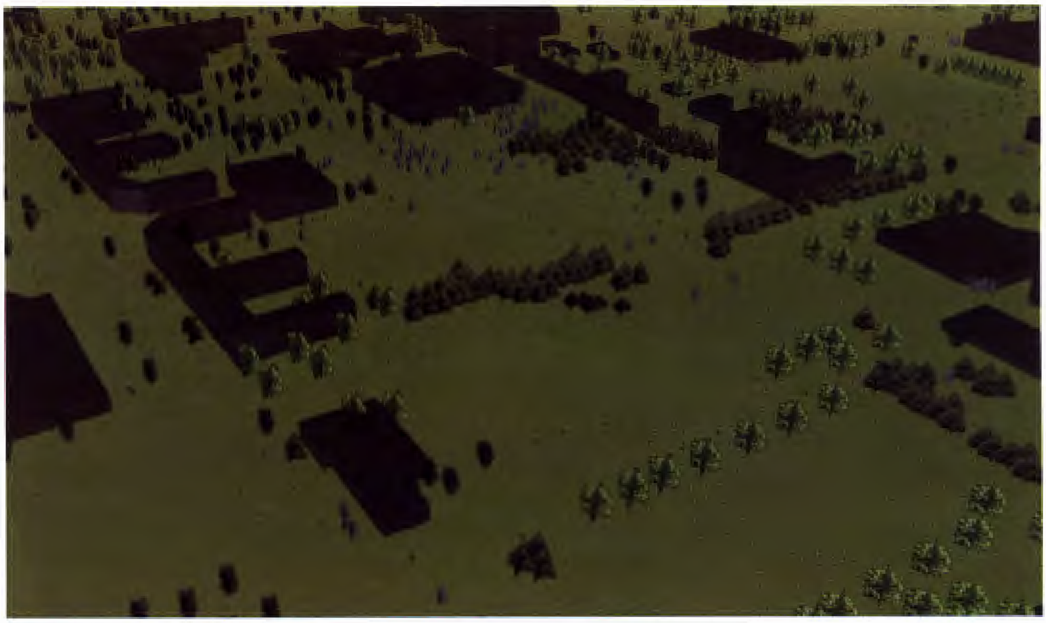

Figure 6. A 3D shapefile developed from the UNI tree database

Data Processing and Classification

The goal of the project is simply to identify trees. This can be achieved by comparing their spectral signatures with reference samples. Figure 7 provides some spectral signatures of selected impervious objects in the study area. These spectra were collected from the October 2006 hyperspectral image. These impervious objects have fairly linear spectral responses. All tend to have low reflectance in the blue portion of the spectrum. Reflectance then grows steadily into the green, red and infrared. Because sidewalks are lighter in color, its sample has higher overall reflectance than do the other samples. However, it exhibits the same trend as the other impervious samples.

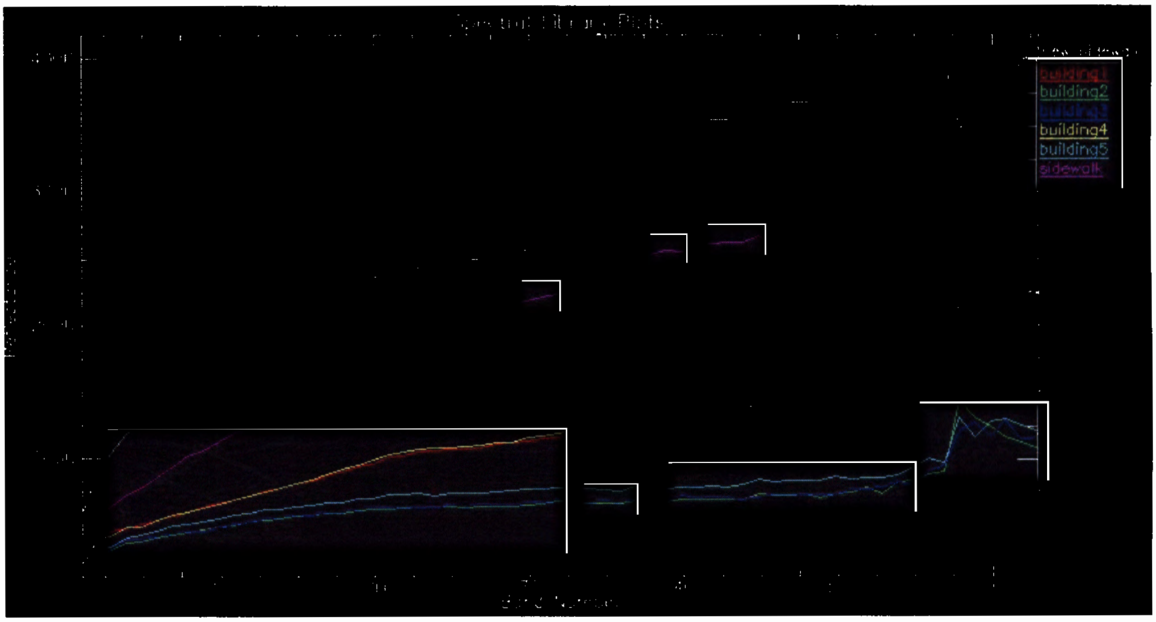

Figure 7. Spectral signatures of assorted impervious objects in the study area

By contrast, Figure 8 displays the spectral signatures of vegetation from throughout the study area, which were also selected from the October 2006 hyperspectral image. Vegetation shows considerably more variation than do the impervious samples. These spectral signatures are typical of vegetation – low reflectance in the blue, a green peak, a trough in the red portion of the spectrum and a high peak in the infrared. The differences in spectral response among different types of classes (vegetation, impervious) and within a type (oak, maple) are what make classification possible.

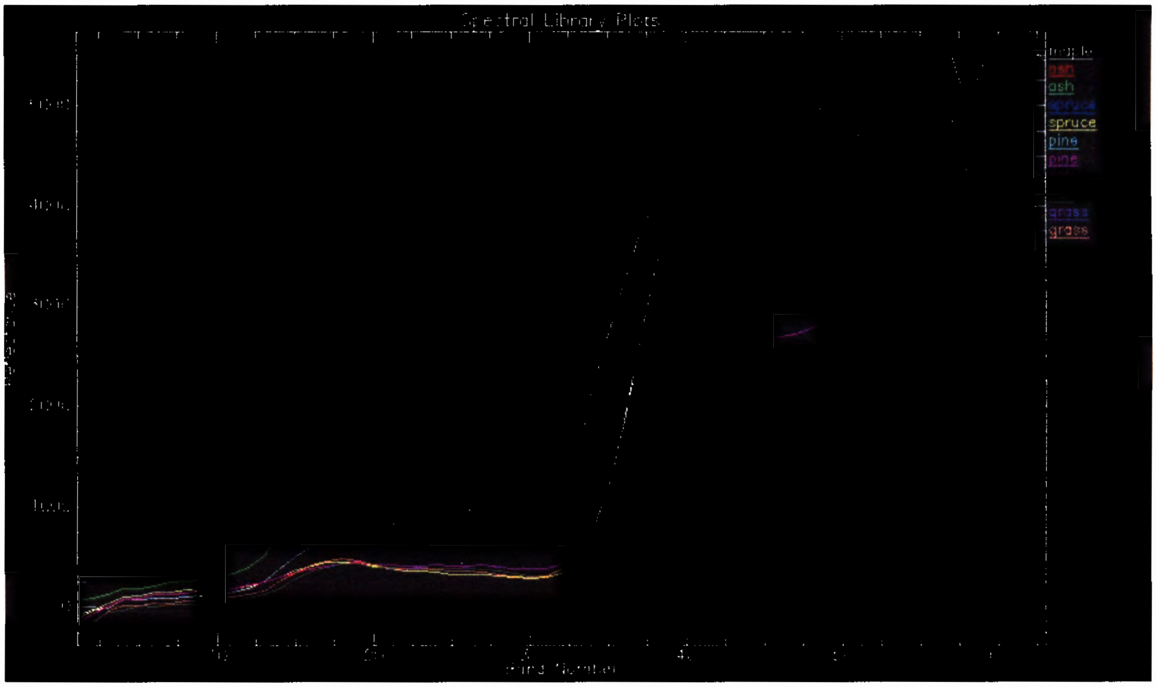

Figure 8. Spectral signatures of assorted vegetation in the study area

Figure 9 is a sample of some of the field data gathered using the ASD hand held spectrometer. The spectral signatures look similar to the signatures displayed in Figure 8. However, here the signatures have a more pronounced trough around 680nm. This is likely caused by humidity in the atmosphere absorbing light at this frequency.

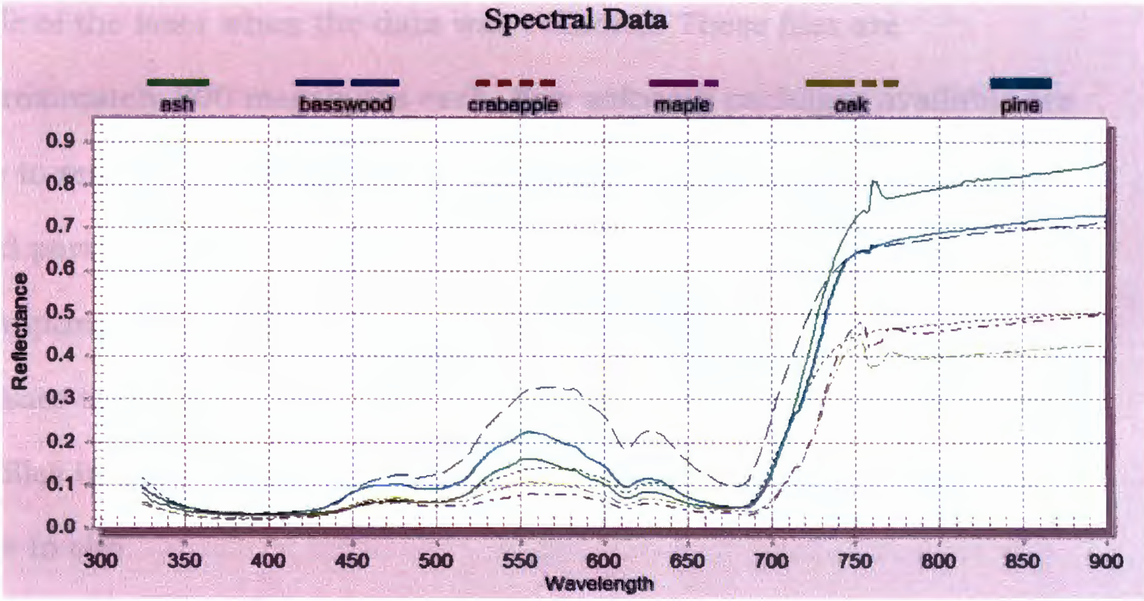

Figure 9. Spectra gathered in the field

While LiDAR was very useful for this project on a variety of levels, it showed more frustrating aspects of its use. LiDAR is comparatively new in the remote sensing world, and it awaits fuller standardization. The goal of much LiDAR processing is to have the file as an image to be combined with other image data. In most cases, this image is a Digital Terrain Model (DTM). Unless specified when ordering, most LiDAR data does not come in this format. The raw, unprocessed LiDAR file type is LAS. This is a format which contains all of the data collected by the sensor, including the first, second, third and fourth elevation returns, the intensity of the reflected laser beam for each of these returns and the angle of the laser when the data was collected. These files are approximately 800 megabytes each. Few software packages available are able to read this file type. An extension to ESRI ArcGIS provided by a third party enables the software to open the LAS files. However, attempting to open these files caused the program to hang or crash because of the sheer size of the file. Several attempts were made to clip the files in order to make them smaller. However, the file was also too large to clip.

RSI ENVI 4.3 also has the ability to import LAS files. Exporting the LAS files as DEMs results in files without projection information, although it is available in an associated file. This meant the LiDAR and hyperspectral images were not aligned.

The solution was a piece of software called QT Modeler, developed by the Johns Hopkins Applied Physics Laboratory. It allows the user to perform some basic analysis of LiDAR data such as line of sight calculations, but most importantly, it permits the exporting of DEMs as well as intensity images. The software was then used to export the first and last return LiDAR as well as an intensity image. These were all necessary for further processing.

After some necessary (and time consuming) formatting, the data were ready for the next stage of processing. Using Visual Learning Systems LiDAR Analyst, a bare earth model was created. Using proprietary algorithms, the software compares the first and last return LiDAR DEMs to estimate the height above sea level of the surface of the earth everywhere in the image. The final result should appear to accurately represent the grown beneath any object such as trees or buildings. In this instance, the image appears to be flat and featureless. This is good because there is little change of elevation on the campus.

Using the Raster Calculator in ArcGIS, the bare earth elevation was subtracted from the first return elevation. This yielded relative heights of campus objects. The altitude above sea level of the campus area ranges between 270 and 280 meters. The goal of this operation was to create a file where the earth has an elevation of 0 meters.

Image preprocessing

Prior to any image processing, both hyperspectral images and the QuickBird image were geometrically referenced to the LiDAR imagery using RSI ENVI 4.3. For the October 2006 hyperspectral image, 30 ground control points were selected and RMS error was 0.9478. There were 39 ground control points for the July 2004 hyperspectral image with a RMS error of 2.9426. There were 44 ground control points for the April 2003 QuickBird image with a RMS error of 2.4494.

Initially, raw images were used for classification. However, image processing was also performed on the two hyperspectral imagery using the hyperspectral tools in ENVI. In particular, a minimum noise fraction (MNF) was performed on the reflectance of both hyperspectral images. As Figure 10 demonstrates, the MNF transform can be useful in accentuating the differences between objects, as this particular combination of bands displays trees well.

Figure 10. An MNF transform of the October 2006 hyperspectral data

The MNF transform is a method of reducing the size of the data utilizing principal component analysis (PCA). Successive bands of imagery are typically highly correlated. PCA is frequently used to reduce the dimensionality of the dataset by producing a new set with the same variance as the original data (Sousa, Martins, Ivim-Ferraz & Pereira, 2007). The transform is achieved by calculating the mean of the data and then using an eigenvalue to rotate the data set orthogonally (Richards, 1999). This maintains the variation of the entire data set while reducing the correlation among bands. Typically, the first band contains the largest amount of variance. The last bands are mostly noise.

The minimum noise fraction is a series of principal component analyses performed back to back. PCA is applied to the dataset to de-correlate and rescale the noise in the data set. A subsequent PCA is performed on this data (ENVI help file). As Figure 11 indicates, by the 20th eigennumber and 20th MNF band, the eigenvalue is nearly zero. This indicates that much of the variation in the data set is contained in the first 20 bands of the resulting MNF image. As a result, only those 20 bands were used for classification.

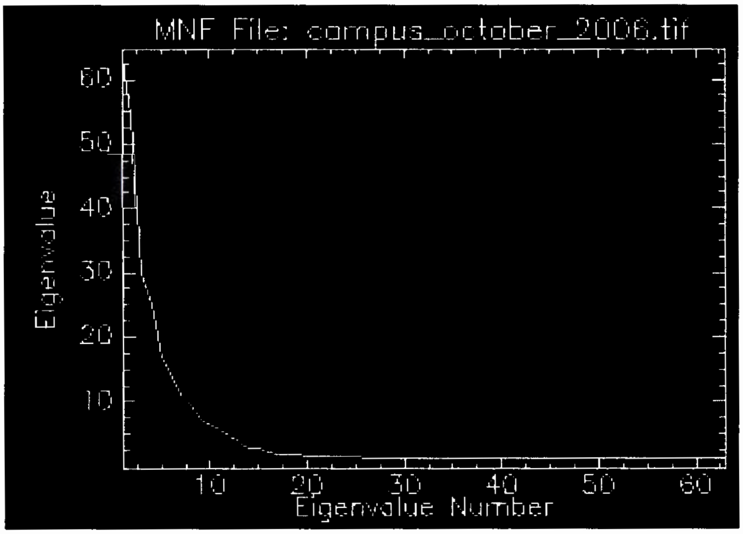

Figure 11. The eigenvalue from the MNF transform of the 2006 hyperspectral image

Likewise in Figure 12, the eigenvalue appears to level off at number 15. Thus the first 15 bands of the MNF were used for classifications.

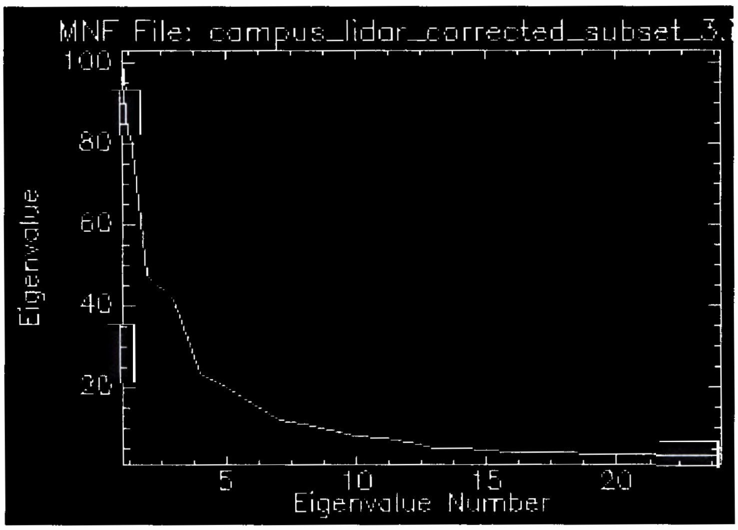

Figure 12. The eigenvalue from the MNF transform of the 2004 hyperspectral image

Classification

Classification is the defining of an object based on the rules of a class (Defininens, 2004). In most cases, these rules are based on the spectral values obtained from an image. For this research, all classification was performed using eCognition™ Professional 4.0 developed by Definiens AG. The company was founded by 1986 Physics Nobel laureate Professor Gerd Binning. eCognition™ treats imagery not as a mass of unrelated pixels, but as groups of related pixels or segments. These segments can then be classified not simply by spectral signature, but also by their relationship to other segments as well as the segment's characteristics. Generally, these characteristics fit into three broad classes: intrinsic features such as the color, texture and form of an object; topological features such as the location of the segment in the image; and context features such as semantic relationships (Definiens, 2004).

A further benefit of eCognition™ is the ability to use all types of spatial data in a classification. Shapefiles and images can be combined in one project. The only limits are computational power and the user's organizational skills. The workflow of classification in eCognition™ is relatively straightforward. Imagery must first be segmented. Segmentation is a bottom up process. Each segment begins as a single pixel. Each iteration of the process adds another pixel to the segment until either marginal pixels exhibit heterogeneity or the user-defined scale is exceeded (Definiens, 2004).

eCognition™ requires that a class hierarchy must be created as the next step in classification. The software allows the creation of more complex structures (such as parent-child structures) than do traditional classification schemes. Classes for this project were buildings, sidewalks, roads, honey locust (*Gleditsia triacanthos)*, eastern white pine (*Pinus strobus)*, crabapple (*Malus ioensis*), sugar maple (*Acer saccharum*), white spruce (*Picea glauca)*, American basswood (*Tilia americana*), pin oak (*Quercus palustris*) and green ash (*Fraxinus pennsylvanica*). These classes were determined statistically. Using the UNI campus shapefile tree database, a frequency plot was created. Table 2 gives the outcome of the frequency analysis.

Table 2.

Most common trees in the study area

Most common trees	
honey locust	607
white pine	426
crabapple	318
sugar maple	306
white spruce	285
American basswood	212
pin oak	132
ash	115

In building the class hierarchy, coniferous and deciduous were parent classes. Trees were grouped into their appropriate parent classes.

Classes may be defined by user-defined membership functions (reflectance value for the infrared band, for example) or by what is referred to as "nearest neighbor" classification, which can function in a multi-dimensional feature space (reflectance values in all bands). In each case, these are fuzzy rules. Rather than a binary, "yes or no" classification, each object in a fuzzy classification system is assigned a value between zero and one, with zero meaning it is absolutely not a member of the class and one being absolutely a member of the class. This system allows for minor variations and vagueness of remotely sensed data (Definiens, 2004).

Further, eCognition™ provides two methods of supervised classification. The user may either train the classifier by selecting representatives of each class or by defining the parameters of each class by creating a membership function. Accurately defining the precise reflectance of each oak tree would of course be impossible using a hard classification system, because the reflectance of each oak tree varies slightly. Thus a soft or fuzzy classification scheme is employed.

One of the methods is the nearest neighbor classification scheme. For each class, it selects a representative sample and plots it as a vector in *n*-dimensional space, where *n* is the number of bands in the image. Each segment is then compared to the class and the segment is then assigned to the nearest class (Definiens, 2004).

This process is illustrated in Figure 13. Two classes are represented: red and blue. The red and blue dots indicate the vectors created by each training sample. The bold, orange vector is the segment being classified. Because its vector is closer to blue class, it will be classified as blue.

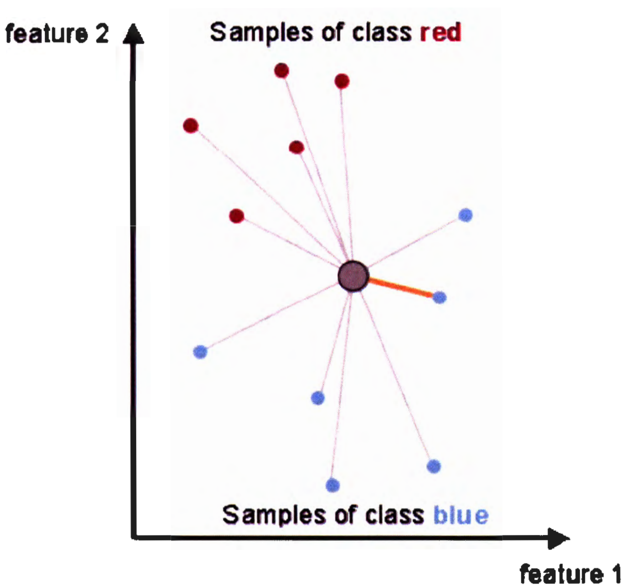

Figure 13. Nearest neighbor classification (Defineins, 2004)

Nearest neighbor classification was used for this project primarily because it provides more data on which to base the classification. Training samples were selected in areas where the sample objects were clearly distinguished from their surroundings. In many cases however, it was necessary to add some knowledge to manually define the parameters of each class. For example, rooftops and parking lots are frequently confused in classifications because they are made of similar materials. Using the relative height LiDAR file, the building class was defined as anything with a height greater than four meters. eCognition™ allows users to incorporate Boolean statements such as "and" or "or." The Boolean operator "and" means that only segments that meet the nearest neighbor and the LiDAR elevation criteria are defined as building. Similarly, accuracy of the grass and sidewalk classifications was improved by defining the elevation as anything below 2 meters.

Figure 14 is an example of a user-defined membership function. The curves in the "Initialize" box determine how the membership function is implemented. In this case, the curve allows the rule some flexibility. The center point of the function is five. It will also accept any value above five and down to approximately 2 where the membership function value is 0.1. These curves are adjustable and can allow nearly any range of values to be included. The membership function currently selected allows for variations. If one of the functions with right angles in it was selected, then every value below five would not be a member while every value above it would. Membership function can be created to fit nearly any range of values by simply editing the shape and border of these functions.

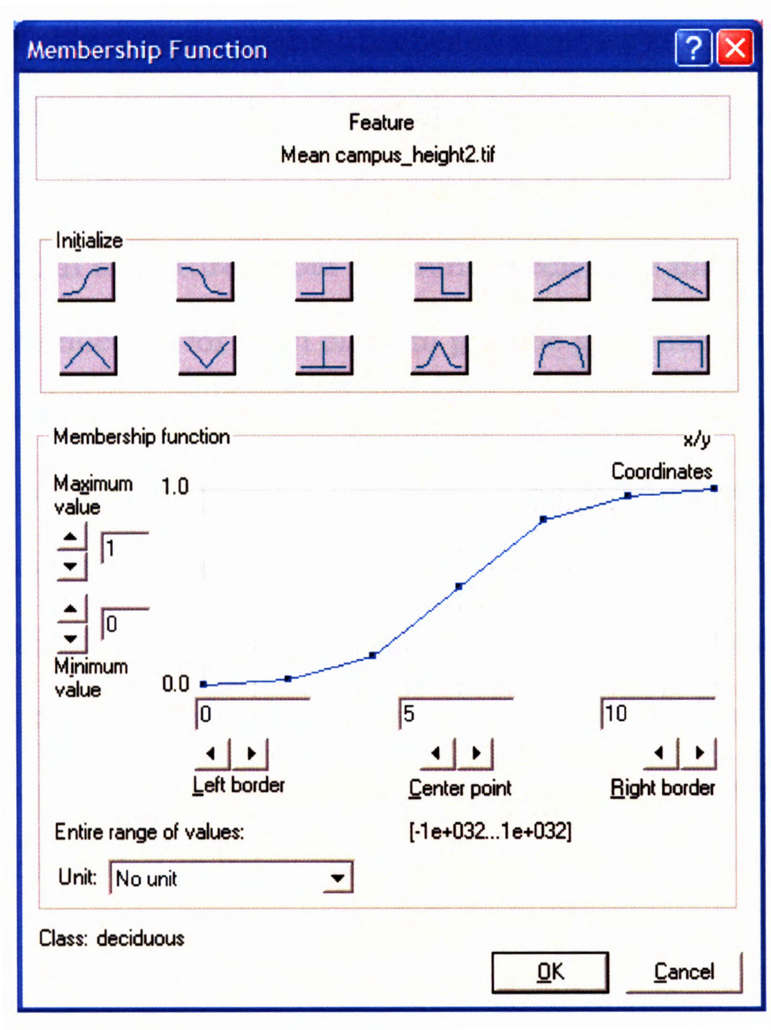

Figure 14. An example of a membership function that only accepts objects with elevation greater than 2 meters

The samples were then saved as a Test or Training Area (TTA) mask. This allows samples to be selected regardless of the image type as long as they are properly geo-rectified. Further, the hierarchy was also saved. The combination of the two saved files allows a user to quickly perform classifications on different types of imagery.

Table 3 displays the number of samples collected for each class. Tree samples were selected based on how distinct they were from other species of tree. This was done to alleviate any possibility of mixing spectral signatures from different species. As many samples as possible were collected for each class to provide good data for accuracy assessment. In some instances, the number of valid sample sites limited the number of samples available. It is important to remember even though a class may have a small number of samples, it is likely that each individual sample contains dozens of pixels. A smaller training data set was created based on the accuracy assessment set. The training data is used by the nearest neighbor classifier to determine which class each segment should belong in.

Table 3.

Samples collected

class	number of samples
American basswood	33
maple	73
pine	20
honey locust	22
spruce	45
crabapple	27
ash	65
buildings	222
oak	65
grass	165
roads	28
sidewalks	12

Six measures of accuracy are provided by eCognition™. These include overall, user, producer, Hellden, Shorts, and Cohen's Kappa accuracies. Overall accuracy is the proportion of all reference pixels that are classified correctly (Definiens, 2004). User accuracy is a measure of errors of commission. These errors involve placing a sample in the wrong category. Producer accuracy is a measure of errors of omission. These occur when a sample is not placed in the correct category. Helldens accuracy is the harmonic mean of the producer and users accuracy (Definiens, 2004). Short's accuracy introduces more statistical analysis into the equation. Generally, Short's accuracy is considered to be more pessimistic while Hellden's is more optimistic (Definiens, 2004). The final measure of accuracy is the Cohen's Kappa (also referred to as Kappa Index of Agreement). It is assumed that both the reference classification (the TTA mask) and the classification are correct, and it provides a measure of how well the two classifications agree. The benefit of this is that kappa takes into account the possibility of chance agreement and corrects for it (Definiens, 2004). Overall and kappa accuracy was used for overall accuracy. Producer and user accuracy statistics are given for individual class accuracy.

CHAPTER 4

RESULTS

Classifications were performed on each of the images available with and without the aid of LiDAR. This was made possible by the eCognition™ workflow. The same hierarchy and samples were used for each classification.

This project originated with only the July 2004 hyperspectral, and those results were questionable at best. Problems encountered in that research also surfaced in various phases of the current research. Chief among them were the coarse spatial resolution of the 2-meter imagery. Getting good separation from neighboring classes was difficult despite the dozens of attempts using various greenness and chlorophyll ratios, and a normalized difference vegetation index.

With the LiDAR data, the classification still did not have sufficient accuracy. A concurrent project utilizing MNF data led to the data reduction, which resulted in increased accuracy.

QuickBird

The first classification was performed using the QuickBird imagery alone. The initial goal of incorporating this image into the classification was to develop a mask separating out the coniferous trees from the deciduous species. Because this image was collected in early April when there were no leaves on the deciduous trees, this would have been an ideal situation because the only green objects in the study area were grass and evergreen trees. This mask could then have been incorporated into further classifications using imagery that had significantly more greenery to confuse the software. However, there was considerable difficulty in separating the coniferous class from the deciduous class. Several factors likely caused this. First, the QuickBird image provides limited spectral resolution. Imagery of this type is perhaps best used to identify broader categories of land cover. Second, the bare trees actually created more problems than they solved. Frequently, these bare trees were classified as coniferous. This is likely due to the shadows they cast on the grass. These created a dark green area that was apparently similar in hue to a conifer, and these shadows were frequently misclassified as conifers. Figure 15 is a portion of the classification attempt. Green areas depict conifers and red areas are deciduous species. The areas classified as coniferous are clearly not correct. Portions of the image classified as coniferous are clearly much larger than the areas which are actually coniferous. Some coniferous trees do appear to be correctly classified, but there are also large vaguely shaped areas which are more likely shadows. As a result, this image was not used to generate a coniferous/deciduous mask.

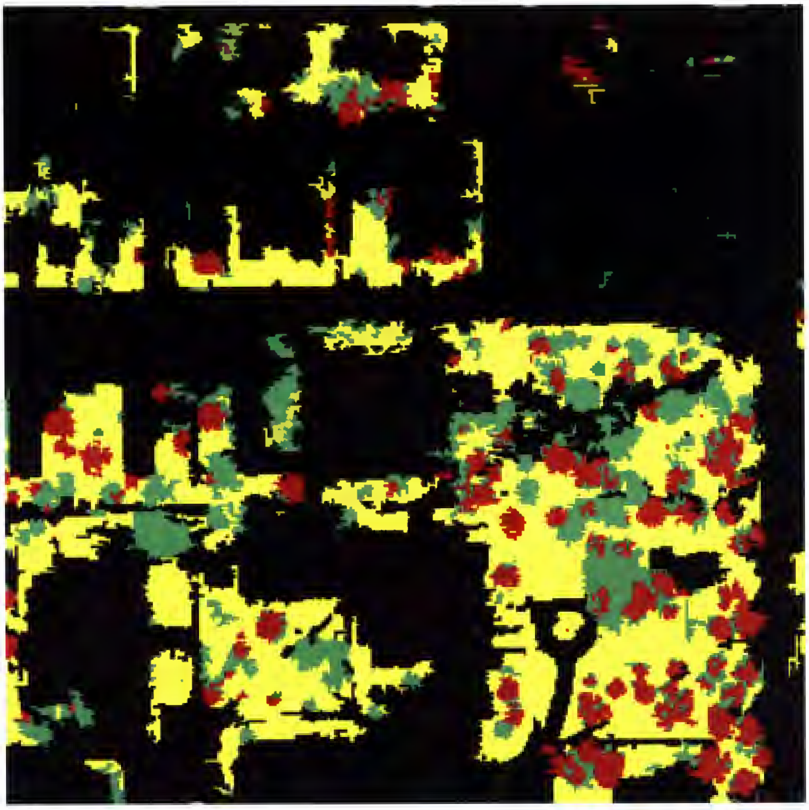

Figure 15. A preliminary QuickBird classification. Yellow portions of the map are grass; red are deciduous species; and green are coniferous.

Regardless of the difficulties encountered while working with the QuickBird imagery, it was utilized in a number of classifications. As can be seen in Figure 16, few of the objects in the final classifications look like trees, particularly in comparison to subsequent classifications of the other imagery. Many of the trees are actually larger than they should be as most of the segments included the shadows cast by the trees as well as the trees themselves. Additionally, sections of individual trees are frequently classified as two separate classes (e.g. the peak of the crown is classified as maple and the extremities of the crown are classified as oak). The most common classification error appears to be placing deciduous trees in a coniferous class, most frequently spruce as was discussed previously.

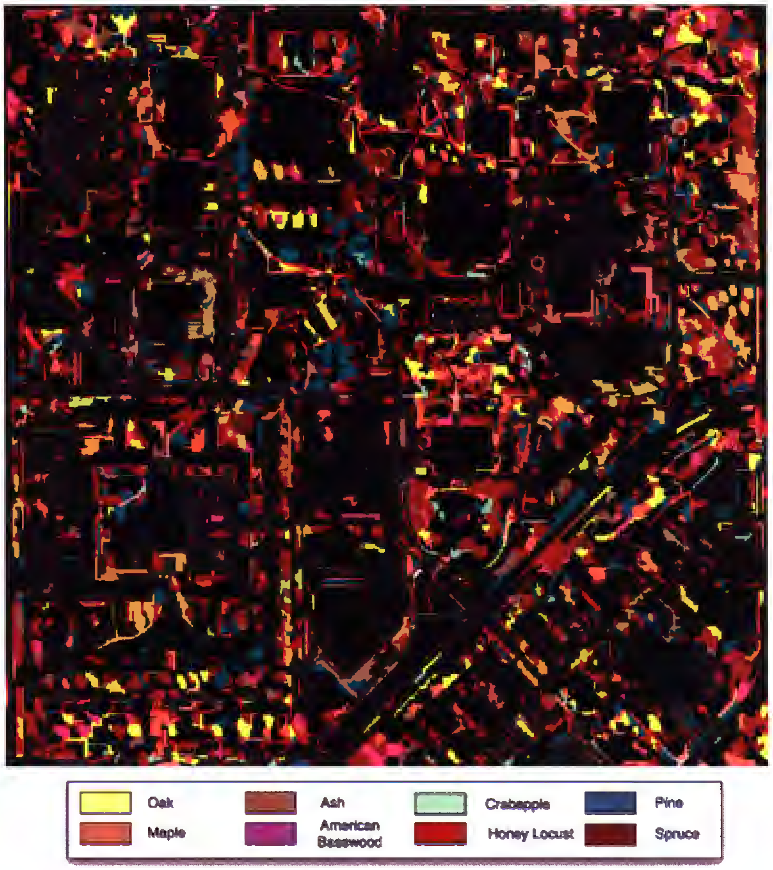

Figure 16. QuickBird-based classification

Table 4 provides accuracy statistics for this classification. Overall accuracy was 0.64 while kappa accuracy was 0.47. Such low accuracy is to be expected as the image was collected when the deciduous species had no leaves, and most of the tree classes are deciduous. The pine class had the highest producer accuracy with 74%. The next closest classes in terms of producer accuracy were spruce with 59% and oak with 52%. The remaining producer accuracies are so low as to not be worth mentioning. The oak and ash classes had the highest user accuracy with 66 and 65% accuracy. Maple, pine and spruce had user accuracies that fell into a range between 59 and 54. High user accuracy means that oak trees are correctly identified as oak trees, for example. However, care must be taken when reviewing these statistics. One can easily have very high user accuracies for the oak class by classifying all of the image as oak. This is why user accuracy should always be accompanied by producer accuracy. Producer accuracy is a measure of misclassification. High producer accuracy for the oak class would mean that very few maple trees were classified as oak trees. Although ash has user accuracy of 65%, its producer accuracy is 26%, which leads one to question the accuracy of the classification. These results really are not surprising. The leaves are the defining characteristic for trees in terms of remote sensing and classification, and the imagery was collected when the leaves were still off the trees.

Table 4.

QuickBird classification accuracy

Class	Producer	User
oak	0.52	0.66
maple	0.36	0.59
Pine	0.74	0.57
Spruce	0.59	0.54
ash	0.26	0.65
honey locust	0.32	0.04
basswood	0.05	0.24
crabapple	0.00	0.01
Overall	0.64	
Kappa	0.47	

July 2004 Hyperspectral

The next step was to determine what sorts of benefits accompany an increase in spectral resolution. The imagery collected July 2004 contains 24 spectral bands and should contain more information, which should improve classification accuracy. One of the primary issues with classification of this image was that the relatively low spatial resolution made it difficult to segment the images accurately. It was very difficult to separate trees from their shadows and even more difficult to separate trees from neighboring trees. For an individual tree classification study, 2-meter spatial resolution does not provide sufficiently high definition to allow separation of groups of trees or trees from their shadows. Although most trees have crowns much larger than each pixel of a 2m image, the image suffers from too much pixel averaging. In this case, borders of trees gradually blend into the background or into neighboring trees. This results in segments that may include both tree crown and shadows and therefore the samples do not truly reflect the classes. The final classification (Figure 17) appears to be very pixilated. It is difficult to even identify portions of the study area. While the previous two classifications give the impression distinct objects on the ground, this image lacks much definition. It appears that at least one of the oak trees was not classified as a tree at all. In many cases, the issue of shadows being classified as conifers appears again. Many of the ash trees are not classified correctly and many of the oak trees were classified as ash trees again.

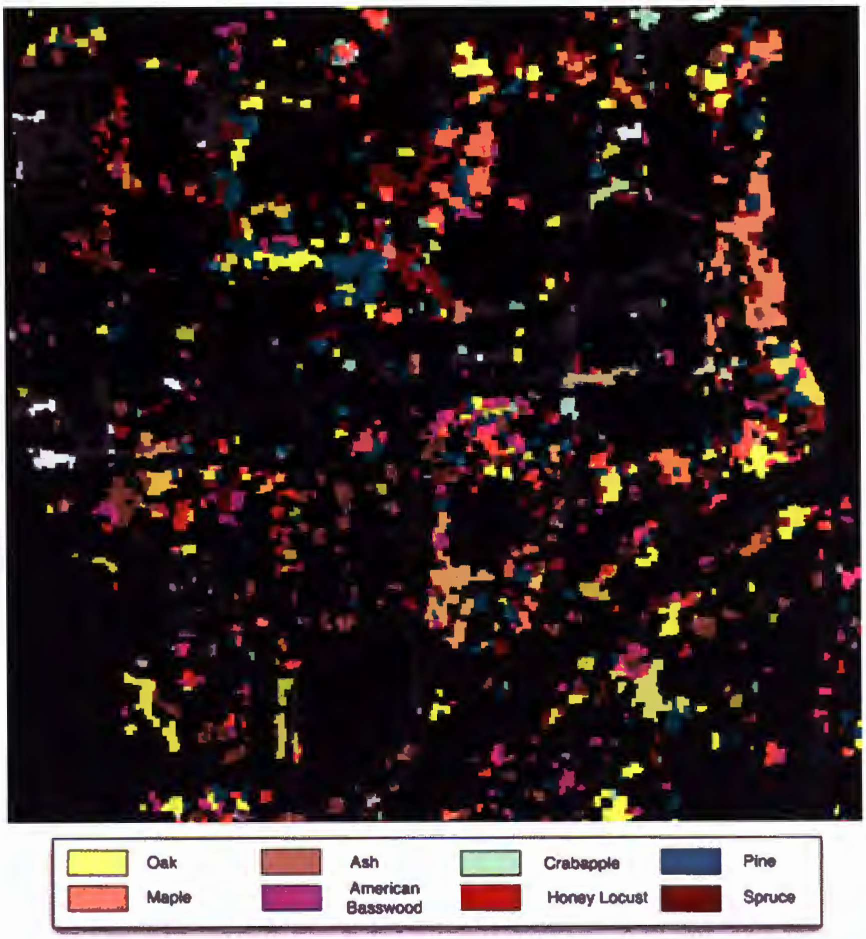

Figure 17. July 2004 hyperspectral classification

The accuracy assessment results are presented in Table 5. Overall accuracy was 0.71 and kappa accuracy was 0.54. There are few noteworthy individual class accuracies here. The highlight is the pine class with a producer accuracy of 69% and a user accuracy of 82%. The honey locust class provides a producer accuracy of 8% while user accuracy is 100%. This calls into question the usefulness of this classification. It is important to note again that the honey locust and crabapple classes which consist of the smallest trees in the study are also the trees with the worst accuracy of any class. The fact that both classes have 100% user accuracy implies that these honey locust and crabapple are being over-classified, which is to say that many trees which should not be crabapple are being classified as such. This classification is not useful.

Table 5.

July 2004 Hyperspectral classification accuracy

	2004 Hyperspectral	
Class	Producer	User
oak	0.40	0.63
maple	0.47	0.82
Pine	0.69	0.82
Spruce	0.54	0.57
ash	0.51	0.82
honey locust	0.08	1.00
basswood	0.51	0.74
crabapple	0.35	1.00
Overall	0.71	
Kappa	0.54	

October 2006 Hyperspectral

The October 2006 image provides 1m spatial resolution. This image provides a number of benefits over the other images. First, it has 63 bands of data. This creates a much more detailed spectral signature than does the 24-band hyperspectral or the four-band QuickBird image. Second, the October collection date highlights some of the differences between species as the leaves change. Additionally, its spatial resolution rivals that of the QuickBird image. Although the segmentation process and subsequent classification provide much better results than the 2004 hyperspectral image, the classification is still questionable (Figure 18). Oak trees that should appear as individual trees frequently appear as one group when there is actually grass between them. Once again, there are problems with areas of shadows being classified as spruce or pine. There are also problems with portions of trees being classified as the incorrect class, such as oaks classified as maples, spruce or pine. In this case, parts of one tree crown will be maple and other parts will be oak. Most of the segments for the trees unfortunately contain the crown and some of the shadow associated with the tree. None of these classes have any particular high accuracy although there is definitely an improvement over the 2m, 24-band hyperspectral MNF classification with an increase in overall accuracy of 0.10. It should also be noted that while MNF reduces the dimensionality of hyperspectral data, it does not lend itself to the segmentation process. It is very difficult to produce segments that accurately represent ground features. The first bands of an MNF image contain the majority of the data while latter bands contain mostly noise. These last bands were not used at all in the classification process. Several segmentations were performed using just the first several bands, which appeared to have the best definition. This did not improve the segmentation.

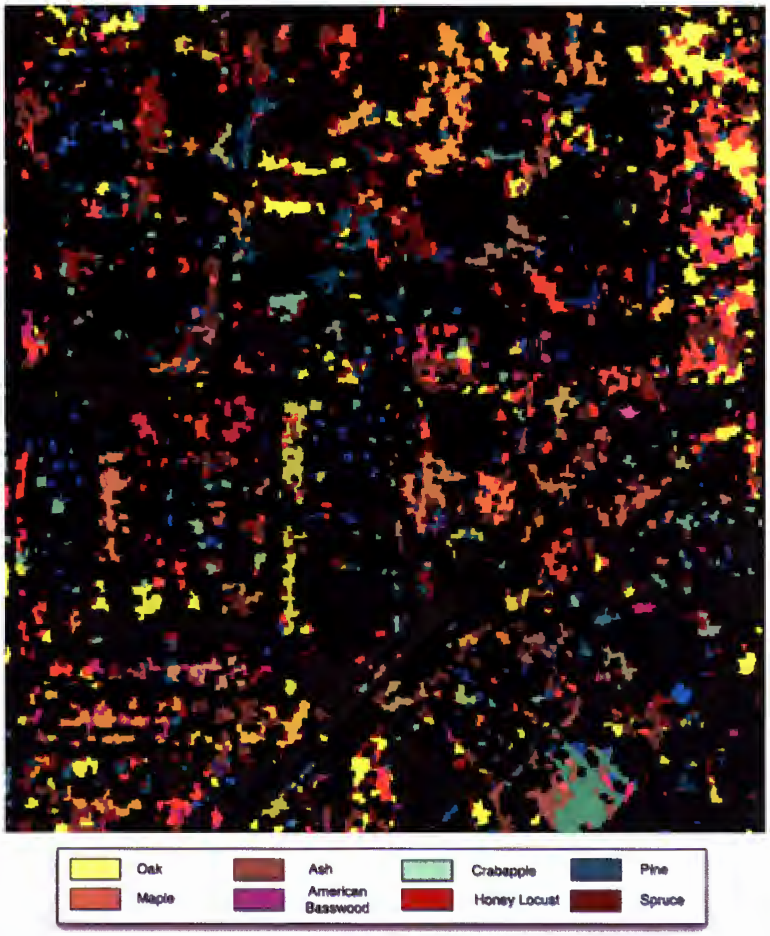

Figure 18. October 2006 hyperspectral classification

Overall accuracy was 0.81 while kappa accuracy was 0.71 (Table 6). This classification produced moderate accuracy for nearly all of the classes. The oak class had the best results with producer accuracy of 82% and user accuracy of 84%. Maple had the second highest accuracy with 70% producer accuracy and 79% user accuracy. The remaining classes share similarly low accuracy. From a mapping standpoint, only the oak class could be considered worth using.

Table 6.

October 2006 hyperspectral classification accuracy

	2006 Hyperspectral	
Class	Producer	User
oak	0.82	0.84
maple	0.70	0.79
Pine	0.66	0.86
Spruce	0.53	0.66
ash	0.57	0.81
honey locust	0.52	0.82
basswood	0.58	0.91
crabapple	0.52	0.75
Overall	0.81	
Kappa	0.71	

QuickBird with LiDAR

Although the results were poor for the QuickBird imagery, a classification was performed using this imagery with LiDAR. Expectations for this classification were not particularly high based on previous work with the data. However, it was easy to perform the classifications again. The only changes to the classification were to incorporate the elevation data. The difference between the QuickBird image with LiDAR and without LiDAR is not as significant as with other data. The LiDAR does appear to have aided in separating out vegetation and impervious objects. In Figure 19, the sidewalks were included in the vegetation class. Here it is evident that the buildings, sidewalks and other impervious surfaces have been excluded from the vegetation. However, in comparing this to the reference shapefile, it is easy to see where the classification comes up short. There are several instances in which oak trees are classified as both ash and basswood trees. In general, the number of honey locust trees is much too high.

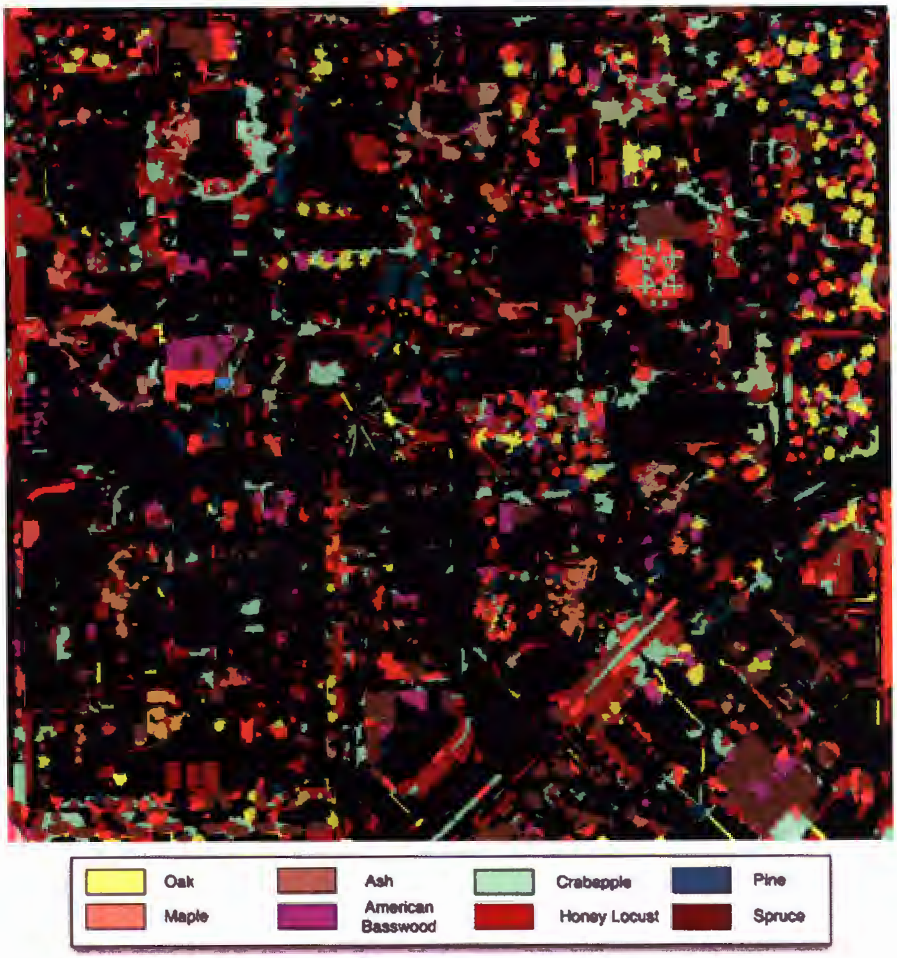

Figure 19. QuickBird and LiDAR classification

Table 7 shows the accuracy statistics for the QuickBird and LiDAR classification. Overall accuracy increased dramatically to 0.88 while kappa accuracy was 0.82 with the inclusion of LiDAR elevation and intensity data. All classes, with the exception of the honey locust class, have acceptably high accuracy. The larger trees, such as oak, maple, pine, spruce and ash, have high accuracy. Smaller trees such as honey locust, basswood and crabapple have lower accuracy. The increase in overall accuracy was surprising. Clearly the spectral information provided by the LiDAR intensity layer is contributing to the increase in accuracy. Additionally, spectral information from the bark of the trees could be providing additional information. Although the overall accuracy is definitely lower than any subsequent LiDAR-added classifications, it is fairly high. Regardless, it bodes well for future classifications with higher degrees of spectral resolution and leaf-on data.

Table 7.

QuickBird and LiDAR classification accuracy

	2003 QuickBird	
Class	Producer	User
oak	0.92	0.96
maple	0.93	0.87
Pine	0.93	0.90
Spruce	0.88	0.89
ash	0.90	0.97
honey locust	0.71	0.14
basswood	0.87	0.95
crabapple	0.87	0.70
Overall	0.88	
Kappa	0.82	

July 2004 Hyperspectral and LiDAR

Many of the issues encountered with the July 2004 hyperspectral image were resolved with the inclusion of LiDAR into the classification process. LiDAR was used to segment objects and it was also used as a membership function to increase overall accuracy. The final image (Figure 20) provides remarkable contrast in comparison to the same image without LiDAR. Here trees are sharply defined and it is much easier to identify objects. It is also much more difficult to spot obvious errors in the classification. There are some smaller errors in classification between the honey locust and crabapple classes. In addition, there are a few small errors with regard to the classification of oak trees. In the crowns of several of the oaks, there are portions which have been classified as either spruce or pine.

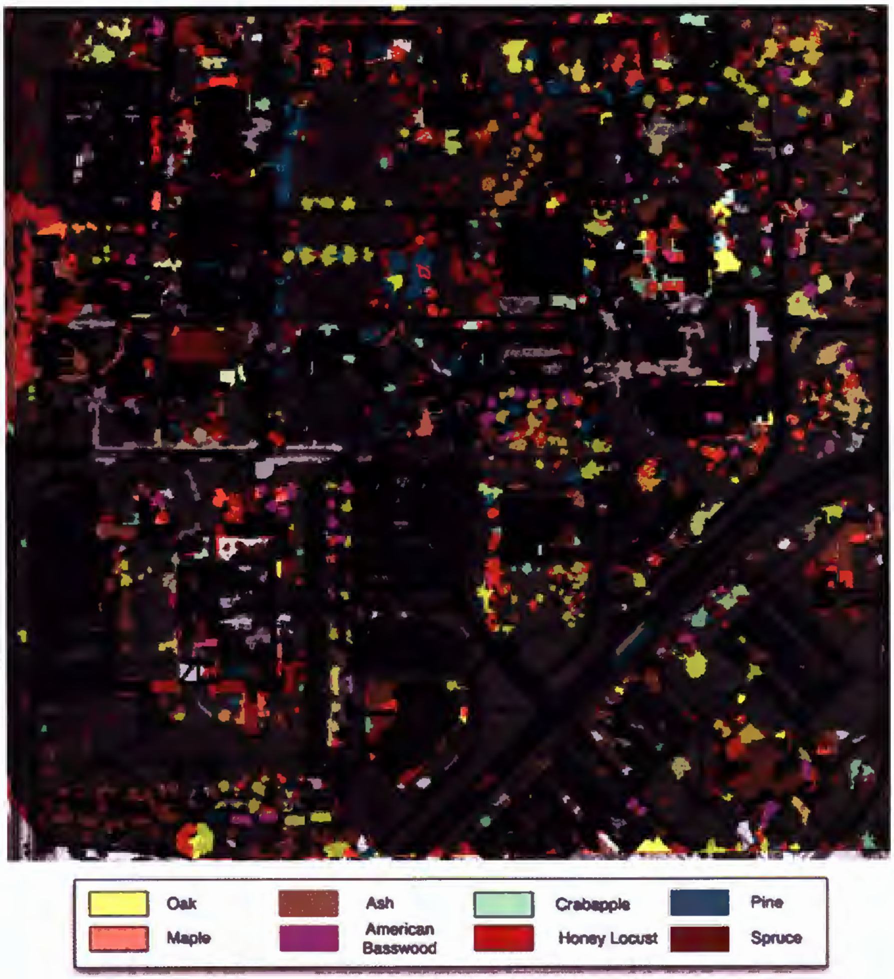

Figure 20. July 2004 hyperspectral and LiDAR classification

Table 8 provides the accuracy statistics for this classification. Overall accuracy improved to 0.92 and kappa accuracy improved to 0.88. This is once again a very significant increase in overall accuracy. Although the honey locust class in this classification appears to be problematic, all of the other classes have high accuracy. Classes that can be mapped with very high accuracy are oak, maple, basswood and pine. Each of these classes has user and producer accuracies that are above 90%. Trees that may be identified with good accuracy are spruce, ash and crabapple. These classes had accuracies ranging between 70 and 80%. The honey locust class was the only class with poor accuracy, having producer accuracy of 46% and a user accuracy of 60%. Overall, this classification lends much credence to the concept that LiDAR can increase overall accuracy.

Table 8.

July 2004 hyperspectral and LiDAR classification accuracy

	2004 Hyperspectral	
Class	Producer	User
oak	0.96	0.92
maple	0.96	0.94
Pine	0.95	0.96
Spruce	0.83	0.93
ash	0.93	0.74
honey locust	0.46	0.60
basswood	0.90	0.99
crabapple	0.77	0.82
Overall	0.92	
Kappa	0.88	

October 2006 Hyperspectral with LiDAR

The final classification was the combination of the LiDAR and the October 2006 hyperspectral data. The same classification hierarchy and classification rules were used for this data as was used for all of the previous classifications. Overall, this appears to be the most realistic classification of all (Figure 21). As with the other LiDAR-based classifications, each tree is well-defined. With this image, it is more difficult to find a misclassified tree. This classification appears to have sufficient resolution to allow clusters of trees to be identified correctly. For example, areas where pine trees and maple trees are intermingled are correctly classified. Further, the recurring problem where portions of tree crowns being incorrectly classified appears to be significantly reduced. The same oak trees that previously had been classified as oak and pine and maple in other classifications are now correctly oak.

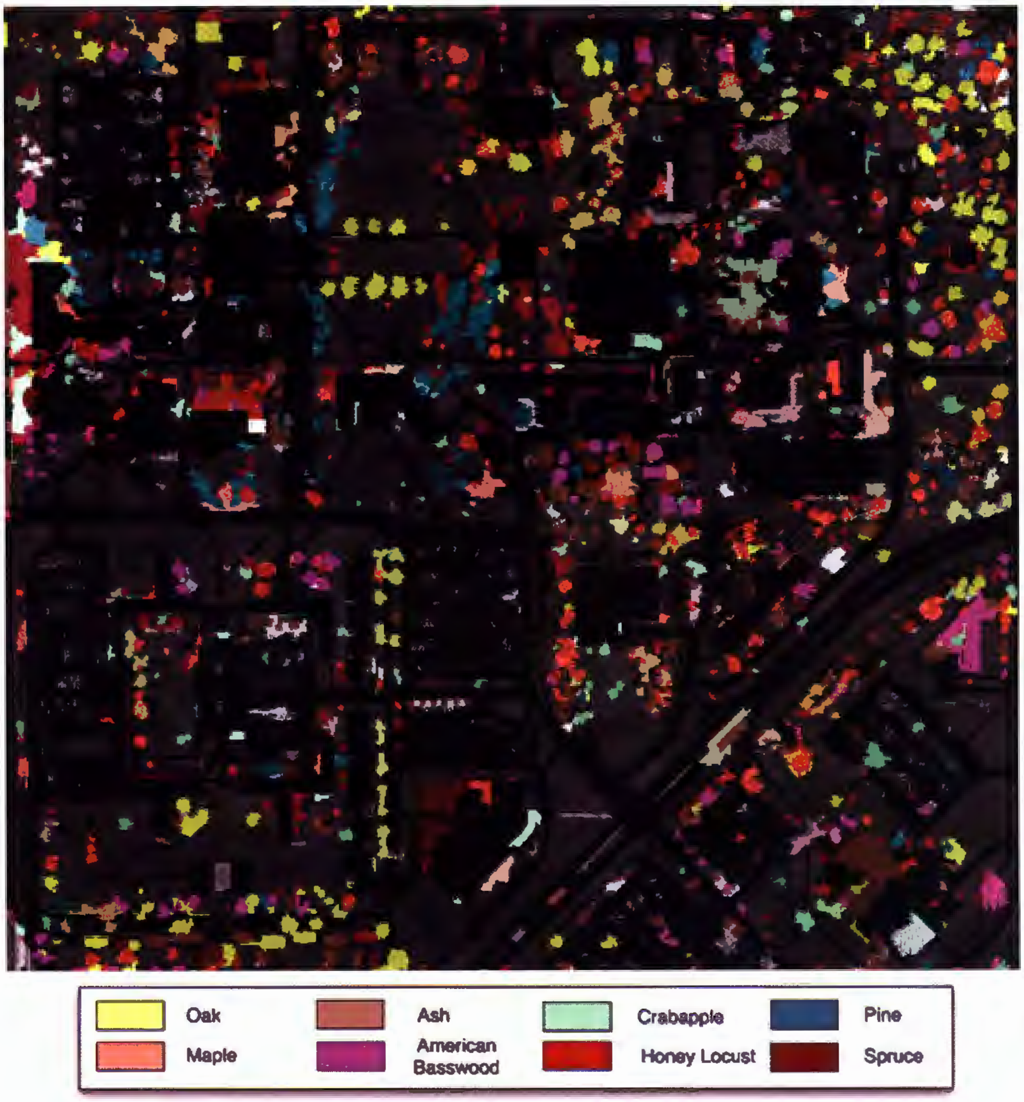

Figure 21. 2006 hyperspectral and LiDAR classification

As one might expect, this provided the best accuracy of all (Table 9). Overall accuracy is 0.93 and kappa accuracy is 0.90. Individual class accuracies are all quite high. Oak, maple, ash, honey locust and basswood all have very high accuracy with user and producer accuracies in the 90s and upper 80s. Pine, spruce and crabapple still have good accuracy with producer and user accuracy in the 60 to 80 range. The crabapple class continues to be troubling with producer accuracy of 87% and user accuracy of 66%.

Table 9.

2006 hyperspectral and LiDAR classification accuracy

	2006 Hyperspectral	
Class	Producer	User
oak	0.96	0.89
maple	0.98	0.98
Pine	0.94	0.83
Spruce	0.87	0.72
ash	0.95	0.96
honey locust	0.94	0.97
basswood	0.95	1.00
crabapple	0.87	0.66
Overall	0.93	
Kappa	0.90	

2004 and 2006 Hyperspectral with LiDAR

In theory, the combination of the two images should provide the most information and therefore produce the most accurate classification. Using the same rules as the previous classifications, both images were combined and evaluated. The resulting image (Figure 22) actually bears more resemblance to the 2004 hyperspectral than to the 2006 hyperspectral. It appears as though there are several instances in which the crowns of trees are classified as more than one species. For example, part of an oak tree is classified as a honey locust. This is fairly common in this image. Again the LiDAR has created shapes that are fairly reminiscent of trees, and many of the trees appear to be classified correctly. It appears that the smaller classes such as crabapple and honey locust are not classified correctly. In some instances, trees that should be in those classes are not classified at all or are assigned to the wrong class.

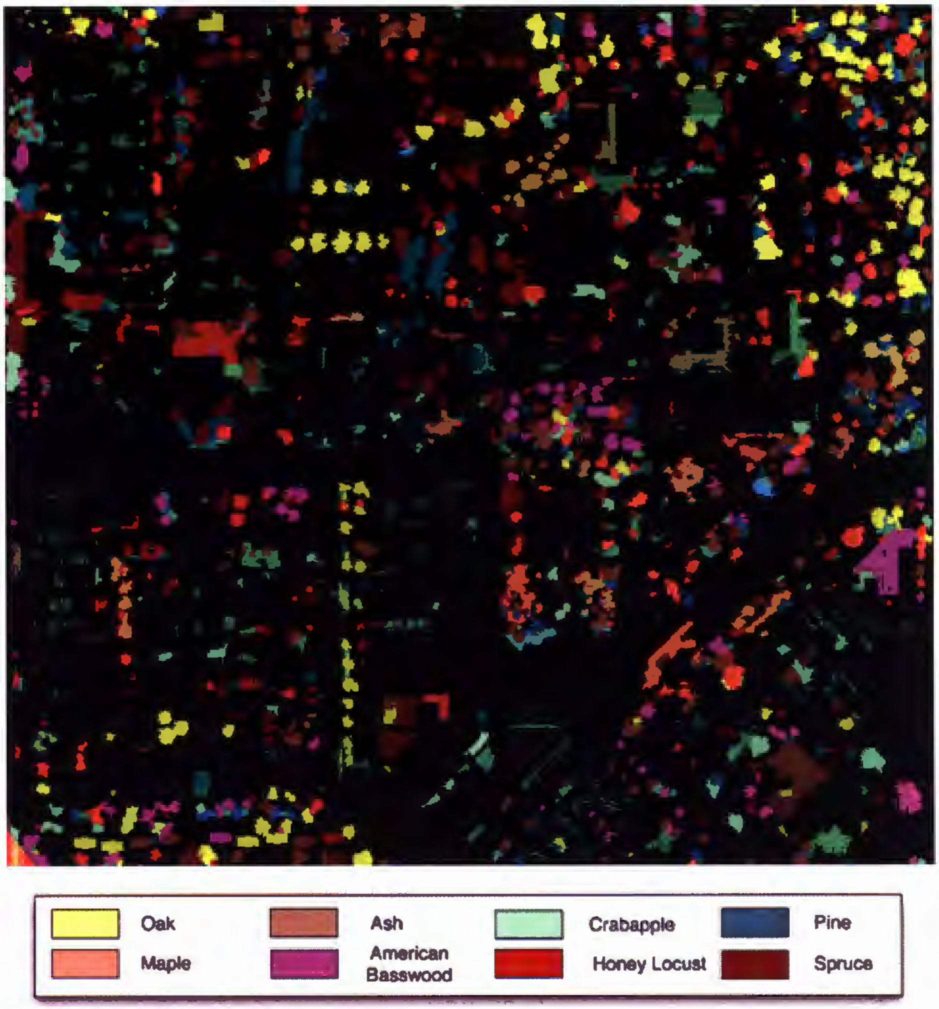

Figure 22. The 2004 and 2006 hyperspectral and LiDAR classification

Overall accuracy is nearly the same as the 2004 hyperspectral and LiDAR-based classification (Table 10). Overall accuracy is 92% and kappa accuracy is 88%. These figures are the same as the 2004 hyperspectral overall and kappa accuracy results. Class accuracies are also similar to the 2004 hyperspectral classification. The oak, maple, pine and ash classes have very high producer and user accuracies with all accuracies above 90%. Spruce has high producer accuracy, however, user accuracy falls to 74%. The basswood class has good accuracy with 85% producer accuracy and 98% user accuracy. The honey locust and crabapple classes have producer accuracies in the mid-40% range while user accuracy is very high.

Table 10.

2004 and 2006 combined accuracy

	Combined hyperspectral	
Class	Producer	User
oak	0.96	0.92
maple	0.94	0.98
Pine	0.91	1.00
Spruce	0.93	0.74
ash	0.91	0.97
honey locust	0.46	0.97
basswood	0.85	0.98
crab apple	0.47	0.98
Overall Accuracy	0.92	
KIA	0.89	

These figures are similar to the 2004 hyperspectral-LiDAR classification, however more over-classification is occurring with the combined imagery. Combining the two hyperspectral images in a single classification did not result in any significant changes in overall accuracy and changes in individual class accuracies were varied.

Comparison

Table 11 lists the differences in accuracy between classifications performed with LiDAR and classifications performed without LiDAR. Overall, the LiDAR resulted in an improvement of 24% for QuickBird, 21% with the July 2004 hyperspectral and 12% with the October 2006 hyperspectral image.

Table 11.

Differences in accuracy between LiDAR and non-LiDAR classifications

	2006 Hyperspectral		2004 Hyperspectral		2003 QuickBird	
	Producer	User	Producer	User	Producer	User
oak	0.14	0.05	0.56	0.29	0.40	0.30
maple	0.28	0.19	0.49	0.12	0.56	0.28
Pine	0.28	-0.02	0.25	0.13	0.19	0.32
Spruce	0.34	0.06	0.30	0.36	0.29	0.35
ash	0.39	0.16	0.42	-0.08	0.64	0.31
honey locust	0.42	0.15	0.38	-0.40	0.39	0.10
basswood	0.37	0.09	0.39	0.24	0.82	0.71
crabapple	0.34	-0.09	0.42	-0.17	0.87	0.69
Overall	0.12		0.21		0.24	
Kappa	0.19		0.34		0.36	

Improvements in individual class accuracies are more dramatic. The largest class accuracy improvements occur with the QuickBird image.

This stands to reason as most of the classes are deciduous and the LiDAR adds some leaf reflectance data. The highest improvement in producer accuracy comes with the crabapple class with 87% and the basswood class with 82%. User accuracies did not provide such large increases. The basswood and crabapple classes had improvements of 71 and 69% respectively. In this image, the smallest improvements occur with the coniferous pine and spruce classes. The pine and spruce classes do not change nearly so significantly with the seasons as do the deciduous classes. With the July 2004 hyperspectral image, individual class accuracies with LiDAR also show significant improvements over the classification with imagery alone. The oak and maple classes had the greatest producer accuracy improvement with an increase of 56% and 49%. Other class producer accuracies increased by 25 to 42%. User accuracy increases were comparatively small. The exceptions to this were the honey locust class which actually had a 40 percentage point decrease in user accuracy with the addition of LiDAR. Spruce had an increase in user accuracy of 36 percentage points. Other classes typically had increases in user accuracy in the teens.

The 2006 hyperspectral saw smaller increases with the addition of LiDAR. The largest increase in producer accuracy was the honey locusts which improved 42 percentage points. This class saw similar improvements for each classification. Oak had the smallest increase with a 14 percentage point increase in producer accuracy. User accuracy increases were less significant and were mostly in the single digits and teens.

CHAPTER 5

CONCLUSION

Overall, this research answers the questions set forth in the introduction. These questions were: what accuracy can hyperspectral imagery in combination with object-oriented classification provide when classifying trees at the species level? What benefits are gained, in terms of classification accuracy, by incorporating multiple images collected at different times of the year? What contributions to overall accuracy can elevation data, such as LiDAR, provide? And finally, can individual tree species be accurately mapped using remotely sensed imagery?

Hyperspectral imagery and object-oriented classification make it possible to classify individual tree species in an urban setting. The majority of the tree species were classified with an accuracy of greater 80% which is a standard for forest managers (Lennartz & Congalton, 2004). The 2006 hyperspectral classification achieved this in all but the spruce and crabapple classes.

There were not any noticeable improvements in overall accuracy by incorporating multiple collection dates into the classification. The overall accuracy of the classification with the combined hyperspectral images was roughly equivalent to the classification with the hyperspectral image with the lowest spectral and spatial resolution.

LiDAR proved to be the source of a significant increase in overall classification accuracy. The addition of LiDAR to a classification led to an increase in overall accuracy of at least 12 percentage points. It proved to be significant particularly in classes with smaller objects such as crabapple trees. This led to increases of class accuracies of 30 percentage points or greater.

Individual tree species can be mapped using remote sensing data. Oak, maple, pine, ash, honey locust and basswood can be mapped with greater than 90% accuracy in this study. The spruce and crabapple classes had accuracies that fell below the 80% mark.

The overall accuracy is dependent on several factors: spatial and spectral resolution, seasonal variations and additional information, in this case, elevation.

The QuickBird image, which had the lowest overall accuracy, suffers mostly from lack of spectral resolution. With only four bands, it was not possible to separate coniferous species from areas of shadow near deciduous species. Additionally, its early spring collection date made it nearly impossible to classify individual deciduous species.

The 2004 hyperspectral without LiDAR classification results were in the middle of the pack in terms of overall accuracy. It has moderately high spectral resolution with 24 bands, but not the 63 bands provided by the 2006 image. It matches the individual class accuracy of the 2006 hyperspectral classification in some classes. However, it appears that it suffers from a lack of spatial resolution. This is made evident in poor performance when classifying smaller trees. Additionally, during the period in which the image was collected trees are most likely to be suffering heat or moisture stress (Birky, 2001). This can lead to decreased chlorophyll production and lower variability among species. Whether this or the spatial resolution attributed to the overall accuracy is difficult to tell.

The 2006 hyperspectral without LiDAR provided the best overall accuracy, which approached the accuracy standards Lennartz and Congalton (2004) refer to. This image provides high spectral resolution and high spatial resolution and was collected in a time when chlorophyll production should be high. However, class accuracies are very low, with the exception of the oak class. This may be partially attributed to the difficulty that was had in segmenting the image properly. Shadows can play a significant role in segmenting an image.

The accuracy of the classification is dependent on several factors: spatial and spectral resolution, seasonal variations and additional information, in this case, elevation. LiDAR proved to be a significant factor in classification accuracy. The two contributions made by LiDAR are providing elevation data that can be used as a classification mask and providing high-resolution, shadow-free imagery for the segmentation process. While all other factors remained equal, overall accuracy of the October 2006 image went from 0.81 to 0.93. Kappa accuracy improved from 0.71 to 0.90. Other images saw an increase in overall accuracy of 0.21 for the July 2004 hyperspectral image and 0.24 for the QuickBird image. From an inspection of the individual class accuracies, it appears that LiDAR reduces over-classification. Producer accuracies generally improved much more than did user accuracies.

The fact that a shadow-less image was utilized to create the segments was perhaps most important of all. This allowed for the creation of segments that allowed pure samples to be identified for each class. In all of the non-LiDAR classifications, the segments for most of the samples contained both the tree crown as well as a portion of the tree's shadow, whether it fell on the ground or on a nearby tree.

Elevation data also helped improve accuracy. One of the greatest problems in this project was the misclassification of shadows on grass as either a spruce or pine. Adding an elevation component to the classification criteria for all classes helped eliminate this confusion. Although it does not relate to the outcome of this study, an excellent example is the classification of building rooftops and parking lots. These two surfaces are composed of tar and small rocks, and they are frequently confused as can be seen in Figure 3, for example. By incorporating an elevation component to the classification, the confusion can be eliminated. How well this works depends largely on the quality of the bald earth layer. In this classification, several areas that should have had an elevation of 0 did not. In these cases, the rules fail and classification errors occur.

Spectral resolution also played a key in the overall accuracy. The QuickBird image with its four bands has the lowest overall classification accuracy (0.64). The 2004 hyperspectral image has 24 bands and it provided overall accuracy of 0.71. The 2006 hyperspectral image with its 63 bands showed further improvement with an overall accuracy of 0.81. Each of these images provides spectral information from 400nm to 900nm, but this information is provided in increasingly high levels of resolution.

The spatial resolution appears also to have improved classification accuracy. Although overall accuracy is quite high in both of the LiDAR-aided hyperspectral classifications, accuracy of smaller trees such as honey locust and crabapple increased by 0.4 and 0.1 respectively. With smaller trees, pixels representing the trees are more likely to be a combination of shadow and tree with a 2-meter image than with a 1m image.

These results appear to compare favorably to those found by other researchers. Huguenin et al. (1997) were able to classify two classes - cypress and tupelo trees – with 89% and 91% accuracy respectively.

Meyer et al. (1997) classified pine, spruce, fir and beech trees with 80% overall accuracy. Key et al. (2001) achieved overall accuracy of 76% when they identified four trees in West Virginia. In classifying a wetland area near a river in Germany, Ehlers et al. (2003) achieved 95% accuracy in their vegetation classes. Collins et al. (2004) were able to identify four tree species with 72% accuracy using LiDAR and multispectral data. Holmgren and Persson (2004) used LiDAR to identify pine and spruce trees with 95% accuracy. Greiwe and Ehlers (2004) were able to classify landcover in a German city with 73% accuracy. Lennartz and Congalton (2004) used QuickBird multispectral data to achieve 17% accuracy. This accuracy was improved to 31% when object-oriented classification was applied. Carleer and Wolff (2004) used IKONOS data to classify seven tree classes with 86% accuracy. Hajek (2005) attained 90% accuracy with coniferous classes, while deciduous classes had 70% accuracy.

While it is difficult to compare accuracy assessment results among studies due to the broad number of variables affecting the outcome, the results of this study are as good, or better, than those obtained by studies in the literature review. This methodology is promising and perhaps further development could improve overall accuracy, and in particular, the accuracy of some of the smaller classes.

Limitations

Although, the LiDAR did improve classification accuracy as was indicated in the Chapter 4, it also created some problems. As was discussed in the Methodology section, rules were established that each segment was required to meet before it could be included in each class. For the deciduous and coniferous classes, the elevation of the segment had to be greater than 2.5 meters, otherwise it would not be included in the class. In certain instances, trees were small enough that they did not have an elevation high enough to qualify according to the elevation file. There are three possible causes for this: the laser missing the tree entirely, the laser striking more of the ground than the tree, or as many of the trees affected were coniferous, the laser hitting the tree at an area other than its apex. The last two are more likely as it is a high density LiDAR data set. Regardless, this resulted in the tree being forced into a category in which it did not belong because it failed to meet the elevation rule.

Georectification can also be problematic. In the case of the July 2004 image, it is very difficult to find a definite, crisp point to use as a reference point. This means that it is quite possible that the LiDAR layer and the July 2004 image do not line up as precisely as they could have. This, of course, would reduce the overall accuracy of the classification because segments based on the LiDAR needed to line up exactly with the imagery of the trees. These segments had great influence on the quality of the samples as well as the samples used for accuracy assessment.

Finally, the LiDAR was collected in the spring before the trees had fully leafed-out. Some of the deciduous trees do not have returns that were as strong as the coniferous trees. The evergreens have clearly defined shape, while the deciduous trees have spikes from areas where the LiDAR passed directly through the trees. This could have affected the shapes of the segments and these shapes (or texture) could have been used to refine the classification.

Future Directions

With the wide variety of data available, there are several possibilities for continued research. Most projects using hyperspectral data utilize some sort of band reduction to eliminate unnecessary data that may confuse classification schemes as well as to speed up classification times. One of the methods of band reduction is called Classification And Regression Tree. Based on samples of desired classes, CART statistically selects the bands that need to be kept for classification and creates a regression tree for classification. A future direction is to combine CART with eCognition™ and its object oriented classification scheme to perhaps increase classification accuracy.

Additionally, the current classification utilizes on the first and last returns of the LiDAR. Holmgren and Persson (2004) noted that pine trees had a more conical shape than other conifers. Using all the returns, a three-dimensional shape can be developed. It may be possible to identify tree species by their shape alone, or at least the shape can be used to increase classification accuracy.

As part of the LiDAR analysis in LiDAR analyst, a shapefile is created that contains the estimated location of each tree as well as estimates of tree crown diameter, trunk diameter and other dimensions. This data should be incorporated in classification as well.

Finally, statistical analysis on the spectrometer data may yield some interesting results.

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