A COMPARISON OF AUTOMATED LAND COVER/USE CLASSIFICATION METHODS FOR A TEXAS BOTTOMLAND HARDWOOD SYSTEM USING LIDAR, SPOT-5, AND ANCILLARY DATA

A Thesis

by

ZACHARY ISAAC VERNON

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2008

Major Subject: Forestry

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Approved by:

Chair of Committee,	Raghavan Srinivasan
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ABSTRACT

A Comparison of Automated Land Cover/Use Classification Methods for a Texas Bottomland Hardwood System Using LiDAR, SPOT-5, and Ancillary Data. (May 2008)

Zachary Isaac Vernon, B.S., Texas A&M University

Chair of Advisory Committee: Dr. Raghavan Srinivasan

Bottomland hardwood forests are highly productive ecosystems which perform many important ecological services. Unfortunately, many bottomland hardwood forests have been degraded or lost. Accurate land cover mapping is crucial for management decisions affecting these disappearing systems. SPOT-5 imagery from 2005 was combined with Light Detection and Ranging (LiDAR) data from 2006 and several ancillary datasets to map a portion of the bottomland hardwood system found in the Sulphur River Basin of Northeast Texas. Pixel-based classification techniques, rule-based classification techniques, and object-based classification techniques were used to distinguish nine land cover types in the area. The rule-based classification (84.41% overall accuracy) outperformed the other classification methods because it more effectively incorporated the LiDAR and ancillary datasets when needed. This output was compared to previous classifications from 1974, 1984, 1991, and 1997 to determine abundance trends in the area's bottomland hardwood forests. The classifications from 1974-1991 were conducted using identical class definitions and input imagery (Landsat MSS 60m), and the direct comparison demonstrates an overall declining trend in bottomland hardwood abundance. The trend levels off in 1997 when medium resolution

imagery was first utilized (Landsat TM 30m) and the 2005 classification also shows an increase in bottomland hardwood from 1997 to 2005, when SPOT-5 10m imagery was used. However, when the classifications are re-sampled to the same resolution (60m), the percent area of bottomland hardwood consistently decreases from 1974-2005. Additional investigation of object-oriented classification proved useful. A major shortcoming of object-based classification is limited justification regarding the selection of segmentation parameters. Often, segmentation parameters are arbitrarily defined using general guidelines or are determined through a large number of parameter combinations. This research justifies the selection of segmentation parameters through a process that utilizes landscape metrics and statistical techniques to determine ideal segmentation parameters. The classification resulting from these parameters outperforms the classification resulting from arbitrary parameters by approximately three to six percent in terms of overall accuracy, demonstrating that landscape metrics can be successfully linked to segmentation parameters in order to create image objects that more closely resemble real-world objects and result in a more accurate final classification.

DEDICATION

To my wife, Tiffany, who completes me and makes me a better man in every facet of my life.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Srinivasan, and my committee members, Dr. Popescu and Dr Lui, for their guidance and support throughout both the course of this research and my academic career. I consider myself extremely lucky to have begun working at the Spatial Sciences Lab when I was a sophomore, and I credit Dr. Srinivasan and Jennifer Jacobs for all their advice, teaching, and patience over the last four years. I have also benefited greatly from the help of Dr. Popescu, Dr. Feagin, Dr. Erickson, Dr. Balaji, Lesli Gomez, and my fellow graduate students and coworkers. I would like to thank them all for the help they have given me during my time at the Spatial Sciences Lab.

Thanks to the Tarrant Regional Water District and the Texas Forest Service for providing data throughout the course of the project. Thanks to Mrs. Kim Hart, Mr. Sivarajah Mylevaganam, and Dr. Erickson for their help in developing some of the datasets. Thanks also to Mr. Martin Gibson, Mr. Mike Trevino, and Ms. Allison Esparza for their assistance collecting in situ samples in the Sulphur River Basin and for making the long stay in Mount Pleasant as enjoyable as possible.

Finally, thanks to my wife for her all her support throughout my graduate career and for all that she means to my life. Thanks to my family, especially my parents, for encouraging me in all my pursuits. Thanks also to my friends for all the good times and support.

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CHAPTER I

INTRODUCTION

This research has been part of a project conducted by the Spatial Sciences Lab for the U.S. Army Corps of Engineers, Freese and Nichols, Inc., and the Sulphur River Basin Authority. The portion of the project that the Spatial Sciences Lab has completed is the land cover/use classification for the potential location of a future reservoir project slated to flood several tens of thousand of hectares in rural Northeast Texas. By delineating the location and extent of the bottomland hardwood forests and emergent herbaceous wetlands, I am aiding those charged with reservoir construction by making it easier to predict the level of mitigation which will be necessary if and when the reservoir is constructed. The Spatial Sciences Lab was contracted to complete the same task in 2000, and conducted land cover/use classifications using historical Landsat TM and MSS data from 1974, 1982, 1991, and 1997.

My strategy for conducting this research was to investigate a variety of data inputs and classification methods in order to achieve the most accurate classification possible. The primary data inputs which were available and included are SPOT-5 multi-spectral medium-resolution data, Light Detection and Ranging (LiDAR) elevation data, National Agriculture Inventory Program (NAIP) multi-spectral high-resolution imagery, and a variety of Geographic Information System (GIS) datasets such as Soil Survey Geographic (SSURGO) data and National Hydrography Dataset (NHD) hydrology lines

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This thesis follows the style of Forest Ecology and Management.

and polygons. In conducting the research, I was able to gain valuable insight into the best classification techniques and inputs to employ for this type of system. I was also able to investigate the object-based classification method in depth, and I developed a new methodology to derive ideal Segmentation parameters using landscape metrics and statistical techniques. The end product, provided to the entities that contracted the lab to conduct the classification, is a highly accurate land cover/use map of the portion of the Sulphur River Basin delineated as the potential reservoir location. As such, insight was also gained into the structure and function of the bottomland hardwood forests in the area, especially when the percent cover was compared to that of previous classifications.

Per my thesis proposal, the primary objective of this study was to "develop a robust classification method for bottomland hardwood systems by examining the utility of pixel-based, rule-based, and object-based classification of a combination of LIDAR data, multi-spectral imagery, and various GIS datasets. Accurately distinguishing between upland and bottomland hardwood forests is of prime importance." The specific objectives listed were as follows:

"1. Compare the implementation, advantages, and disadvantages of pixel-based classification, rule-based classification, and object-based classification of LIDAR data, multi-spectral imagery, and various GIS datasets as related to the accuracy as ease of implementation for land use/land cover classification of bottomland hardwood systems.

2. Quantitatively evaluate the effect of various classification inputs, such as LIDAR and ancillary data, on each classification method, in order to determine the most crucial image classification inputs for distinguishing bottomland hardwood forests.
3. Use the most accurate classification result to discuss the quality of the bottomland hardwood forests at the Marvin Nichols site, based on the LIDAR derived canopy height and the abundance and patchiness of the cover type.
4. Determine the abundance and patchiness of bottomland hardwood forests from previous classifications of Landsat imagery from 1974, 1982, 1991, and 1997, and compare the results to current conditions in order to gain insight into general trends in forest abundance and health."

The third objective changed somewhat after the research was begun in earnest. Rather than spending a lot of man hours creating a deliverable which was not requested, I focused instead on developing a methodology to optimize segmentation parameters for the object-based classification. This investigation was encouraged by my advisors, as it had the potential to result in an important contribution to the knowledge base of remote sensing science. The investigation into segmentation parameters became a chapter that stands alone. My thesis, therefore, is organized as two separate chapters. The first, titled "Maximizing Classification Accuracy for a Texas Bottomland Hardwood System Using LiDAR, SPOT 5, and Ancillary Data," deals with the first, second, and fourth objectives as stated in my thesis proposal. It is a revised version of the technical report submitted to the entities that contracted the Spatial Sciences Lab to complete the classification, and should be extremely useful to hybrid foresters or remote sensing

scientists conducting image classification of forested wetland areas. Forested wetlands are a difficult system to classify, as there is often confusion between upland and bottomland forests. The inputs and classification techniques that were used and compared are at the forefront of the discipline. This chapter demonstrates the advantages of certain data and techniques, and also discusses the trend in bottomland hardwood forests in the Sulphur River Basin. The second chapter, as previously mentioned, fills a vital gap in knowledge of object-based classification techniques. Specifically, there are few guidelines for determining segmentation parameters. Segmentation is the crucial sub-procedure of object-based classification, as the creation of image objects that represent real-world objects is imperative for a successful classification. I used landscape metrics to analyze previous classifications, in addition to statistical techniques, to derive the ideal homogeneity criterion and scale parameter for use in object-based classification. Both chapters are presented subsequently and the results are summarized in the conclusion.

CHAPTER II

MAXIMIZING CLASSIFICATION ACCURACY FOR A TEXAS BOTTOMLAND HARDWOOD FOREST USING LIDAR, SPOT-5, AND ANCILLARY DATA

Background

At present, the most repeatable and cost-effective method for land cover mapping of large landscapes is via the classification of digital imagery obtained through satellite remote sensing. A myriad of classification approaches have been developed, including pixel-based classification, rule-based classification, and object-based classification. Pixel-based classification represents the most common approach, but several studies have demonstrated the advantages of rule-based and object-based approaches for areas with land cover types that are difficult to separate (Bolstad and Lillesand, 1992; Burnett and Blaschke, 2003; Arroyo et al., 2006; Baker et al., 2006; Daniels, 2006; Yu et al., 2006). Wetlands, specifically forested wetlands, are frequently landscapes with many land cover types that are difficult to separate. Image classification studies of forested wetlands often report confusion between upland forested areas and forested wetland areas (Sivanpillai et al., 2000; Federal Geographic Data Committee, 2007). Due to these classification difficulties, landscapes containing a large portion of forested wetlands are an ideal study area for the evaluation of different image classification approaches.

Forested wetlands are dominated by woody vegetation greater than six meters in height, can occur in palustrine or estuarine systems, and experience permanent, seasonal,

or intermittent flooding (Cowardin et al., 1979). Intermittent and seasonally flooded forested wetlands can also be referred to as bottomland hardwood forests (Cowardin et al., 1979); this nomenclature will be used for the remainder of the paper. The bottomland hardwood forests of Texas are highly productive ecosystems and perform many important ecological services, such as improving water quality, reducing erosion, and preventing floods. The forests afford many recreational opportunities as well. Unfortunately, many bottomland hardwood forests have been degraded or lost due to agricultural development, timber production, urbanization, and reservoir construction (Liu et al., 1997; Sivanpillai et al., 2000). Texas has experienced heavy losses to bottomland hardwood forests; it is estimated that approximately 6.5 million hectares were found in Texas before European settlement, whereas there are less than 2.5 million hectares today (Minahan, 2003).

Additional losses will continue into the future. Due to the increasing water demands of Texas, over 200,000 acres of remaining bottomland hardwoods in Texas are threatened by proposed reservoir construction (Texas Center for Policy Studies, 2000). The topography of these areas makes them highly suitable locations for reservoirs, and, due to the frequent flooding that already occurs, many of these areas are rural enough that the direct impact on human populations will be minimal. The Sulphur River Basin in Northeast Texas contains a significant portion of the remaining bottomland hardwood forests in Texas and is also the slated location for several future reservoir projects. This study classifies the land cover at one potential reservoir site.

A spatially explicit inventory of the existing land cover in the area is useful for several reasons. A reliable map of the land cover in the area will provide greater insight into the structure and function of the landscape. Additionally, if and when a reservoir is constructed, mitigation must occur for the forested wetlands that are impacted and a spatial inventory will largely determine the extent of mitigation. Furthermore, comparing the most accurate classification result to those from previous years will provide information about land cover trends in the area. Specific attention is paid to the abundance of bottomland hardwoods over time, as the cover type is most significant for both ecologic and economic reasons. The broadest contribution that the study will provide will be through the comparison of classification approaches in terms of accuracy while describing their implementation. The evaluation of several different classification approaches will help those conducting classification studies in similar landscapes to decide on an effective classification approach and methodology. Each of the classification methods are evaluated and compared in terms of the best overall approach for each method, which does not necessarily mean in identical data inputs.

Classification Approaches

Pixel-based classifications have been widely used to classify forested wetlands and the surrounding areas. The specific approaches, algorithms, and inputs vary. The two primary approaches used in pixel based classification are supervised and supervised approaches. Studies which have utilized these approaches to classify forested wetlands are described in greater detail. Supervised classification approaches utilize training

pixels of known land cover types to define the properties of each class based on the spectral, and sometimes ancillary, values at each training pixel. All other pixels are then classified based on these properties. Training pixels for each class are collected in the field via Global Position Systems (GPS) or through interpretation of scanned aerial photographs. According to an extensive review conducted by Ozesmi and Bauer (2002), the most common algorithm used for supervised classification of wetlands is the Maximum Likelihood Classifier (MLC). MLC determines the probabilities that a pixel belongs to a specific class by using the location of training pixels in the feature space, plotted in the n-dimensions using all input bands (Richards and Jia, 2006). There have been a number of studies that utilize MLC to classify forested wetland areas. Hewitt III (1990) used MLC to classify Landsat TM data for the Yakima River Valley in Central Washington. The study achieved 81% accuracy for the coarse class definitions of Water, Riparian, and Other. Lo and Watson (1998) used MLC to classify Landsat TM data for portions of the Okefenokee Swamp in Oklahoma. They detected six vegetation groups with 63% accuracy. Another pixel-based classification approach is the unsupervised approach. Rather than using training data to define the properties of desired classes, the classifier uses clustering techniques to create a user-specified number of separable classes based on the properties of the input data. These classes are then interactively grouped to fit the needs of the user. Ozesmi and Bauer (2002) found unsupervised approaches to be the most common approach to classify wetlands. Ramsey III et al. (1998) used unsupervised clustering of Landsat TM data to classify a portion of the Atchafalaya River Basin. After grouping the clusters and applying a 3x3 majority filter,

six classes were detected at 85.9% accuracy. Unsupervised clustering was also used by Goodin (1995) to classify Landsat TM data for an area in the Nebraska Sand Hills.

Rule-based classification approaches differ from pixel-based approaches in that a pixel or cluster is classified based on a hierarchical series of decisions, rather than a single probabilistic or distance measure (Richards and Jia, 2006). Rule-based approaches are more directly comparable to supervised pixel-based classifications, since both utilize training pixels of known land cover types to construct a classifier. Rule-based approaches utilize training pixels to develop classification trees that are used to classify the remainder of the image and have demonstrated success in separating difficult to distinguish classes where the spectral properties are extremely similar, such as the riparian areas and forested upland areas of the Gallatin River Watershed in Southwest Montana (Baker et al., 2006). Rule-based approaches focus on the development of classification trees, which are a series of decision nodes that separate classes based on the properties of the input data, both spectral and ancillary. These trees can be developed manually; however, machine learning techniques employed by data mining software are commonly used since these techniques can detect splitting criteria unknown even to expert users. Daniels (2006) manually developed a rule-based classifier based on expert knowledge that was used to reclassify portions of a MLC/Parallelepiped classified image based on rule-based analysis of weighted inputs. The addition of rule-based analysis improved the detection of 6 land cover types in the Tempique Watershed in Costa Rica for data from three different years by 11%, 14%, and 29%. Generally speaking, rule-based methods more effectively capture the within-class variability of

classes by more effectively incorporating a larger number of inputs, while maintaining or improving on the accuracy of pixel-based methods.

Splitting criteria are developed in an automated fashion by recursively dividing the values of the input data at known class types, resulting in a classification tree with cutoff values corresponding to various input data values at each node. After the decision tree is developed, different techniques, such as cross-validation, can be used to reduce the number of nodes and improve performance (Rulequest Research, 2007). Classification trees were used by Rogan et al. (2003) to detect nine land cover change classes using multi-temporal Landsat TM imagery and several ancillary inputs, such as slope, aspect, and fire history. There are advanced rule-based methods as well. One approach is to develop multiple classification trees through a process called Stochastic Gradient Boosting (SGB), which uses two techniques known as "bagging" and "boosting" to create refined versions of classification trees. Bagging creates trees using random subsets of the data, which results in more accurate detection of variable classes. Boosting uses errors in older trees to refine new trees. Rather than being a one-step-look-ahead method where splits of training data produce a single tree, boosting is an iterative process that self-corrects to some degree and uses multiple trees to vote on the classification of a single pixel (Baker et al., 2006; Rulequest Research, 2007). Baker et al. (2006) compared the performance of SGB techniques to the performance of single classification tree for classifying wet, non-wet, and riparian classes in the Gallatin River Watershed in Southwest Montana. They found the SGB methods improved classification by 13%.

Object-based classification approaches focus on the segmentation of imagery into homogeneous objects and the subsequent classification of these segments. According to Schneider and Steinwendner (1999), the segmentation criteria can be based on spectral or textural homogeneity, spectral or textural resemblance to adjacent pixels, edge properties of each segment, or domain knowledge. The complexities of the segmentation process distinguish it from previously described unsupervised clustering algorithms, which only allow control over the number of classes, the number of iterations, and the standard deviation within each cluster. Specific factors which can be adjusted in Definiens Professional 5.0, the primary object-based classification software, include the scale parameter, the composition of homogeneity criterion, and the individual weights assigned to each layer (Definiens, 2006). Segmentation also separates itself from unsupervised clustering because the segments can be created at multiple scales to form hierarchical structures of class types.

Several recent studies have examined the use of object-based classification for land cover mapping, though few have been specific to forested wetlands. Yu et al. (2006) utilized object-based classification of high resolution imagery to detect 43 vegetation alliances on a peninsular area located in California's Point Reyes National Seashore. The authors demonstrate that object-based classification outperforms supervised MLC methods in terms of overall accuracy, though the object-based classification had difficulty identifying small classes with few training samples. Arroyo et al. (2006) performed segmentation of QuickBird imagery across multiple scales to classify six fuel types in northwest Madrid with 80% accuracy. Kressler et al (2003)

utilized object-based classification of SPOT-5 imagery to detect five general land cover classes with 86% accuracy.

Previous Studies

Due to the potential reservoir construction, the study area under investigation has been classified using remotely sensed imagery in several previous studies. In 1997, a classification study was conducted by Liu et al. (1997) for the Texas Parks and Wildlife Department (TPWD) which analyzed the land cover at three proposed reservoir sites in Northeast Texas. Landsat TM imagery from June 1994 was used in a pixel-based classification approach. Both an unsupervised clustering and a supervised classification using ground truth data were performed via the maximum likelihood classifier algorithm. The study detected nine general land cover types at the site: water, bottomland hardwood, bottomland hardwood swamp, oak-hickory, cedar-hardwood/pine-hardwood, pure pine/cedar, grassland, crops/managed grassland, and bare soil/ground. There was no accuracy assessment performed for the classification; however, based on a qualitative assessment by the authors, the classification performed well(Liu et al., 1997).

A more recent study was conducted by the Texas A&M Spatial Sciences Lab in 2000. Landsat TM data from May 1997 was used to perform an unsupervised classification of a nine-county region in Northeast Texas which included the current study area. There were nine classes identified in this study: water, wetlands, pine/pine mix, bottomland hardwood, upland hardwood, grassland, agriculture, and urban/bare

ground/other. Approximately 80 ground control points collected in the field and 240 collected from base maps were used to obtain an accuracy of 79%. The authors also classified historical Landsat MSS data from 1974, 1984, and 1991 at a coarser level (Sivanpillai et al., 2000). These classifications provide the historical data needed to perform trend analysis in bottomland hardwood abundance**.**

Objectives

1. Compare the implementation, advantages, and disadvantages of pixel-based classification, rule-based classification, and object-based classification of LIDAR data, multi-spectral imagery, and various GIS datasets as related to the accuracy as ease of implementation for land use/land cover classification of bottomland hardwood systems.
2. Quantitatively evaluate the effect of various classification inputs, such as LIDAR and ancillary data, on each classification method, in order to determine the most crucial image classification inputs for distinguishing bottomland hardwood forests.
3. Determine the abundance of bottomland hardwood forests from previous classifications of Landsat imagery from 1974, 1982, 1991, and 1997, and compare the results to current conditions in order to gain insight into general trends in forest abundance and health.

Materials and Methods

Study Area

The study area is a portion of the Sulphur River Basin located in Northeast Texas which is slated as a possible location for a future reservoir project. It covers approximately 74, 630 hectares (Figure B-1) and the largest percentage of the area is located in Red River County. The closest city with a population greater than 10,000 is Mount Pleasant which is located approximately 15 miles south. The Sulphur River is the dominant hydrologic feature in the study area and the tributaries considered in this study include Cuthand Creek, Langford Creek, Kickapoo Creek, Shawnee Creek, and Little Sandy Creek. The average precipitation, average temperature, and minimum and maximum temperature from 1970-2000 were compared to the annual averages for 2004 in an effort to determine the degree of departure from normal weather patterns during the period immediately preceding image acquisition. In addition, the 30-year averages for December and January were compared to the December 2004 and January 2005 values (Table A-1).

Description of Major Land Cover Types

The dominant land cover types in the region include pine, pine mix, upland hardwood, and bottomland hardwood forests (woody wetlands), as well as emergent herbaceous wetlands and grassland mosaics. The grassland type is a mixture of managed hay and winter wheat fields in addition to pasture. For this study, nine land cover classes are defined. These definitions were a combination of class definitions

from previous studies and land cover types described by the Texas Land Classification System (TLCS). The TLCS was developed by experts from several Texas state agencies, and provides a comprehensive classification system specific to Texas (Interagency LULC Working Group, 1999).

Urban land cover is classified as any area containing greater than 30% constructed materials, bare rock, gravel, or other earthen material where no vegetation was present. Water is classified as any area of open water, generally with less than 25% soil or vegetation cover. Vegetation types include pine, pine-hardwood mix, upland hardwood, and bottomland hardwood forests, wetlands, grasslands, and agriculture. The following is a brief description of each vegetation type.

Agriculture: Areas where a majority of vegetation is planted and/or maintained for the production of food, feed, fiber, pasture, or seed. Due to timing of image acquisition, this type primarily includes plowed fields of exposed soil.

Bottomland hardwood: Areas dominated by woody vegetation where the water table is at, near, or above the land surface for a significant part of most years and vegetation indicative of this type covers more than 25% of the land surface. Includes seasonally flooded bottomland and wooded swamps. Species include water oak, willow oak, American elm, green ash, and Chinese tallow.

Emergent Herbaceous Wetlands (EHW)/Secondary Bottomland Hardwood: Areas located in floodplains that are dominated by wetland herbaceous vegetation which is present for most of the growing season, frequently flooded grasslands, and areas that are

likely successional to the bottomland hardwood class, such as areas that have been logged where natural regeneration is occurring.

Grassland: Areas dominated by true grasses and broad-leaved herbaceous plants. Less than 25% tree cover is present. This class includes pastures and natural grasslands.

Pine: This vegetation type is dominated by loblolly and shortleaf pine stands. It includes slash pine plantations. Areas dominated by trees where 75% or more of the canopy cover can be determined to be trees which maintain their leaves all year. This is the predominant vegetation type of the eastern portion of the study area and can be found throughout the region, except in the wettest areas.

Pine mix: This type is a mixture of pines (and other softwoods) and hardwood species including oak, hickory, and others. These areas are dominated by trees where neither deciduous nor evergreen species represent more than 75% of the canopy cover.

Upland hardwood: This vegetation type is comprised primarily of post oak, blackjack oak, hickory, white ash, and winged elm. It is commonly found on dry ridges and well drained soils. Areas are dominated by trees where 75% or more of the canopy cover can be determined to be trees which lose all their leaves for a specific season of the year.

Methodology

A large number of datasets were obtained or developed as classification inputs. SPOT-5 satellite imagery, which provides 2.5m resolution images in panchromatic mode and a 10m resolution image in multi-spectral mode, functions as the primary input for spectral reflectance values of land cover types. Two scenes were obtained for this study.

Scene 589-283, collected on January 20, 2005, covers approximately 80% of the study area and scene 590-283, collected on February 21, 2005, covers approximately 10% along the eastern side. The remaining 10%, located along the western edge of the study area, was covered by high resolution aerial photography and National Agriculture Inventory Program (NAIP) imagery. Normalized Difference Vegetation Index (NDVI), near infrared (NIR) texture variance, short wave infrared (SWIR) texture variance, and Principal Component (PC) bands were derived from the SPOT imagery to aid in the classification. All SPOT and SPOT-derived image products were projected to match the LiDAR data (NAD83 State Plane – Texas North Central 4202), since the LiDAR data has a higher spatial resolution and would suffer a greater level of decreased accuracy from a projection transformation. However, meters were preserved as the unit of measure in order to aid interpretability and the conversion was accomplished in ENVI. NDVI is calculated as (NIR – Red) / (NIR + Red) and eliminates noise from bands that have limited response to vegetative properties (Jensen, 2007).

Several important datasets were also derived from LiDAR data, which is a remote sensing system used to collect topographic data. LiDAR scanning systems rapidly deliver pulses of laser light from an aircraft to the ground and these pulses are returned to the system, with the travel time used to determine the range, or distance, to the feature or features that the pulse encountered. Each pulse can have multiple returns, resulting in an accurate picture of the ground cover and terrain of a remotely-sensed area. The LiDAR data used in this study was collected by M7 Visual Intelligence from January 17, 2006 to January 26, 2006 using a Leica ALS 50 Scanner. The input into the

classification were mosaicked, smoothed last return elevation and digital surface model grids, with a 4.572 square meters (or 15 square foot) resolution, which were first gridded and cleaned from the raw LAS file by an experienced LiDAR analyst using Terrascan. The data was collected in conjunction with high-resolution aerial photography in one foot false color composites, which were used to validate and supplement ground truth points.

National Agriculture Imagery Program (NAIP) Digital Ortho Imagery, which is collected and compiled each year by the United States Department of Agriculture Farm Service Agency during a portion of the agricultural growing season at a one or two meter resolution, was also used to supplement the classification. The data provides a useful snapshot of "leaf-on" conditions in the Sulphur River Basin and were obtained in county mosaics at a spatial resolution of two meters. Several GIS datasets were also developed to supplement the imagery and LiDAR inputs. The National Hydrography Dataset (NHD) is a combination of the United States Geological Survey Digital Line Graph Hydrography files and the United States Environmental Protection Agency Reach Files version 3.0 (rf3), and provides nationwide coverage of hydrologic features. ArcGIS was used to subset the NHD lines for the Sulphur River and its major tributaries, and the continuous distance to these water features was used as a classification input and the dataset represents the distance to potential flooding. Soil Survey Geographic (SSURGO) data is developed and maintained by the USDA Natural Resource Conservation Service, provides detailed spatial and tabular information about soil series, and is gathered via National Cooperative Soil Survey field surveys (United States

Department of Agriculture, 1995). The data is provided at the county level where available, though some counties are provided in groups. Visual Basic scripts were developed to import and merge the spatial and tabular data for all involved counties. Component tables were used to determine the percent hydric soils for each SSURGO map unit. National Wetlands Inventory (NWI) data is collected and compiled by the U.S. Fish and Wildlife Service. The data for the study area was last updated in September of 2002, and was developed through the manual interpretation of aerial photographs and field verification (U.S. Fish & Wildlife Service, 2002). The National Land Cover Dataset (NLCD) was developed using 2001 Landsat 7 imagery by the USEPA Multi-Resolution Land Cover Consortium. The NLCD was developed using a decision-tree classification approach for multi-temporal Landsat imagery and several ancillary datasets (Homer et al., 2004) and the forested wetland categories from both of these datasets were extracted.

Ground truth data were crucial inputs to the classification. Samples for each land use/cover class within the study were gathered using Trimble GeoXT GPS units, as well as digital sampling of high-resolution aerial photography. The primary focus of the field collection process was to collect ground control points across the entire area, particularly in classes which were difficult to distinguish, including bottomland hardwoods, upland hardwoods, and emergent herbaceous wetlands. Where access was limited, sample points were offset from the road using distance and bearing. A total of 519 field points were collected from February 16, 2007 - February 20, 2007 and photographs were taken at the majority of these locations. The horizontal accuracy of the points ranged from 0.4

to approximately 4 meters. Prior to classification, spatially redundant and erroneous points were removed from the dataset. Erroneous points were identified by looking at the pictures taken on site, the high-resolution aerial photography, and the LiDAR nDSM. The high-resolution aerial photography was provided by M7 Visual Intelligence in one foot false color composites. The aerial photographs were collected in conjunction with the LiDAR data. Additional class samples were collected in ArcMap for under-sampled classes and areas, after establishing a baseline of knowledge about the appearance of each class by overlaying the in situ samples. The total number of points collected totaled 881 (Figure B-1).

Image Classification

All data was stacked into a single file using ENVI's Layer Stacking command. The final stack contained the following bands: the four original SPOT bands, NDVI, NIR texture variance, SWIR texture variance, the two PCA bands derived from SPOT imagery, LiDAR derived nDSM, LiDAR derived DTM, DTM derived slope, DTM derived aspect, the three original NAIP bands, the PCA band derived from NAIP imagery, the NHD derived distance to the Sulphur River and tributaries, SSURGO percent hydric soils, and NWI/NLCD wetland locations. Since spectral subsets can be used for nearly all image processing operations, the stacked data served as the final data source for all classifications. Image classification was performed on both SPOT scenes covering approximately 90% of the study area. The remaining 10%, along the western

edge of the study area, was delineated manually using high resolution aerial photography and NAIP Imagery.

Two pixel based classification approaches were investigated, supervised and unsupervised. In order to divide points into sampling and training for the supervised classification, the points were plotted in an n-dimensional visualizer. Approximately 150 points occurred in potential areas of spectral overlap between classes; these points were removed from the full set and randomly divided the data into training points, which accounted for 30% of the dataset, and accuracy assessment points. Removing the potentially confusing points improved the quality of the training data while avoiding the bias which would be introduced by manually selecting the purest samples for each class.

I performed the land cover classification using iterative band combinations in order to determine the impact of including the various inputs based on quantitative and qualitative accuracy assessment. Specifically, supervised pixel-based classifications were performed using the entire final stack, the final stack omitting all of the ancillary datasets, and the final stack iteratively omitting each of the ancillary datasets. Classifications were also performed to determine the impact of using the original image bands vs. the PCAs, as well as the impact of including NAIP imagery, the PCAs, and the various LiDAR inputs. Any datasets shown to decrease the overall accuracy of the classification were omitted from further pixel-based classifications. The unsupervised classification approach used the ISODATA clustering algorithm to group all of the input bands which were deemed useful by the iterative supervised classification into homogeneous groups of pixels. The algorithm performed ten iterations using a 95%

convergence threshold. The clusters were then grouped into the nine land cover types and the final classification accuracy was assessed using the full count of ground truth points.

I used several tools to complete the rule-based classification. The Classification and Regression Tree (CART) Module for ERDAS Imagine and the Hawth's Tools extension in ArcGIS were both used to create input files for the data mining software, See5, used to create the decision trees. A total of 400 training samples were selected from the 881 ground truth points to be used in the rule-based classification. A large number of points were used in the training set because the recursive splitting techniques employed by See5 rely on points capturing the variability within each class, thereby improving the accuracy of the classification tree. The remaining 481 points were held aside for accuracy assessment. Less bias is introduced by including potential accuracy assessment points in a rule-based classifier, since each pixel is classified based on a set of decision trees, rather than a probabilistic measure. Cross validation, boosting, and pruning techniques were also employed to improve the effectiveness of the classification trees. I allowed the data mining software to base splits on all twenty input bands so that useful splits, which may or may not be user intuitive, can be identified. The software output a ranking of datasets in terms of importance, based on how often each was used to create splits. Twenty boosted decision trees were used in the final classification, with each undergoing 25% global pruning. The CART module used all twenty trees to vote on the classification of each pixel for the entire study area. A 3X3 majority filter was applied to the final rule-based classification in order to remove isolated misclassified pixels and an error matrix using the ground truth points assessed classification accuracy.

The object-based classification was conducted using Definiens Professional 5.0 with a focus on optimizing segmentation parameters prior to classification using landscape metrics and statistical techniques. I used the methodology outlined in the third chapter to develop ideal segmentation parameters. The specific segmentation parameters were: a scale parameter of 5, a shape weighting of 0.2, and a compactness weighting of 0.6. The same training and accuracy points which were used in the supervised pixel-based classification were also used in the object-based classification. Post classification, accuracy assessment was conducted for all classifications using an error matrix, and generated an overall accuracy, kappa coefficient, and producer's and user's accuracies for each class. The producer's accuracy involves the failure to include a reference data pixel in an image class, while the user's accuracy involves inclusion of a pixel in the incorrect image class. The kappa coefficient assesses the accuracy of classification in terms of whether it could have occurred by random chance. The most accurate classification was merged with the manual delineation of the western portions of the study area to produce a final study area layer.

Results and Discussion

Results from the supervised classifications demonstrate that the classifications improved substantially when the SPOT PCAs were utilized rather than the original SPOT bands. This is expected, since the PCAs reduce data redundancy while retaining the uncorrelated spectral values. The classifications did not improve by including the texture variance measures, topographic derivations, NAIP leaf-on imagery, or other

ancillary datasets. The most accurate supervised classification method resulted from using the two SPOT PCAs, NDVI, LiDAR nDSM, and the LiDAR last return elevation as inputs. This resulted in an accuracy of 78.66%. The inputs from the most accurate supervised classification were used in an unsupervised clustering procedure. However, the accuracy for this procedure was very poor, as the clusters provided limited separation between land cover types. The classification containing 250 clusters represented the most separability between land cover classes, with an accuracy of 43.36% after the clusters were grouped into the nine land cover classes. Accuracies for the pixel-based classifications are summarized in Table A-2.

The rule-based approach produced better results, as the method more effectively incorporated the additional NAIP, topographic, and ancillary datasets. These additional datasets were better suited for the rule-based classification because they were only incorporated when useful in separating a specific class. The machine developed decision tree also produced unexpected and useful rules for class splitting. An overall accuracy of 84.41% was achieved after rule-based classifications were processed. The overall accuracy for the rule-based classification is summarized in Table A-3, along with the accuracies for the 3x3 filtered classifications. The producer's and user's accuracy for each class identified by the rule-based classification is shown in Table A-13. Three classes experienced mediocre accuracy results: Pine Mix, Emergent Herbaceous Wetlands, and Agriculture. The difficulty in identifying Pine Mix class stems from the fact that the class is similar in terms of both class definition and spectral response to the Pine class. Higher resolution data could improve the detection of this class. The

difficulty in identifying the Agriculture and Emergent Herbaceous Wetlands classes is due to the fact that the timing of image acquisition was not ideal for these two classes, since the study focuses on identifying bottomland hardwood forests. The spectral response of both of these classes becomes much more distinct during the growing season, as the vegetation of both land cover types is the primary distinguishing characteristic. In addition to the classification trees, another valuable output of the See5 software used to create the rule-based classification is a ranking of datasets in terms of their importance to the 20 boosted decision trees. This is based on the number of times a specific band was used to differentiate between classes. In this analysis, all twenty inputs were utilized to some degree (Table A-4).

The object-based approach did not perform as well as expected, with an overall accuracy of 76.37%. There is little improvement in classification accuracy when switching to object-based methods because the primary input is medium-resolution SPOT-5 satellite imagery. The advantages of object-based classifications are more obvious when working with high-resolution imagery, since random misclassification of pixels is much more of a problem when there are a greater number of pixels and a greater variety of spectral responses. With the SPOT-5 medium-resolution imagery, spectral responses are averaged across a 100 square-meter area, meaning that the overall spectral variety throughout the landscape is far less than it would be if the primary input was high-resolution imagery such as Quickbird (2.4m resolution). Thus classifying the landscape on a per-pixel basis still results in a high accuracy and object-based methods do not necessarily guarantee an improvement in quantitative accuracy. However, many

of the object-based classification features more closely resemble real-world features based on qualitative assessment of the classifications. The object-based classification still has some use for this reason, as initial visual analysis of the landscape is quite pleasing. The rule-based methods produced the best classification to use for any sort of analysis or comparison, however. The final producer's and user's accuracies for all classes are shown in Table A-5 and the final map is displayed in Figure B-2.

Comparison to Previous Studies

The land cover/use estimates in hectares and percent of total cover, as derived from the 2000 study by the Texas A&M Spatial Sciences Lab, are presented in Tables 6 and 7. The 1974-1991 classifications utilized 60 meter Landsat MSS imagery, while the 1997 classification utilized 30 meter Landsat TM imagery. The bottomland hardwood percent cover steadily decreased from 1974-1997. This decrease was also evident for the upland hardwoods. The urban/other class increased from 1974-1991 and essentially leveled off in 1997. Based on the imagery, however, much of the area classified as urban from 1974-1997 was actually brightly reflecting grassland and transition zones. Another trend that is evident is an increase in the water percent cover across all four dates. This increase is notably large from 1991 to 1997 due to heavy flooding captured in the 1997 imagery.

Slight discrepancies (e.g. 74,621.20 ha in 1974 vs. 74,585.29 ha in 1984) in the total area are due to missing data along the border caused by fitting an image to the study area boundary and as well as differences in the exact area covered by each of the images

used in the classifications. These discrepancies can also be attributed to minor variations introduced during the process of assigning a geographic location to raw satellite imagery. The total area computed for each land cover/use type in the 1997 TM scene is presented in Table A-8. Improved detection of bottomland hardwood from 1991 to 1997 is a result of the increased resolution of the TM imagery. The land cover/use estimated in hectares and percent of total cover, as derived from the current study assessing 2005 conditions, is presented in Table A-9. The total area under bottomland hardwood and emergent herbaceous wetland/secondary bottomland hardwood increased from 1997 to 2005. There was a decrease in the amount of urban/bare ground and water from 1997 to 2005. These changes in area occur for several reasons: differences in the time the images were captured, differences in image resolution, and improvements in input data and methodology.

The seasonal differences between the two datasets had a large effect on the variability in class area. The 1997 TM Scene was acquired in May, while the 2005 SPOT-5 imagery was obtained in February. The 1997 imagery was collected during the typical Texas rainy season and much of the bottomland was flooded when the imagery was collected, meaning that much of the 1997 areas classified as water are actually bottomland hardwoods and the flooding is indicative of wetland hydrology. Additionally, the May 1997 imagery was collected during the leaf-on summer months. This makes distinguishing between upland and bottomland hardwoods difficult, as the closed tree canopy obscures soil moisture conditions. In fact, the image analyst noted this challenge in the 2000 report, and therefore, relied on a manual reclassification of

upland to bottomland based on slope and distance from stream features. Classifications for previous years also used leaf-on imagery; therefore, these classifications likely exhibit similar issues with overestimation of water and confusion between upland and bottomland hardwoods. Leaf-off time periods are regarded as ideal by many experts for collecting remotely sensed data to be used in forested wetland classifications (Johnston and Meysembourg, 2002; Ozemsi and Bauer, 2002). Thus, the classification of the 2005 imagery, which is leaf-off, is a more accurate representation of actual ground conditions. The resolution of the source imagery also contributed to the differences in class areas. The 1997 imagery was from collected by the Landsat TM satellite with a pixel resolution of 30 by 30 meters. In other words, the smallest distinguishable feature in the imagery is 900 square meters (0.22 acres) in area or greater. Features smaller than 900 square meters, such as small groups of trees surrounded by water, would not be identifiable in this imagery and would therefore be missed by the classification. The 1974-91 studies used 60 meter Landsat MSS imagery, with a minimum mapping area of 3600 square meters (0.88 acres). In comparison, the 2005 SPOT-5 imagery has a minimum mapping area of 100 square meters (0.02 acres). The 15 foot LiDAR data, also used in the 2005 classification, has an even better minimum mapping area of 20.9 square meters (0.005 acres). This finer resolution means that features in heterogeneous areas were more likely to be identified correctly in the 2005 classification. In addition to the seasonal differences and lower resolution imagery in the previous studies, the area of the 1997 classification covers approximately nine times the area of the 2005 classification (1,432,926 ha vs. 74,565 ha). The current study focuses efforts on a much smaller area

and is more likely to maximize accuracy across the Sulphur River Basin, while the 1997 study maximized accuracy across a nine-county region. Improvements in data inputs and methodology also help to explain the differences between the 1997 and 2005 classifications. These include valuable additional inputs, improved classification methods, and differences in class definitions. The current study utilizes many valuable inputs that were either not available or not affordable when the 1997 imagery was classified. These inputs include the higher resolution SPOT-5 imagery, a LiDAR-derived nDSM and DTM, and high-resolution aerial photography (one foot resolution). The use of higher resolution SPOT-5 imagery is a large part of the improved accuracy of the current classification. In addition, the LiDAR nDSM greatly improved the detection of forested vs. non-forested areas as it provided a highly accurate estimate of ground feature heights. The previous study relied solely on imagery, thereby increasing the possibility of misclassifying forested areas since the ground feature heights were unknown. Further, the LiDAR DTM provided a highly accurate measure of ground elevation, which is crucial in distinguishing between upland and bottomland areas. The high-resolution aerial photography also helped to improve the 2005 classification results, as it allowed ground truth points to be verified and expanded. For the 2005 classification, a total of 519 points were collected in the field. These points were edited for errors and expanded using the high-resolution imagery. As a result, the total number of points increased to 881. It would not have been possible to obtain such a large number of quality points without the high-resolution aerial photography. Improved classification methods also aided the 2005 classification. Multiple classification

methods were investigated to determine which methods performed best in the current study.

Based on the findings of this research, rule-based classification outperformed both pixel-based and object-based classification. Since rule-based classification employs data mining techniques that can incorporate inputs (imagery or GIS datasets) only when necessary, valuable additional data such as height (nDSM), percent hydric soils, slope, and distance to the river could be included in the 2005 classification. Additional improvements, such as better GPS receivers and more powerful software packages also aided the 2005 classification. These improvements all contributed to a more accurate picture of land cover/use across the Sulphur River Basin. The 1997 study also used a slightly different set of class definitions. For example, the wetlands class is defined as an area that undergoes frequent flooding or permanent inundation with water-resistant vegetation species. The 2005 class definitions were structured based on the Texas Land Cover Classification System, and split wetlands into forested wetlands and non-forested wetlands. The 2005 bottomland hardwoods class definition better conforms to the actual definition of bottomland hardwood forests, whereas there is ambiguity in the 1997 definitions, given that both the wetlands and bottomland hardwoods classes could be considered bottomland hardwood forests. Though the comparison between the different years is still valuable, the differences in definitions contribute to the slight differences in overall class area.

Figure B-3 shows the differences in bottomland hardwood between years, based on the classifications at their original cell resolution. Note that for 1997, the bottomland

hardwoods and wetlands classes were grouped since both classes contain areas that meet the definition of bottomland hardwoods, whereas the 2005 percentage includes only bottomland hardwoods. The 2005 classification shows an increase of approximately six percent. A high level of confidence should be placed on the 2005 classification as a reflection of actual ground conditions; however, only the 1974-1997 classifications should be directly compared in order to identify trends as they used the same cell resolution throughout the classification process. When the classifications are re-sampled to the same resolution (60m), the percent area of bottomland hardwood consistently decreases from 1974-2005. Figure B-4 demonstrates this trend. It is apparent that the 2005 classification picked up many patches of bottomland hardwood forest that were undetectable using previous imagery, as these areas are no longer present when the classification is re-sampled to the same coarse cell size used in previous classifications.

Conclusions

Overall, this study resulted in a highly accurate picture of actual ground conditions in the Sulphur River Basin study area. In this study, the rule-based classification method outperformed the pixel-based and object-based methods because additional datasets (high resolution imagery and GIS data) could be used to refine the final classification only when these data helped to improve the overall accuracy. An overall accuracy of 84.41% was achieved in the final classification. This is well above the common accuracy goal (75%) for image classification, and also represents a substantial improvement over previous image classification studies in the area. The

most common problem encountered in the 2005 classification was the overestimation of urban areas and the underestimation agriculture. Brightly reflecting grasslands and those in transition zones between land cover types were often misclassified as urban. To correct the overestimation of urban pixels the rule-based classification created using random samples was combined with a rule-based classification focused on the differences between urban areas and grasslands. In addition, irrigation ditches used in agricultural activities were misclassified as emergent herbaceous wetlands due to the standing water that is often found in these ditches. To correct this underestimation, a mask was created to reclassify irrigation ditches as agriculture. The SPOT data, captured in February, was ideal for this study. By capturing the images during the winter months there is less likelihood that areas will be misclassified as water due seasonal issues, such as flooding. More importantly, differences in soil moisture can be easily detected since the imagery is leaf-off. In general, there was a visible decline in bottomland hardwood forest from 1974-1991 in the Sulphur River Basin. The classifications for this these time periods were conducted using identical class definitions and input imagery from the same sensor (Landsat MSS 60m), thus the direct comparison provides a good indication of the overall trend. The trend seems to level off in 1997, when medium resolution imagery was first utilized (Landsat TM 30m), likely because additional forest patches were detected at that time. However, the 2005 classification shows an increase in bottomland hardwood from 1997-2005. This is caused by the change in time of image capture, differences in image resolution, and improvements in input data and methodology. Additionally, the class definitions for wetlands were

slightly different between the two studies, which may account for some of the discrepancies. The improvements in the 2005 classification all contribute to a highly accurate picture of current land cover/use across the Sulphur River Basin study area. Any increase in bottomland hardwood area should be discounted, as this classification captured many acres of bottomland hardwoods missed in the previous study. When the classifications are re-sampled to the same resolution (60m), the percent area of bottomland hardwood consistently decreases from 1974-2005.

CHAPTER III

INTELLIGENT SEGMENTATION OF IMAGERY IN OBJECT-BASED CLASSIFICATION

Background

Image classification is a vital sub-discipline of digital image processing. At its core, the process entails identifying a range of spectral responses that correspond to information classes, primarily land use/cover types (Jensen, 2007). As the spatial and spectral resolution of remotely sensed imagery continues to increase, so does the value of applicable and innovative classification techniques. Many classification techniques have been developed. The most established technique is pixel-based classification, in which imagery is classified on a per pixel basis based on a probabilistic or distance measure (Richards and Jia, 2006). However, several recent studies have demonstrated the advantages of rule-based (Bolstad and Lillesand, 1992; Baker et al., 2006; Daniels, 2006) and object-based classification approaches (Blaschke et al., 2005; Arroyo et al., 2006; Yu et al., 2006). In rule-based classification approaches, a pixel or cluster is classified based on a hierarchical series of decisions, rather than a single probabilistic or distance measure (Richards and Jia, 2006). Rule-based approaches utilize training pixels and data mining techniques to develop classification trees, which are a series of decision nodes that separate classes based on the properties of the input data, in order to classify an area. Generally speaking, rule-based methods more effectively capture the within-class variability of classes by more effectively incorporating a larger number of inputs,

while maintaining or improving on the accuracy of pixel-based methods. For automated development of classification trees, splitting criteria are developed by recursively dividing the values of the input data at known class types, resulting in a classification tree with cutoff values corresponding to various input data values at each node. After the decision tree is developed, different techniques, such as cross-validation, can be used to reduce the number of nodes and improve performance (Rulequest Research, 2007).

The primary way that object-based classification differs from both pixel-based and rule-based classification is that input imagery is not classified on a per-pixel basis. Instead, the imagery is segmented, or clustered, into homogeneous image objects which are then classified. The complexities of the segmentation process distinguish it from unsupervised clustering algorithms, which typically only allow control over the number of classes, the number of iterations, and the standard deviation permitted within each cluster. Specific factors which can be adjusted in Definiens Professional 5.0, the most commonly used object-based classification software, include the scale parameter, the composition of homogeneity criterion, and the individual weights assigned to each layer (Definiens, 2006). Object-based classification also separates itself from other techniques because image objects can be created at multiple scales to form hierarchical structures of class types.

Object-based classification is especially useful when working with medium- and high-resolution imagery, since pixel-based classifications of similar resolution imagery face problems with misclassification and a “salt-and-pepper” effect due to local heterogeneity among classes of the same type. Object-based classification avoids this

problem by grouping individual pixels into image objects with minimized within-object heterogeneity and maximum between-object heterogeneity. The segmentation process merges individual pixels through a pair-wise clustering process based on user-defined heterogeneity criteria and scale parameter (Benz et al., 2004). A major shortcoming of object-based classification is limited or non-existent justification for the selection of parameters that guide the segmentation process. In general, the majority of studies that utilize object-based classifications fall into two camps: those that justify segmentation parameters by conducting a large number of segmentations and using the set of parameters that result in the most accurate final classification (Darwish et al., 2003; Collins et al., 2004) and those that assign segmentation parameters based on general guidelines (Kressler et al., 2003; Syed et al., 2005; Brennan and Webster, 2006). This research aims to create a useable framework to guide the selection of segmentation parameters within a widely-used object based classification software, Definiens Professional 5.0 (Definiens, 2006).

There has been research pushing towards intelligent segmentation. Some researchers, such as Intajag et al. (2006), develop their own custom segmentation algorithms outside the context of object-based classification software. Although these algorithms are impressive and often perform very well, they do not aid non-expert users in conducting intelligent segmentation using standard software. Zhang and Maxwell (2006) propose an interesting methodology to obtain intelligent segmentation parameters. The initial segmentation over-segments the input imagery and these primitive image objects are input to a fuzzy logic system which determines ideal

segmentation parameters. In the fuzzy logic system, the primitive objects' texture and stability are used to determine the appropriate scale parameter, which is the parameter in Definiens Professional 5.0 that governs the resulting average size of image objects. This method was successful on four small image subsets, consisting of single real-world objects such as a building and a baseball field. This method represents an improvement over trial-and-error or arbitrary assignment of scale parameter, for these small subsets at least. However, it is unknown how the method performs for an entire landscape and it would require expertise outside of the range of a typical user to design and implement the fuzzy logic system. Additionally, this method focuses on the selection of the ideal scale parameter but does not deal with the heterogeneity criteria.

I believe that a framework for the intelligent selection of segmentation parameters, including both heterogeneity criteria and the scale parameter, can be developed using a combination of landscape metrics and statistical techniques. Landscape metrics formally quantify the spatial characteristics of landscapes via algorithms that operate on data developed from field work, GIS data, or remotely sensed imagery. The field of landscape ecology, which studies and develops landscape metrics, hinges on the fact that landscape structure influences landscape function and functionality can be inferred by analyzing the spatial characteristics of landscape structure. Several studies have taken steps towards integrating landscape metrics and object-based classification. Ivits et al. (2002) analyze connectivity of an object-based classification and mention the increased efficacy of using metrics in the context of object-based classification, since the salt-and-pepper effect of pixel-based classification

is avoided due to the creation of homogeneous image objects. Frohn (2006) assesses the use of landscape metrics in the post-segmentation classification of image objects in three different studies. He demonstrates the utility of landscape metrics in image classification and argues that they are under-utilized in image classification. I aim to integrate landscape metrics with the segmentation of image objects in order to improve the overall classification accuracy, as the success of object-based classification is determined in large part by the quality of the input image objects. The overall objective of this research is to produce a usable, repeatable framework to determine ideal segmentation parameters. The specific objectives of this research are as follows:

1. Produce >75% accurate classifications, as evaluated by error matrices created with ground truth points, using pixel-based and rule-based classification methods of SPOT-5, LiDAR, and ancillary data for a Texas bottomland hardwood system.
2. Analyze the more accurate of the two classifications with relevant landscape metrics and link landscape metrics to heterogeneity criteria in Definiens Professional 5.0.
3. Determine the ideal scale parameter through multiple iterations and statistical techniques.
4. Compare accuracy of two object-based classifications.
    a) Intelligent Segmentation Parameters
    b) Arbitrary Segmentation Parameters

Materials and Methods

Study Area and Class Definitions

The study area is a portion of the Sulphur River Basin located in Northeast Texas. Portions are located in eight counties, with the largest percentage of the area located in Red River County. The study area covers approximately 74, 630 hectares (Figure B-1) and the closest city with a population greater than 10,000 is Mount Pleasant, located approximately 15 miles south. The Sulphur River is the dominant hydrologic feature in the study area; tributaries of the Sulphur River include Cuthand Creek, Langford Creek, Kickapoo Creek, Shawnee Creek, and Little Sandy Creek. The dominant land cover types in the region are bottomland hardwoods, upland hardwoods, grassland mosaics, pine/hardwood mix, emergent herbaceous wetlands, and pine. For this study, nine land cover classes were defined. These definitions were a combination of class definitions from previous studies conducted in the area (Liu et al., 1997; Sivanpillai et al., 2000) and the land cover nomenclature developed for the Texas Land Classification System (TLCS). The TLCS was developed by experts from several Texas state agencies, and provides a comprehensive classification system specific to Texas (Interagency LULC Working Group, 1999). Urban land cover is classified as any area containing greater than 30% constructed materials, bare rock, gravel, or other earthen material where no vegetation was present. Water is classified as any area of open water, generally with less than 25% soil or vegetation cover. The following is a brief description of each vegetation type.

Agriculture: Areas where a majority of vegetation is planted and/or maintained for the production of food, feed, fiber, pasture, or seed. Due to timing of image acquisition, this type primarily includes plowed fields of exposed soil.

Bottomland hardwood: Areas dominated by woody vegetation where the water table is at, near, or above the land surface for a significant part of most years and vegetation indicative of this type covers more than 25% of the land surface. Includes seasonally flooded bottomland and wooded swamps. Species include water oak, willow oak, American elm, green ash, and Chinese tallow.

Emergent Herbaceous Wetlands (EHW)/Secondary Bottomland Hardwood: Areas located in floodplains that are dominated by wetland herbaceous vegetation which is present for most of the growing season, frequently flooded grasslands, and areas that are likely successional to the bottomland hardwood class, such as areas that have been logged where natural regeneration is occurring.

Grassland: Areas dominated by true grasses and broad-leaved herbaceous plants. Less than 25% tree cover is present. This class includes pastures and natural grasslands.

Pine: This vegetation type is dominated by loblolly and shortleaf pine stands. It includes slash pine plantations. Areas dominated by trees where 75% or more of the canopy cover can be determined to be trees which maintain their leaves all year. This is the predominant vegetation type of the eastern portion of the study area and can be found throughout the region, except in the wettest areas.

Pine mix: This type is a mixture of pines (and other softwoods) and hardwood species including oak, hickory, and others. These areas are dominated by trees where neither deciduous nor evergreen species represent more than 75% of the canopy cover.

Upland hardwood: This vegetation type is comprised primarily of post oak, blackjack oak, hickory, white ash, and winged elm. It is commonly found on dry ridges and well drained soils. Areas are dominated by trees where 75% or more of the canopy cover can be determined to be trees which lose all their leaves for a specific season of the year.

Datasets

The primary image input for this research is medium-resolution SPOT-5 satellite imagery, which provides 2.5m resolution images in panchromatic mode and a 10m resolution image in multi-spectral mode. Two scenes were obtained for this study. Scene 589-283, collected on January 20, 2005, covers approximately 80% of the study area and scene 590-283, collected on February 21, 2005, covers approximately 10% along the eastern side. The remaining 10%, along the western edge of the study area, was covered by high resolution aerial photography and National Agriculture Inventory Program (NAIP) imagery. Several products were derived from the SPOT imagery and examined in this study. Specifically, the Normalized Difference Vegetation Index (NDVI), near infrared (NIR) texture variance, short wave infrared (SWIR) texture variance, and Principal Component (PCA) bands were derived to aid in the classification. All image processing techniques, unless otherwise noted, were completed using the ITT Visual Information Solutions software ENVI 4.4. All SPOT and SPOT-

derived image products were projected to match the LiDAR data (NAD83 State Plane – Texas North Central 4202), since the LiDAR data has a higher spatial resolution and would suffer a greater level of decreased accuracy from a projection transformation. However, meters were preserved as the unit of measure in order to aid interpretability. The conversion was accomplished in ENVI. In regards to the other inputs which were derived, NDVI is calculated as (NIR – Red) / (NIR + Red) and eliminates noise from bands that have limited response to vegetative properties and distinguishes between vegetated and non-vegetated areas, in addition to distinguishing between vegetation types, and thus is extensively used in land cover/use classification studies. The NIR and SWIR bands are the two available multi-spectral bands which are most sensitive to differences in vegetation type, soil moisture, and plant water content (Jensen, 2007). Examining the NIR and SWIR texture variance is therefore useful, as areas with abrupt changes in NIR and SWIR reflectance will be magnified. This allows for more accurate identification of small areas such as roads in a forest or small clusters of pine trees in a field. The texture variances were calculated using an occurrence texture filter with a 3X3 moving window which computes the variance between all of the NIR or SWIR pixel values within the 3X3 window and assigns that value to the center pixel of the window. A forward PC rotation was conducted on the four original SPOT bands in order to create the PCA bands which effectively reduce the imagery to two bands which accounted for greater than 99% of the variance. The usefulness of Principal Components Analysis centers on the fact that classification will perform more accurately if the input bands are uncorrelated, as the classifier is less confused by redundancies

between bands. Since multi-spectral data is inherently correlated between bands, reducing the number of bands is a commonly applied technique prior to image classification. For this study, the forward PC rotation was conducted using the covariance matrix, and the first two bands were output and analyzed in the classification.

Several datasets were also derived from LiDAR data. LiDAR is a remote sensing system used to collect topographic data by rapidly delivering pulses of laser light from an aircraft to the ground. These pulses encounter ground features and are bounced back to the system, and the travel time is used to determine the distance to the encountered features. The LiDAR data used in this study was collected by M7 Visual Intelligence from January 17, 2006 to January 26, 2006 using a Leica ALS 50 Scanner. Smoothed first and last return elevation grids, with a 4.572 square meters (or 15 square foot) resolution, were gridded from the raw LAS file and cleaned up by an experienced LiDAR analyst using Terrascan. The LiDAR data was collected in conjunction with high-resolution multispectral aerial images with a one-foot resolution. The processed first and last return grids were imported and mosaicked and the null values were replaced using a conditional statement and smoothing technique. Band Math was used in ENVI 4.4. to derive a normalized Digital Surface Model (nDSM) by subtracting the last return elevation from the first return elevation. The mosaicked last-return grid provides a Digital Terrain Model (DTM) used to derive slope and aspect as additional inputs.

An additional input was National Agriculture Imagery Program (NAIP) Digital Ortho Imagery from 2005. NAIP imagery is collected and compiled each year by the

United States Department of Agriculture Farm Service Agency during a portion of the agricultural growing season at a one or two meter resolution (United States Department of Agriculture, 2006). Thus, the data provides a useful snapshot of "leaf-on" conditions in the Sulphur River Basin. The 2005 images for Texas were obtained in county mosaics at a spatial resolution of two meters. A forward PC rotation was conducted on the three original NAIP bands to reduce the imagery to a single band that accounted for greater than 98% of the variance.

Several GIS datasets were developed to supplement the imagery and LiDAR inputs. The National Hydrography Dataset (NHD) is a combination of the United States Geological Survey Digital Line Graph Hydrography files and the United States Environmental Protection Agency Reach Files version 3.0, and provides nationwide coverage of hydrologic features (USGS, 2000). The Sulphur River and its major tributaries were subset from the full NHD data, and the continuous distance to these water features was used as a classification input. Soil Survey Geographic (SSURGO) was another valuable input. The data is developed and maintained by the USDA Natural Resource Conservation Service. SSURGO provides detailed spatial and tabular information about the soil series in the country and is gathered via National Cooperative Soil Survey field surveys (United States Department of Agriculture, 1995). Visual Basic scripts were developed to import and merge the spatial and tabular data for all involved counties. Component tables were used to determine the percent hydric soils for each SSURGO map unit. Another GIS input was a combination of National Wetlands Inventory (NWI) data and selected features from the National Land Cover Dataset

(NLCD). The NWI data is collected and compiled by the U.S. Fish and Wildlife Service. The data for the study area was last updated in September of 2002, and was developed through the manual interpretation of aerial photographs and field verification (U.S. Fish & Wildlife Service, 2002). The National Land Cover Dataset (NLCD) was developed using 2001 Landsat 7 imagery by the USEPA Multi-Resolution Land Cover Consortium. The NLCD was developed using a decision-tree classification approach for multi-temporal Landsat imagery and several ancillary datasets (Homer et al., 2004). The forested wetland categories were extracted from both of these datasets and combined into a single file representing documented wetlands.

Ground truth data was a crucial input to the classification. Samples for each land use/cover class within the study were gathered using Trimble GeoXT GPS units, and these GPS samples were supplemented via digital sampling of high-resolution aerial photography. The primary focus of the field collection process was to collect ground control points across the entire area, particularly for classes which were difficult to distinguish such as bottomland hardwoods, upland hardwoods, and emergent herbaceous wetlands. Where access was limited, sample points were offset from the road using distance and bearing. A total of 519 field points were collected from February 16, 2007 - February 20, 2007. The horizontal accuracy of the points ranged from 0.4 to approximately 4 meters. Prior to classification, spatially redundant and erroneous points were removed from the dataset. The high-resolution aerial photography provided by M7 was used to collect additional class samples for under-sampled classes and areas, after

establishing a baseline of knowledge about the appearance of each class by overlaying the in situ samples. The total number of points collected numbered 881 (Figure B-1).

Methodology

All image and GIS data were stacked into a single file compatible for classification within multiple software packages: Definiens Professional 5.0, ERDAS Imagine 9.0, and ENVI 4.4. The final stack contained the following bands: the four original SPOT bands, NDVI, NIR texture variance, SWIR texture variance, the two PCA bands derived from SPOT imagery, LiDAR derived nDSM, LiDAR derived DTM, DTM derived slope, DTM derived aspect, the three original NAIP bands, the PCA band derived from NAIP imagery, the NHD derived distance to the Sulphur River and tributaries, SSURGO percent hydric soils, and NWI/NLCD wetland locations. Supervised pixel-based classification was performed first. In order to divide points into sampling and training, the points were plotted in an n-dimensional visualizer. Approximately 150 points occurred in areas of spectral overlap between classes. These points were placed in the accuracy subset of points in order to avoid using potentially confusing points to train the classifier. The remaining points were randomly split into accuracy and training. Approximately thirty percent of the full count of points was used for training with approximately seventy percent used for accuracy assessment after the classification was complete. Removing the potentially confusing points improved the quality of the training data while avoiding the bias which would be introduced by manually selecting the purest samples for each class.

I performed the supervised pixel-based classification using iterative band combinations in order to determine the ideal band combination, based on quantitative and qualitative accuracy assessment. The Maximum Likelihood Classification method was the specific technique used. For the rule-based classification, I created input files for See5 data mining software and randomly selected 400 training samples in order to create the decision trees. A large number of points were used in the training set because the recursive splitting technique employed by See5 relies on a large number of points per class in order to capture within-class variability and create meaningful splits. The remaining points were held aside for accuracy assessment. Cross validation, boosting, and pruning techniques were also employed to improve the effectiveness of the classification trees. I allowed the data mining software to create splits based on all twenty input bands so that useful splits, which may or may not be user intuitive, could be identified. The software output a ranking of datasets in terms of importance; based on how often each input band was used to create class splits (Table A-4). Twenty boosted decision trees were used in the final classification, with each undergoing 25% global pruning. All twenty decision trees "voted" on the classification of each pixel for the entire study area. A 3X3 majority filter was applied to the final pixel-based and rule-based classifications in order to remove isolated misclassified pixels. Accuracy assessment was conducted using an error matrix which generated an overall accuracy, kappa coefficient, and producer's and user's accuracies for each class.

The object-based classification was conducted using Definiens Professional 5.0 with a focus on optimizing segmentation parameters prior to classification. I used the

See5 ranking of inputs to determine which inputs to incorporate. The homogeneity criteria were determined by analyzing the more accurate of the two classifications with class-level landscape metrics. The homogeneity criteria are governed by two sets of weightings: shape vs. color and compactness vs. smoothness. The weightings are crucial in the segmentation process as they determine which characteristics are more important for the creation of image objects. A higher shape weighting increases object heterogeneity at the expense of spectral homogeneity (Definiens, 2006). The ideal shape vs. color weighting was determined by calculating the shape complexity of real-world patches, as represented by the most accurate classification conducted using non-object-based methods. The metric used to quantify shape complexity was the average class-level Shape Index, which is the border length of the image object divided by four times the square root of the object's area. The denominator approximates the border length of a square with the same area, thus the ratio computed using the actual border length approximates how fractal, or complex, the image objects actually are. Shapes are more complex as the ratio increases above 1. I multiplied the average Shape Index for each class by the class' area and determined how much this deviated from an average Shape Index of 1, which represents perfectly symmetrical non-complex shapes. I took the average "Percent Complexity" across the entire landscape and adjusted the shape vs. color weighting accordingly (Table A-10). The ratio exceeding 1 was allocated to the shape weighting; subtracting 0.1 since the shape criterion is only allowed by Definiens to be adjusted to 0.9 (Definiens, 2006).

The ideal compactness vs. smoothness weighting was determined by calculating the compactness of real-world patches, as represented by the most accurate classification conducted using non-object-based methods. A higher compactness weighting optimizes creation of image objects that are more compact, even if these objects are weakly separated by spectral contrast. If this weighting was allocated towards smoothness, the objects would be less compact with large perimeters in relation to their area (Definiens, 2006). I approached the weighting determination from the compactness standpoint. The metric used to quantify the level of object compactness was the average class-level Compactness, which is the border length divided by the square root of the number of pixels within the object. A feature with a value of 1 is perfectly compact. I multiplied the average Compactness for each class by the class' area and determined how close the value was to ideal compactness. I took the average "Percent Compactness" across the entire landscape and used it to adjust the compactness vs. smoothness weighting (Table A-11). The ratio out of 1 was allocated to the compactness weighting.

I determined the ideal scale parameter by analyzing the mean patch size of iterative segmentations, using the heterogeneity criteria determined through the previous steps. I performed segmentation using these parameters with a number of different scale parameters, in order to establish a relationship between scale parameter and the mean patch size. Specifically, I segmented the imagery using scale parameters of 5, 7.5, 10, 12.5, 15, 17.5, and 20. I determined the mean patch size that resulted from each and formed a linear relationship between the scale parameter and the mean patch size. I then plugged the minimum class-level patch size, as represented by the most accurate

classification conducted using non-object-based methods, into the regression in order to determine the ideal scale parameter to produce image objects nearest in size to the real-world objects. After the ideal parameters were determined, I performed one object-based classification using these parameters and three using the default segmentation parameters with varying scale parameters. The same training points were used in both classifications and accuracy assessment was conducted using an error matrix to generate an overall accuracy, a kappa coefficient, and producer's and user's accuracies for each class.

Results and Discussion

Results from the iterative supervised classifications demonstrate that the classifications improved substantially when the SPOT PCAs were utilized rather than the original SPOT bands. The classifications did not improve by including the texture variance measures, topographic derivations, NAIP leaf-on imagery, or other ancillary datasets. The most accurate supervised classification method resulted from using the first two SPOT PCAs, the NDVI, the LiDAR nDSM, and the LiDAR last return elevation as inputs. This resulted in an accuracy of 78.66% after the majority filter was applied. The rule-based approach produced better results, as the method more effectively incorporated the additional NAIP, topographic, and ancillary datasets. The rule-based classifier developed robust decision trees via data mining techniques using training samples and multiple independent variables. Twenty boosted decision trees were used in the final classification, with each undergoing 25% global pruning. The

additional datasets were better suited for the rule-based classification since they were only incorporated when the data mining software found them useful in separating out a specific class. The machine developed decision tree also produced unexpected and useful rules for class splitting. An overall accuracy of 84.41% was obtained after the majority filter was applied.

Since the rule-based classification outperformed the pixel-based classification in terms of both qualitative and quantitative accuracy, I analyzed it using landscape metrics in order to determine the ideal segmentation parameters. I used the See5 ranking of inputs to determine which inputs to incorporate. The following bands were incorporated in the segmentation process: the four original SPOT bands, the NDVI, and the nDSM. The nDSM was given a weighting of four with the expectation that image objects would be formed around real world objects, due to a greater emphasis on the laser-derived elevation of ground features. All other bands were given a weighting of one. A few additional bands were included in the classification process but were not used in the segmentation process: both SPOT PCAs, the NIR Variance, and the Percent Hydric Soils. The results of the homogeneity criteria calculations are summarized in Tables A-10 and A-11. The shape vs. color weighting is presented first. The average class-level shape index multiplied by area is 10,684.68, and the ideal average shape index multiplied by area is 8,285.09. After subtracting 0.1 from the actual over ideal ratio, to compensate for the fact that the Definiens shape weighting can only be set as high as 0.9, the ratio minus 1 was 0.19. Thus I set the shape weighting as 0.2 and the color weighting as 0.8. The compactness vs. smoothness weighting is presented next. The

average compactness multiplied by area is 4,789.92 and the ideal average compactness multiplied by area is 8,285.09. The actual over ideal ratio came to 0.58. Thus I set the compactness weighting as 0.6 and the smoothness weighting as 0.4. The results of the scale parameter calculations are presented in Table A-12. After plugging the minimum mean patch size (0.075 ha) into the regression, the resulting scale parameter is found to be 5.74. I then rounded down to the nearest whole number and set the scale parameter in Definiens to a value of 5.

The arbitrary parameters that I used are the default segmentation parameters in Definiens Professional 5.0: a color weighting of 0.9, a compactness weighting of 0.5, and scale parameters of 5, 10, and 15. The same input layers and layer weights which were used in the ideal classification were used in the segmentation and classification processes. Respectively, 462,418, 101,613, and 42,515 image objects were created as a result of these segmentations. The overall accuracies after these image objects were classified were 70.67% (scale parameter of 5), 73.72% (scale parameter of 10), and 72.13% (scale parameter of 15). The kappa coefficients were 0.6612 (scale parameter of 5), 0.6977 (scale parameter of 10), and 0.6793 (scale parameter of 15). The final ideal parameters were a color weighting of 0.8, compactness weighting of 0.6, and a scale parameter of 5. 499,574 image objects were created by this segmentation, and an overall accuracy after classification was 76.37%. The kappa coefficient was 0.7277. The ideal parameters led to image objects better representing real-world landscape patches; the results also proved better quantitatively once they were classified using identical training

and accuracy settings. The final map, developed using the ideal parameters, is displayed in Figure B-5.

The initial classifications which were performed to establish the representation of real-world landscape patches proved useful in several ways in addition to providing the basis for landscape metric analysis. First, the ranking of band usage which was output by the rule-based software helped determine which bands should be incorporated in the object-based classification. Second, the comparison between pixel-based and rule-based classification demonstrates the value of both methods and the error matrix reveals specific class-level benefits of each method. A greater comparison between the use of pixel-based, rule-based, and object-based methods for this study area and data inputs is provided in the second chapter. The results of this study confirm the work of other studies that demonstrated accuracy improvements of rule-based (Bolstad and Lillesand, 1992; Baker et al., 2006; Daniels, 2006) and object-based classification methods over traditional pixel-based methods. However this study represents an improvement over standard object-based classification due to the use of intelligent segmentation methods prior to classification of image objects. This intelligent segmentation represents an advance beyond the justification of segmentation parameters through repeated trials (Darwish et al., 2003; Collins et al., 2004) or the assignment of parameters based on general guidelines (Kressler et al., 2003; Syed et al., 2005; Brennan and Webster, 2006). Additionally, the research expands on the work of Ivits et al. (2002) and Frohn (2006) as landscape metrics are integrated with the segmentation phase of object-based classification rather than the classification or assessment phase. The segmentation

process is a powerful process that has not been fully exploited to maximize the accuracy of object-based classification. I feel that the landscape metric analysis and statistical techniques presented here are an important step in maximizing the validity of the segmentation process by bringing image objects to more closely resemble real-world landscape patches.

Conclusions

Each of the stated objectives was achieved throughout the course of this research. The pixel-based and rule-based classifications of SPOT-5, LiDAR, and ancillary data both resulted in an accuracy >75% as evaluated by error matrices created with ground truth points. The rule-based classification outperformed the pixel-based classification, with an approximately six percent improvement in overall accuracy. Since the rule-based classification was the more accurate of the two classifications, it was analyzed using landscape metrics which were subsequently linked to heterogeneity criteria in Definiens Professional 5.0. The ideal scale parameter was determined by performing several segmentations and using the various scale parameters and resulting mean patch sizes to create a linear regression, into which the actual mean patch size was input in order to determine the ideal scale parameter. The performance of the ideal parameters was compared to the performance of arbitrary parameters, and the accuracy resulting from the classification of objects created using ideal parameters was approximately three to six percent higher than the accuracy resulting from arbitrary parameters. These results demonstrate that landscape metrics can be successfully linked to segmentation

parameters in order to create image objects that more closely resemble real-world objects and result in a more accurate final classification. Additional research into intelligent segmentation should be a priority for remote sensing scientists interested in image classification, and working within the framework of widely-used software is the most useful avenue. The methodology demonstrated here should be tested in different landscapes in order to see if it is effective in maximizing segmentation validity for a variety of land cover types. Other image inputs should be tested as well, especially high-resolution imagery. Again, the more common image inputs are the most useful to investigate. Further investigation of landscape metrics that can be linked to segmentation parameters would be an extremely useful area of research.

CHAPTER IV

CONCLUSIONS

The results of Chapter II found that the rule-based classification outperformed both pixel-based and object-based methods for this system and for these inputs. The rule-based had an 84.41% overall accuracy and outperformed the other classification methods because it more effectively incorporated the LiDAR and ancillary datasets when needed, without confusing the classifier. The rule-based classifier accomplished this via data mining techniques that use training samples and multiple independent variables to develop robust decision trees. Twenty boosted decision trees were used in the final classification, with each undergoing 25% global pruning. The rule-based classification output was compared to previous Landsat MSS and Landsat ETM derived classifications from 1974, 1984, 1991, and 1997 to determine abundance trends in the area's bottomland hardwood forests. The classifications from 1974-1991 were conducted using identical class definitions and input imagery (Landsat MSS 60m), thus the direct comparison provides a good indication of the overall declining trend. The trend levels off in 1997 when medium resolution imagery was first utilized (Landsat TM 30m), as additional forest patches were detected at that time. Likewise, the 2005 classification shows an increase in bottomland hardwood from 1997 to 2005 when SPOT-5 10m imagery was used. However, when the classifications are re-sampled to the same resolution (60m), the percent area of bottomland hardwood consistently decreases from 1974-2005.

The results of Chapter III found that the “ideal” segmentation parameters outperformed the arbitrary segmentation parameters. This research justified the selection of segmentation parameters through an iterative process that utilized landscape metrics and statistical techniques to determine “ideal” segmentation parameters prior to classifying SPOT-5 Imagery and LiDAR data. The Shape Index and Compactness were computed for real-world land cover features, as represented by the more accurate of two previously conducted classifications: rule-based and supervised pixel-based. The classification resulting from “ideal” segmentation outperforms the classification resulting from arbitrary segmentation by approximately three to six percent in terms of overall accuracy. This methodology should be tested in different landscapes in order to see if it is effective in maximizing segmentation validity for a variety of land cover types. Other image inputs should be tested as well, especially high-resolution imagery. Further investigation of different landscape metrics that can be linked to segmentation parameters, including the development of custom metrics, would also be an extremely useful area of research.

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APPENDIX A

Table A-1. Climatic Conditions for the Study Area

Climatic Variable	30-year Annual	2004 Annual	30-year December	2004 December	30-year January	2005 January
Precipitation (cm)	122.58	104.62	11.46	4.67	7.77	10.08
Average Temp (°C)	17.46	17.88	7.46	7.38	6.06	8.93
Minimum Temp (°C)	10.90	11.88	1.22	0.34	-0.14	3.33
Maximum Temp (°C)	24.02	23.89	13.72	14.43	12.26	14.54

Table A-2. Accuracy Assessment of Supervised Classification Inputs

	Maximum Likelihood Classification Inputs	Overall Accuracy	Kappa Coefficient
1	SPOT, NDVI, nDSM, LR	72.13%	0.6804
2	PCA, NDVI, nDSM, LR	78.66%	0.7553
3	PCA, NDVI, nDSM, LR, NIR and SWIR Var	77.43%	0.7415
4	PCA, NDVI, nDSM, LR, Slope and Aspect	78.31%	0.7514
5	PCA, NDVI, nDSM, LR, Slope	78.31%	0.7515
6	PCA, NDVI, nDSM, LR, Aspect	78.13%	0.749
7	PCA, NDVI, nDSM, LR, NAIP	75.84%	0.7224
8	PCA, NDVI, nDSM, LR, PCANAIP	77.78%	0.7454
9	PCA, NDVI, nDSM, LR, NHD, NWI, SOILS	40.74%	0.3319
10	PCA, NDVI, nDSM, LR, NHD	75.49%	0.7193
11	PCA, NDVI, nDSM, LR, NWI	43.39%	0.3604
12	PCA, NDVI, nDSM, LR, SOILS	77.95%	0.7472

Table A-3. Accuracy Assessment of Additional Classifications

	Classification	Overall Accuracy	Kappa Coefficient
13	Grouped ISODATA Clusters	43.36%	0.37
14	Rule-Based, random training	81.49%	0.79
15	Filtered MLC Pixel-Based Classification	78.50%	0.76
16	Filtered Rule-Based, random training	83.58%	0.81
17	Rule-Based, edited training	77.23%	0.74
18	Filtered Rule-Based, edited training	79.37%	0.76
19	Rule-Based, with mask	84.41%	0.82
20	Object-Based Classification	76.37%	0.73

Table A-4. Rule-Based Input Usage

Input	Usage		Input	Usage		Input	Usage
SPOT PCA 1	100%		NIR Variance	95%		NAIP PCA	61%
SPOT PCA 2	100%		% Hydric Soils	85%		LiDAR Last Return	50%
NDVI	100%		Spot Band 1	84%		Aspect	50%
SPOT Red	100%		NWI/NLCD data	73%		NAIP Green	46%
SPOT SWIR	100%		Slope	63%		SWIR Variance	30%
NAIP Red	100%		Spot Band 2	61%		Distance to NHD	16%
LiDAR nDSM	100%		NAIP Blue	61%			

Table A-5. Classification Accuracies for Final Map

Class	Producer Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (%)	User Accuracy (Pixels)
Agriculture	65.71	23/35	92.00	23/25
Bottomland	89.74	70/78	82.35	70/85
EHW/Sec. BL	53.13	17/32	80.95	17/21
Grassland	92.65	63/68	77.78	63/81
Pine	90.91	50/55	87.72	50/57
Pine Mix	65.22	15/23	68.18	15/22
Upland	86.15	56/65	78.87	56/71
Urban/Other	81.82	54/66	100.00	54/54
Water	98.31	58/59	89.23	58/65

Table A-6. Land Cover/Use Classes (1974-1991)

LC/LU class		hectares		
		1974	1984	1991
1	Water	216.12	130.25	313.33
2	Pine and Pine Mix	324.05	294.08	604.15
3	Bottomland hardwood	10,394.15	8,363.65	7,948.37
4	Upland hardwood	6,346.14	5,533.34	5,257.72
5	Grass / Agriculture	8,747.55	11,002.17	11,227.08
6	Urban/Other	174.11	871.51	853.67
	Total Area	26,202.12	26,195.00	26,204.32

Table A-7. Land Cover/Use as Percent of Total Area (1974-1991)

LC/LU class		% of area		
		1974	1984	1991
1	Water	0.82	0.50	1.20
2	Pine and Pine Mix	1.24	1.12	2.31
3	Bottomland hardwood	39.67	31.93	30.33
4	Upland hardwood	24.22	21.12	20.06
5	Grass / Agriculture	33.38	42.00	42.84
6	Urban/Other	0.66	3.33	3.26
	Total	100.00	100.00	100.00

Table A-8. Land Cover/Use Classes (1997)

	LC/LU class	Hectares	%
1	Water	5,668.43	21.63
2	Wetlands	383.55	1.46
3	Pine/ Pine Mix	42.01	0.16
4	Bottomland hardwood	6,565.52	25.06
5	Upland hardwood	4,403.96	16.81
6	Grass	8,022.28	30.61
7	Agriculture	723.68	2.76
8	Urban/Other	394.71	1.51

Table A-9. Land Cover/Use Classes (2005)

	LC/LU class	Hectares	%
1	Agriculture	149.24	0.57
2	Bottomland Hardwood	10,870.84	41.49
3	EHW/Secondary Bottomland Hardwood	1,085.36	4.14
4	Grassland	6,599.17	25.19
5	Pine	306.49	1.17
6	Pine Mix	581.20	2.22
7	Upland Hardwood	5,811.90	22.18
8	Urban/Other	69.90	0.27
9	Water	725.66	2.77
	Total Area	26,199.75	100.00
	LC/LU class	Hectares	%

Table A-10. Percent Complexity Calculations developed using Landscape Metrics

Class	Total Area (ha)	Shape Index	Shape Index Multiplied by Area
Agriculture	2124.50	1.19	2518.39
Bottomland Hardwoods	20809.75	1.26	26181.84
Emergent Herbaceous Wetlands	2645.18	1.23	3263.54
Grasslands	22897.32	1.32	30157.97
Pine	1788.69	1.18	2113.50
Pine Mix	1809.10	1.22	2209.41
Upland Hardwoods	19646.92	1.32	25983.13
Urban	368.11	1.23	454.13
Water	2476.23	1.32	3280.24
	Average Actual Shape Index:		10684.68
	Average Ideal Shape Index:		8285.09
	Percent of ideal:		1.29
	Percent after subtracting 0.1:		0.19

Table A-11. Percent Compactness Calculations developed using Landscape Metrics

Class	Total Area (ha)	Compactness	Compactness Multiplied by Area
Agriculture	2124.50	0.62	1317.03
Bottomland Hardwoods	20809.75	0.59	12210.86
Emergent Herbaceous Wetlands	2645.18	0.60	1577.80
Grasslands	22897.32	0.57	13113.30
Pine	1788.69	0.62	1106.97
Pine Mix	1809.10	0.60	1083.16
Upland Hardwoods	19646.92	0.57	11121.17
Urban	368.11	0.61	223.60
Water	2476.23	0.55	1355.35
	Average Actual Compactness:		43109.24
	Average Ideal Compactness:		74565.80
	Percent of ideal:		0.58

Table A-12. Scale Parameter Calculations developed using Linear Regression

Scale Parameter	Resulting Mean Patch Size
5	0.210715
7.5	0.499869
10	0.901689
12.5	1.395736
15	1.998064
17.5	2.710008
20	3.506899
Minimum Actual Patch Size (ha)	0.075
Forecast Scale Parameter Output	5.74

Table A-13. Class-level accuracies for final map, developed by rule-based methods

Class	Producer Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (%)	User Accuracy (Pixels)
Agriculture	65.71	23/35	92.00	23/25
Bottomland	89.74	70/78	82.35	70/85
EHW/Sec. BL	53.13	17/32	80.95	17/21
Grassland	92.65	63/68	77.78	63/81
Pine	90.91	50/55	87.72	50/57
Pine Mix	65.22	15/23	68.18	15/22
Upland	86.15	56/65	78.87	56/71
Urban/Other	81.82	54/66	100.00	54/54
Water	98.31	58/59	89.23	58/65

APPENDIX B

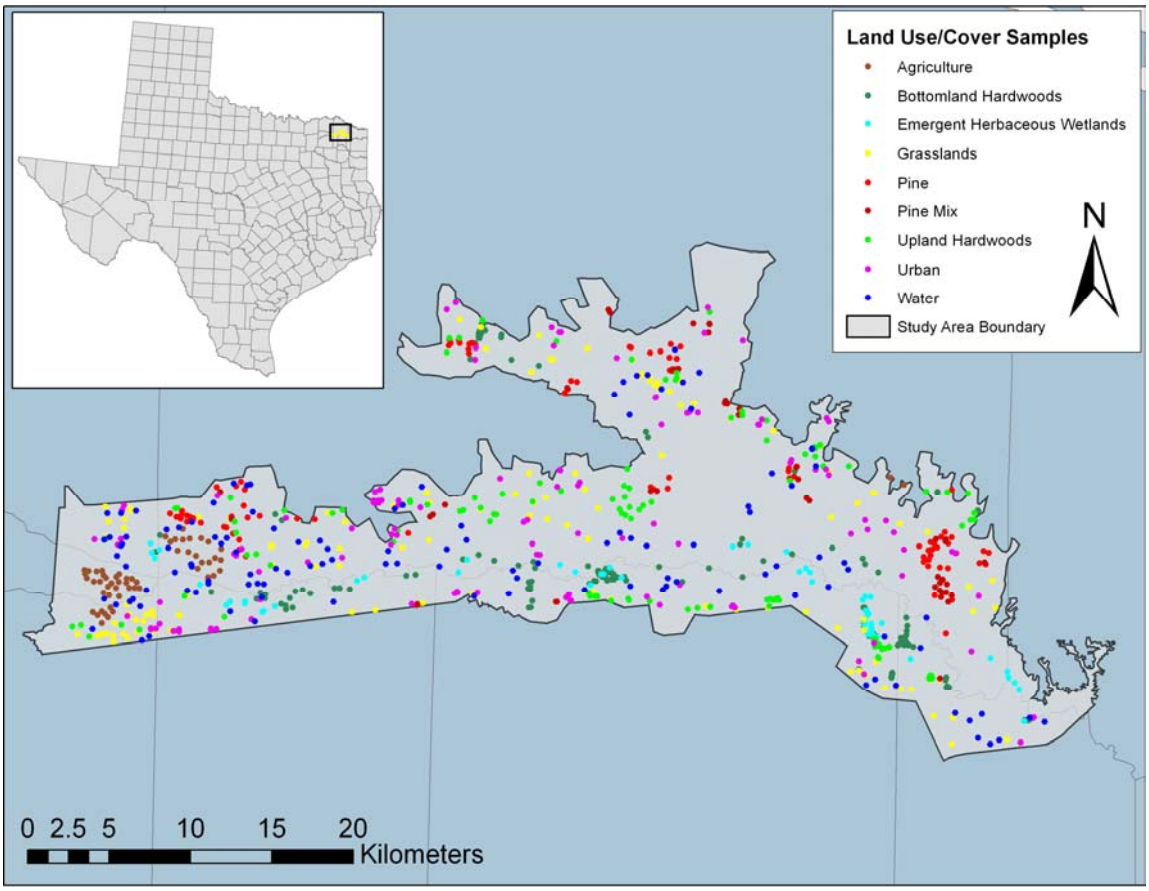

Figure B-1: Location of study area and distribution of ground truth points utilized in classification

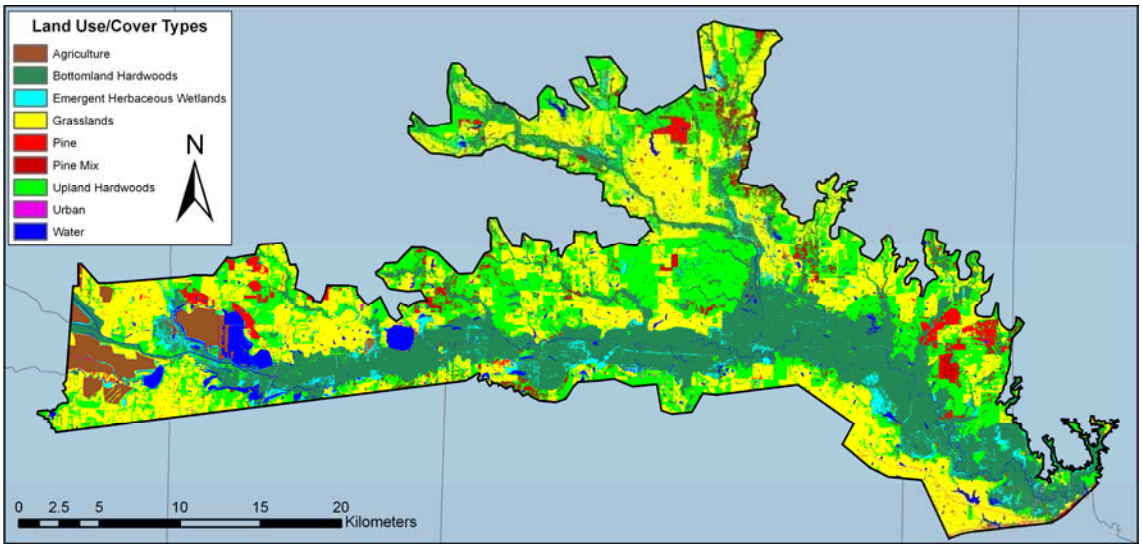

Figure B-2: Final land cover/use map produced using Rule-based methods and manual delineation

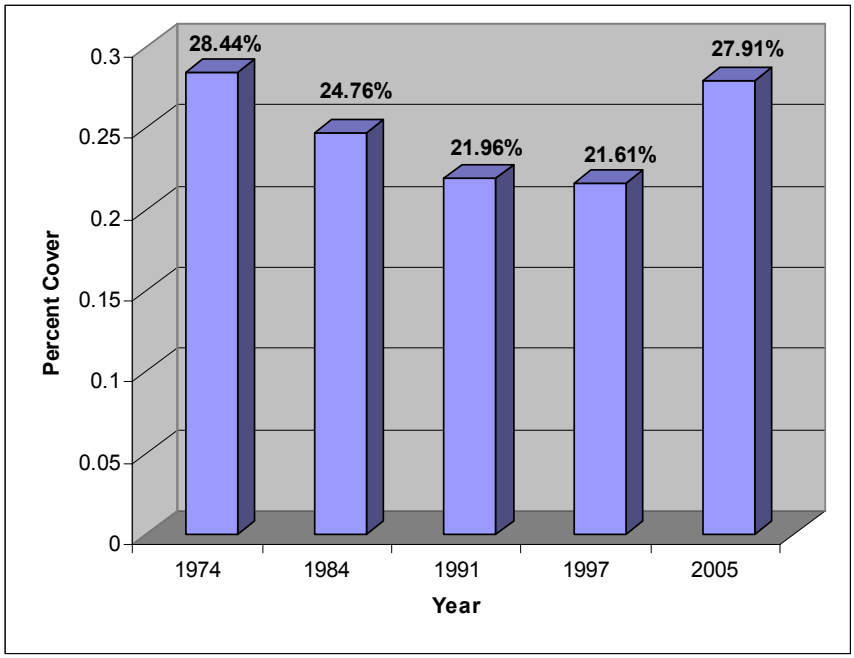

Figure B-3: Change in bottomland hardwood percent cover from 1974-2005 based on 60m, 30m, and 10m resolutions

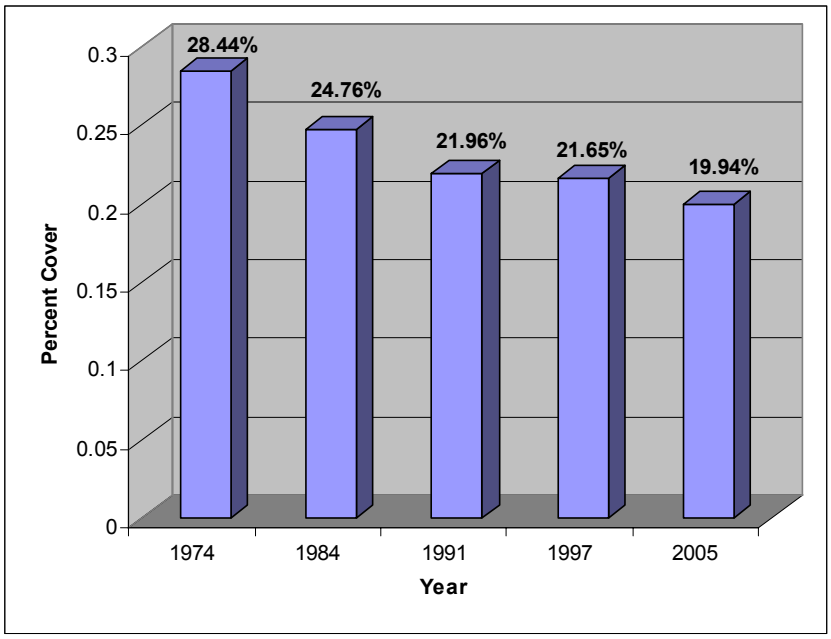

Figure B-4: Change in bottomland hardwood percent cover from 1974-2005 based on 60m resolutions as re-sampled from original results

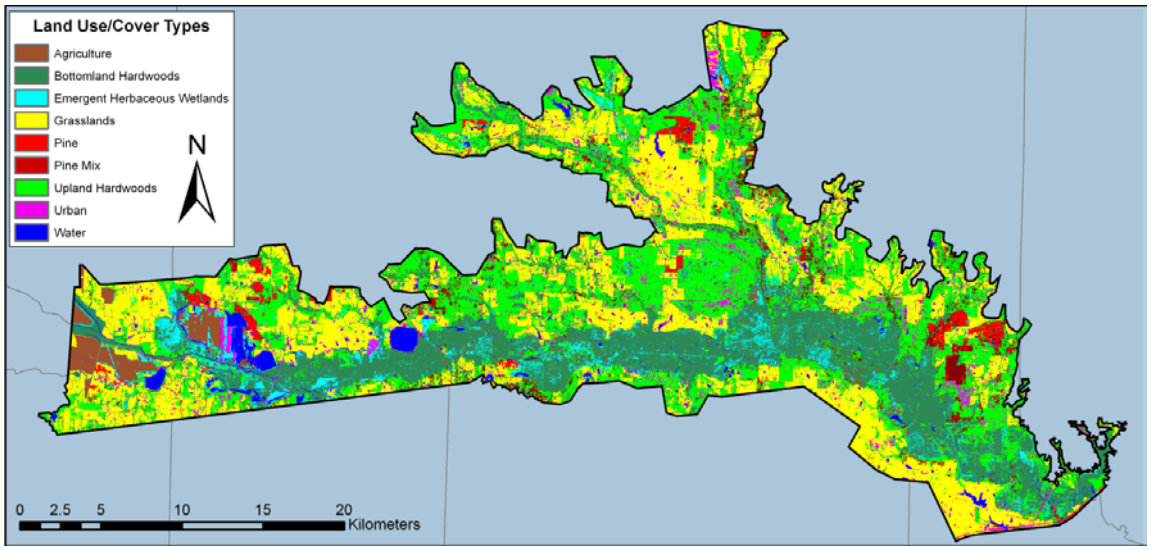

Figure B-5: Final land cover/use map produced using ideal segmentation parameters and object-based classification methods

VITA

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