ABSTRACT

BAILEY, ANDREW DANIEL. Detection and analysis of changes in clear-cut harvest patterns using remote sensing and GIS. (Under the direction of Dr. Heather M. Cheshire.)

During the last two decades of the 20th century, policies and practices affecting clear-cut harvesting in North Carolina have changed. Increased harvesting levels, voluntary limits on clear-cut size and location within the forest products industry, and the introduction of wood chip mills are potential sources of change in clear-cutting patterns across the landscape. An investigation of potential changes was conducted by mapping clear-cuts and using landscape metrics to quantify landscape pattern change.

For a 13,000 square kilometer area in northwestern North Carolina, unsupervised image classification techniques were used to classify multiple Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) datasets collected in 1984 and 2000. General land use and land cover maps were produced in which clear-cut areas had been separated from agricultural and developed cleared areas. Clearcut area was slightly overestimated during this procedure to minimize the chance of misclassifying clear-cut areas. An accuracy assessment was completed using digital and hardcopy aerial photography, finding overall accuracy of 82% for 2000 and 76% for 1984 land use and land cover datasets. Superior data from the Landsat ETM+ sensor accounted for the higher accuracy of the 2000 dataset when compared the dataset compiled for 1984 using lower quality

Landsat TM datasets. Potential methods for increasing the accuracy of future studies are discussed. Based on the results of this study, it is likely that further refinement of the detection technique could lead to greater clear-cut detection accuracy.

Several metrics were calculated on the 1984 and 2000 datasets to estimate landscape change in clear-cut harvest patterns in response to changing practices and policies. Over the study time period, the amount of clear-cut area detected increased. This change is coincident with an increase in the number of wood chip mills in and around the study area. Most of the increase in area is attributable to a large increase in the number of small clear-cut patches, while large clear-cut patches occurred less frequently in 2000 than in 1984. This change is coincident with the development of policies designed to restrict the size of individual clear-cut patches. Also, more clear-cut patches were detected in mountainous areas in 2000 than in 1984. Suspected reasons for this change include improved transportation infrastructure into high elevation areas and changing tree species needs by wood products companies. Distances from clear-cut patch to chip mill increased during the time period, indicating that the arrival of chip mill technology at the beginning of the study time period has not resulted in clear-cuts that are located closer to mill sites. Measurements of forest patch shape showed no significant change between 1984 and 2000 though visual analysis of the classified land cover maps suggests that changes have occurred. Potentially more useful approaches to measure effects of policy and practice change on forest patch shape are discussed.

DETECTION AND ANALYSIS OF CHANGES IN CLEAR-CUT HARVEST PATTERNS USING REMOTE SENSING AND GIS

by

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DEDICATION

This work is dedicated to my parents, Carl and Ruth Bailey, who raised me to think freely and to think big, and started me out camping at a young age.

BIOGRAPHY

The author is a native North Carolinian born in Greenville North Carolina, in 1978. After a short stay in Ayden, NC, his family moved to the Raleigh area, where he attended public schools, began to love reading, and learned to camp. A sincere appreciation for all things natural was nurtured as he rose through the ranks of Boy Scout Troop 216 in Cary, North Carolina, where he achieved the Eagle Scout Award just before his 18th birthday. Participation in the Cary High School marching band and church activities at First Baptist Church of Raleigh rounded out a busy and rewarding high school experience. After graduating from Cary High School he began an undergraduate program at NC State University, graduating in 2001 with a Bachelor of Science in Forest Management and a minor in computer science. Combining his interests in natural resources and computers, he enrolled as a Master of Science student in Forestry, becoming proficient in using Geographic Information System (GIS) technology to solve natural resource management problems. As a graduate research assistant, he worked on diverse projects including growth and yield simulation programming, clear-cut detection and mapping, and forest management database design. This document is the summation of his clear-cut detection work.

The author hopes to continue applying his knowledge and experience in GIS to natural resource issues, particularly in the field of forest ecology. As a scientist, he will seek to protect for future generations the natural world which provoked his curiosity and wonder as a child.

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Chapter 1

Literature review: Changing forestry policies and practices in North Carolina, vegetation classification, and clear-cut detection

1.1 Changes in harvesting policies and practices in North Carolina

1.1.1 Policy change

During the last 40 years, the attitude of the American public regarding natural resources has changed (Kessler et al. 1992). This has led to a variety of policy changes directed at changing the way forests are used to benefit the public, including changes in forest harvesting policy. Voluntary limits to clear-cut size have been enacted due to concerns that clear-cutting leads to watershed pollution, negative visual impacts, and changes in natural processes. Among these voluntary limits is the Sustainable Forestry Initiative (SFI) program, endorsed by the American Forest and Paper foundation (Sustainable Forestry Initiative 2002). SFI includes a set of industry guidelines that imposes a maximum average clear-cut size limit of 120 acres (48 hectares) for all harvesting activities during any year. The guidelines are designed to allow some flexibility for adapting management to a given site, but serve to discourage companies from using large numbers of very large clear-cuts. Forest products companies must adhere to this standard to maintain membership in the American Forest and Paper Association. Other trade associations have similar guidelines. In addition to adopting voluntary harvesting regulations, many private industries, government agencies, and private non-industrial forest landowners have voluntarily reduced maximum individual clear-cut size to between 60 and 90 hectares (Boston and Bettinger 2001). Several states additionally regulate private forests by mandating maximum clear-cut sizes, separation zones between clear-cut patches, and green-up requirements which specify periods of time during which land adjacent to a clear-cut may not be harvested (Barrett et al. 1998). The state of North Carolina currently has no such regulation.

1.1.2 Change in practices

Forest harvesting practices in the southeastern United States have also changed during the last 25 years. In the Pacific Northwest, the timber producing heartland of America, controversy over the effects of timber harvesting on water quality and endangered or threatened species prompted forest industry to seek more hospitable political and social climates. Forest harvesting rates in North Carolina increased as the focus of forest industry shifted to the southeast. As of 1997, more wood was being harvested from the southeast than from any other wood-producing region in the world (Cubbage and Richter 1998). In addition, large areas of forest land in North Carolina have been converted to other uses between 1982 and 1997, averaging 31,000 hectares (77,000 acres) per year (Schaberg et al 2000 [2]).

The introduction of chip mill harvesting technology has also raised concerns, particularly in western North Carolina. Chip mills are designed to use the wood of smaller diameter trees more efficiently than traditional sawmills, potentially opening more areas to harvest and increasing the amount of forest land harvested. This potential increase and the perceived reductions in water quality, degradation of wildlife habitats, and reduction in aesthetic qualities of forests as a result of harvesting (Warren 2000) raised citizen concerns in western North Carolina and helped prompt a comprehensive study of chip mill impacts in the late 1990s (Cubbage and Richter 1998). The chip mill study did not find direct evidence of chip mills leading to increased clear-cutting, but did find that chip mills can increase production efficiency to such a level that timber prices decline and increased clear-cutting becomes necessary to sustain profits (Schaberg et al. 2000 [1]).

To generate data for analyzing the impacts of clear-cut harvesting, clear-cuts and land cover can be located using remotely sensed satellite images. The generation of a land cover map requires the knowledge of the science of vegetation classification.

1.2 Vegetation mapping and classification

1.2.1 Basis of classification and impact of technology

Vegetation mapping in the United States began in earnest in the 19th century, and developed alongside the field of plant community ecology throughout the 20th century. Developments and theories presented in the field of plant community classification spurred new maps, and the latest maps fueled revolutions in vegetation classification theory (Kuchler 1967). Because humans can significantly alter the environment and change both what land is used for as well as what covers the ground, land use and land cover classifications have become equally as important as vegetation classifications. New technologies for data capture and analyses have been responsible in large part for the rapid advance of classification and mapping techniques in the latter part of the 20th century (Koch 2001). These advances include computers, aerial photography, and satellite sensors that have simplified the process of creating vegetation maps by providing new ways to gather and organize land cover and vegetation information (Muller 1997). Though technology has provided scientists the tools of Geographic Information Systems (GIS) and remote sensing (RS), the quality of a vegetation map still rests more heavily on the selected system of classification than on any other feature (Kuchler 1967). The basic tenets of vegetation, land use, and land cover classification remain the same: the method of classification must be appropriate for the intended use of the classification, and a

classification should satisfy the needs of its users “with minimum cost, time, and commitment of resources” (Kimmins 1997).

1.2.2 Classification schemes

The variety of land use, land cover, and vegetation classification schemes and the approaches used to develop them are an indicator of the many applications of land use and land cover maps. It is unlikely that a single method will ever emerge, because different user needs and environmental conditions favor different approaches (Kimmins 1997). This is not intended to be a definitive list of all classification approaches; indeed, entire books are devoted to the subject. Instead, several popular approaches and their applications are described.

The Danish ecologists Warming and Raunkiar dealt only with vegetative classes (Kimmins 1997), which they defined as plant communities with similar growth forms growing in the same type of environment. In this system, called physiognomic classification, the most general classes are called *formations*, and *associations* within these formations consist of plant communities with specific compositions. This approach has proved very useful for describing vegetation on a broad scale and for comparing vegetation types between continents (Kimmins 1997).

For classifying vegetation, many federal agencies are now using the Federal Geographic Data Committee (FGDC) National Vegetation Classification Standard (NVCS). In this scheme, the broad physiognomic approach has been merged with a more detailed floristic

approach (FGDC 1997). This classification system uses seven hierarchical levels, with the most general levels based on physiognomic traits and the most specific on floristic characteristics (FGDC 1997). This system allows flexibility for classifying at a very high level of detail while providing a basis for comparison of classifications between ecosystems. While this system is the newest classification system available, it is only designed to classify vegetation, and is not a land use or land cover classification scheme.

A popular approach at smaller scales, especially in the United States, involves classifying areas based on dominant species. The Society of American Foresters (Eyre 1980) created one such system that has found widespread use among scientists (Kimmins 1997). This system is closer in style to a land cover classification, because location, moisture regime, and other typical physiognomic traits are not considered. Advantages of this system include its simplicity and rapid implementation, as dominance is a very commonly cited attribute when describing forests. Certainly this system is very useful for classifying areas where individual stands have clear dominant species, at scales where stands are easily identified and delineated. Problems arise, however, when many species are co-dominant, or when the classified area is so large that classes defined by dominance begin to exhibit heterogeneity in non-dominant species makeup, or when non-forest areas must also be classified (Kimmins 1997). The low information requirement for this approach may still make it a more attractive method than other floristic approaches (Kimmins 1997).

Land use classification places areas into classes based on the anthropogenic use of an area. This can be difficult to determine without some ancillary data. Example of land use categories would be residential land, agricultural land, or pasture land. Land cover classification, on the other hand, takes into account the type of feature present on the surface of the earth. Examples of land cover classes are forested land, developed land, and grassland. Combining the two types is necessary for any task where land use must be inferred from land cover, such as when detecting clear-cuts. The US Geological Survey classification scheme, described below, is a combination of the two types of classification.

The US Geological Survey (USGS) designed one of the first land use and land cover classifications specifically for use with remotely sensed data in the mid-1970s (Anderson et al. 1976). This system was designed for use throughout the country and has four hierarchical levels for use with different resolutions of data. Level one is appropriate for data with 20 to 100 meter resolution, while level two requires 5 to 20 m data (Lillesand and Kiefer 2000). Categories in levels one and two are generalized land use and land cover types specified by the USGS, while categories at levels three and four are intended to be specified by users, generally for large-scale local and regional efforts. Lillesand and Kiefer (2000) note that many users who develop specialized classification schemes often base the concepts and structure of their classifications on the USGS/Anderson scheme.

1.3 Clear-cut detection

1.3.1 Beginnings of clear-cut detection

Clear-cut detection using remotely sensed data has traditionally focused on the tropics, particularly in the Amazon basin, where widespread clearing has resulted in the loss of 15,000 to 50,000 hectares annually beginning in 1970 (Brondizio et al. 1996). Several studies have successfully identified clear-cut areas in the Amazon using a variety of remotely sensed data sources with varying pixel sizes and image repeat intervals (Brondizio et al. 1996, Booth 1989, Skole and Tucker 1993). Early studies used the Advanced Very High Resolution Radiometer (AVHRR), which is designed to collect regional information on vegetation condition and water temperature daily with complete global coverage (Jensen 1996). AVHRR data has a very large pixel size (1 km per side), making it appropriate for applications involving very large areas. The Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM), and Systeme Pour l'observation de la Terre (SPOT) sensors have longer repeat intervals, are designed for larger-scale applications, and have multispectral pixel sizes of 60, 30, and 20 meters per side, respectively. Many early studies involved tracing deforested area boundaries on color transparencies of satellite images rather than using spectral information to separate land cover classes. Using transparencies lowers the cost of image acquisition but has the effect of lowering resolution and spatial accuracy.

1.3.2 Clear-cut studies in the United States

While much of the Amazon work is sponsored by South American nations, clear-cut detection has not received as much attention in the United States (Booth 1989). Clear-cut

detection using spectral information from Landsat TM and SPOT satellite sensors has been performed in the U.S. at an accuracy level at or above federal accuracy standards (Verbyla and Richardson, 1996), but dedicated detection efforts have been rare. Also, successful studies have been located in heavily forested areas rather than areas undergoing extensive anthropogenic disturbance.

Government agencies state that monitoring forests is not included in their mandates, or that funds are not available for such projects (Booth, 1989). To overcome funding shortages, the Multi-Resolution Land Characteristics Consortium (MRLC) was created by several federal agencies that have committed to funding the National Land Cover Dataset (NLCD), a consistent land use and land cover dataset for the U.S. (USGS 1999). This dataset is complete and was classified using a modified Anderson (1976) classification scheme, but clear-cuts are not separated from other transitional land cover types. The U.S. Department of Agriculture (USDA) Forest Service compiles statistics on the state of forests within US borders, but uses plot-based sampling methods rather than remotely sensed data, and does not release plot locations, citing privacy concerns.

Although the U.S. does not have a comprehensive program to monitor clear-cuts using remote sensing, several clear-cut studies have been conducted in North America. Silvicultural clear-cutting in the U.S. is a forest regeneration technique used to mimic widespread severe disturbances that kill virtually all vegetation (Seymour and Hunter 1999). This is different from cutting for development, which will not be covered here. Landscape ecologists have compared spatial patterns resulting from clear-cutting to the

natural disturbances mimicked by clear-cuts, finding significant differences. Clear-cutting produces a more heterogeneous landscape with smaller patches than does severe fire disturbance (Schroeder and Perera 2002).

Harvesting has been shown to change wildlife species composition. Because of their very nature, clear-cuts in a forested landscape create edge habitat and reduce forest interior habitat. Foundational research in landscape ecology states that when harvesting begins on an undisturbed forest, biodiversity increases as pioneer species populate the newly disturbed cutover area (Franklin and Foreman 1987). As harvesting continues to reduce the amount of undisturbed forest, species losses occur as the forest becomes more fragmented, culminating when all undisturbed forest is gone. This is true particularly for large interior forest dwelling carnivores such as wolves and bear. Other wildlife show opposite effects, for example, a study by Rudnicky and Hunter (1993) found that bird species diversity responds positively to increasing clear-cut size.

1.3.3 A clear-cut map for western North Carolina

The combination of changes in policy and practice in addition to shifting public perception of natural resource management activities has prompted interest in clear-cut harvesting activities among policy makers, concerned citizen groups, and scientists. This concern is especially visible in the western North Carolina piedmont and mountains, where tourism is a valuable industry and forest products are important to local economies. Voluntary restrictions designed to protect water quality and reduce visual impacts have been the primary response of forest managers and policy makers. A study

of changes in clear-cut sizes, shapes, and locations combined with a map of harvest activity could prove useful in measuring impacts of changing harvesting policy and practice on western North Carolina forests. No prior study has generated a map of clear-cut impacts or examined the problem spatially.

Chapter 2

Clear-cut detection using remotely sensed data

2.1 Introduction

2.1.1 Clear-cut harvesting

Clear-cut harvesting is a common forest harvesting technique in the eastern United States that involves harvesting all the trees in a forested area. While a clear-cut can be of any size, clear-cuts in the southeastern United States generally range from 4 to 60 hectares (10-150 acres) in size. Recently, in agreement with the Sustainable Forestry Initiative (SFI) and other forest certification standards, many forest products companies have voluntarily lowered their average clear-cut size to 48 hectares (SFI 2002) and set maximum individual clear-cut size limits between 60 and 90 hectares (Boston and Bettinger 2001). These guidelines give forest managers some flexibility, but are designed to discourage very large clear-cut patches.

Even as changing attitudes about forest harvesting have prompted a shift in industry policies, changing economic factors have altered harvesting practices in North Carolina. The introduction of chip mill harvesting technology starting in1982 (Schaberg et. al. [1] 2000) has raised concerns, particularly in western North Carolina. Chip mills are designed to more efficiently use the wood of smaller diameter trees than traditional sawmills, thus opening more areas to harvest and potentially increasing the amount of forest land harvested. Currently, more wood is being harvested from the southeast than from any other wood-producing region in the world (Cubbage and Richter, 1998), and clear-cutting is the dominant method of wood production in North Carolina (Schaberg et. al. [1] 2000). Because clear-cutting allows full sunlight to reach the forest floor, it favors shade-intolerant species such as Loblolly pine (*Pinus taeda*), white pine (*Pinus strobus*),

and yellow poplar (*Liriodendron tulipifera*), which can result in forest composition change if the regenerated forest replaces a hardwood-dominated forest type. While high levels of biodiversity are often apparent for the first years after a clear-cut, the needs of species dependent on mature forest are not provided for in stands of early successional species managed for timber (Moore and Allen 1999).

Because current legislation in North Carolina does not require landowners to report forest harvest activities, sizes, or locations, alternative methods for quantifying this landscape change must be pursued. Remote sensing using satellite data is an ideal way to approach this problem, providing multi-temporal data high in information content over a large area. High rates of growth are typical of early successional species during their first years of life, and the vigor of this growth is easily detectable by Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) data (Jensen 1996). The characteristic remnant vegetation left after harvesting operations cause clear-cut patches to appear very characteristically in remote sensing data (Lillesand and Kiefer, 2000), and provides a means for separating clear-cut areas from other bare earth areas using remote sensing classification techniques.

2.1.2 Study Area

The study area consists of 11 counties in the western Piedmont and Mountain regions of North Carolina covering 13,000 square kilometers (Figure 2.1). Elevations in this area range from 180 to 1740 meters (591 to 5709 feet) above sea level, and the topography becomes more rugged as elevations rise from east to west. As is true throughout the

North Carolina piedmont and mountain regions, forest is the dominant land cover (56% in 1990), followed by agriculture (39% in 1990) (Bailey in preparation). A wide range of forest types include loblolly pine plantations, oak-hickory uplands, nearly pure stands of both yellow poplar and white pine, and high-elevation spruce-fir. The counties selected for study were chosen based on their large percentage of forest cover and the abundance of chip mills, which may be associated with increasing clear-cut harvesting. Analysis of a USDA Forest Service geographic dataset containing chip mill locations for 2000 reveals that 13 mills are located inside or within 50 miles of this study area, 10 of which began operation after 1984 (Prestemon et. al. 2000). Fifty miles is the typical range from within which a chip mill will receive trees.

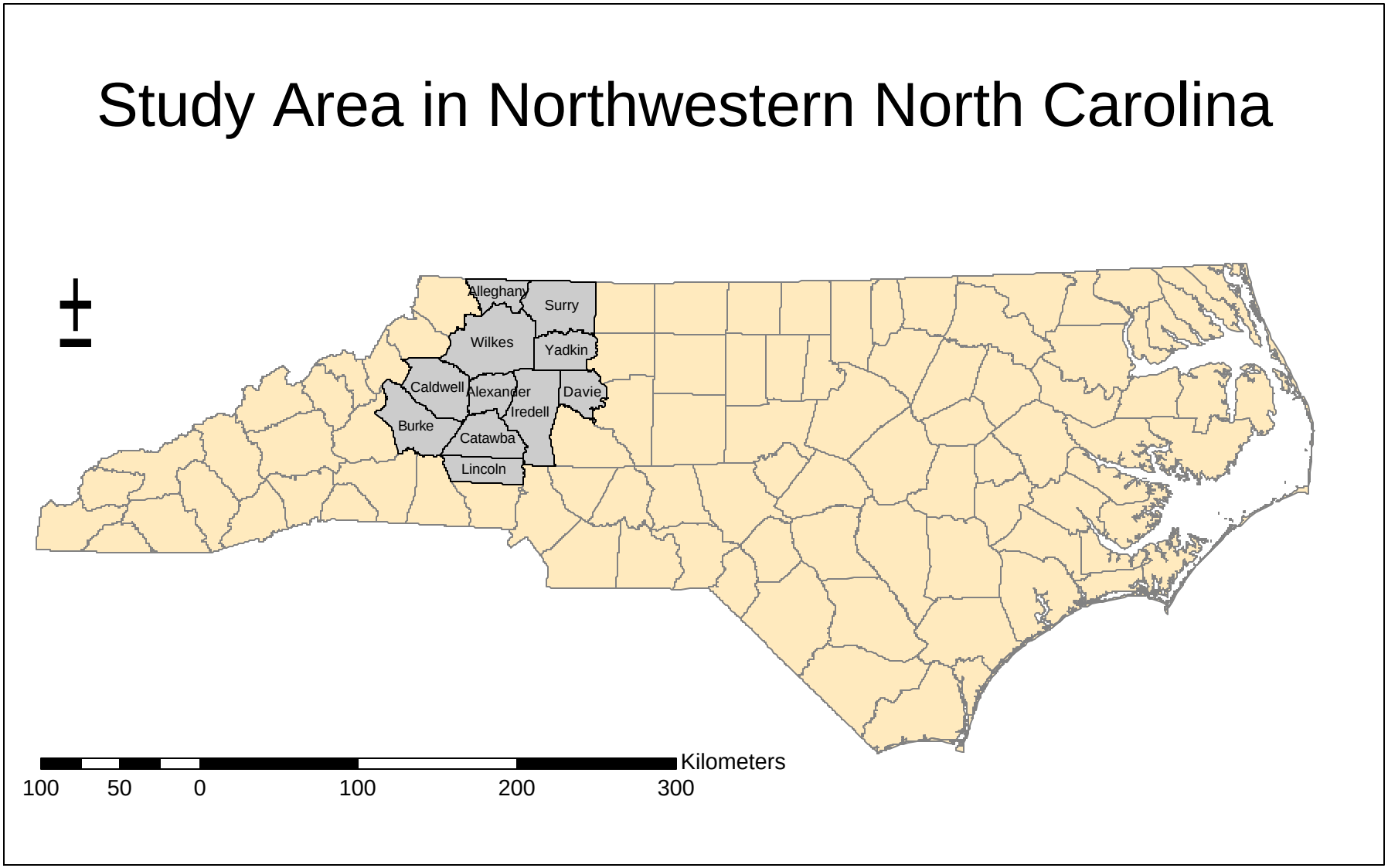

Figure 2.1 11-county study area in Norrth Carolina.

2.1.3 Objectives

- Develop a technique to identify and map forest clear-cuts in the western piedmont region of North Carolina using Landsat data.
- Generate land cover maps for the years 1984 and 2000 using the technique.
- Perform an assessment of classification accuracy.

2.2 Materials and Methods

All image manipulation, classification, and accuracy assessment were performed at the NC State University Center for Earth Observation (CEO) using the IMAGINE software package from Leica Geosystems (formerly ERDAS, inc.).

2.2.1 Data

The study takes advantage of existing satellite data that is available to the general public with the anticipation that the technique can be used in areas other than the original study area. Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data were used to find clear-cuts in 2000, while Landsat 5 Thematic Mapper (TM) data were used for 1984. Landsat records three visible spectral bands and three infrared bands at 30-meter resolution, two thermal infrared bands at 60-meter resolution, and one 15-meter resolution panchromatic band. Only the 30-meter visible and near-infrared bands were used in this analysis because of the very coarse resolution of the thermal infrared bands and the difficulty of interpreting panchromatic data. Use of both summer and winter images for both image dates emphasizes phenological differences and provides more data to aid in classification. Small-scale color infrared (CIR) digital and hardcopy aerial photography were used for

accuracy assessment. Chip mill locations were available in digital format from the USDA Forest Service Southern Research Station at http://www.rtp.srs.fs.fed.us/econ/data/mills/chip2000.htm (Prestemon 2000). The study area occupies the western half of one Landsat scene (Path 17, Row 35). Image data information is described in Table 2.1.

Table 2.1
Image data used for classification and accuracy assessment.

Image source	Resolution	Acquisition Date	Source
Landsat 7 ETM+	30 meter	June 10, 2000	NC State Libraries GIS Services
Landsat 7 ETM+	30 meter	March 6, 2000	NC State Libraries GIS Services
Landsat 5 TM	28.5 meter	June 6, 1984	US Geological Survey EROS data center
Landsat 5 TM	28.5 meter	November 13, 1984	US Geological Survey EROS data center
CIR NHAP Photos	1:58,000	1982-1984	Available in hardcopy from CEO
CIR NAPP Photos	1:40,000	January-March 1998	Digital and hardcopy coverages from CEO

2.2.2 Classification Scheme

The original USGS Anderson level I land cover classification scheme was used as the basis for classification in this study and consists of 9 classes present throughout the United States (Anderson et. al. 1976) and considered to be appropriate for image resolutions of 20 to 100 meters (Lillesand and Kiefer 2000). The USGS Anderson scheme was modified for this project by adding a class for clear-cut forest, and removing the barren land, perennial ice/snow, and tundra categories because they do not exist in North Carolina. Rangeland was combined with the agricultural land category, and the "other" class was added to capture areas of indeterminate land cover and areas obscured by clouds (Table 2.2).

Table 2.2
Classification scheme after modifying Anderson scheme to add a clear-cut class and remove classes not represented in the study area.

Class Number	Description
1	Urban/Built Up
2	Agricultural/Pasture
3	Forest
4	Water
5	Clear-cut Forest
6	Other

2.2.3 Preprocessing

Before classification, all Landsat images were geographically referenced to the June 10, 2000 image using 2nd order polynomial image-to-image rectification. Following registration, boundaries of all Landsat scenes standardized using the county boundaries of the study area. Feature space images and a variance-covariance matrix were analyzed to determine which spectral bands contained the most information and to remove bands containing redundant information, reducing computation time (Jensen 1996). To separate agriculture, forest, and water, spectral subsets of bands 3, 4, and 5 were determined to contain the most information and a subset was created from each image. Using the same process, spectral subsets of each image containing bands 2, 3, and 4 were determined to contain more useful information for separating agriculture and clear-cut areas.

2.2.4 Classification

2.2.4.1 2000 Dataset

The ISODATA unsupervised classification technique was used to classify the June 6, 2000 image into 25 spectral clusters based on spectral differences in bands 3, 4, and 5. The ISODATA technique is an automated intensity-based classifier that allows the user

to specify the number of classes generated (Jensen 1996). The algorithm starts by determining an arbitrary number of means and assigning pixels to clusters based on the spectral distance from each mean. After assigning all of the pixels in an image, means are recalculated and pixels reassigned to the closest cluster. The process repeats iteratively until a convergence threshold is reached representing the percentage of pixels that go unchanged between iterations. A maximum number of iterations is set because the algorithm can loop infinitely in some cases (ERDAS 2000, Ball and Hall 1965).

Following unsupervised classification, class values were manually assigned based on the modified USGS Anderson classification scheme described previously. Categorical assignments were determined by examining both the June and March 2000 Landsat images as well as 1998 color infrared (CIR) digital orthophoto quarter quadrangles (DOQQs). Because certain land cover types appear similar on Landsat images, some clusters contained more than one land cover class. These clusters were designated "mixed" clusters after the first unsupervised classification. Mixed clusters were then separated into 4 new images based on the most predominate land cover type contained in each cluster. Each new image was subjected to a second unsupervised classification using bands 3, 4, and 5, resulting in 25 clusters. This second clustering further separated clear-cut areas from agricultural and urban areas. Class values were then assigned to each cluster in the same manner as the first classification. After these classification steps, 15% of the pixels in the image remained in mixed clusters.

Temporal variation in phenology was used to help classify the remaining mixed areas for which the category was indeterminate. The spectral bands for the summer and winter images were combined into one 14-band dataset. A principal components analysis (PCA) transformation was then applied to the combined dataset. Principal components analysis is a technique used to reduce large datasets into simpler ones by capturing major axes of variation across multiple spectral bands (Lillesand and Kiefer 2000). The first five principal components explained 94.5 % of the variation in the 14-band image and were used in subsequent analyses. The PCA transformation captured seasonal variation between the two image dates in 2000. An unsupervised classification was run on the PCA image producing 25 clusters. After assigning land cover classes to each cluster, 1.43% of the image remained in mixed clusters. A final unsupervised classification produced 10 clusters, all of which could be sorted into identifiable classes.

2.2.4.2 1984 Images

To simplify classification of the 1984 image, a binary change mask was generated to identify areas that changed spectrally between 1984 and 2000. A PCA transformation was used to create the change mask by stacking the images from 1984 and 2000, transforming the data, and using an unsupervised classification on the first few principal components. Values of change or no change were assigned to the results of the unsupervised classification. A combination of unsupervised classification and PCA were used to classify the changed portion of the 1984 image, following the same procedures used to classify the 2000 image.

2.2.5 Post processing

After classification, the land cover class maps for both dates were then filtered using a neighborhood focal majority analysis with a 3x3 window. The procedure simulates using a minimum mapping unit of approximately 0.8 hectare (two acres) by smoothing the "salt and pepper" effect created when isolated pixels have different classifications than those of surrounding pixels.

2.2.6 Accuracy Assessment

Accuracy assessment was performed on all categories for both the 1984 and 2000 land cover maps. 1998 Digital Orthophoto Quarter Quadrangles (DOQQs), winter and summer Landsat images, and 1999 National Aerial Photography Program (NAPP) photographs at 1:40,000 scale were the reference dataset for the 2000 classification. 1982-83 National High Altitude Photography (NHAP) program hardcopy photographs at a 1:58,000 scale, and winter and summer Landsat images were the reference dataset for the 1984 classification. Using a stratified sample, 50 points were placed randomly on the image in each land cover class for a total of 300 points in accordance with the recommendations of Congalton (1991). Due to gaps in hardcopy photography for 1984, only 149 points could be used to assess accuracy for the 1984 map, while 300 points were used for the 2000 map. The data sources listed above were used to determine the land cover type for each point used in the assessment. An error matrix, overall classification accuracy, user's and producer's accuracy, and kappa statistics were generated for each land cover category for both classifications.

2.3 Results

2.3.1 Land Cover

Landcover was classified according to the modified USGS Anderson classification scheme and accuracy was assessed using standard accuracy assessment techniques. Both classifications indicate that forest, followed by agriculture, are the dominant land conditions in the northwestern Piedmont (Figure 2.2). While all land covers maintained the same relative rank between 1984 and 2000, significant changes in land cover did occur within each category.

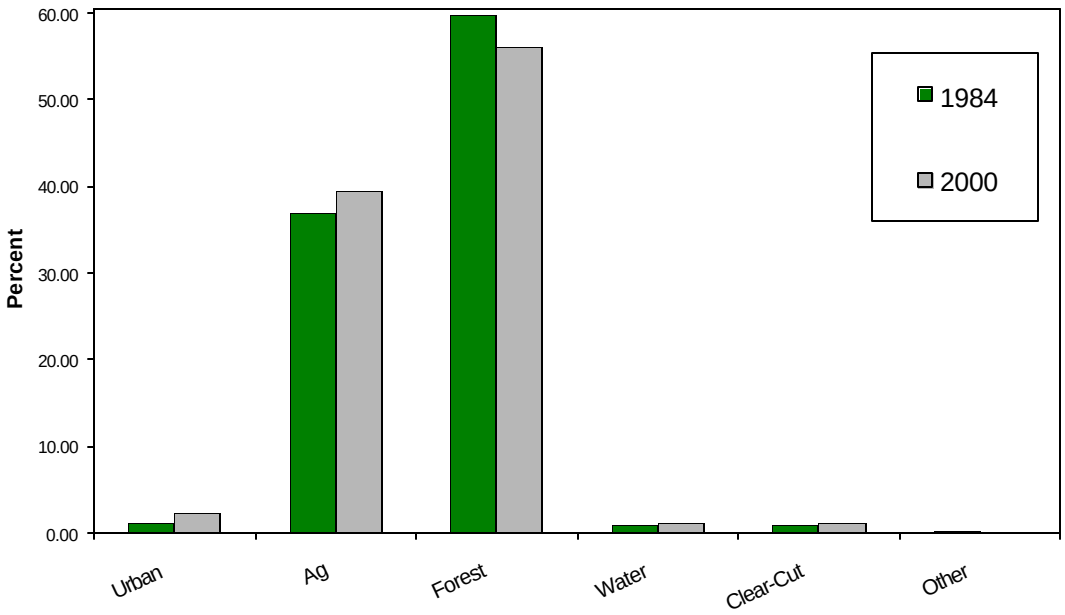

Figure 2.2. Percentage cover of each land-cover class in the western Piedmont at both time steps.

The decline in forested area was due to increases in urban, agricultural, and clear-cut area. The urban land cover class increased in area by 84.8% (Table 2.3). Clear-cut forest area showed an increase of 6.7% (866 ha) between 1984 and 2000. Agricultural land, which includes golf courses and some parks and other open space, increased a modest 7.1%. Increases in all categories came at the expense of forest area resulting in a 6.3%

decrease (-42,916 ha) in forested area. Water increased about 10% in area between time steps due to slightly higher water levels in 2000 vs. 1984 and the construction of several reservoirs between 1984 and 2000.

Table 2.3
Land-cover change as a percent during the study time period.

Cover type	1984 area km^2 (mi^2)		2000 area km^2 (mi^2)		Percent change
Urban	145.30	(56.10)	269.38	(104.07)	84.8%
Ag	4471.87	(1726.60)	4808.67	(1856.64)	7.1%
Forest	7253.70	(2800.67)	6824.54	(2634.97)	-6.3%
Water	125.61	(48.50)	137.99	(53.28)	9.4%
Clear-Cut	121.44	(46.89)	130.10	(50.23)	6.7%
Other	17.22	(6.65)	10.49	(4.05)	-39.2%
Total	12135.16	(4685.41)	12181.36	(4703.25)	

Comparison of the 2000 and 1984 land cover maps reveals that 63.7% of the clear-cut area identified in 1984 returned to forest cover, while 26.5% of clear-cut area became agriculture. Nine percent of 1984 clear-cut area was still recognizable as clear-cut using the 2000 classification because of misclassified agricultural areas, slow re-growth of some harvested areas, and clearing for development misidentified as clear-cut area.

2.3.2 Accuracy Assessment

The final error matrices as well as user's and producer's accuracies are listed in tables 2.4 and 2.5. Producer's accuracy indicates the probability of a reference pixel being correctly classified, and user's accuracy indicates the probability that a pixel's classification on the map actually represents that category on the ground (Jensen 1996). Overall classification accuracy was 81.60% for the 2000 land cover classification and 75.84% for the 1984 land cover classification. The high producer's accuracy and lower user's accuracy for the clear-cut class in both classifications indicates that clear-cut area is slightly overestimated by these classifications. These results indicate that if a clear-cut

is identified on the ground, there is a high probability that the clear-cut will be identified on the map as such, at the expense of including some land as “false positives”.

Table 2.4
Error matrix; producer's and user's accuracies for the 2000 land cover classification.

	Reference Data							
Classified Data	Urban	Agriculture	Forest	Water	Clear-cut	**Row total**	**Commission Error**	**User’s Accuracy**
Urban	37	11	1	1	0	50	13	74.00%
Agriculture	4	39	6	0	1	50	11	78.00%
Forest	1	1	44	2	2	50	6	88.00%
Water	0	0	0	49	1	50	1	98.00%
Clear-cut	2	7	4	2	35	50	15	70.00%
Column Total	44	57	62	54	39	250		
Omission Error	7	19	11	5	4			
Producer’s Accuracy	84.09%	67.24%	80.00%	90.74%	89.74%			
Overall Classification Accuracy = **81.60%**								

Table 2.5
Error matrix; producer's and user's accuracies for the 1984 land cover classification.

	Reference Data							
Classified Data	Urban	Agriculture	Forest	Water	Clear-cut	**Row total**	**Commission Error**	**User’s Accuracy**
Urban	32	3	3	1	0	39	7	82.05%
Agriculture	4	21	2	0	3	30	9	70.00%
Forest	0	4	24	0	1	29	5	82.76%
Water	0	0	0	24	0	24	0	100.00%
Clear-cut	0	10	2	3	12	27	15	44.44%
Column Total	36	38	31	28	16	149		
Omission Error	4	17	7	4	4			
Producer’s Accuracy	88.89%	55.26%	77.42%	85.71%	75.00%			
Overall Classification Accuracy = **75.84%**								

The kappa statistic (Table 2.6) is another measure of the performance of a classification that takes into account both producer’s and user’s accuracies. A kappa of 0 indicates that a classification is only as good as a random classification, while a kappa of 1 indicates that the classification is significantly better than could be achieved through chance alone. A negative kappa indicates that a classification actually performed worse than a random classification would be expected to perform (ERDAS 1999). The kappa values revealed

that all cover types are reliably identified in both classifications. All condition classes were shown to be far better than a random classification in cover type maps from both years. Overall kappa is 0.7700 for the 2000 classification and 0.6962 for the 1984 classification. The kappa corresponding to the clear-cut class is significantly lower for the 1984 classification than for the 2000 classification, but can be thought of as 69% better than a random classification (Lillesand and Kiefer, 2000). The low kappa value for the clear-cut class is due to the low user's accuracy component, signifying an over-predication of clear-cuts.

Table 2.6.
Table showing kappa statistics indicating classification performance relative to a random classification.

Classification	2000 kappa	1984 kappa
Urban	0.6845	0.7633
Agriculture	0.7135	0.5973
Forest	0.8462	0.7823
Water	0.9745	1.000
Clear-cut	0.6445	0.3776
Overall	0.7700	0.6962

2.4 Discussion

An objective of the study was to capture all clear-cut area in one class, and to make sure that clear-cut areas were not "lost" by including them in other classes. Achieving this goal required that some non-clear-cut areas be included in the clear-cut class, deliberately overestimating clear-cut area. Using an unsupervised classification aided in making this overestimation possible. When assigning classes to spectral clusters, a decision was made to include small percentages of other cover types in the "clear-cut" designation, rather than include clear-cut areas in other class designations. This process ensured that little or no clear-cut area would be included in other classes on the final map, although some non-clear-cut areas may be inadvertently identified as clear-cut area.

Unsupervised classification also made the task of classifying an area without a priori knowledge easier. As the ISODATA routine separated spectrally different areas into clusters, any troublesome or unknown areas could be identified with aerial photography on an as needed basis rather than before the classification, as would have been necessary with a supervised classification technique. This removed the need for a detailed knowledge of the study area before the study began and made it possible to handle errors in classification as they occurred rather than attempting to anticipate errors.

Due in part to variations in topography, elevation, plant community age structure, and moisture regimes present throughout the study area, there were many spectral representations for each cover type. Occasionally these factors cause non-clear-cut areas to appear similar to the spectral representation of clear-cut areas. Agriculture was mistaken most often for clear-cut, with forest a distant second. Because the percentage of the study area classified as clear-cut is small, the amount of forest and agriculture misclassified as clear-cut is probably a very small percentage of the total area for those cover types. The high producer's accuracy and especially low user's accuracy indicates that clear-cut area may be substantially overestimated in the 1984 classification. If true, the increase in clear-cut area for the 16-year study period may have been even larger than the 6.7% found here.

Challenges in identifying clear-cut areas included: the coarse spatial resolution of Landsat data, spectral similarities between agricultural, clear-cut, and urban areas, and

variation in landforms throughout the image area. The coarse image quality was an issue during image registration, because pixels in a coarse-resolution image are often made up of reflectance from multiple sources. The boundaries between these sources are rarely coincident with the boundaries between pixels; hence matching points between remotely sensed images can be exceedingly difficult (Jensen 1996). Similarities between class appearances were more pronounced on the 1984 image, where classification involved considerably more effort due to poorer 1984 image quality and available imagery dates. Compared to the 2000 Landsat 7 ETM+ image, the 1984 Landsat 5 TM dataset had lower contrast, tended to be grainier, and had an abundance of clouds obscuring the image clustered along the western edge of the study area. Specifically, compacted/developed surfaces and agriculture were difficult to distinguish, and low, scrubby, forest vegetation appeared similar to some herbaceous pasture areas. Accuracy was degraded due to this fact, resulting in more overestimation of clear-cut area in 1984 than in 2000. Image collection date also had adverse effects on accuracy. Winter Landsat ETM+ imagery for 2000 was collected in March, providing clear distinction between forest and agricultural areas. Use of November imagery in 1984 concealed some of this distinction and was reflected in the lower classification accuracy for the 1984 dataset. This made discerning clear-cut areas on the 1984 images a much more difficult task than using the 2000 images.

Additional improvements in classification technique may yield even higher accuracies, particularly for the 1984 dataset. Image fusion techniques could be used to fuse the 15-meter panchromatic band with the 30-meter visible and infrared bands, creating a more

interpretable image (Lillesand and Kiefer 2000) and leading to better clear-cut detection accuracy. Using a low-pass filter and a contrast stretch may have mitigated for some of the image quality problems in the 1984 image. Because the study area included mountainous terrain, normalizations for slope and shadow could have led to further improvements in classification accuracy for both dates. These techniques were not employed due to the exploratory nature of the study, but could prove useful in future mapping efforts. Other possible improvements include using a smaller study area to reduce variation in cover types, limiting the study area to a more homogenous, forested area, or examining an area with less variation in elevation.

2.5 Conclusions

The goals of this study were to devise a method of clear-cut detection, use the method to generate a land cover map for the western piedmont of North Carolina, and to assess the accuracy of that classification. This study determined that detection of clear-cut areas is feasible using Landsat TM and ETM+ data and standard remote sensing techniques. Unsupervised classification was crucial in allowing classification to take place without *a priori* knowledge of the study area. The deliberate overestimation of clear-cut area to ensure capture of all clear-cut areas in the correct class was another advantage of the classification technique used in this study. While there are certainly improvements that would almost certainly improve the accuracy of this process, it is worth noting that overall classification accuracy exceeds the USGS/National Park Service standards of 80% accuracy in thematic classifications for 2000, and is very close for 1984. Improvements in the image processing technique that could potentially increase accuracy

include correction for topographic variation and use of haze reduction techniques. Individually, clear-cut class accuracy is above the standard for 2000 and slightly below for 1984. The superiority of the 2000 classification indicates that data generated using the modern Landsat 7 ETM+ sensor is likely to produce better results in clear-cut detection than Landsat 5 TM data. This is simply an indication of how much sensor technology has improved during the final two decades of the 20th century.

Chapter 3

The effects of change in policy and practices on clear-cut harvesting in western North Carolina

3.1 Introduction

3.1.1 Policies affecting forest harvesting

Over the last 40 years, the attitude of the American public regarding natural resources has changed (Kessler et al. 1992). This has led to a variety of policy changes directed at changing the way forests are used for profit and to benefit the public good.

Among the policy changes of the late 21st century were forestry best management practice (BMP) guidelines designed to keep forestry operations from polluting water supplies. North Carolina BMP guidelines state that forested buffers must be maintained on both sides of perennial and intermittent streams, at a width sufficient to stop eroded soil from entering a stream, even on steep slopes (NC Division of Forest Resources 1989). Clear-cut harvesting is not permitted inside buffered areas, so these patches have vegetation composition different from the surrounding clear-cut area, even as the cut area begins to regenerate. Thus, leaving buffers can cause landscape change by altering forest structure. Buffers are by definition linear features because they are adjacent to streams. Buffered areas, then, are linear habitat fragments. Research on linear habitat fragments indicates that fragment-dwelling plants and wildlife are often subjected to outside influences, small habitat size, isolation from other populations, and edge effects (Lord and Norton 1990). If a buffer connects two patches of habitat, it can be used as a corridor. This can result in the positive benefits of increased gene flow and protection from extinction (Simberloff and Cox 1989). Negative consequences are also possible, including increased risk of fire, disease, and predators (Simberloff and Cox 1989, Hess 1996). The specific consequences of corridors on a population depend on the corridor

size, shape, and configuration, and species mobility, population size, and reproductive capacity.

Voluntary limits to clear-cut size are another policy change that has occurred due to shifting perceptions and attitudes about natural resources. The Sustainable Forestry Initiative (SFI) program, endorsed by the American Forest and Paper foundation, is a program that enforces a maximum average clear-cut size of 48 hectares (120 acres) in any year for all the land a company manages (Sustainable Forestry Initiative 2002). This guideline allows forest managers the flexibility to use large clear-cut harvests when necessary, but discourages the practice of using many very large clear-cuts. Forest products companies must adhere to these standards to maintain membership in the American Forest and Paper Association. Other trade associations have developed similar guidelines. Many private industries, government agencies, and private non-industrial forest landowners have voluntarily reduced maximum individual clear-cut size to between 60 and 90 hectares (Boston and Bettinger 2001). In addition to voluntary restrictions, several states regulate private forests by establishing maximum clear-cut sizes, separation zones between clear-cut patches, and exclusion periods for harvesting surrounding land (Barrett et al. 1998). The state of North Carolina currently has no such regulation. If the voluntary restrictions in North Carolina have had a noticeable effect, the results may be measurable using land use and land cover data from different time periods.

3.1.2 Changes in forest harvesting practices

Forest harvesting practices in the Southeast have also changed during the last 25 years. In the Pacific Northwest, the timber producing heartland of America, controversy about the effects of timber harvesting on water quality and endangered or threatened species prompted forest industry to seek more a hospitable and profitable political climate. Forest harvesting rates increased in North Carolina as the focus of forest industry shifted from the Pacifica Northwest to the Southeast. By 1997, more wood was being harvested from the Southeast than from any other wood-producing region in the world (Cubbage and Richter, 1998). In addition, large areas of forest have been converted to other uses in North Carolina between 1982 and 1997, averaging 31,000 hectares (77,000 acres) per year (Schaberg et al 2000 [2]).

The introduction of chip mill harvesting technology has also raised concerns, particularly in western North Carolina. Chip mills are designed to efficiently use the wood of smaller diameter trees than traditional sawmills, thus opening more areas to harvest and potentially increasing the amount of forest land harvested. This potential increase and the perceived reductions in water quality, degradation of wildlife habitats, and reduction in aesthetic qualities of forests as a result of harvesting (Warren 2000) raised citizen concerns in western North Carolina and helped prompt a comprehensive survey of chip mill impacts in the late 1990s (Cubbage and Richter 1998). The chip mill study did not find direct evidence of chip mills leading to increased clear-cutting, but did find that chip mills can increase production efficiency to such a level that timber prices decline and increased clear-cutting becomes economically desirable (Schaberg et al. 2000 [1]).

3.1.3 Objective

The overall goal of this study was to quantify the effects of changes in the policies and practices affecting clear-cut forest harvesting on clear-cut harvesting patterns. The effects of these changes were examined using land cover maps for 1984 and 2000 generated by Bailey (in preparation). Each hypothesis is related to a specific change in landscape composition that could be caused by a change in forest policy or practice between 1984 and 2000.

Four hypotheses were tested:

- H_1: The distribution of clear-cut patch sizes changed significantly between 1984 and 2000.
- H_2: Average shortest distance between clear-cut patches and chip mills changed significantly during the study time period.
- H_3: Harvest levels have increased in mountainous areas.
- H_4: Forest patch shape has become more linear over the study time period.

3.1.4 Study area

The study area consists of 11 counties in the western Piedmont and Mountain regions of North Carolina spanning 13,000 square kilometers (Figure 3.1). Elevations in this area range from to 180 to 1740 meters (591 to 5709 feet) above sea level, and the topography becomes more rugged as elevations rise from east to west. Work by Thornbury (1965) indicates that land in the study area with an elevation above 610 meters (2000 feet) will occur only in the mountain region. As is true throughout the North Carolina Piedmont and Mountain regions, forest is the dominant land cover (56% in 1990), followed by

agriculture (39% in 1990) (Bailey in preparation). A wide range of forest types include loblolly pine plantations, oak-hickory uplands, nearly pure stands of yellow poplar and white pine, and high-elevation spruce-fir. Throughout the study area, particularly towards the east, the landscape consists of a mosaic of forest and agriculture, with very fragmented forested areas. Counties were selected for study based on the large percentage of forest cover and the presence of chip mills within the area. According to geographic data compiled in 2000, 13 mills are located inside or within 50 miles of this study area, 10 of which began operation after 1984 (Prestemon et al. 2000). 50 miles is the typical range from within which a chip mill will receive trees.

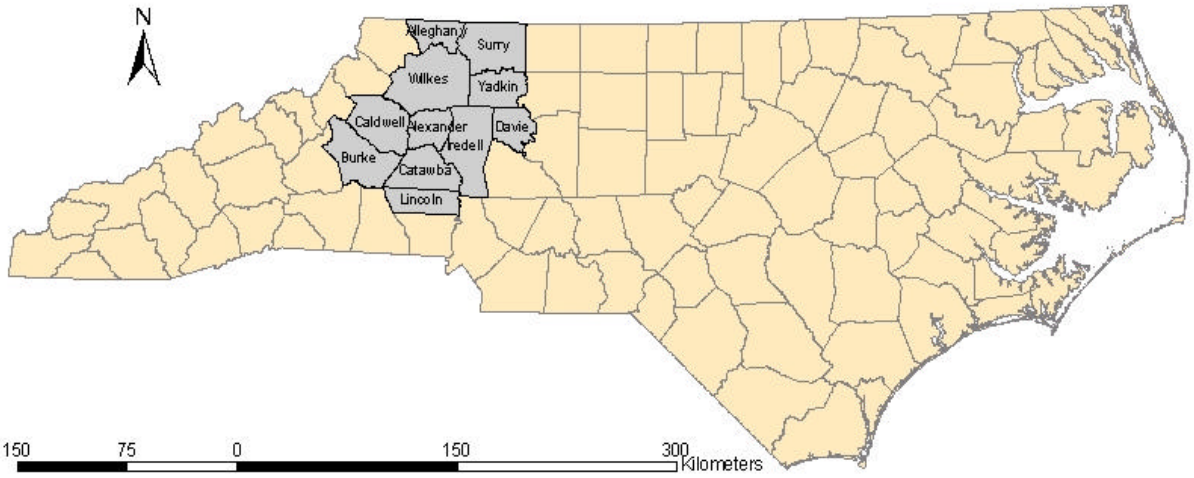

Figure 3.1 11-county study area in North Carolina.

3.2 Materials and methods

3.2.1 Land cover maps

Bailey (in preparation) generated maps of clear-cut land use and general land cover for the northwestern piedmont of North Carolina for 1984 and 2000. The study found that clear-cuts could be mapped and separated from agricultural and other bare land categories

accurately using remotely sensed satellite data. Both maps covered the same study area, with a land area slightly less than 13,000 square kilometers (5,019 mi^2). These land cover data were used for all hypotheses tests. Land cover was classified using a USGS Anderson level 1 land cover classification scheme modified to remove categories not present in North Carolina and add clear-cut and other categories as described in table 3.1 (Anderson et al. 1976).

Table 3.1
Classification scheme after modifying the Anderson level 1 scheme to add a clear-cut class and remove classes not represented in the study area.

Class Number	Description
1	Urban/Built Up
2	Agricultural/Pasture
3	Forest
4	Water
5	Clear-cut Forest
6	Other

Overall accuracy was 82% for the 2000 land cover map and 76% for the 1984 land cover map. Because the clear-cut detection study was concerned with capturing all clear-cut areas in the correct class, non-clear-cut areas were occasionally wrongly assigned to the clear-cut class.

3.2.2 Landscape metric calculations

3.2.2.1 Measures of patch size

Patch size was calculated for all clear-cut patches in the region. A patch is defined as a group of contiguous cells of the same class type sharing a common border or diagonal. This patch definition was preferred over using only orthogonal neighbors because linear patches might be lost if they are oriented diagonal to the image. Smith et al (2002) found

that increasing patch size has a significant positive effect on classification accuracy, so that small patches tend to be classified incorrectly. For this reason, analyses of clear-cut patches and forest patches were restricted to patches greater than 5 pixels in size, approximately 4,500 m^2 (one acre). Economic factors generally prohibit clear-cutting on areas smaller than 1 acre, so it is likely that very small patches are non-clear-cut areas with spectral signatures similar to clear-cut patches.

Summary statistics calculated include the total number of patches, mean patch size, and quantiles for each distribution, as well as histograms. Because of the large number and broad range of clear-cut patch sizes, comparing means between datasets can be misleading. More thorough analysis of large samples can be conducted by comparing distributions of patch size. The Kolmogorov-Smirnov (K-S) two-sample test for a common distribution was used to compare distributions of several variables from each year. The Kolmogorov-Smirnov test is a non-parametric test designed for continuous data, with assumptions that hold for data distributed non-normally. The null hypothesis for this test states that both sets of observations come from identical distributions. A rejection of the null hypothesis can reflect change in location, skewness, or variance (Sprent and Smeeton 2001).

3.2.2.2 Measurement of distance between clear-cuts and chip mills

The shortest distance from each clear-cut patch to the closest chip mill was calculated by measuring the distances in a GIS. Summing the distances for all patches and dividing by the total number of patches calculated the shortest average distance from clear-cut to chip

mill. The Kolmogorov-Smirnov test, histograms, and summary statistics were used to compare distance distributions for each year.

3.2.2.3 Measures of patch shape

Forest patch linearity was estimated by measuring patch elongation and patch complexity using the shape index and related circumscribing circle metrics. The shape index metric is a measure of shape complexity calculated by comparing patch perimeter and the minimum patch perimeter possible for a square patch of the same area. (McGarigal et al. 2002). Because shape index uses a square or almost square area for comparison, it corrects for the size sensitivity present when using a simple perimeter-area ratio. Shape index is equal to 1 when a patch is maximally compact, and increases without limit as patch shape becomes more irregular.

The related circumscribing circle metric is a measure of patch elongation based on the minimum area of a circle that could surround the entire patch. Related circumscribing circle is equal to zero for circular patches and approaches one for elongated, narrow patches one cell wide (McGarigal 2002).

Both metrics were calculated using the Fragstats 3.3 spatial analysis package (McGarigal et al. 2002). Once these indices were calculated for each patch, the Fragstats software calculated mean, standard deviation, and range values for the shape index and related circumscribing circle metrics. Detailed mathematical formulas for the minimum circumscribing circle and shape index metrics are located in Appendix C.

3.2.2.4 Measurement of association between clear-cut and physiographic region

To examine changes in clear-cutting practices in the mountain physiographic region, elevation values were assigned to each pixel classified as clear-cut for both time periods using a 30-meter Digital Elevation Model (DEM) covering the study area (McCoy 2001). Calculating the area of all cells classified as clear-cut with elevation values higher than 610 meters (2000 feet) provides a good estimate of the amount of clear-cut area within the study area in the mountain physiographic region rather than the piedmont.

3.3 Results

3.3.1 Overall land cover

Forest and agriculture were the dominant land cover in the northwestern Piedmont in both 1984 and 2000 (Figure 3.2). While all land covers maintained the same relative rank between 1984 and 2000, changes in land cover occurred within each category (Table 3.2). Most notably, urban land cover increased in area by 84.8% of the urban value in 1984 (4,123 ha). Forest land showed a 6.7% decrease from the amount of forest area in 1984, representing 42,900 hectares.

The increase in urban area came at the expense of forest and agricultural area (Table 3.2). Agriculture gained area from the conversion of forest resulting in a 6% decrease in forested area (-47,921 ha) while agricultural area actually increased 7% (34,075 ha). Water increased 1% in area due to slightly higher water levels in 2000 vs. 1984 and the construction of several reservoirs between 1984 and 2000.

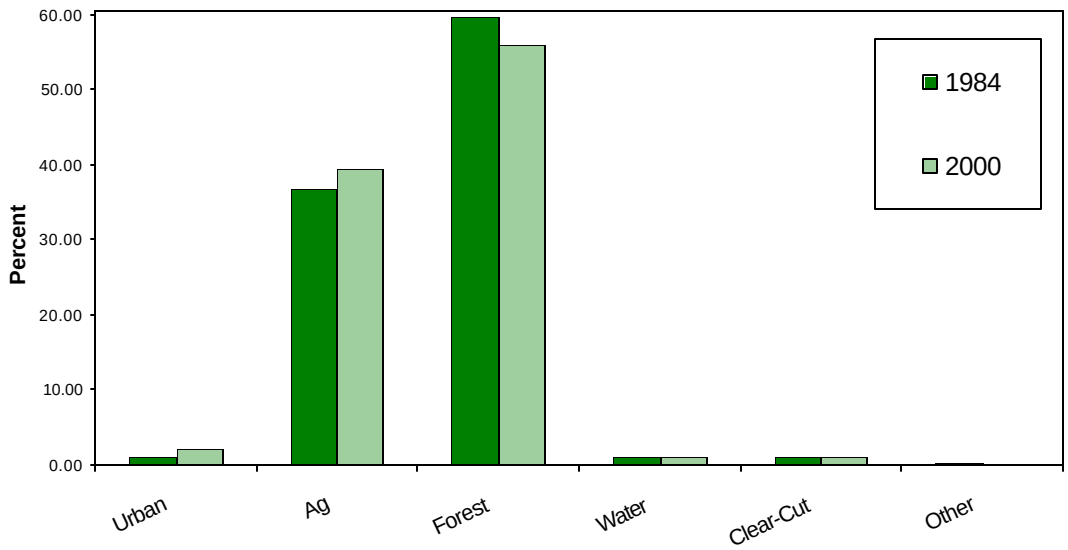

Figure 3.2 Percentage cover of each land-cover class in the western Piedmont at both time steps.

Clear-cut area increased 7%. Underestimation of clear-cut land area in the 1984 classification may mean that the true increase in clear-cut area may be larger than 7%. Misclassifications in the datasets used in this analysis account for the unlikely estimates of change from urban to other classes. Confusion between forest and urban classes can be common in remotely sensed datasets.

Table 3.2
Land use and land cover change in the western piedmont of North Carolina between 1984 and 2000. Highlighted categories indicate land that did not change classes during the study period. Read across the table to find the number of hectares converted from a category into a new use between 1984 and 2000. Read down the table to find the sources hectares converted into a new use between 1984 and 2000. (Table format and terminology adapted from Hess et al. 1999)

		|----------1984-2000 Land Use Change (Hectares)----------|					
1984 Land Use (Hectares)		**Urban**	**Agriculture**	**Forest**	**Water**	**Clear-cut**	**Other**
Urban	16,099	13,445	2,075	540	10	7	20
Agriculture	490,311	10,948	406,634	68,580	99	3,890	159
Forest	788,701	4,930	112,000	661,677	859	8,995	241
Water	13,897	23	79	701	13,092	0	2
Clear-cut	13,440	97	3,505	8,564	1	1,272	0
Other	868	7	92	718	7	10	34
2000 Land Use (hectares)		29,450	524,385	740,781	14,068	14,174	457
Change from 1984 (hectares)		13,352 ***(83%)***	34,075 ***(7%)***	-47,921 ***(-6%)***	171 ***(1%)***	734 ***(5%)***	-411 ***(-47%)***

Looking specifically at clear-cut regeneration, it was found that 64% of the clear-cut area identified in 1984 returned to forest cover, while 26% of clear-cut area became agriculture. Nine percent of clear-cut area was still recognizable as clear-cut using the 2000 classification, either because the areas had been cut again, or because vegetation regrowth over 16 years was insufficient to cause the areas to appear as forests in the classification. Less one percent of identified clear-cuts in 1984 became urban.

3.3.2 Landscape metrics

Using the Kolmogorov-Smirnov test to compare the distributions of clear-cut patch sizes yielded a p-value of < .0001, indicating that the distribution of clear-cut sizes changed significantly between 1984 and 2000. Most notably, the number of clear-cut patches increased from 5,377 to 6,081 (13.1%), while the mean clear-cut patch size decreased from 1.63 ha to 1.45 ha (12.4%). The distribution of patch sizes was heavily skewed towards smaller patch sizes in both datasets, with only a few very large patches present.

Examining a histogram of clear-cut patch sizes revealed a different trend in clear-cut patch sizes smaller than nine hectares when compared to patch sizes larger than nine hectares. The number of clear-cut patches smaller than nine hectares increased by 14% between 1984 and 2000, and the number of patches larger than nine hectares decreased by 50% (figures 3.3 and 3.4). Because the number or smaller clear-cuts is large for both years, the increase in patches smaller than nine hectares caused an increase in overall clear-cut area even though the number of larger patches decreased.

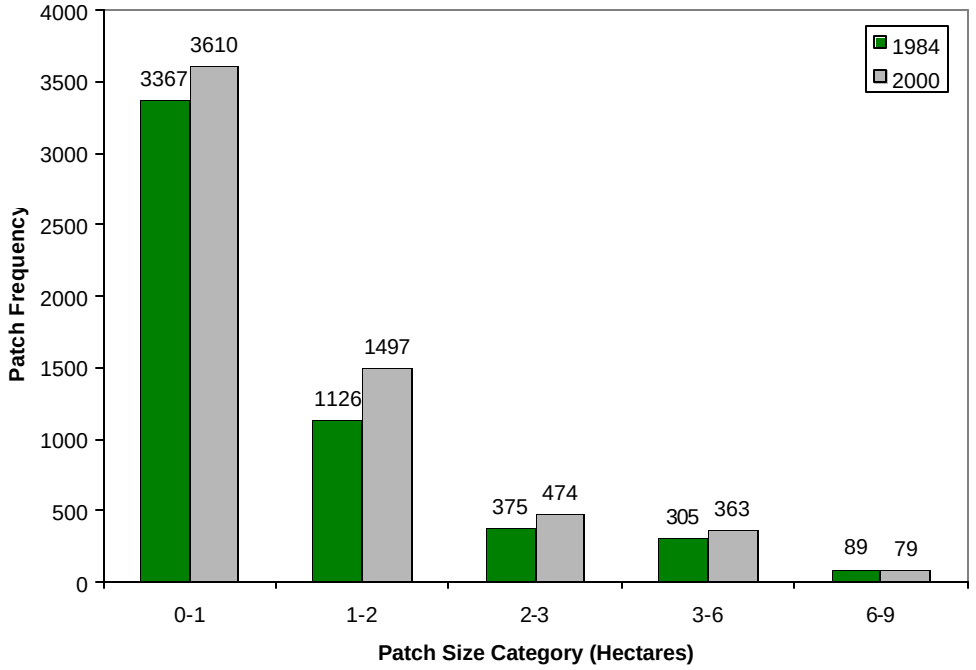

Figure 3.3 Frequency distribution of clear-cut patch sizes smaller than 9 hectares. The 2000 dataset has noticeably more small clear-cut patches compared to the 1984 dataset.

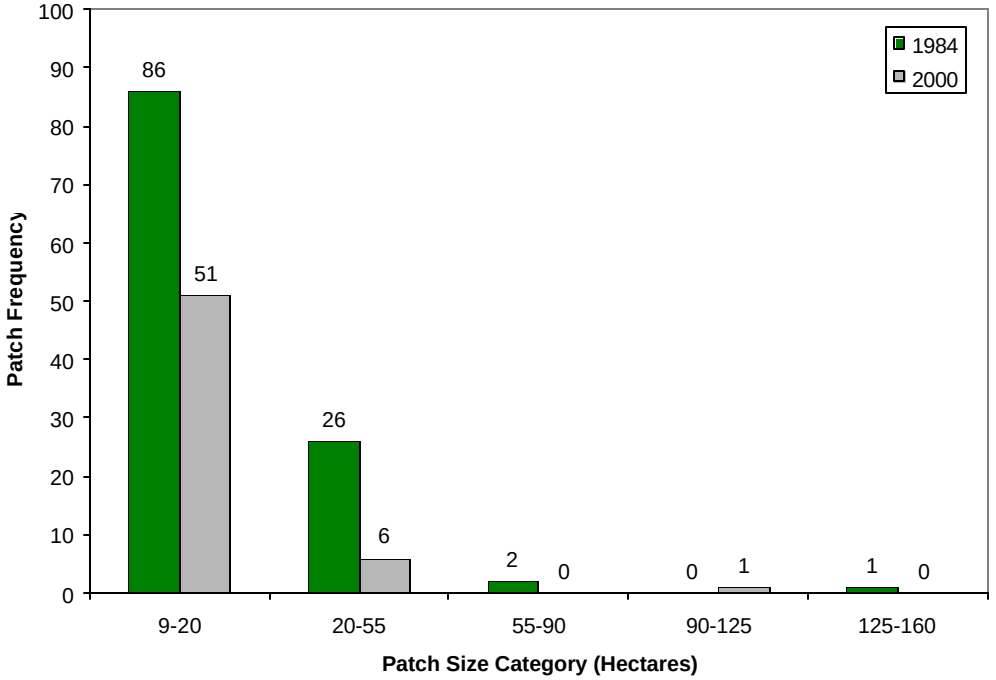

Figure 3.4 Frequency distribution of clear-cut patch sizes larger than 9 hectares. Note that medium and large sized clear-cut patches in 1984 outnumber those detected in 2000.

Comparison of the means for shape index and nearest circumscribing circle metrics showed little change between 1984 and 2000. Forest patches displayed a tendency to be slightly elongated (*CIRCLE* = .58 for both years) but not particularly irregular (*SHAPE* = 1.59 for 1984 and *SHAPE* = 1.60 for 2000) on both dates. Standard deviations were similar for both metrics between years.

Average distance from clear-cut patch to the closest chip mill increased between 1984 and 2000, from 38.6 km (24.0 mi) to 43.0 km (26.7 mi). Using the Kolmogorov-Smirnov test, we were able to reject the null hypothesis that the distribution of clear-cut patch to mill distances was identical for both years with a p-value <.0001. While the distribution shapes are similar and are somewhat bimodal in appearance, the 2000 dataset is skewed towards larger distances compared to the 1984 dataset (figure 3.5).

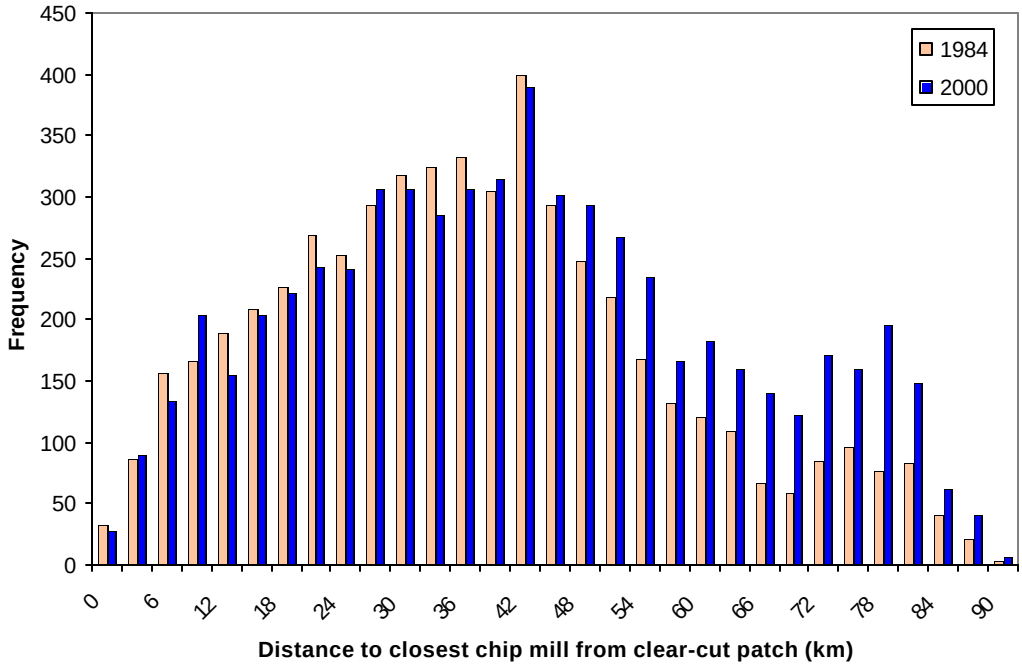

Figure 3.5 Distance distribution compared between 1984 and 2000.

Examination of clear-cut patches with respect to elevation reveals that the amount of clear-cut area present in mountainous areas (those areas at and above 610 meters [2000 ft] in elevation) increased from 456 hectares to 1169 hectares, an increase of over 150% between time periods.

3.4 Discussion

The measurable decline in clear-cut patch size and increase in the number of clear-cut patches are indications that forest harvesting practices are being altered in the manner suggested by SFI and other voluntary standards. The number of large clear-cut patches decreased, while the overall amount of land harvested increased. An increase in small patches accounts for the majority of increased harvesting levels.

Increasing the number of small clear-cut patches while maintaining or increasing the area harvested may lead to habitat fragmentation for some species by shrinking and breaking apart contiguous forest habitat areas. Because green-up constraints prohibit the harvest of adjacent patches generally within 3 years of one another, a clear-cut can be the source of forest fragmentation even when cuts are not dispersed over the landscape. When adjacent patches of the same forest type are regenerated at different times the resulting stands may differ in structure to such a degree that the stands may not provide a contiguous habitat for a species.

The study results indicate no direct link between clear-cut harvesting and chip mills, only circumstantial evidence that the area clear-cut has increased over the time span that chip

mills have been introduced in western North Carolina. Demand in local, regional, and national markets for wood products and shifting national focus of timber production from the Pacific Northwest to the Southeast are all potential reasons for this observed increase.

The average distance from chip mill to clear-cut patch increased during the study time period, which suggests that chip mills do not attract clear-cutting to the immediate mill vicinity. Because the number of clear-cuts increased in northwestern portion of the study area, and chip mills are predominantly located in the southeastern portion of the study area, average distance increased. Measuring average distance may not have been a definitive way to test this hypothesis. Overlapping mill sourcing areas, harvesting for traditional lumber mills, and changing transportation routes all affect clear-cut locations and distance between mill and harvest site.

Harvesting in mountainous areas over 2000 feet in elevation increased between 1984 and 2000. This can potentially lead to increased pressure on healthy animal and plant populations that depend on the close proximity of a wide variety of habitat types present in the mountains. Improvement in access routes to the western mountains, change in tree species desired by forest products companies, and decrease in supply in the areas immediately surrounding Piedmont mills are all potential reasons for increased harvest activities in these previously remote areas, though the results do not implicate any one cause.

There are several reasons for forest patch shape showing no discernable trend during the study time period time period. Future analysis should focus on forests near streams rather than all forests, since forests without streams are not subject to BMP regulations and should show no change. Using ancillary stream data to select forest areas near streams would help to more appropriately define the sample dataset. It is also likely that the effects of BMP regulations and 50-foot wide streamside management zones occur on such a small scale that 30-meter resolution Landsat data are too coarse to use for these measurements. In many cases buffers were less than one pixel wide and boundaries between buffer and clear-cut areas unclear. A more appropriate dataset for this type of analysis might be small-scale (1:40,000) NAPP aerial photography. Visual examination of the landcover maps used in this study along with aerial photography used for accuracy assessment by Bailey (in preparation) suggests that streamside buffers are being used more frequently in 2000 than 1984, however, metrics generated in this study did not detect these changes for the reasons listed above.

3.5 Conclusions

The goal of this study was to examine the effects of changes in forest harvesting policies and practices on clear-cut harvesting patterns. Voluntary restrictions attempting to decrease clear-cut size are achieving measurable reductions. At the same time, changing timber industry practices have increased harvest levels in the study area. The results of these changes are the existence of more clear-cut area and more clear-cut patches in 2000 when compared to 1984. An increase in the number of small clear-cuts is responsible for most of the increase in area. These changes could lead to the dispersal of clear-cut

patches across the landscape. Franklin and Forman (1987) found that clear-cutting small, non-adjacent forest patches, rather than harvesting contiguous blocks of forest, can lead to a decline in species diversity when habitat used by interior forest dwelling species is harvested and becomes unsuitable.

The report "Economic and ecological impacts associated with wood chip production in North Carolina" by Schaberg et al. (2000 [1]) suggests that the economic impetus behind the increased harvest levels observed between 1984 and 2000 are still present. Further monitoring may help determine if increased harvesting will lead to further dispersal of clear-cut patches and fragmentation of forest throughout the landscape. It is also worth noting that forest harvesting expanded in mountainous areas during the study period. This trend may also require further monitoring to assess the cause of this change and the potential effects on montane plant and animal communities.

There were no detectable changes in forest patch shape. It is possible that no changes have occurred, but also likely that Landsat data is too coarse for examining the effects of watershed protection buffer policies. Limiting the study set to measure linearity of only forest areas near streams, rather than measuring linearity for all forest patches, could make the sample set more suitable for this analysis.

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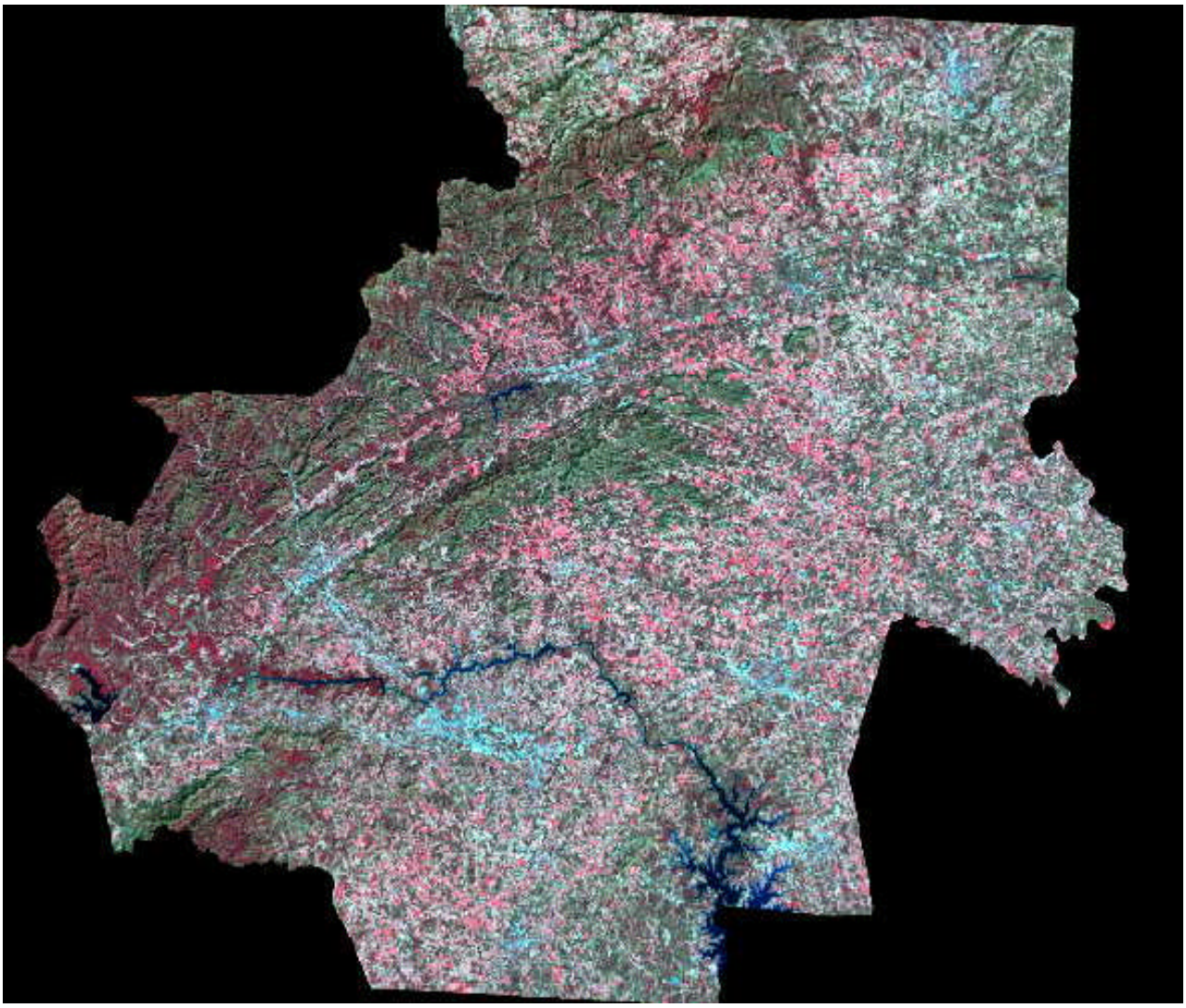
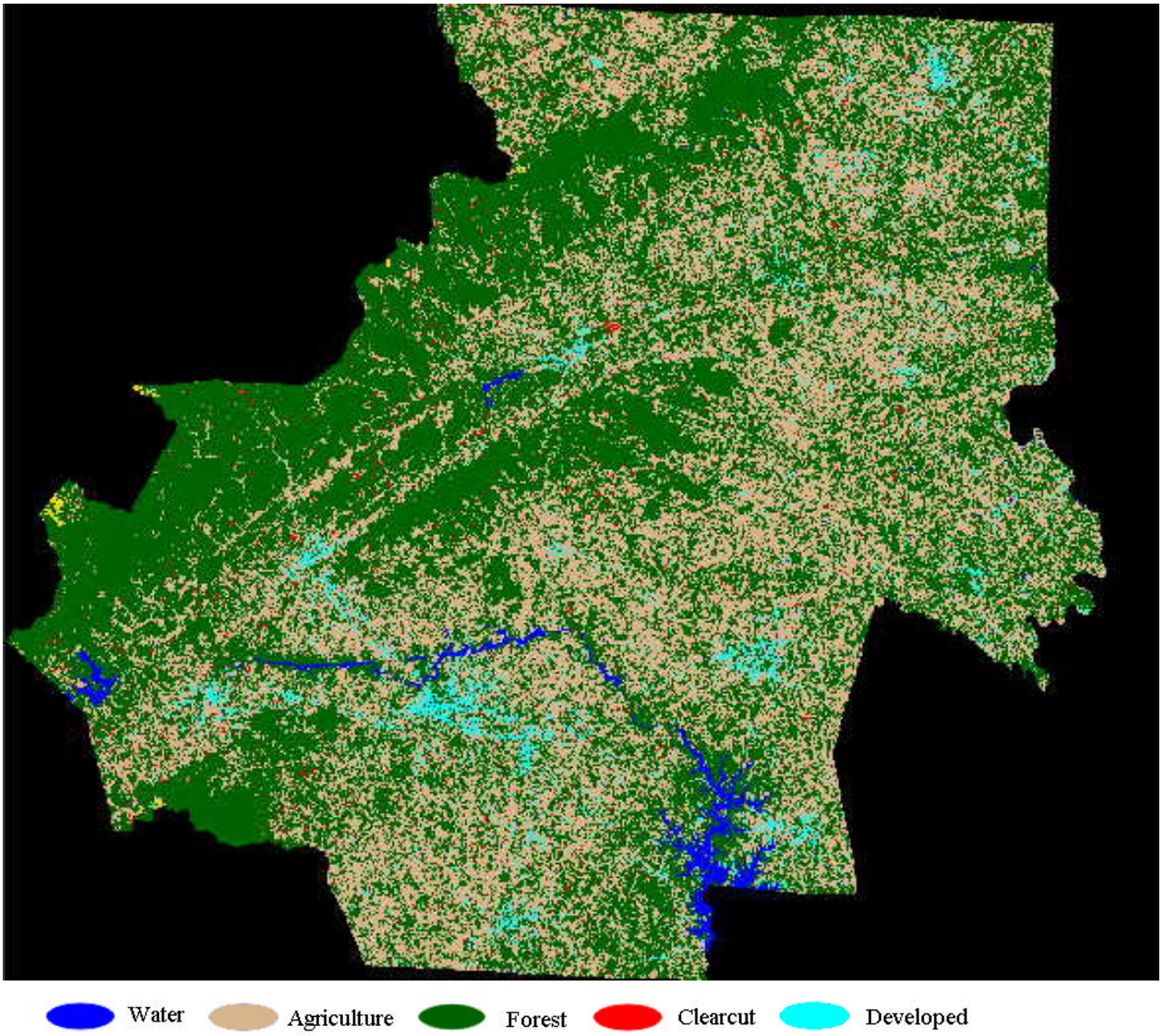
Appendix A. Leaf-off false-color composite image of study area: March 06, 2000.

Image recorded by Landsat 7 ETM+ sensor.



Appendix B. Final classified image after running 3x3 focal mean filter.



Appendix C. Landscape metric calculations

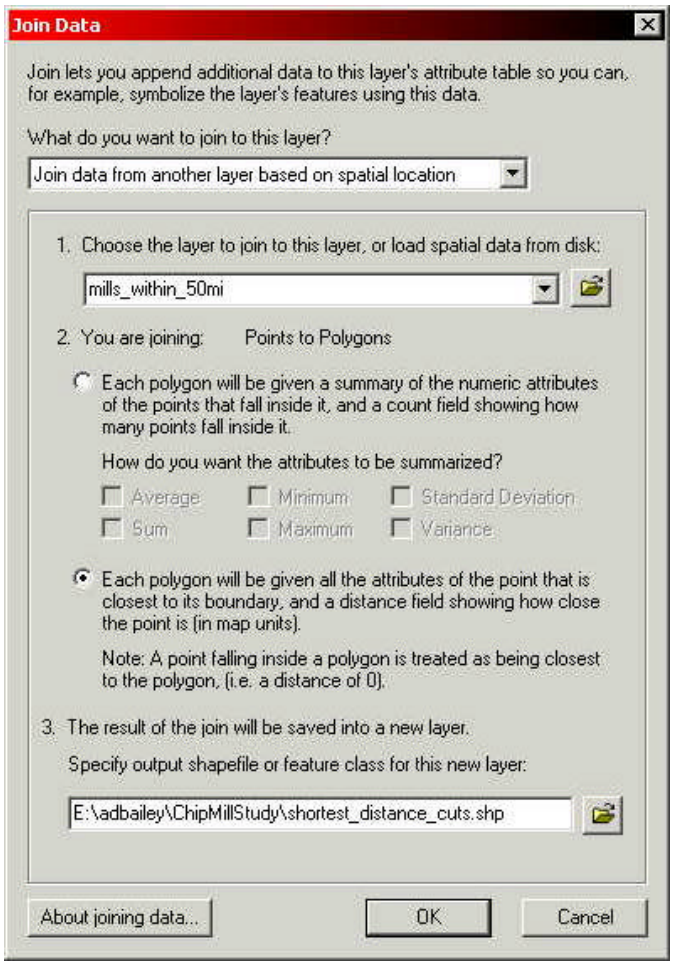
Patch size calculation

Patch size was calculated by running a regiongroup function on the land cover data sets from both years using ArcGIS GRID (McCoy 2001). The regiongroup function assigns classified cells to patches based on proximity and calculates the size of each patch (ESRI 1994). The eight-neighbor rule, by which cells are assigned to the same patch if they share a common border or a corner, was enforced during this procedure.

The command was executed as follows:
PatchGrid = regiongroup(in_grid, #, EIGHT, WITHIN, #, #)

Shortest average distance from clear-cut to chip mill calculation

Shortest average distances from each clear-cut patch to the nearest chip mill were calculated by performing a spatial join in ArcMap. Clear-cut patches larger than five pixels were converted to vector polygons before performing this analysis, and smaller patches were dropped from analysis. Patch boundary lines were held strictly to pixel edges so as to not lose clearcut area. When spatially joining the clear-cut polygon layer to the chip mill point layer, ArcMap joins the attributes of the closest chip mill to each clear-cut patch and adds a straight-line distance field to the polygon attribute table.



Appendix C. Landscape metric calculations (Continued)

Shape Index Metric Formula (from McGarigal 2002)

Formula used to calculate the shape index metric.

$$SHAPE = \frac{p_{ij}}{\min\ p_{ij}}$$

p_{ij} = perimeter of patch ij in terms of number of cell surfaces.

min p_{ij} = minimum perimeter possible for a patch with the same area as patch ij in terms of number of cell surfaces.

Minimum Circumscribing Circle Metric Formula (from McGarigal 2002)

Formula used to calculate the related circumscribing circle metric.

$$CIRCLE = 1 - \left[\frac{a_{ij}}{a_{ij}^{s}} \right]$$

a_{ij} = area (m^2)of patch ij.

a_{ij}^{s}= area (m^2) of smallest circle that will completely enclose patch ij.