Land Use and Terrestrial Carbon Storage in Western North Carolina from 1850-2030: A Historical Reconstruction and Simulation Study

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Abstract

The Southern Appalachian Mountains have experienced large and dynamic land-use changes since arrival of Euro-American settlers in the late 18th and early 19th centuries. Following transfer of the land from Native American societies, successive waves of immigration, development, resource extraction, and abandonment have driven land use over the past 200 years. There are large uncertainties regarding the timing and magnitude of these changes, and as a result, there are large uncertainties on the effects these land use legacies have on ecological processes and services. This dissertation addresses these uncertainties by quantifying and spatializing land use in the region since 1850, forecasting land use through 2030, and evaluating the effects of land-use change on the storage of carbon in terrestrial forest ecosystems.

The study area is the 21-county region of Western North Carolina that is part of the Blue Ridge physiographic province. Macon County, NC, and four watersheds within Macon County are used as detailed case studies. Decadal land use patterns were reconstructed using sparse spatial data derived from historic maps, aerial photographs, and satellite imagery, more frequent tabular estimates of land use from census data, and terrain-based geospatial models. Carbon accrual in aboveground woody biomass was estimated from yield models and applied across the landscape using terrain-based estimates of site quality.

Within Macon County, timber harvest and agriculture area peaked during 1900-1910, and following recovery, total forest area peaked from 1960-1980. Since 1950, the total development footprint has tripled, with over 2/3 of new houses expanding into areas that were predominantly forested. Across the region, total agriculture and forest area are forecasted to decline 12% and 5%, respectively, by 2030 as development expands.

Carbon in aboveground woody biomass decreased an estimated 80% between 1850 and 1930, from an average of 201 Mg ha^{-1} in 1850 to a low of 40 Mg ha^{-1} in 1930, with 84% of this loss due to industrial logging and 16% due to agriculture expansion. Since 1930, the forests have been aggrading carbon at a decreasing rate of 24% per decade in 1940 to 5% per decade since 1990. Although total forest area will decrease 4%, carbon storage is forecasted to increase 10% by 2030 assuming no large disturbance.

Table of Contents

List of Tables

Introduction

Chapter 1

Chapter 2

Chapter 3

Chapter 4

Appendix A

List of Figures

Introduction

Chapter 1

Chapter 2

Chapter 3

Chapter 4

Introduction

There are few places in the United States where the histories of the people and the environment are as fully intertwined as in the Southern Appalachian Mountains. Since our arrival in the region over 10,000 years ago, humans have significantly altered the mountain ecosystems through a complex of land-use practices ranging from meeting the individual basic needs for food and shelter to meeting the resource demands of a global economy (Davis 2000; Gragson and Bolstad 2006). One of the most challenging research problems in studying ecosystems is understanding the types, causes, and magnitudes of these land-use practices, how and why they change over time, and what short-term and long-term impacts they have on ecosystem patterns and processes (Meyer and Turner 1994; DeFries et al. 2004). This dissertation aims to address one aspect of this research problem by evaluating the dynamics between land use practices and the ecosystem process of the cycling and storage of carbon (C) in terrestrial forest ecosystems. The spatial extent of the research is focused on one geographic sub-area within the Southern Appalachian Mountains, namely a 21-county region in the Blue Ridge physiographic province of western North Carolina, across a time period extending from the antebellum period of the 1850s to present, with forecasts projected through 2030.

The structure of this dissertation is the combination of a spatio-temporal reconstruction of major historic land-use patterns and practices with spatially-explicit C cycle models. In effect, this is a synthesis study bridging the disciplines of land use science (Veldkamp and Lambin 2001; Rindfuss et al. 2004), environmental history (Hughes 2006; Merchant 2007) landscape ecology (Turner et al. 2001; Turner 2005) and terrestrial ecosystem ecology (Chapin III et al. 2003), and is built upon the remarkable and far-reaching collection of social and ecological research on the Southern Appalachian region over the past 150 years. In fact, the earliest regional scientific publication referenced (excluding U.S. census publications) was a 1883 book by Peter M. Hale entitled “The Woods and Timbers of North Carolina” that was based on research dating to the 1860s (Hale 1883). While there has long been interest and concern over the uses of the natural landscapes in the Southern Appalachians, there are still plenty of opportunities to add to the knowledge base on the effects of past land use on the current and future environment.

Rationale

Land use has been identified as a primary control of C flux and storage in temperate ecosystems (Birdsey et al. 1993, Houghton 2003b). Key uncertainties in the global terrestrial C budget include C dynamics in individual regions (Canadell 2007, Houghton 2003a, Wallin et al. 1997, Delcourt and Harris 1980), the role of forest age structure in C cycling (Song and Woodcock 2003, Houghton 2003b), the effects of natural disturbance on C budgets (Houghton 2003a), and the influence of enhanced forest growth due to global change (Schimel et al. 2004, Casperson et al. 2000) or forest management (e.g., Hurtt et al. 2002). Overall, it is still unclear what individual and combined effects these factors have in determining the global C budget. Ultimately, resolving these issues may help in greatly reducing the uncertainty of global change forecasts. Improved historical reconstruction of land use at the regional scale has been identified as a priority for evaluating these potential effects (Houghton 2003; Canadell et al. 2007).

In order to fully understand the terrestrial C budget in the Southern Appalachian region, three historic periods must be adequately studied as they influence C stocks significantly more than all others. First, the period of industrial expansion and industrial logging in the mountains, from approximately 1880-1920, must be considered since most of the present second and third growth forests date to that period. Second, the expansion and abandonment of agriculture must be included. At the peak of agriculture in 1910, over 630,000 ha of the 21 county region was cleared farmland (27% of the total area), and by 2002 the total cleared farmland area had been reduced to 220,000 ha (9%). Much of this abandoned land is now in other developed land uses, but a large portion was afforested naturally or planted to forest. Third, the effects of the Chestnut Blight, a fungal disease introduced to the United States in at the beginning of the 20th century that killed or stunted nearly all of the Chestnut trees in North Carolina by 1940, must be included. Chestnut accounted for approximately one-fourth of all timber volume in the mountains (Slocum and Ross 1945), so the mortality had very large effects on the forest composition and C budget. A fourth emerging land use practice that is driving smaller-scale forest loss in the area and altering forest management regimes is the expansion of suburban and exurban development, although the magnitude and effects on C cycling has not been extensively studied. Other lesser factors, such as dynamic fire regimes and fire control measures, evolving logging practices, and shifting timber and mining market demands, also have had significant effects on C cycling. Clearly, the land use history of the region over the past 150 years has resulted in extremely large effects on the terrestrial C budget, so grounding C research within the land use framework is warranted.

Objectives

The overarching goal of this dissertation is to improve the quantification and understanding of C cycling as it relates to land use change in temperate deciduous forest regions in general, and in the Southern Appalachian Mountain region in particular. To meet this goal, the following 4 research questions define the agenda of this study:

1) How has land use and land cover in western North Carolina changed over the past 150 years, and what are possible changes over the next 30 years?

2) What are the primary rates and drivers of land use and land cover change in the region. How have those rates and drivers changed over the past 150 years, and how are they likely to change over the next 30 years?

3) What are the primary natural and anthropogenic disturbances of terrestrial C pools in the southern Appalachian Mountains, and what are the magnitudes of their influence on the region's terrestrial C budget. Additionally, how have those disturbances changed over the past 150 years, and how are they likely to change over the next 30 years?

4) Incorporating the information from questions 1-3, what is the terrestrial C budget of western North Carolina? How has the C budget changed over the past 150 years, and how is it likely to change over the next 30 years?

Study Area

The mountains in Western North Carolina are part of the Blue Ridge Physiographic province of the Appalachian Mountain region (Fenneman 1916). The Blue Ridge bedrock is dominated by Gneiss and Schist of the Paleozoic period, and soils are predominantly in the Inceptisol order (Gade and Stillwell 1986). Vegetation cover is predominantly a temperate deciduous forest with mixed conifer species (Braun 1950). The area receives a relatively high amount of precipitation, ranging from a 100-180 cm/year. Temperatures are generally cool in the winter (2-4^{o} C) and mild in the summer (20-27^{o} C).

To address the objectives above, a strategy of using nested study areas is adopted for spatial data development and modeling. Three levels of nested study areas of varying categorical detail and spatial scale (i.e., extent and Minimum Mapping Unit, MMU) are used (Figure 1). The level of detail and accuracy increases for each finer scale (Table 1).

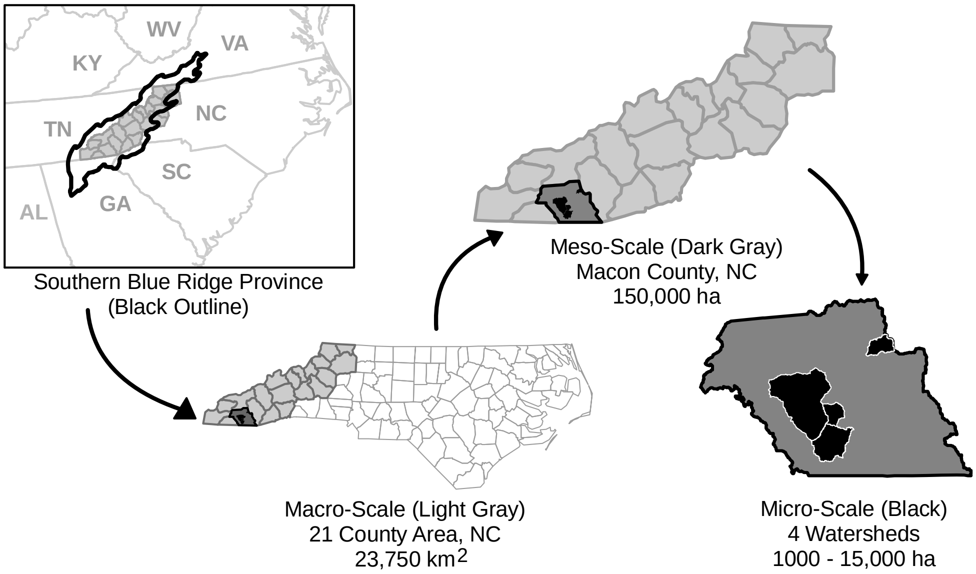

Figure 1: Nested study areas used in this dissertation

The broadest spatial extent (macro-scale) is the 21-county region of western North Carolina, an area that was selected for two reasons. First, the Blue Ridge province of western North Carolina is often delineated as a unique sub-region of the larger Southern Appalachian region, which consists of several mountain ranges, including the tallest peaks in the eastern United States, interspersed with valleys of varying sizes. The rugged and inaccessible terrain in part caused western North Carolina to remain in a “frontier” status longer than other areas of the Southern Appalachians as indicated by the relatively late arrival of railroads and subsequent industries in the late 19th century (Eller 1982). The predominant natural resources of the Blue Ridge are forests, water, and some mining interests, but notably excluding bituminous coal, indicating that western North Carolina was not directly affected by the rise and collapse of the coal mining industry that has heavily impacted the people and environments of West Virginia and eastern Kentucky since the late 19th century (Raitz and Ulack 1984). The scenic mountainous terrain has also driven the strong tourism industry that has steadily expanded over the past century (Taylor 2001; Starnes 2005). Approximately half of the Great Smoky National Park and a majority of the Blue Ridge Parkway National Scenic Highway are in western North Carolina. There are also two national forests (Nantahala and Pisgah) that contain five designated wilderness areas. Four hundred kilometers of the Appalachian National Scenic Trail, three state parks, and over 4,000 km of rivers are also scattered throughout the North Carolina Mountains or along its borders. Besides the natural resources, the political mechanisms of state governments in the region have also influenced land use practices in direct and indirect ways, suggesting a separation of the Southern Appalachian region by state boundaries. For example, North Carolina employed some of the first professional foresters in the country, which led to many of the earliest efforts for fire control and forest management in the region (Pomeroy and Yoho 1964; Mastran and Lowerre 1983). While western North Carolina is clearly a part of the Southern Appalachian cultural and physiographic region, there are justified reasons for studying the sub-area as a microcosm of the larger region.

The second reason for limiting the study to the 21-county area was data development logistics. Simply, the 21-county boundary was well matched to the variety of available data sources. Many historic government reports and academic studies provide information at the state or sub-state level, with western North Carolina having a large number of forest-related publications over the past 120 years (Ashe 1893; Pinchot and Ashe 1897; Holmes 1912; Etheridge and Holmes 1939; Pomeroy and Yoho 1964). Similarly, many of the historic maps used in spatial analysis are for individual counties or the state of North Carolina. In addition, the 21-county region has been delineated as one of the U.S. Forest Service's Forest Inventory and Analysis (FIA) survey units, named the "Mountains of North Carolina" unit, from whose publications and data are a major source for this research (Cruickshank 1941; Knight and McClure 1966; Cost 1974; Craver 1984; Johnson 1990; Brown 2002). While a broader study area boundary such as the entire Blue Ridge province or a multi-state Southern Appalachian boundary may have been useful in addressing the research questions, data collection and database assimilation limitations made such boundaries unfeasible.

Table 1: Nested study area descriptions.

Name	Area Description	Extent	MMU	Relative Accuracy
Primary watersheds	4 watersheds, including the Coweeta Basin, representing various land use changes	Each watershed on the order of 1,000-15,000 ha	1/16 ha	Maximum categorical and spatial accuracy; enforced temporal consistency
Single county	Macon County, NC	150,000 ha	1 ha	Moderate efforts to improve accuracy and temporal consistency, including 100m nominal accuracy requirement for all historic data sets
Multi-county	21 counties comprising the "Mountains of NC" FIA Unit	23,750 km^2	1 ha	Minimal efforts to increase accuracy of data sets

The moderate, or meso-scale, study area is Macon County, NC, which is used as an intensive case study for exploring land use change patterns and drivers, and for testing spatial modeling techniques. Large amounts of spatial data have been developed for the county as part of the on-going Coweeta LTER research agenda (Coweeta 2002), and a large body of ecological research has been conducted in the county. Furthermore, using a county boundary allows for the integration of spatial data with government census data and agricultural and forest inventory data, which are most often published at county or broader scales.

For the smallest spatial extent (micro-scale analysis), 4 watersheds in Macon County, NC, are used for the most detailed analysis with highest data accuracy. These watersheds, named Cartoogechaye Creek, Coweeta Creek, Skeenah Creek, and Watauga Creek and generally described in this dissertation as the “Primary Watersheds,” were selected because they contain a range of land use trends representative of the region and are studied by other researchers within the Coweeta LTER organization. They are used primarily to identify land use trajectories, quantify land use transition rates over the past 60 years and settlement rates over the past 100 years, and to help identify heuristics for broader scale modeling.

General Methodologies

As this is a synthesis study, the methodologies used are diverse, but generally fall under the categories of historical research methods and literature synthesis, geospatial modeling, and C cycle modeling. The historical research methods and literature synthesis focus on quantitative data extraction, primarily from secondary sources except in the case of census data, and on heuristic development for spatializing land use practices and C disturbance trends. The narrative history of the region is adopted from several extensive studies, with full titles listed here in recognition of the large influence they had on this research. These include the books by Eller (*Miners, Millhands, and Mountaineers:*

Industrialization of the Appalachian South, 1880-1930, 1982), Davis (*Where There are Mountains: an Environmental History of the Southern Appalachians*, 2000), Raitz and Ulack (*Appalachia: A regional geography: land, people, and development*, 1984) and Starnes (*Creating the land of sky: tourism and society in western North Carolina*, 2005); the US Forest Service history reports by Mastran and Lowerre (*Mountaineers and rangers: a history of federal forest management in the southern Appalachians*, 1983) and Yarnell (*The Southern Appalachians: a history of the landscape*, 1998); and the review article on land use legacies in the region by Gragson and Bolstad (2007). Combined, these sources and several related publications provide a broad foundation for understanding changes in the region consistent with the growing acceptance among researchers of a more syncretic and integrated view of Southern Appalachia's dynamic role in the New South (Raitz and Ulack 1984; Gragson and Bolstad 2006). This dissertation adds to this body of work by 1) re-evaluating the environmental history and land-use periodization from the framework of the emerging discipline of land use science, 2) spatializing and more rigorously quantifying land-use trends often described only in anecdotal form, and 3) quantitatively assessing the relative magnitudes of major land-use practices and their influence on land-use change and C storage.

Statistical methods for literature synthesis and spatialization include standard ANOVA tests, quantile regression, logistic regression, and classification trees. Geospatial modeling techniques include spatial logistic regression, multi-criteria evaluation, decision-rule modeling, and remote sensing image classification and change detection. C growth modeling is conducted using an inventory-based empirical bookkeeping model

(Houghton et al. 1983). It is the explicit aim of this research to use well-established methodologies and tools that are widely accepted and extensively reported in peer-reviewed literature. Given that this is a synthesis study rather than a sample-based study, the primary method for testing general hypotheses related to the objectives above is a convergence of evidence from a broad range of qualitative and quantitative assessments, including computer simulations.

Organization

The dissertation is organized into four interrelated chapters, which are structured in the format of manuscripts to be submitted to peer-reviewed journals. Chapters 1 and 2 are companion studies on development and land use change in Macon County and the 4 primary watersheds within the county. Chapter 1 focuses on the identification of land-use trajectories and modeling of land-use change, and is aimed at a land use science-related journal. Chapter 2 focuses on the changing spatial patterns of development trends, including building locations, road locations, and the land cover classification of "developed" areas. It is written with a land-use planning journal in mind. Chapter 3 is a regional analysis of land use periodization and spatial reconstruction of agriculture, forest, and development across all 21 counties, and will be submitted to an environmental history journal. Chapter 4 is the ultimate synthesis point of the research, and combines the knowledge gained in the first three chapters with a synthesis of C research in the region and a spatially-explicit C model to study terrestrial C storage in the region. The chapter will be submitted to a forest ecology related journal.

Chapter 1: Quantifying land-use trajectories and biophysical constraints on land use in a Southern Appalachian County, USA, 1850-2030.

Abstract

The Southern Appalachian Mountains have experienced large and dynamic land use changes since arrival of Euro-American settlement in the late 18th and early 19th centuries. In Macon County, NC, the fertile agricultural valleys drew settlers following Treaties with the Cherokee nation in 1819 and 1835. Successive waves of immigration, development, resource extraction, and abandonment have driven land use from then through the present. We modeled land-use patterns for each decade between 1850 and 2030 using a variety of spatial (historic map and aerial imagery) and tabular (census and government report) estimates of land use in order to define rates of change, identify land-use trajectories, and evaluate the influence of soil fertility on land-use change. Land-use patterns for dates with spatial data were used to interpolate and extrapolate land-use patterns for dates without spatial data using an iterative, decision-rule model that combines simple logic rules and logistic regression. Both timber harvest and agriculture area peaked in 1900-1920, and following recovery, the total forest area peaked in 1960-1980. From 1950 to 2008, the population in the county doubled and the total development footprint quadrupled. By 2030, we forecast a 4% loss of forest area as development pressures increase. These results have important implications for regional planning and ecological services such as water quality and wildlife habitat.

Introduction

Past land use data are crucial for understanding many current and future human-environment dynamics (Foster et al. 2003; DeFries et al. 2004). Many ecological conditions are directly or indirectly related to the “land use legacies” of practices that occurred decades or centuries ago (Foster et al. 2003; Gragson and Bolstad 2006). Ecological issues of concern such as soil degradation (Dupouey et al. 2002; Bakker et al. 2005), water quality (Bolstad and Swank 1997; Wear et al. 1998; Jones et al. 2001), habitat loss and fragmentation (Sinclair et al. 1995; Pearson et al. 1999), and biodiversity decline (Harding et al. 1998; Sala et al. 2000; Dupouey et al. 2002; Huston 2005) have all been linked to historic land use. The long-term legacy of agricultural abandonment, forest regrowth, and fire suppression is also an important contributor to the sequestration and cycling of carbon in forests, and improving the understanding and quantification of historic spatio-temporal patterns of land use at the landscape to regional scale may help reduce uncertainties in the global carbon balance (Houghton 2003).

A large body of research has focused on land-use change models in recent decades, yet uncertainty remains. Several summary articles have discussed needs and priorities in land use research (Veldkamp and Lambin 2001; Agrawal et al. 2002; Parker et al. 2003; Burgi et al. 2004; Rindfuss et al. 2004; Verburg et al. 2004; Manson et al. 2006). Veldkamp and Lambin (2001) identify 4 key trends in land-use modeling research: a) modeling the drivers of change, b) modeling scale dependency of drivers, c) modeling the quantity of change versus the location of change, and d) incorporating biophysical feedbacks into land-use models. Verburg et al. (2004) call for improved techniques for assessing and quantifying neighborhood effects on land use change and improving the analysis of temporal dynamics rather than just spatial dynamics. Insight into all of these research needs will be improved with a more temporally detailed land use record.

The Southern Appalachians Mountains, like many mountainous areas in the United States, have undergone dramatic and dynamic changes in land-use practices and patterns since the time of human arrival, and particularly since the arrival of Euro-American settlers (Davis 2000; Gragson and Bolstad 2006). In western North Carolina, many of the wider valleys have experienced intensive habitation by Native American societies for at least 1000 years, with major land-use practices prior to European contact including agriculture, hunting, and regular burning of the forests (Yarnell 1998). As Euro-American settlers arrived in the region in the late 18th and 19th centuries, agriculture steadily expanded deeper into the coves and higher up the hillslopes, reaching the peak total area in 1910 (This Dissertation, Chapter 3), with the most intensive agricultural use on the most marginal lands occurring during the 1920s and 1930s (Lewis 1931; Taylor 1938). With the arrival of the railroads and depletion of northern US forest supplies in the 1880s and 1890s, widespread logging and industrial expansion devastated most of the Southern Appalachian forested areas by the 1920s (Lambert 1961; De Vivo 1986), leading to large destructive fires, increased soil erosion, and a significant alteration of the forest composition (Holmes 1911; Eller 1982; Davis 2000). Logging decreased and fire suppression increased throughout the first half of the 20th century due to a large decrease in timber supply, changes in national and global timber demand, the rise of conservation-minded citizen groups and focused government programs, and the purchase of large tracts for National Forests and National Parks (Frome 1966; Mastran and Lowerre 1983). The total area of cleared agriculture land decreased slightly between 1910 and 1940 as marginal lands were abandoned, and plummeted following WWII during the Appalachian out-migration of the 1950s and 1960s in which millions of Appalachian families left rural areas for cities (Brown and Hillery Jr. 1962; Raitz and Ulack 1984). Since the 1970s, the primary land use trend has been a sharp increase in population and residential development, in large part due the arrival of retirees, second-home owners, and others attracted to the amenity-driven lifestyle and scenic quality of the region (Raitz and Ulack 1984; Gade and Stillwell 1986).

While the narrative story of land use in the Southern Appalachian Mountains has long been studied, the short- and long-term ecological consequences of these practices across the landscape cannot be fully understood without detailed, spatially-explicit data with which we may study the consequences. For example, small-scale, field-based studies in the region have shown a strong link between past land use and water quality (Bolstad and Swank 1997; Wear et al. 1998; Jones et al. 2001), aquatic communities (Harding et al. 1998; Scott 2006; Burcher et al. 2007), and forest communities (Pearson et al. 1999; Turner et al. 2003; Fraterrigo et al. 2006), but the magnitude of the effects across the landscape cannot be fully analyzed without landscape-level data on land use. In addition, spatially and temporally detailed land use records provide a strong foundation for forecasting both land-use change and potential ecological consequences.

We present here the results of a case study of land use and land cover change (LUCC) patterns in Macon County, NC, from 1850 to 2000, and forecasts from 2010 to

2030. The starting decade of 1850 represents the period after the entire county in its present boundary was transferred from the Cherokee Indians to the State of North Carolina in the treaties of 1819 and 1835. Approximately 80% of the county was transferred during the treaty of 1819, during which the first spatial land survey in the area was conducted, by Robert Love (Jurgelski 2004). The remaining 20%, mostly rough mountainous terrain on the western edge of the county, was transferred in the 1835 treaty that is more widely documented because it led to the final attempted removal of the Cherokee from the region in the episode known as the “Trail of Tears” (Malone 1956; Finger 1991). The 1850 starting date is also useful since it coincides with the earliest U.S. Census that reported the area of agriculture, and it pre-dates the U.S. Civil War and the reconstruction and industrial expansion period of the late 19th and early 20th centuries.

The goal of this paper is to study the countywide changes over this 180-year period as a basis for exploring the rates and drivers of major land use changes in the region, and to evaluate the role of biophysical feedbacks on land-use changes over time. We addressed two primary hypotheses. First, we hypothesized that decadal spatial patterns of major land use classes (Forest, Transitional forest, Agriculture, and Developed) in the Southern Appalachian Mountains could be reconstructed to a relatively high level of accuracy (> 75%) at a 1 ha resolution using terrain models, infrequent spatial data of land use, and more frequent tabular estimates of land-use intensity provided by population censuses, agricultural censuses and forest inventories. Second, we hypothesized that terrain and soil variables were historically the most important limiting factors on land-use change, but that these constraints have become less important in recent decades. Both of these hypotheses are based upon the well-documented trends that the steep terrain and limited transportation access strongly constrain land use in the Southern Appalachian region (Eller 1982; Wear and Bolstad 1998; Davis 2000). To address these hypotheses, the specific objectives of this study were to (1) identify major land use changes and quantify land use trajectories and rates of change in a Southern Appalachian county, (2) reconstruct major land use patterns in the county for each decade from 1900 to 2000 using sporadic spatial data and more frequent census data, (3) develop spatio-temporal models to backcast land use from 1850-1890 and forecast land use from 2010-2030, and (4) evaluate the role of terrain and soil variables on LUCC over this period.

Study Area Description

Macon County is part of the southern Blue Ridge physiographic province and is located in the southwestern mountainous section of North Carolina, U.S.A. (Figure 1). The county is characterized by steep topographic relief (500-1800m elevation), mild winters, cool summers, and high levels of precipitation (130 - 200cm/yr). Forests presently cover over 75% of the county, and consist primarily of mixed deciduous species with scattered pine. Forty-five percent of the county is publicly owned, with nearly all of this public area included as part of the Nantahala National Forest. The two primary cities in the county are Franklin, the county seat and largest city, and Highlands, a recreation resort town in the southeastern corner of the county.

During the Antebellum period Macon County was one of the more isolated counties in the Southern Appalachians, with difficult over-mountain access to the largest city in the region, Asheville, NC, and less challenging but still prohibitive access to the state of Georgia to the south. However, given the large and fertile central valley of the Upper Little Tennessee River, the area was used extensively by the Cherokee (Gragson and Bolstad 2007) and was coveted by white settlers after the treaty of 1819 (Jurgelski 2004). The first railroad in the area, the Western North Carolina Railroad Asheville-Murphy branch, was completed in 1885 (Van Noppen and Van Noppen 1973), but the line only passed the rugged northwest corner of the county and was used by citizens in the county primarily for forest product extraction (Holmes 1911). It was not until 1908, when the Tallulah Falls and Franklin Railroad was completed across the Georgia-North Carolina border, that the city of Franklin had regular rail service (Arthur 1914).

The area of cropland and pastureland agriculture steadily expanded in the county following the Civil War until the 1910s, then declined at varying rates until the late 1980s, after which the agriculture area has remained fairly constant (Figure 2). The population trend was a growth pattern from the Civil War until WWII, then a decline during the years of the Appalachian out-migration in the 1950s and 1960s. Since the 1970s, the population growth has been strong, and the trend is expected to increase at least through 2030 (North Carolina Office of State Budget and Management 2008). In a companion study on the trends in building development, we summarized the county as being predominantly rural before 1960, primarily exurban between 1960 and 1975, and increasingly suburban since 1975 (This Dissertation, Chapter 2). We forecasted a continued increase of suburban-density development through 2030, with this future trend being nearly inevitable given the widespread subdivision of parcels into suburban-density units over the past 30 years.

Within the county, four watersheds were chosen for intensive study (Figure 1), and were selected based primarily on aerial photograph availability and overlap with other research projects of the NSF-sponsored Coweeta Long Term Ecological Research site (Coweeta 2002). These watersheds, which range in size from 1,000 ha to 15,000 ha, have experienced a variety of urban, suburban, and exurban development trends since the 1940s, and one of them (Cartoogechaye Creek) is also the water supply watershed for the city of Franklin. Combined, these watersheds cover 22,878 ha, or 17% of the total 134,656 ha county area.

Methods

Database Development

To reconstruct historic land use and quantify land use trajectories and rates of change, an extensive geospatial database was developed and organized within a Geographic Information System (GIS). Land use data layers at discrete moments in time were manually interpreted from current and historic aerial photography, with the goal of at least decadal coverage between 1954 and 2006 for the primary watersheds, and for 1954, 1993, and 2003 for the entire county. For two of the watersheds, Coweeta and Skeenah, 1942 photographs were also included. For a description of photograph processing, see Kirk et al. (This Dissertation, Chapter 2). For each of the watersheds, a lattice of points was generated at 25 m spacing, with each point representing the center point of a 1/16 ha (25 m resolution) raster cell. Six broad land-use categories of Forest, Transitional Forest (< 75% forest canopy cover and transitioning towards closed-canopy forest), Agriculture (row crop and open pasture), Shrubland, Water, and Developed areas were simultaneously interpreted as attributes of the lattice to ensure logical consistency. That is, a given point or group of points was examined on all of the photograph dates, and the land use for each date was assigned to represent the true land use trajectory. For the countywide data set, vector polygons of land use were digitized for 1954 and 2003 with a minimum mapping unit of 0.4 ha (1 acre), and aggregated for this study to a 1 ha resolution lattice of points using a majority area "winner-takes-all" aggregation decision rule (Bolstad 2008). For each of the 1 ha points, the land use categories for the two dates was visually compared on the photographs and manually modified if needed to ensure logical temporal consistency. Land cover for 1993 was manually interpreted off of USGS Digital Orthophoto Quadrangles for each point with reference to the 1954 and 2003 classifications. Mid-1970s and mid-1980s forest/non-forest classifications derived from Landsat satellite imagery (unpublished data, Coweeta LTER, available at http://coweeta.ecology.uga.edu/) were also collected. The final source of spatial land use was the 1904 Ayers/Ashe map, a product of a joint US Geological Survey-US Forest Survey assessment of the forest conditions in the Southern Appalachian Mountains (Ayers and Ashe 1905). The map identified cleared and forested areas, as well as estimates of forest stand volumes. Based on a sample of 60 points across the entire Ayers/Ashe region, which covers portions of 21 counties in North Carolina plus scattered counties in Northern Georgia, Eastern Tennessee, and Southwestern Virginia, we estimated the spatial accuracy of the Ayers/Ashe map to be approximately 500m, with a nominal minimum mapping unit of 4 ha (This Dissertation, Chapter 3). To improve this accuracy, we manually interpreted the 1904 land cover for Macon County onto 10 m DEM-derived contour lines by cross-referencing polygon boundaries against the contour lines on the Ashe/Ayers map. A second sample of 20 points within the county indicated an improved spatial accuracy on the order of 200 m.

Buildings (points) and road locations (lines) were also digitized off of the aerial photographs, and historic map sources containing building and road locations from 1907, 1929, and 1942 were acquired for years prior to the photographic record (for details, see This Dissertation, Chapter 2). All data were developed into or reprojected to the Universal Transverse Mercator (UTM) coordinate system, Zone 17, and converted to 1/16 ha (25 m cell size) raster data formats for the four watersheds and 1 ha (100 m cell size) raster formats for the countywide data.

Tabular estimates of land use area and population for the county were compiled from the decennial census records of the US Census Bureau (U.S. Census Bureau 1850-2000), the quinquennial USDA Census of Agriculture reports (National Agricultural Statistics Service 1954-2002), the periodic USFS Forest Inventory and Analysis (FIA) reports (Cruickshank 1941; Knight and McClure 1966; Cost 1974; Craver 1984; Johnson 1990; Brown 2002), and miscellaneous government publications (Ayers and Ashe 1905; Holmes 1911; North Carolina Department of Conservation and Development 1929; Wager and Thomson 1932; Mason and Forster 1950; Pomeroy and Yoho 1964). For the agriculture area estimates, the sum of the area of cropland and non-woodland pastureland were combined into the single class of "agriculture" used in this study. USDA definitions of "improved farmland" historically included farmyards, idle fields, and other miscellaneous areas, but in the Southern Appalachian region farmyards were sufficiently small during the peak agriculture period that we feel they will not influence the analysis at the county scale relative to other sources of error. For example, in Macon County, a mean farmyard size in 1954 was estimated to be 0.2 ha based on a sample of 50 randomly selected farmyards, an area much smaller than the 1 ha sample unit. Idle or abandoned fields in this classification are captured in the transitional forest class.

Models of land use change

We utilize two classes of LUCC models to evaluate land use trends in Macon County. First, we define a decision-rule model for reconstructing decadal land use between 1900 and 2000, which are the nominal bounding dates where spatial data are available. The decision-rule model uses census estimates, logic rules, and terrain-based models to fill in the periods between the spatial data sampling dates. The second model uses a hierarchical suite of logistic regression models for backcasting land use prior to the period of detailed geospatial data (1850-1890) and forecasting land use into the future (2010-2030). Each model is described in detail below, but an overview of logistic regression modeling is introduced first.

Logistic regression has been widely used to model land-use change (Mertens and Lambin 2000; Schneider and Pontius Jr. 2001; Manson et al. 2006)**,** and has proven useful for applications in mountainous terrain (Turner et al. 1996; Theobald and Hobbs

1998; Wear and Bolstad 1998). Variants of the approach include multiple logistic regression of two classes (e.g., Forest vs Non-Forest), multinomial logistic regression, where the dependent variable has multiple categories (i.e., land uses), and spatial logistic regression (Irwin and Geoghegan 2001), which include spatial weighting in the independent variables or error term to account for spatial autocorrelation. In this study, we develop multiple logistic regression models of individual classes using a logit link function (Agresti 2002):

$$\ln\left(p_y / (1 - p_y) \right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \varepsilon \qquad (1)$$

where p_y is the probability of land use class y equaling 1, $ln(p_y/1\text{-}p_y)$ is the natural log of the odds of a cell equaling 1, k is the number of independent x variables, $\beta_0 \ldots \beta_k$ are the regression parameters, and ε is the error term. We address the spatial autocorrelation problem (Dubin 1995; Overmars et al. 2003) by adopting the method of Wear and Bolstad (1998), in which the sample set of points for model development is spatially random and a local spatial weight term is added to the set of candidate dependent variables. The local spatial weight is defined as the proportion of the 8 neighboring cells that have the same land use class as the sample cell. Logistic models are used to create raster-based probability maps for spatial modeling, so our primary criterion for model selection is capturing the maximum spatial variation across the landscape. Thus, we select the broadest model from the set of candidate independent variables that consists of all statistically significant independent variables.

Agriculture Suitability Index

In addition to land use modeling, we use logistic regression for the second purpose of defining a probability-based Agriculture Suitability Index (ASI) that is generalized from the Natural Resources Conservation Service Land Capability Classification (LCC) included with the SSURGO data set (Soil Survey Staff 2008). The LCC provides a categorical estimate of the capability of a given soil unit for growing common crops or pasture grasses, and is based on an assessment of the risks of soil damage (e.g., erosion potential) and limitations on use (e.g., stoniness, shallowness of the rooting zone). Rather than using the discrete boundaries of the LCC classification, we convert the data to a probability index for three reasons. First, since we are relying on a variety of data with varying degrees of spatial and categorical accuracy, using a derived, continuous variable is one way to loosen, or “fuzzify”, the data set to more appropriately match other data sets (Dragicevic et al. 2001). Second, historic agricultural practices in the region often involved using the most fertile land for small patches of row crops and neighboring hill slopes for pastureland regardless of site suitability. A continuous probability index better captures some of this trend. Finally, a probability index is useful for spatial modeling since it helps identify the areas that are most likely to be used for agriculture rather than just the areas that are suitable for agriculture.

We convert the categorical LCC data to a probability index by creating a logistic function derived from the available SSURGO data with LCC Classes 1 and 2 (slight to moderate limitations) defined as suitable areas, and Classes 3-8 (various types of severe to very severe limitations) defined as unsuitable. A set of 5 terrain variables were used as dependent variables: 1) slope (*slpp*, in percent); 2) elevation (*elev*, in m); 3) Terrain Shape Index (*TSI*), which is a measure of terrain shape from ridges to coves (McNab 1989); Topographic Relative Moisture Index (*TRMI*), which estimates the relative moisture content of varying terrain positions (Parker 1982); and distance from the nearest stream or river (*d2stream*, in m). We generated a random sample of 2000 points throughout the county for calibrating the ASI model. We utilize the ASI in two ways. First, the ASI is used for land-use modeling in order to identify areas most likely to have been agriculture for periods prior to the availability of spatial data. Second, for the primary watersheds, we test the relationship between ASI and land use change for all dates using a standard ANOVA test in order to evaluate the role of biophysical feedbacks in historic land use change patterns.

1900-2000 decision-rule reconstruction model

In order to develop a countywide, temporally-detailed, and logically-consistent data set, decadal land use from 1900 (the decade of peak agriculture and earliest spatial data) to 2000 were reconstructed using geospatial data where available, simple logic rules where defensible, and general transition trends estimated from census records and historic documents in all other cases. The primary spatial data sets used in the reconstruction were the 1954, 1993, and 2003 photograph-interpreted land use layers, the 1904 Ayers/Ashe forest cover map, Landsat-derived mid-1970s and mid-1980s forest/non-forest classifications (Coweeta LTER, unpublished data, available at http://coweeta.ecology.uga.edu/), 1929 and 1942 soil surveys, the digitized buildings data sets, and the Nantahala National Forest stand database (SAMAB, 1996). The 1942 soil survey, along with providing building and road locations, contained a polygon attribute that distinguished areas with eroded soils, which we assumed were areas that had contained agriculture sometime in the previous 40 years. The 1929 soil survey did not include any direct indication of agriculture areas or agriculture suitability, so was used only for building and road locations.

The total number of cells in the Agriculture and Developed classes for decades without spatial data was constrained by the quantity and rates of change in improved farmland and Housing Units, respectively, which were obtained from the census data. Based on the land cover derived from aerial photographs for the primary watersheds, the mean number of years following observed agriculture abandonment until observed forest canopy closure was 18 years, with a standard deviation of 9 years. Thus, we considered a cell to be Transitional for three decades after abandonment on severely eroded or gullied lands (as reported in the 1942 Soil Survey), two decades after abandonment on less eroded lands, and one decade following a forest harvest. All cells not classified as Developed, Agriculture or Transitional were assigned as Forest.

The reconstruction sequence is detailed in Table 1. In effect, the reconstruction was an iterative process starting with the best available data and filling in gaps at each iteration using data with the next lowest level of detail and certainty until the aggregate area estimates from the census records were reached or all cells were classified. The Developed cells for all decades were reconstructed first, using the existing spatial land use data and building location densities as a proxy for development (for a description of the processing for the building density data sets, see This Dissertation, Chapter 2).

Development was assumed to persist once established. That is, after a cell was classified as Developed, the land use of the cell for all subsequent years was also assigned as Developed. This rule is supported by trends observed in the Primary Watersheds (Figure 4).

Agricultural areas were identified next using the existing land use data, agriculture census records, the ASI, and the 1942 soil survey attributes of erosion class. For dates without spatial data, the quantity of agriculture was determined from the census records, and the location of change in agriculture was determined by logic rules where possible, or else by deterministically selecting cells based on the values of the ASI and 1942 erosion class. All other areas were assumed to be Forest, and forest harvest areas were identified for the National Forest for all years using the National Forest stand database and on private areas for the period of satellite records (1975-present). Filling in the logical trajectories of regrowth following abandonment and harvest, these iterations resulted in the classification of over 98% of the total area for 1970 and 1980, 91% of the area in 1960, and between 45% and 47% of the area for the decades between 1900 and 1940. The remainder of the area consisted of forest areas on private land that may have been harvested. Harvest areas were identified by first ruling out areas of unlikely harvest (i.e., sites that were harvested or abandoned before a standard 80-year rotation), and then selecting additional harvest sites at a rate drawn from the periodic USFS and state forest reports and in a spatial pattern consistent with the 1904 Ashe/Ayers map and report. This reconstruction was based entirely on the existing data set and detailed knowledge of the study area, so is not readily reproducible in other studies outside this region, although the concept of using logic rules to account for easily identifiable trajectories may be a useful method for greatly reducing the area of uncertainty in land-use change studies.

Accuracy of the countywide reconstruction is estimated by comparison against the independently digitized land use for the four watersheds within the county, using the Components of Disagreement and Null Resolution method of Pontius et al. (2004), and the standard Kappa statistic of agreement (Congalton and Mead 1983). All statistics were calculated using the Validate Module of the Idrisi Andes Edition software package (Eastman 2006). The Components of Disagreement statistics compares the two maps on a cell-by-cell basis using fuzzy set theory (Foody 1996) and divides the comparison into 3 percentages which sum to equal 100% of the map area. Map Agreement is the total percentage of the map area where the two maps agree, and is equivalent to the "Overall Accuracy" statistic of a stand error table or contingency matrix (Bolstad 2008). Quantity Disagreement is an estimate of the percentage of map disagreement that is due to differences in the total quantities of each category. Location Disagreement is an estimate of the percentage of map disagreement that is due to pixel mismatch. The Null Resolution is an estimate of the raster cell resolution at which the modeled land cover is a better fit than a null model of no change. The Null Resolution is a useful indicator of the appropriate scale of interpretation while helping account for the common problem of individual cell mismatch even if the model is generally acceptable. The standard Kappa statistic is a measure of map agreement that tests whether the two maps are more similar than would be expected from a random result.

Backcast and forecast models

We adopt a hierarchical decision-tree approach for backcast and forecast models, in which each land use category is modeled in successive order starting with Development, followed by Agriculture and then Forest. Transitional Forest is logically inferred using the rules described above.

For backcasting from 1850-1890, the total quantity for the Agriculture and Development classes are determined by the improved farmland and Housing Unit census data, respectively. Since the county boundary changed shape multiple times between 1850 and 1900, we approximate the census variables for the extent of the modern county boundary by applying an area-weighted interpolation procedure, where the weighting is defined by the percentage of suitable agriculture area in the county (This Dissertation, Chapter 3). Forest harvest independent from agriculture clearing is assumed to be negligible before the Civil War since the primary harvest method was single-tree selection and consumption was local (Eller 1982; Davis 2000). The quantity of forest harvest area for 1870-1890 is estimated by extrapolating the harvest area trends moving backwards from 1920-1900 using an exponential decay function.

For forecasting from 2010-2030, the total area of Developed land is estimated by applying the average population-to-development area ratio from 1980-2000 to the projected population growth estimates (North Carolina Office of State Budget and Management 2008), a ratio that has held fairly constant over the past 20 years (This Dissertation, Chapter 2). The quantity of Agriculture area is estimated by linearly extrapolating the trend in Agriculture from 1980-2000. Forest harvest quantity is set equal to the average decadal quantity observed from 1980-2000. The locations of forecasted change in Development are determined by selecting the areas with the largest change in building density as determined by the building density forecasts in a companion study (This Dissertation, Chapter 2). The location of any Agriculture loss not accounted for by Development growth is determined by selecting those areas with the lowest ASI values. Forest harvest sites are selected randomly from the set of Forest cells that are at least 80 years of age. Transitional areas are logically inferred.

Since the publicly owned areas (predominantly National Forest land) are an unrepresentative sample of larger public administrative units, they are excluded from analysis beyond county-level data summaries or modeling of years prior to National Forest establishment. Only privately owned lands are considered in all other cases. Validation of the land use change uses the same Components of Disagreement, Null Resolution, and standard Kappa statistic described above.

Results

Primary Watersheds

The types, rates, and trajectories of land-use change on private lands in Macon County were dynamic over the 100 years of available spatial data and 150 years of tabular data. Results are presented first for the primary watersheds, and then for the entire county. Between 1954 and 2003, 27% of the private lands of the primary watersheds experienced at least one change in land use classification. The rate of change steadily decreased, from a peak annualized rate of 1.3% of the landscape during the 1950s to under 0.5% annually from 1984 to 2003. Combined, the changes on private lands can be grouped into 9 land use trajectories since 1942 (Figure 3). The total area of agriculture decreased from 25% of the private area in 1954 to 10% in 2003. Of the lost agriculture, 47% was eventually developed and 53% reverted to forest. However, across the county, agriculture abandonment had peaked at least two decades before 1954, so the total percent of abandoned agricultural land that reverted to forest is likely higher than the 53% indicated here. Of the 47% of agriculture that was eventually developed, over 2/3 was developed immediately, while 1/3 was abandoned for at least 1 decade before being developed. The abandonment occurred at a decreasing rate during the latter half of the 20th century (Figure 4), and the proportion of abandoned agriculture that was developed increased over that period (Figure 5).

Forest area on private land peaked in 1976, but has since steadily declined, primarily due to increased development. This pattern is consistent with regional trends (This Dissertation, Chapter 3). The area of Transitional Forest was large following the initial recovery from agriculture abandonment, but declined significantly in subsequent decades. Transitional Forest since the 1960s is primarily in the form of forest harvest, although small agriculture fields are occasionally abandoned.

The Agriculture Suitability Index (ASI) provides evidence for a very close connection between soil and land-use change. We validated the ASI model against the 2,000 sample points excluded from the model. We tested for significantly different ASI values for the binary “suitable” classification generalized from the LCC, as well as for the original agriculture suitability severity classes of the LCC. In both situations, the model fit is highly significant (ANOVA *F*-Test, $F > 500$, $p < 0.0001$). This strong trend also holds across the 21-county region of Western North Carolina (This Dissertation, Chapter 3).

Figure 6 illustrates the dynamic connection between soil suitability and land-use change. Across all classes of land-use trajectories, change occurred on lands with higher average ASI values (i.e., more suitable soils) than the countywide distribution. However, this trend weakens over time as land-use changes become further disconnected from agriculture. Marginal lands were abandoned in higher proportions in 1942 and 1954, and the agriculture areas most resistant to development or abandonment were generally the most suitable. Development in the 1950s and 1960s was concentrated on more agriculturally suitable lands, but this relationship has weakened over time as homeowners built in more remote locations.

Countywide

Since 1850, all but the most isolated forest stands in the county have experienced major land cover change or forest harvest at least once (Figure 7). Between 1954 and 2003, the dates of detailed aerial-photograph interpreted land cover, 20% of the total area and 35% of the private areas changed land uses at least once. The primary changes at the county scale since 1954 have been a large loss in agricultural land and a large gain in residential and commercial development. The total development footprint increased from 655 ha in 1954 to 7403 ha in 2003, although in 2003 this comprised only 10.1% of the private land in Macon County, and 5.5% of the total county area. Concentrated residential development in forested areas is a phenomenon of the past 50 years, with over 1000 ha of new development falling in this category. Although Forest area has grown since 1954, the land use reconstruction and Primary Watershed analysis indicate that total Forest area peaked between 1960 and 1980 following recovery from agriculture abandonment, and has steadily declined since (Figure 9). At the peak of agriculture use and forest harvest in 1910, 56% of the county was closed canopy forest, with 26% of the remaining areas in a transitional state from cut to forest.

The model validation indicates that the reconstruction and backcast models were a significant improvement over a null model of no change for all spatial resolutions (Table 2). The validation compared the countywide land uses, which were modeled using county-level census estimates and infrequent county-level spatial classifications, against the independently created Primary Watersheds land use data sets for all available years: 1942, 1963, 1976, and 1984. Overall accuracy ranged from 72.8-78.8%. Disagreement due to Accuracy ranged from 3.6-5.1%, and Location Disagreement ranged from 16.3-28.5%. The overall agreement and Location Disagreement improved from 1942-1984, while the Quantity Disagreement slightly decreased over the period. Agreement in land cover classes also showed a temporal trend. The accuracy for the Developed class improved from 33% in 1942 to 62% in 1984. Conversely, the accuracy of the Agriculture class was higher in 1942 (72%) than in 1984 (63%). This is likely due to the changing dominance of these two classes over time. Figure 8 compares the photograph-interpreted and modeled land cover in the Skeenah Creek watershed for three independent dates.

Our forecast suggests that the primary land-use changes over the next several decades will be a growth in Development, a slight decrease in Agriculture, and an overall decreasing rate of change across the landscape (Figure 9). We estimate that total forest area will decrease 3% by 2030 due to new development. Assuming growth patterns match recent trends, we estimate that the total development footprint will grow from 11604 ha in 2000 to 17161 ha in 2030, a 47% increase.

Discussion

Several trends emerge from the combined analysis of the Primary Watersheds and countywide modeling. First, there is a trend towards increased fragmentation across the landscape. Large agricultural fields have been replaced by smaller residential yards, and residents seeking relative solitude are constructing new houses in previously forested areas. This trend has important implications for water quality. Water quality is strongly influenced by paved and unpaved road surfaces (Bolstad and Swank 1997). In our study of changes in development patterns (This Dissertation, Chapter 2), we estimate that the total road length in these Primary Watersheds tripled between 1954 and 2003, with nearly all of the growth being the result of long driveways and sub-division roads. Since a large proportion of the population in the two main cities receive drinking water from surface water sources, this fragmentation may have a negative effect on drinking water supplies.

Similarly, the increasingly fragmented forest and changing forest ownership may affect forest management and timber supply. In Figure 10, we estimate the history of forestland ownership in the county based on this reconstruction and literature search. Forest industry landowners have effectively left the county over the past 50 years, while private non-industrial owners are now responsible for nearly all lands outside of the National Forest boundaries. Private owners historically have spent little time and effort in active forest management (Pomeroy and Yoho 1964; Anderson 1968). Assuming that the likelihood of forests being harvested for timber decreases as the land is subdivided into smaller parcels, it is possible that the forests on private land in Macon County may reach older ages.

While the approach to analyzing land-use change applied in this study provides novel insights, there are limitations to these methods. In all, this multi-phase, iterative modeling effort relied heavily on the detailed understanding of the land-use change processes in the region and in the realization that mountainous terrain has a very strong influence on landscape patterns. Where reconstruction and logical consistency are important, a decision-rule model appears quite valuable. For situations where such terrain constraints are not available, or for identifying driving factors across regions, a less deterministic model might be warranted.

It would be useful and possible to use more than four general land cover classes for modeling. However, there are particular challenges in the Southern Appalachian region to increasing the categorical detail of land cover classifications. The forests are extremely complex (> 130 species of trees), which render the separation of forest types difficult (Bolstad et al. 1998). Splitting agriculture into at least row crop and pasture categories would aid understanding of the evolving agricultural practices, but distinguishing the two on old aerial photographs proved extremely challenging. In addition, the agricultural history of the region often involved rotating land use categories (e.g., corn, then pasture, then abandoned to forest for two or more decades until the soil recovers) rather than rotating crops (Hart 1977; Otto 1989). The evolving development patterns were explored peripherally in this paper, but warrant further investigation.

We relied on county-level aggregate estimates of key variables in order to determine the quantity of change for many of the land use classes. This approach has been used in many other studies (Pontius Jr. 2000; Radeloff et al. 2000; Pontius Jr. et al. 2003). We relied on the accuracy of the source data sets, such as the US Census of Population and US Census of Agriculture, but did not factor uncertainty in those data sets in our analysis, and we also assumed that patterns visible on aerial photographs matched categories in the censuses. We digitized land cover at a very high level of spatial detail in the county for 1954 and 2003. Our classification mapped visible land cover, and we estimated 13,578 ha of agriculture in 1954 and 5,351 ha in 2003, while the 1950 census of improved farmland in 1950 and 2000 were 15,346 ha and 5,855 ha, respectively. This difference is likely due to a combination of our classification methodologies and inaccuracies in the census data, which relied on farmer responses without validation. Irrespective of the error source, the net effect of error propagation is unknown, and this may have differential effects on the types of trajectories modeled. However, given that such data are often the only data available, this approach is still a significant improvement over the alternative of no quantitative estimates.

It would also be useful to analyze changes in landscape pattern in the county (Turner 2005; Iverson 2007). While the validation justified our use of decision-rule and suitability-based modeling approach, pattern analysis on the modeled data set would likely be biased since patterns very likely are a function of the modeling approach rather than the true conditions. As evidence, our model validation identified the Location Disagreement as the primary source of error.

While the Macon County landscape has changed in dynamic ways over the past 150 years, the recent trend of a steady increase in the Development footprint is likely to be the dominant change for the coming decades. Evaluating the spatial patterns and magnitude of this trend may ultimately help in identifying smart growth strategies to minimize the adverse consequences on ecological service and the overall quality of life in this scenic region.

Table 1: Sequence of land use reconstruction, 1900-2000. Dev = Developed, Ag = agriculture, For = Forest, and Transitional = non-forested lands transitioning towards forest.

Phase 1: Identify water, public forest, and highway classes

1) Identify water cells on 2000. Assign Water for all previous decades, except for the two primary reservoirs, Emory and Nantahala, which were constructed before 1920 and 1940, respectively.
2) Identify major 4-lane highway routes and assign as Developed backwards until the decade of construction. Assume all other roads are aggregated into other classes at 1ha resolution.
3) For public lands, assign Forest and forest harvest based on the National Forest Stand Database.

Phase 2: 1950-2000 land cover

1) Establish 1954, 1993, and 2003 land cover data sets as the 1950, 1990, and 2000 dates, respectively.
2) If Dev in 1950, then Dev from 1960-1980
3) If Ag in 1950 and Ag in 1990, then Ag from 1960-1980
4) If Dev in 1990 but not 1950, identify quantity of Dev in 1960-1980 from changes in Housing Units as reported on the US census, and determine location of Dev areas by changes in building density
5) If Forest or Ag in 1950, and new Dev sometime between 1960-1980, fill in Forest or Ag for intermediate years
6) If on private land and Forest in 1950 and 1990, determine forest harvest sites for 1970 and 1980 from satellite-derived Forest/Non-Forest classifications
7) Identify quantity of Ag in 1960-1980 from agriculture census, calculate the difference against the 1950 Ag area, and identify the Ag cells to "abandon" as those with the lowest ASI values
8) If abandoned Ag, fill in subsequent 1-3 decades as Transitional based on 1942 Erosion class rules if not already classified
9) If abandoned Ag, fill in all un-classified decades following Transitional period as Forest
10) Fill in all remaining unclassified cells as Forest

Phase 3: 1900-1940 land cover

1) Moving backwards from 1940-1900, define changes in quantity of Dev cells as proportional to change in census Housing Unit counts. Determine locations of Dev as those areas Dev in the subsequent decade and with the highest building density derived from the digitized building data sets.
2) Determine quantity of Ag from agriculture census. Moving backwards from 1940-1900, identify Ag cells with the highest ASI values on private land, constrained by the 1942 Erosion class.
3) If Ag assigned, fill in subsequent 1-3 decades as Transitional based on 1942 Erosion class rules.
4) If abandoned Ag, fill in all un-classified decades following Transitional period as Forest
5) For all remaining Forest areas, assume an 80-year stand rotation and define total area as those reported in USFS FIA reports (Cruickshank 1941) and miscellaneous government reports (Ayers and Ashe 1905; Holmes 1911; Wager and Thomson 1932). For 1900-1940 unclassified cells labeled as harvested during 1950-2000, fill in Forest for applicable years. For remainder of unclassified cells, identify harvest timing and location moving forward from 1900-1940 as those areas with the highest ASI value. This is based on the assumption that soils suitable for agriculture are also more suited for economically viable forest extraction.

Table 2: Validation of decision-rule models. The reference data for all years are the independently classified land cover data sets for the primary watersheds. The modeled dates include the subset of the county-wide model that overlaps with the primary watersheds.

Class / Reference Area	**Reference Date**	**Modeled Date**	**Agreement[*] (%)**	**Disagreement due to quantity (%)**	**Disagreement due to location (%)**	**Kappa**	**Null Resolution[**]**
All classes	1942	1940	72.8	3.6	28.5	0.512	100m
Forest			*82.1*			*0.577*	
Agriculture			*71.7*			*0.604*	
Development			*33.3*			*0.313*	
All classes	1963	1960	77.8	3.8	18.3	0.550	100m
Forest			*87.1*			*0.625*	
Agriculture			*54.1*			*0.604*	
Development			*50.3*			*0.471*	
All classes	1976	1970	78.0	5.1	16.9	0.534	100m
Forest			*87.9*			*0.601*	
Agriculture			*69.4*			*0.647*	
Development			*48.7*			*0.426*	
All classes	1984	1980	78.8	4.9	16.3	0.554	100m
Forest			*87.5*			*0.601*	
Agriculture			*63.1*			*0.582*	
Development			*62.5*			*0.568*	

* For the “all classes” group, the map agreement is the total spatial agreement. For the individual classes, the map agreement is the percent difference in the total quantities irrespective of spatial location.
** The Null Resolution uses the 1954 digitized land cover data as the baseline.

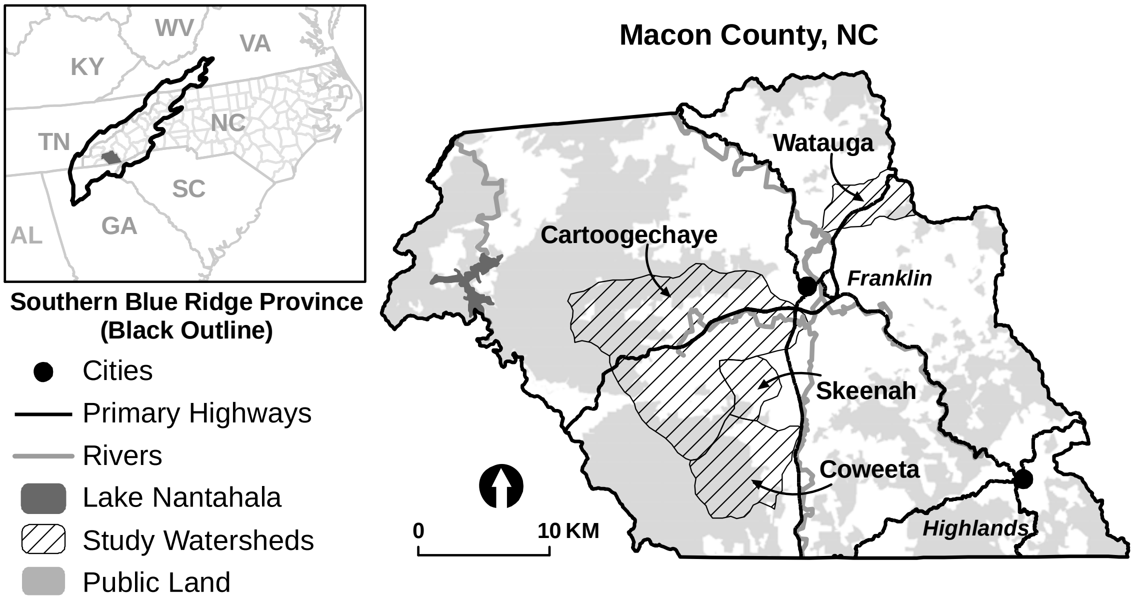

Figure 1: Study area reference map.

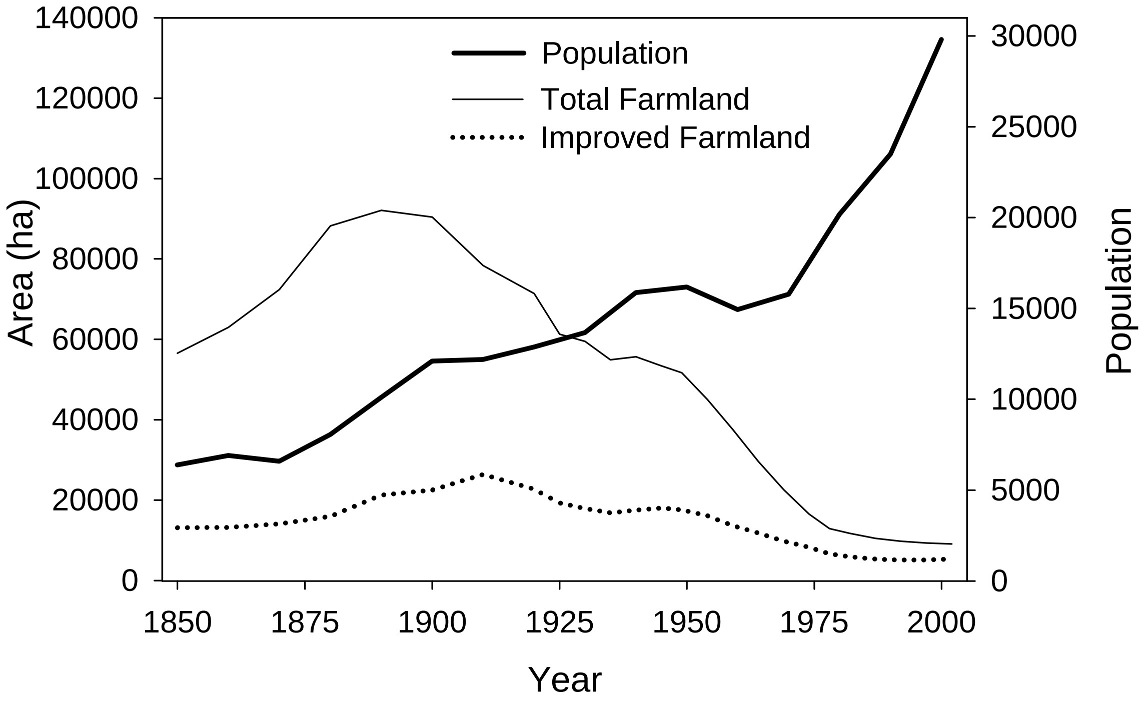

Figure 2: Population and Agriculture area of Macon County, 1850-2002, derived from the US Census and Census of Agriculture records. For census dates prior to 1890, when the county boundary was finalized in its present form, farmland areas were estimated from an areal interpolation procedure weighted by the area of suitable agriculture (This Dissertation, Chapter 3). This was necessary since the 1850 Macon County boundary was almost 2.5 times larger than the present county area, and extended to the Tennessee border.

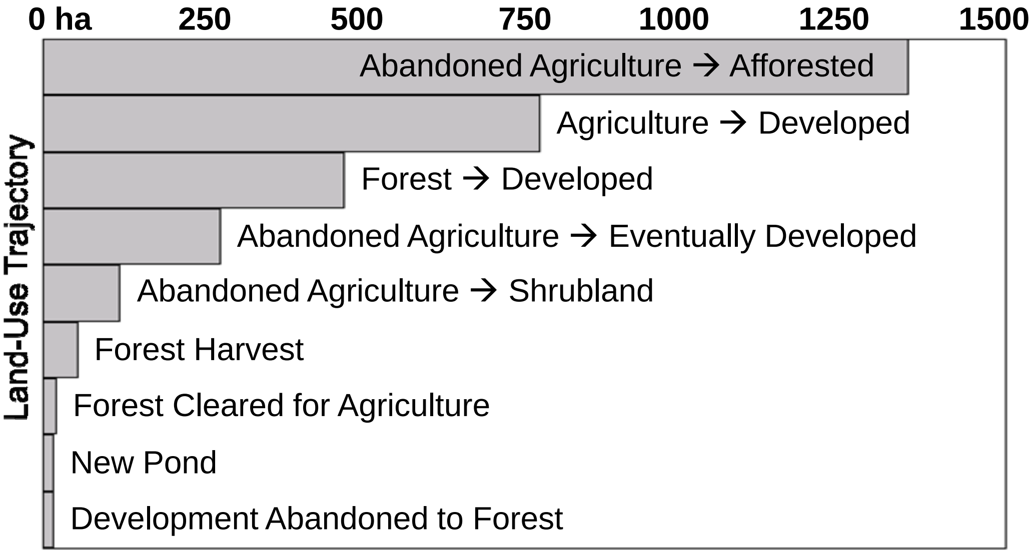

Figure 3: Major land use trajectories on the primary watershed, 1954-2003.

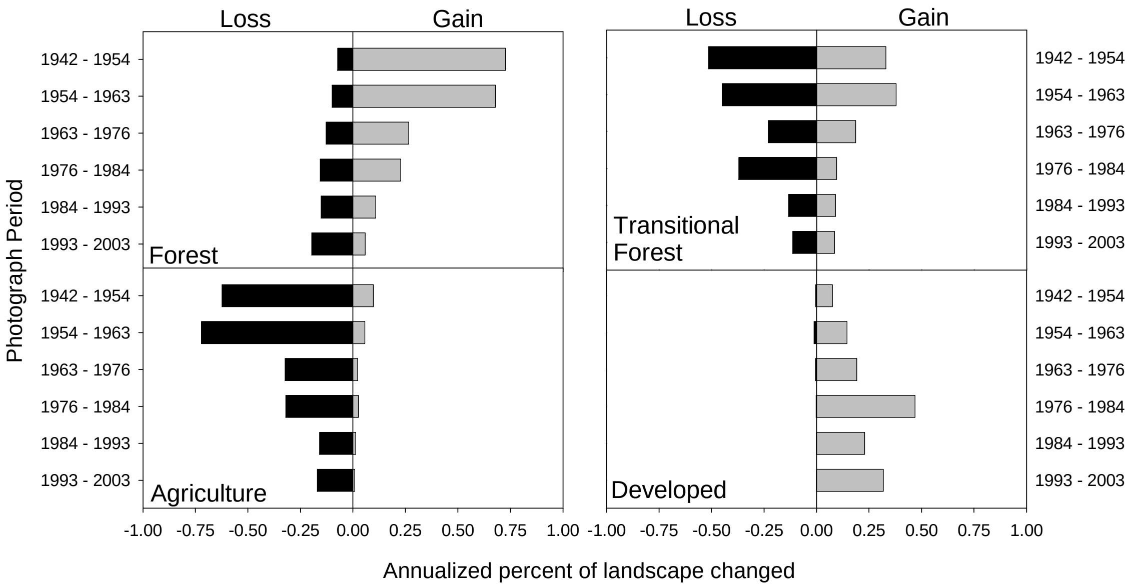

Figure 4: Gain and loss of land cover classes within the primary watersheds, 1954-2003.

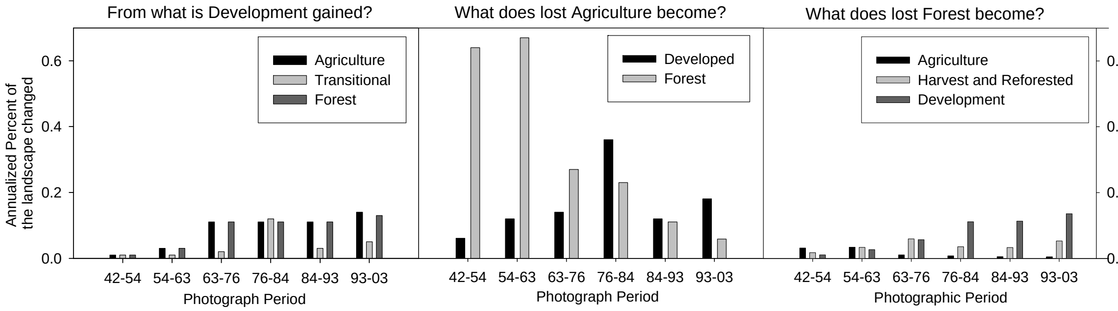

Figure 5: Dynamic trends of primary land use trajectories on private land in Macon County, 1942-2003.

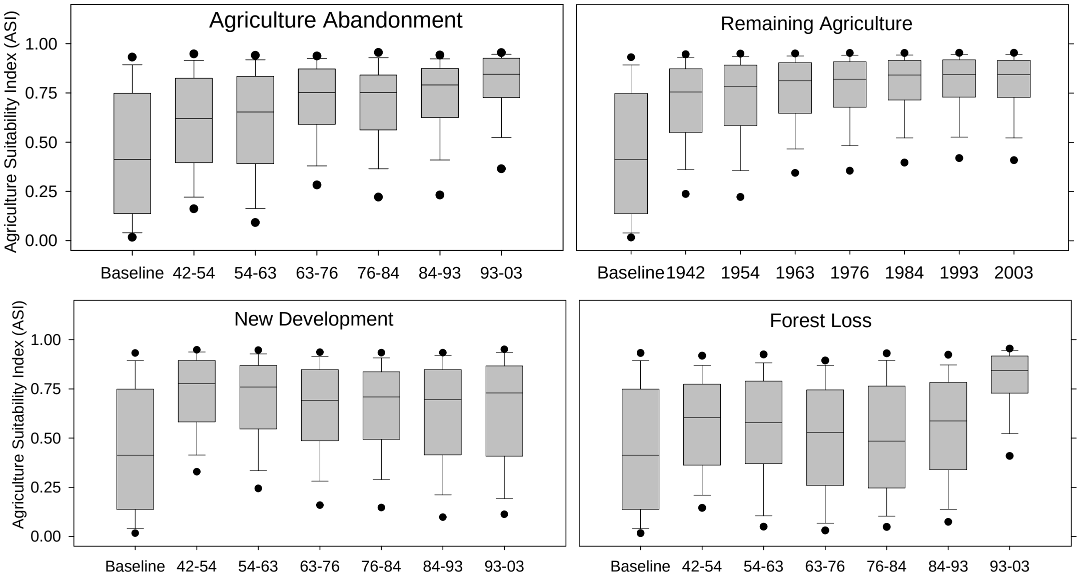

Figure 6: Land use change in relation to Agriculture Suitability. The boxes illustrate the 25th, 50th and 75th percentile. The extended lines represent the 10th and 90th percentile, and the points represent the 5th and 95th percentiles. The "baseline" is the distribution for all private lands in the county.

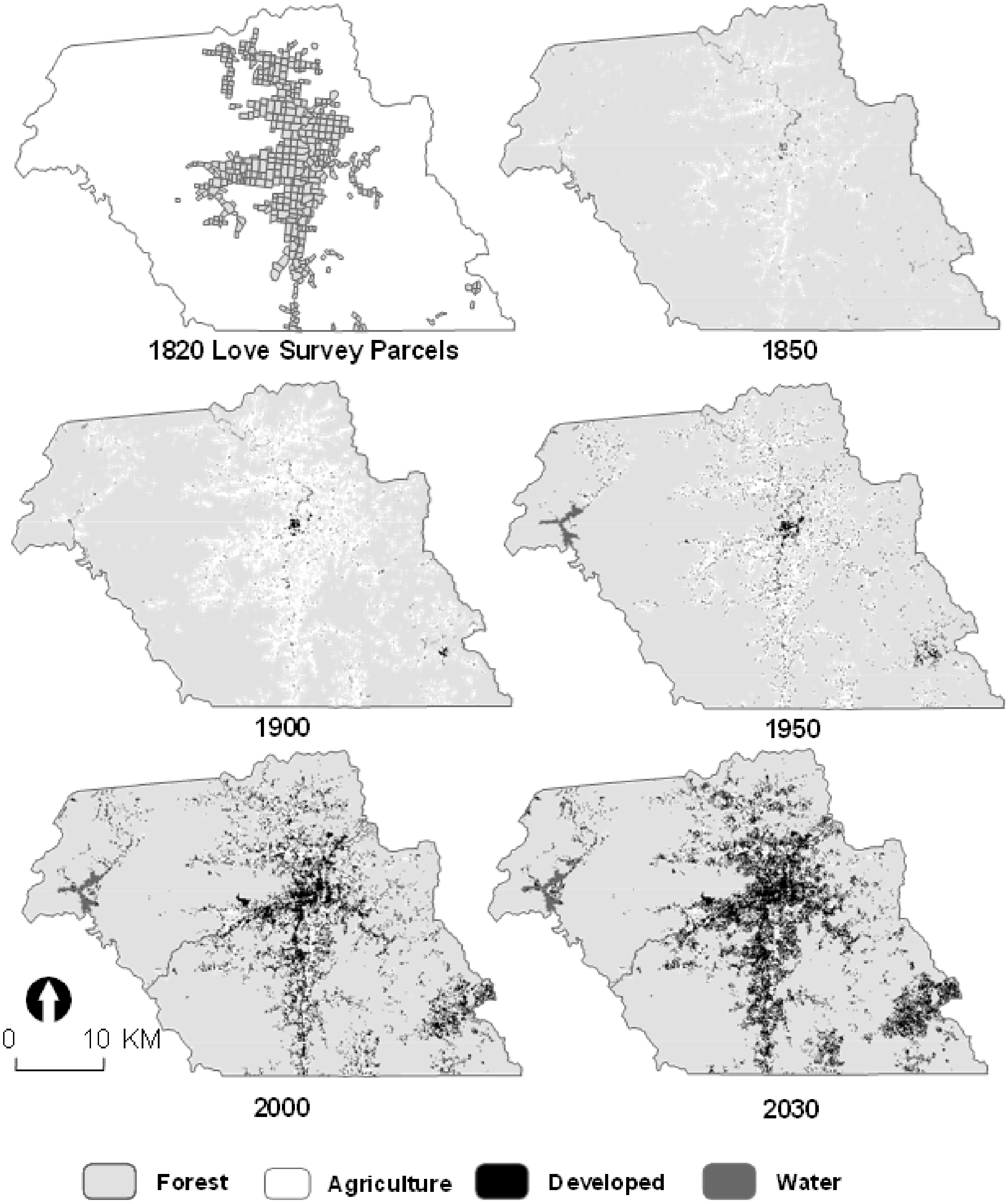

Figure 7: Mapped and modeled land cover for Macon County, 1820-2030. The 1820 Love Survey was the first spatial survey following the Treaty of 1819 (Jurgelski 2004). The 1950 and 2000 classifications were extracted from aerial photographs. The 1850, 1900, and 2030 classifications were modeled in this study.

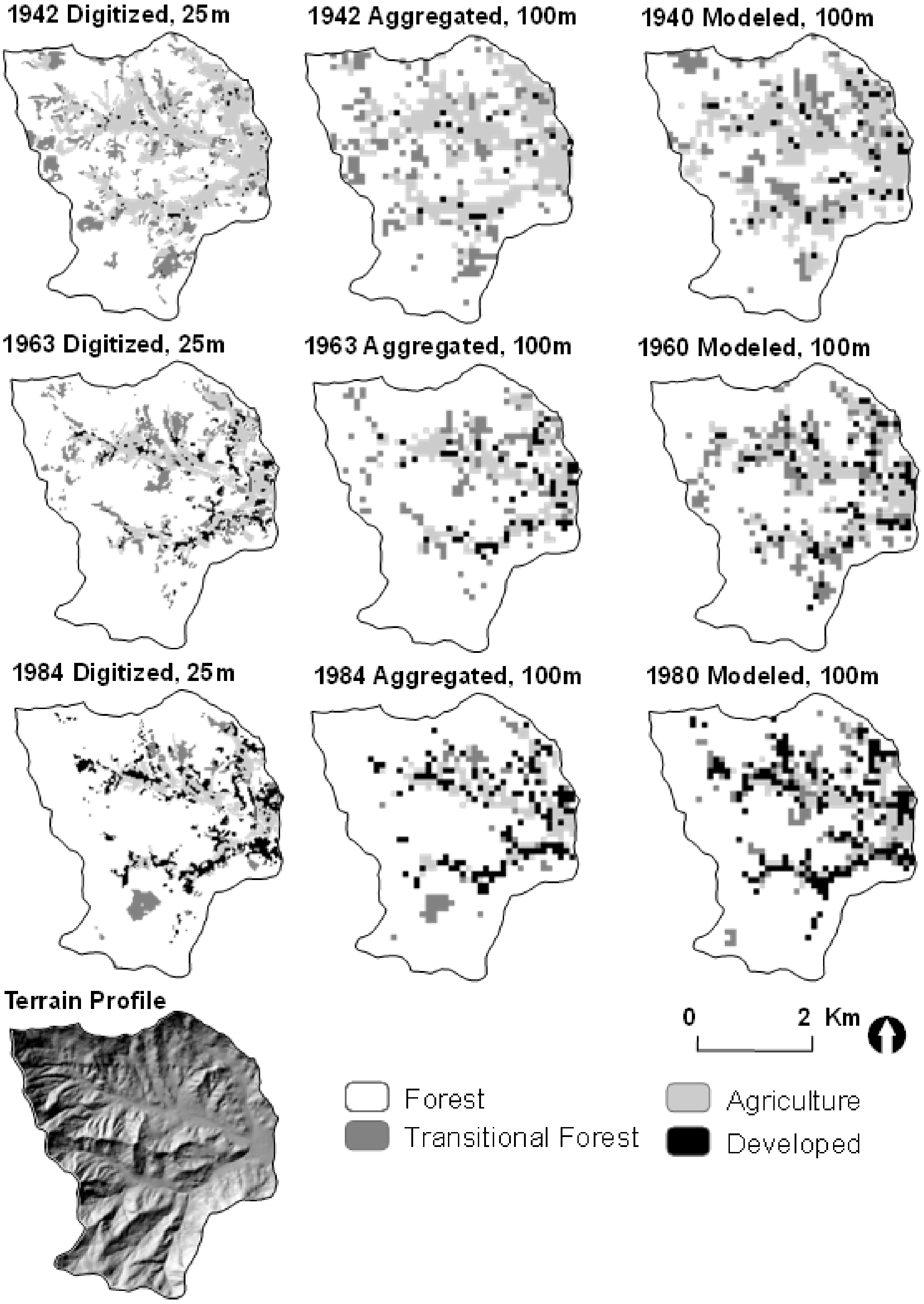

Figure 8: Comparison of photograph-interpreted and modeled land cover in the Skeenah Creek. The left and center columns contain the original 25m photograph-interpreted data and a 100m data set aggregated from the 25m data. These data were not used in the county-wide model. The right column contains the modeled 100m land cover subset from the county-wide data.

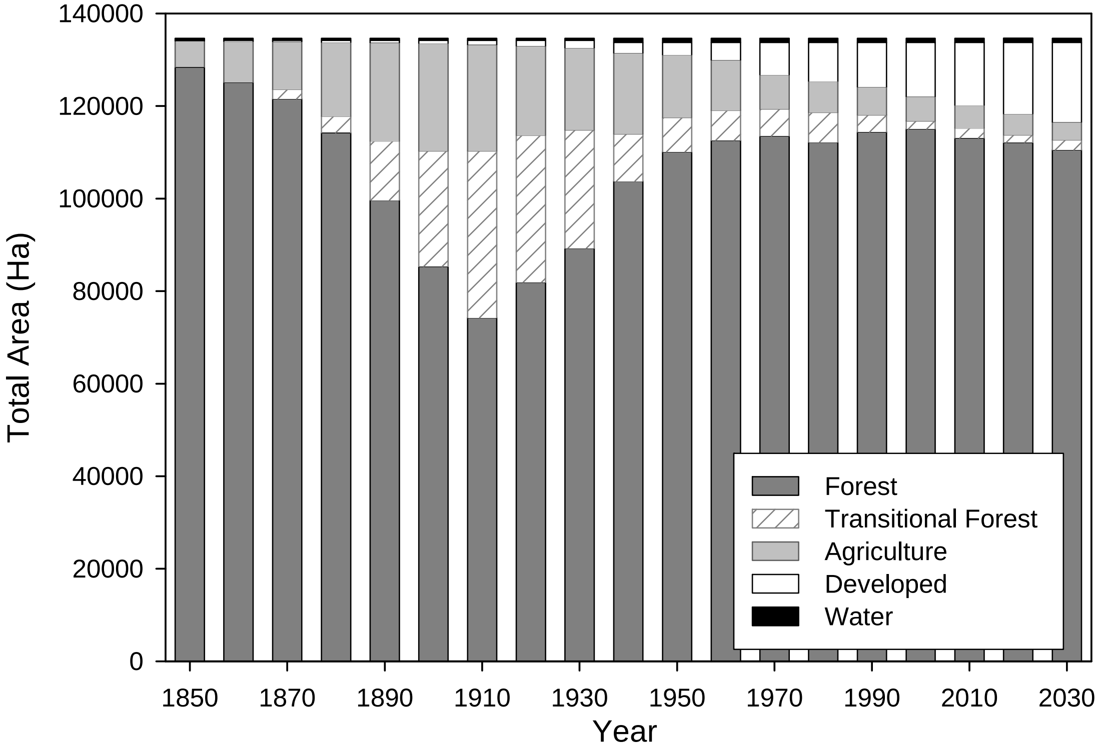

Figure 9: Aggregate land use in Macon County, 1850-2000, with forecasts from 2010-2030.

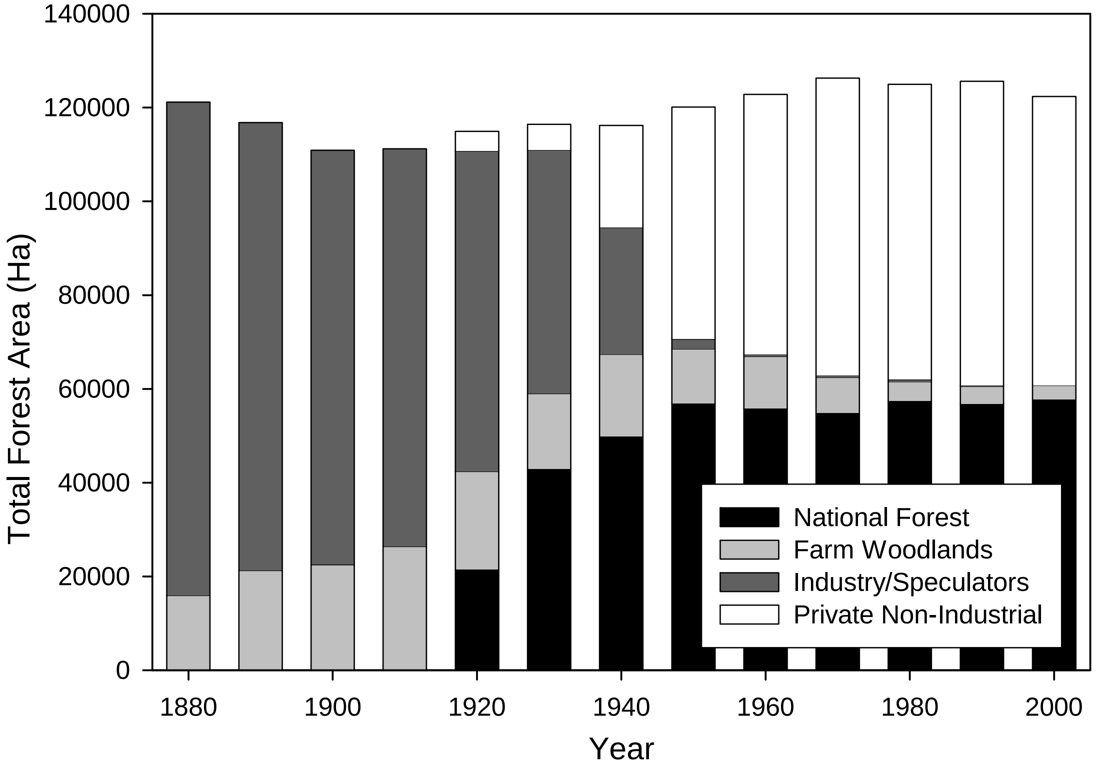

Figure 10: Estimate of ownership trends of the total forested area in Macon County. Where available, ownership estimates were extracted from US Census of Agriculture reports (U.S. Census Bureau 1850-1950; U.S. Department of Agriculture 1954-2002), USFS FIA surveys (Cruickshank 1941; McCormack 1956; Knight and McClure 1966; Cost 1974; Craver 1984; Johnson 1990; Brown 2002), and miscellaneous government reports (Ayers and Ashe 1905; Holmes 1911; North Carolina Department of Conservation and Development 1929; Wager and Thomson 1932; Mason and Forster 1950; Harris et al. 1963; Appalachian Land Ownership Task Force 1983). Forest ownership between FIA sampling years were linearly interpolated.

Chapter 2: Dynamic development patterns in the Southern Appalachian Mountains: a case study in Macon County, North Carolina, USA, from 1900-2030

Abstract

Many mountainous areas in the U.S. have experienced significant growth in low-density residential development over the past 40 years, in large part due to in-migration from outsiders seeking the scenic resources of these areas. In Macon County, North Carolina, this trend has led to 36% of the new buildings constructed since 1965 being located in areas surrounded by at least 70% forest, a tripling of the total road length in some watersheds due to subdivision roads, private roads and driveways, and an estimated 285% increase in the total development footprint. We reconstructed building and road locations in the county since 1907 from historic maps, aerial photography, county parcel records and emergency response program data, and analyze growth trends using spatio-temporal classification and quantile regression analysis. While the rate of population growth and new building construction peaked in the 1980s, the growth rate in development on forested areas and total road length increased between 1990 and 2007. With the population expected to increase 36% by 2030, we forecast that approximately 75% of new buildings will be constructed at urban and suburban densities and that 67% of all new buildings will be constructed in areas greater than 70% forested. These trends have important implications for land-use planning, hydrology, forest management, and wildlife conservation in the region.

Introduction

Low density residential development outside of urban and suburban areas has shown the largest areal change in the United States since the 1970s (Brown et al. 2005), and is expected to increase at least through 2020 (Theobald 2005). This trend of exurbanization, also known as rural sprawl or rural residential development, was initially defined as residential development in areas beyond the urban/suburban fringe with ties to the urban environment (Spectorsky 1955; Nelson 1992). The definition has since been a topic of debate (Nelson and Sanchez 1997; Crump 2003), and the term is now generally applied to geographic areas that meet one or more of three broad categories: 1) low density residential development beyond the suburban limits but still within the commutershed of metropolitan areas (Nelson 1992), 2) recreation or second-home areas associated with, but not necessarily in immediate proximity to, metropolitan areas (Lamb 1983), or 3) non-metropolitan areas with economic activity similar to those found in urban areas, but with social relations more commonly associated with rural areas (Duane 1999; Crump 2003). The methods for separating exurban from urban/suburban and rural areas have been developed on two fronts, either by spatially delineating classes of housing density (Theobald 2005) or housing patterns (Irwin et al. 2007) across the landscape, or by analyzing the socio-economic and demographic characteristics of the inhabitants (Crump 2003; Fernandez et al. 2005).

Mountain regions in particular have experienced strong population growth, much of it fitting the definition of exurbanization (Riebsame et al. 1996; Duane 1999; Cho et al. 2005) and driven by perceived quality-of-life benefits and natural amenities such as scenery and recreation opportunities (McGranahan 1999; Culbertson et al. 2008). Many areas of the Southern Appalachian Mountains in the southeastern U.S. are clear examples of this trend. The 21 counties within the Blue Ridge Mountains physiographic province of North Carolina, for example, experienced population growth rates in the 1980s and 1990s that were double the national average (Pollard 2005). During the same period, the percentage of total developable area (i.e., the total area minus all public and protected lands) classified as exurban in one national study increased from 54% to 65% between 1980 and 2000 and is estimated to increase to 74% by 2020 (Theobald 2005). In addition, the number of seasonal housing units, as reported by the U.S. Census, quintupled between 1970 and 2000, from 8,800 to over 44,000 (U.S. Census Bureau 1900-2000). As a consequence of these changes in population and development patterns, housing prices in the Southern Appalachians have greatly increased, with significant factors including the rise of second home development (Efird and Moretz 1980; Cho et al. 2003) and proximity to natural amenities such as streams or National Forests (Cho and Newman 2005). Given these trends, concerns have been raised over negative net effects on the local tax base due to increased strain on waste management, emergency response and health services programs (Jones and Kask 2000), visual blight (Gade and Stillwell 1986), and degradation of ecological processes and services such as water quality (Wear et al. 1998) and wildlife habitat (Pearson et al. 1999).

This growth in the Blue Ridge province, however, is contrasted by recent regional-scale studies of land cover change from satellite imagery (Loveland et al. 2002; Griffith et al. 2003; Brown et al. 2005) which indicate that the Blue Ridge has experienced the slowest rate of land cover change in the southeastern U.S. This suggests that the increase in population and growth of exurban development has not led to widespread land cover change, at least at the regional scale. Thus, there is need to explore this discrepancy between relatively high population growth rates, increasing exurban development, and the relatively low amount of land cover change in the Southern Appalachian Mountains.

In general, there have been three groups of methodologies for analyzing development patterns at landscape to regional scales. First, several studies have used aggregated and disaggregated census data to map development trends (Radeloff et al. 2000; Hammer et al. 2004; Theobald 2005). Second, many studies use interpretation of current and historic aerial photography to map trends of building locations as a proxy for residential development (Wear and Bolstad 1998; Kline et al. 2003). Third, a few studies extracted data from government sources such as county parcel records or permitting programs (Aspinall 2004; Carlson and Dierwchter 2007). These differing approaches are often defined by the data availability and geographic scale of analysis. Detailed locations of individual buildings are generally available only for smaller-scale studies within county or sub-county areas, while multi-county to national scale studies rely on aggregated data.

In this study, we analyzed spatial patterns of development trends over the past 100 years in Macon County, NC, as an intensive case study for evaluating the patterns and processes of human habitation trends in the Southern Appalachian Mountains and in densifying mountain regions in general. We addressed two specific questions: (1) how have the spatial patterns and types of development in the county changed since 1900?, and (2) what development trends are likely over the next 20+ years?

Methods

Study Area Description

Macon County is located in the southwestern mountainous section of North Carolina, U.S.A. (Figure 1), and is part of the southern Blue Ridge physiographic province of the Southern Appalachian region. The county is characterized by steep topographic relief (500-1800m elevation), mild winters, cool summers, and high levels of precipitation (130 - 200cm/yr). Forest covers over 75% of the county, and consists primarily of mixed deciduous species with scattered pine. Forty-five percent of the county is publicly owned, and nearly all of this public area is part of the Nantahala National Forest. The cleared areas are generally concentrated in the main river valleys and larger coves, but many of the more remote areas were used for small-scale agriculture in the early decades of the 20th century and exurban development in the later decades.

Like many Southern Appalachian counties, the demographic composition and land use practices of the inhabitants have been highly variable over the past 100 years. At the dawn of the 20th century, the county economy was centered on agriculture production and timber extraction, both of which peaked between 1900 and 1920 (De Vivo 1986). The U.S. government began purchasing marginal lands for the Nantahala National Forest in 1911 due primarily to concerns over erosion, flooding, and the forest degradation caused by widespread industrial logging (Eller 1982). The total cropland and pastureland area declined precipitously following World War II through the 1950s and 1960s, as families sought employment and amenities in metropolitan areas (Raitz and Ulack 1984). Concurrent with this decline in the resource-based industries was the expansion of tourism and recreation industries (Taylor 2001; Starnes 2005). Beginning around 1970, the population in the county increased dramatically as second-home owners, retirees, and others seeking the natural amenities of the region migrated into the Southern Appalachians (Raitz and Ulack 1984), a trend that has continued to the present. Combined, these changes have led to a diverse community, ranging from multi-generational farmers to suburban commuters to wealthy seasonal residents, and, similar to other scenic recreation areas, these different groups are often at odds over the use and value of the land (Branscome and Matthews 1974; Duane 1999; Culbertson et al. 2008). Given the minimal zoning regulations in the county, the development patterns and land use practices strongly reflect this diversity. Identifying these overlapping patterns and quantifying their extent and temporal trends may help developers and planners meet the needs of the citizens while promoting smart growth strategies.

Within the county, four watersheds were chosen for intensive study (Figure 1), and were selected based primarily on aerial photograph availability and overlap with other research projects of the NSF Coweeta Long Term Ecological Research (LTER) site (Coweeta 2002). These watersheds, which range in size from 1,000 ha to 15,000 ha, have experienced a variety of urban, suburban, and exurban development trends since the 1940s, and one of them (Cartoogechaye Creek) is also the water supply watershed for

Franklin, the largest city and county seat. Combined, these four watersheds cover 22,878 hectares, or 17% of the total 134,656 ha county area. Given the balance of private and public ownership, the strong growth of primary and secondary home ownership (Cho et al. 2005), a 20th century transition from a predominantly resource-based to predominantly service- and tourism-based economy (Taylor 2001), and a general environmental history matching broader studies of the region (Lewis 1998; Davis 2000; Gragson and Bolstad 2006), we believe these watersheds and Macon county as a whole are suitably representative of the southern Blue Ridge province and Southern Appalachian region.

Database development

To reconstruct development patterns, a geospatial database was organized within a Geographic Information System (GIS). Building, road locations, and land use at discrete moments in time were manually interpreted from current and historic and aerial photography, with the goal of at least decadal coverage between 1954 and 2006 for the primary watersheds, and for 1954 and 2003 for the entire county. All photographs that were not acquired in an orthorectified format were scanned at a resolution of 600dpi, and georegistered and terrain-corrected using either OrthoMapper (OrthoMapper 2004) or ERDAS Leica Photogrammetry Suite version 9.1 (ERDAS 2005). Ground control points were collected from differentially-corrected GPS points, or were identified on 1993 USGS DOQQ photographs. For each photograph, 12-25 ground control points were identified, and a Root Mean Square Error of less than 5m was required in rural forested terrain and less than 2m in all other more populated areas. In all, over 200 individual photographs were orthorectified, with 160 consisting of the countywide data set for 1954.

All buildings were digitized as points, with each building receiving one point, except in the case of farmyards, which received one point to represent the house and all other related adjacent buildings on the property. All roads and driveways longer than 20m were digitized as lines and classified into four general categories of Highway, Primary Road, Subdivision Road/Private Road/Driveway, and Forest Road. For years prior to the availability of aerial photographs, historic map sources containing building and roads locations were acquired. These include 1:125,000 scale USGS topographic maps from 1906-1907 (U.S. Geological Survey 1906; U.S. Geological Survey 1907), and early edition county soil survey maps that were surveyed in 1925 (Devereux et al. 1929) and 1942 (Goldston and Gettys 1956). Spatial accuracy of the historic maps was estimated by identifying a sample of 20 widely dispersed road intersections that likely have not changed, and calculating the distance between each point on the historic map and on the 1993 DOQQs. The estimated horizontal errors for the 1907, 1925, and 1942 historic maps are 323m, 98m, and 34m, respectively. The categorical accuracy of these data sets is unknown, but is assumed to be acceptably high given the reputations of quality from the USGS and soil survey surveyors and cartographers. For the primary watersheds, the roads and buildings were spatially snapped between years in order to track exact development and abandonment rates. For the 1954 and 2003 countywide data sets, roads and buildings were digitized simultaneously in order to improve interpretation and classification, but no efforts were made to shift the locations of points and lines. The 1907 and 1925 buildings and roads, however, were manually shifted in reference to the 1954 roads data set with the aim of having nominal horizontal errors of less than 50m.

A second source of countywide building locations was derived from the county parcel mapping records, which contain records of building age, and the county "Structures" point data set used for emergency response programs (Macon County 2007). These were combined to create a Parcel Buildings data set. The construction date of the primary building on each parcel was assigned using a point-in-polygon spatial join. All structures were assumed to be buildings, and all structures on parcels without a "Year Built" attribute were removed from the data set. Henceforth, we refer to the two countywide building data sets as the "Digitized Buildings" and "Parcel Buildings." These two building data sets are complimentary (Figure 2), but have different sources of error (Figure 3). The Digitized Buildings likely underestimate the true number of buildings due to errors of omission (digitizer error or missed buildings under forest canopy), and underestimate the number of housing units since multi-unit structures such as apartments receive a single point. The primarily strength of the Digitized Building data set is that they are more complete for periods prior to 1954. The Parcel Buildings data set is a more continuous temporal record, but likely overestimates the number of buildings and housing units since all multi-unit structures (e.g., town homes or strip malls) receive multiple points in the Structures data set. In addition, the Parcel Buildings data set contain no records of removed, replaced, or abandoned buildings, which are notably evident for dates prior to approximately 1965 (Figure 2), and all structures on a parcel are assigned the same date in the spatial join, which likely biases the age distribution of buildings. Total quantity accuracy of the parcel and digitized building data sets was examined by comparison against the countywide census estimates of the number of dwellings (Figure

2), and spatial accuracy was estimated by comparing building density estimates from the Parcel Buildings data set and the Digitized Buildings for the primary watersheds (Figure 3).

Census data on population and housing for the county were compiled from the decennial census records of the US Census Bureau (U.S. Census Bureau 1900-2000). As part of a companion study (This Dissertation, Chapter 1), we reconstructed decadal land use patterns across the county at 1 ha resolution (100 m cell size) from 1905-2005 using a variety of spatial and aspatial sources of land use data and a decision-tree model. Additional terrain and infrastructure-related datasets, described below, were collected or derived from widely available sources. All data were developed into or reprojected to the Universal Transverse Mercator (UTM) coordinate system, Zone 17, and converted to 10 m raster data sets for analysis.

Neighborhood Definition

To evaluate spatial changes in development, we measured and analyzed both the locations of buildings and building density. Density estimates are useful since they represent a continuous variable for modeling and can partially account for spatial errors inherent with point data derived from different sources. We define building density as the number of buildings per ha measured within a radius of 564 m around a given location, which equates to a total local neighborhood area of 1 km^2. For each raster cell, the number of buildings within 564 m is counted, and the value is divided by 100 to get buildings per ha. In order to smooth the density estimates across the landscape, we applied the density calculation as a quadratic kernel function (Silverman 1986) as implemented in the ArcGIS 9.2 software package (ESRI 2004), which has the formula:

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K \left\{ \frac{1}{h} \left(x - X_i \right) \right\} \quad (1)$$

where $\hat{f}(x)$ is the density estimate of location x, n is the number of observations, h is the window width, d is the number of dimensions (in this case, d=2), and $K(x)$ is the kernel density function based on the weighted distance between location x and all other X_i observations within the search radius.

Development type classification

In order to stratify the spatial and temporal trends in patterns of development, we define a set of classification rules for determining the development type for all buildings between 1907 and 2007, and for new buildings constructed each year between 1965 and 2007 for the Parcels Building data set. We identify eight development types based on relative building density and density of forest cover in the previous decade. This approach follows the common method of mapping household density thresholds to separate urban, suburban, exurban and rural areas (Hammer et al. 2004; Theobald 2005), but with two modifications. First, we identify the development density thresholds relative to the building density within our local neighborhood of 1km^2, rather than household unit density within census block group or other census boundaries. This difference results in generally smaller spatial boundaries used to calculate densities and a reliance on the use of buildings of all types as a proxy for residential households. We adopt the thresholds of Theobald (2001), where urban areas have densities greater than 2.5 buildings/ha (~1.6

buildings/acre, or more than 250 buildings in the 1 km^2 neighborhood), suburban areas have between 0.25 and 2.5 buildings/ha, exurban between 0.6 – 0.25 buildings/ha, rural between 0.01 – 0.06 buildings/ha, and undeveloped areas < 0.01 buildings/ha. We feel these thresholds are well suited for Macon County, which has two urban centers in the cities of Franklin and Highlands that are above the urban density threshold, and the average parcel size for all new subdivisions delineated over the past 20 years falls within the defined suburban density range.

The second distinction in our development type classification is the inclusion of local forest density. The percent of the area that is forested within 150m of a building location was used to separate development that occurred within the general area of existing agriculture or other non-forest land uses (Densification), and development that expanded into previously forested areas (Expansion). The neighborhood radius of 150m was selected as a compromise between including an area large enough to ensure a high correlation between building density and forest density and small enough to represent the local footprint of each building. A cut-off threshold of 70% forest was used to separate Densification (< 70%) from Expansion (>= 70%). The 70% threshold is supported by a clear separation of the proportion of new buildings in the two classes from 1954-2005. That is, the proportion of buildings located in areas with greater than 70% forest has steadily increased, while the proportion at all forest densities less than 70% has decreased. Without historic parcel data, land value or purchase price information, we did not attempt to stratify development types by parcel size or socio-economic variables. For a parcel-based analysis on 2002 housing values within Macon County, see Cho et al. (2005).

Trend Analysis

We use quantile regression (Koenker and Bassett 1978; Koenker 2005) with the Parcel Buildings data set to evaluate landscape trends of new building construction between 1965-2005. The dependent variables fall under two general categories of terrain variables (slope, elevation relative to the watershed outlet point, and forest density of the previous decade), and infrastructure variables (distance to main roads, road distance to primary markets, and building density at previous period). For each of these continuous variables, the values for all new buildings constructed in a given year is regressed against the independent variable of time in years. Quantile regression (QR) differs from linear regression (LR) in that models are fit for a defined portion of a conditional probability distribution function, such as the conditional median, or all portions the function, rather than for the conditional mean function as implemented with LR. This approach has the statistical benefits of robustness for measures of central tendency (lowering the influence of large outliers) and indifference to heteroscedasticity, unlike LR models, but also the practical benefit of being able to analyze portions of the conditional distribution beyond measures of central tendency (Koenker 2005). A single-variable LR model can be written with the form:

$$E(y \mid x) = \beta_0 + \beta_1 x + \varepsilon \qquad (2)$$

where $E(y|x)$ is the expected value of y given x, β_0 and β_1 are the intercept and slope parameters, respectively, and ε is the error term. A single variable QR model has a similar form:

$$Q_y(\tau \mid x) = \beta_0(\tau) + \beta_1(\tau)x + \varepsilon(\tau) \tag{3}$$

where τ is the defined quantile, $Q_y(\tau \mid x)$ is the estimate of percentile τ of the distribution of *y*, and the intercept, slope, and error terms are conditional on τ (Cade and Noon 2003). For example, at the 75% percentile, $Q_y(0.75 \mid x)$ specifies that 75% of the values of *y* are less than or equal to the defined function of *x*. A QR model is fit using a linear optimization method as opposed to a least squares method.

Here, we are interested in identifying temporal trends in both the central tendency and the upper limit extremities of the independent variables, so we limit analysis to the 50th percentile (median), 75th percentile (upper quartile), and 95th percentile. QR models are fit for each independent variable at each of the three identified quantiles. Statistical tests for differences between the three fits (H_0: slopes are equal) and between the fits and a null hypothesis of no temporal trend (H_0: slopes = 0) are based on the robust Wald ANOVA tests as implemented in the *quantreg* package (Koenker 2004) of the *R* statistical software (R Development Core Team 2008).

Forecast

As a means of forecasting both the quantity and types of future development in the county, we combine population growth projections with the development type and trend analysis results of this study. Population growth projections were acquired from the North Carolina Office of State Budget and Management (2008) for 2010, 2020, and 2030.

We estimated the number of new buildings by assuming a constant building/population ratio of 0.763 buildings/person, which is calculated as the average ratio over the past 20 years and is relatively consistent over the period (Figure 2). We then stratify the projected building count into development types based on extrapolation of the trends in the proportions of each development type over the past 20 years. Non-linear equations for temporal extrapolations of the proportion of buildings in each development type class are selected from a conservative set of asymptotic models that flatten over time. The models selected for each class are those with the highest pseudo-R^2 value.

We create a single forecast scenario of the locations of new development through 2030 by generating random building locations from a weighted distribution defined by a simple logistic regression model and constrained by previous development. The forecast is a four-step process applied for each 5-year period from 2005-2030. The first step is to estimate the number of new buildings in the period for each development type using the extrapolated estimates. Second, a logistic regression model is developed from the set of 6 terrain and infrastructure variables analyzed in the trend analysis above, plus an additional variable of the change in building density over the previous 5 years to identify “hot spot” areas of growth. The binary dependent variable is the combination of the new building locations over the previous 5 years plus an equal number of randomly generated points that are at least 50 m from an existing building. A logistic regression function is developed that includes all statistically significant variables ($p < 0.1$) from the 7 candidate independent variables, and consists of the traditional form using a logit link function (Agresti 2002):

$$\ln\left(\frac{p_y}{1-p_y}\right)=\beta_0+\beta_1x_1+\cdots+\beta_kx_k+\varepsilon \tag{4}$$

where p_y is the probability of building y occurring at a given location, $ln(p_y/1-p_y)$ is the natural log of the odds of a building y occurring at a given location, k is the number of independent x variables, $\beta_0\cdots\beta_k$ are the regression parameters, and ε is the error term. From this model, the probability of development is calculated by solving eq. 4 for p_y:

$$p_y=\frac{e^{(\beta_0+\beta_1x_1+\cdots+\beta_kx_k)}}{1+e^{(\beta_0+\beta_1x_1+\cdots+\beta_kx_k)}} \tag{5}$$

A probability map is then generated by applying eq. 5 to the applicable raster data sets. These probabilities, which range from 0 to 1, are used as a weighting for random point selection.

The third step in the forecast is to constrain the model to exclude areas where new development is most unlikely. We use the simple constraint of not allowing new development on any parcel that contains a building and is smaller than 3 ha in size. This is based on the assumption that parcels smaller than 3ha would not be further subdivided, but any parcel larger than 3ha, including those with a previously existing building, are susceptible to subdivision. The value of 3 ha was selected as a conservative, but representative, threshold based upon an analysis of 30 random parcels subdivided over the past 30 years.

In the fourth and final step of the forecast for each 5-year period, the location of buildings are separately generated for each of the 4 development classes by randomly selecting locations weighted by the logistic regression-derived probability map and excluding the populated parcels less than 3ha from the previous period. This weighted and constrained random point generation was implemented using the Hawth's Tools extension for ArcGIS (Beyer 2004). Once the buildings for a given period are generated, all building density and parcel data layers are updated to reflect the changes, and those updated data are used as input for the next period. We validated the forecasting model by applying the 4-step sequence for the observed data set from 2002, the earliest year for which parcel data were available in a usable form, through 2007, and then comparing the modeled versus observed building counts for each development type class and modeled versus observed spatial patterns using three metrics: 1) the total area within 50m of any building, 2) the median and 95th percentile distance from the main road network, and 3) the median and 95th percentile distance from the cities.

Results

Descriptive Statistics

The spatial patterns of building construction over the past hundred years have steadily changed, mirroring the transition of the local economy from natural resource-based to recreation- and service-based. The average population:building ratio decreased from over 5 people per dwelling between 1900 and 1930 to approximately 1.5 people per dwelling since 1980. The average building density on private land over the same period increased from approximately 1 building for every 27 ha in 1929 to 1 building for every 3.5 ha in 2007. Based on the census-derived density thresholds of Theobald (2005), the dominant development trend in Macon County transitioned from a predominantly rural county (< 0.6 buildings/ha) before 1950 to a mostly exurban county in the 1950s and

1960s (0.6-0.25 buildings/ha), but since approximately 1970 the county has been dominated by development at suburban densities (0.25 –2.5 buildings/ha) (Figure 4).

According to our classification scheme (Figure 4), Macon County experienced strong exurban growth in the 1960s and 1970s, with 40-50% of all new buildings each year falling in the exurban category, but the proportion of buildings at exurban densities has steadily declined since 1975 to a rate of approximately 25% of all buildings in the 1990s and early 2000s. Including the forest density criteria, exurban growth expanding into forested areas has held fairly constant since the 1980s, but exurban densification in less forested areas has steadily decreased. Conversely, the largest increase in growth rate has been development in forested areas at suburban densities, particularly since the mid-1990s. Combined, new buildings expanding into areas >70% forested now account for almost 50% of all new construction, and the trend is for this proportion to increase in the coming decades.

Rates of building abandonment were estimated from the photograph and map interpreted data sets for the primary watersheds. Between 1907 and 1963, we estimate that one building was removed for every 5.6 buildings constructed, and this rate dropped after 1963 to a rate of approximately 1 building removed for every 45 buildings constructed. This drop is consistent with the shift from net out-migration to net in-migration in the county in the late 1960s and early 1970s. Many of the abandoned buildings before 1950 were in areas that reforested, suggesting abandonment of farmhouses, while removals since 1950 is most often associated with new construction on the same parcel. Thus, no building removal in forecasting models appears to be a safe assumption relative to other sources of forecasting uncertainty.

The road network has also changed over the past 50 years. Although the surface type and widths of roads have changed, the extent of the main road network in the county, which we define as all interstate highways, US routes, state routes, and secondary roads as defined by the NC Department of Transportation (2006), has changed very little over the past 50 years. The notable exception is the approximately 30 km section of U.S. Highway 64 between the city of Franklin and the western edge of the county, which was constructed in the 1970s as part of the Appalachian Regional Commission’s mission of increasing accessibility in the Appalachian Mountains in order to help reduce isolation and poverty (Raitz and Ulack 1984). All other main roads follow historic routes along the flow of terrain or along cross-mountain transportation routes established by the early 1900s. What has changed dramatically, however, is the spread of subdivision roads, private roads, and long driveways extending from this main road network. Within the primary watersheds, we estimate that the length of subdivision roads, private drives and driveways has tripled the total road length since 1950 (Figure 5). Countywide, evidence of this trend is apparent in the distance between new buildings and the main road network, which has steadily increased from an average of 100 m in the 1960s to over 250 m in the 1990s and 2000s. Approximately 5% of new buildings were over 500 m from the main road network in the 1970s, while over 15% of new buildings between 2000 and 2005 exceeded this distance.

Trend Analysis

The results of the QR models are listed in Table 2 and illustrated in Figure 6. In general, over the past 40 years there have been significant increasing trends in the number of new buildings constructed further from the main road network, further from the primary cities, in more densely populated areas, and in more heavily forested areas. However, there is only a negligible significant increasing trend in construction on steeper slopes, and no significant trend for development at higher elevations. As the development densifies around the cities, those seeking isolation are expanding further away from the urban areas and further from the main road network, but are not generally building on steeper slopes or at higher elevations. These trend analysis results support the development type classification. The strong increasing trend in development at higher building densities across all quantiles matches the development type classification that indicates increasing suburban and urban development.

Forecast

By extrapolating the building density development type classification trends, we predict that development in exurban and rural areas will decrease 14% by 2030, while development in suburban and urban areas will increase by 3% (Figure 7). There also appears to be a strong trend towards development in forested areas. Extrapolating the combined building and forest density classification trends indicates that development in forested areas will hold relatively constant at approximately 70% of all new buildings, with the increase in urban and suburban expansion into forested areas being offset by a decrease in exurban and rural expansion.

The forecast of new building construction using a constant building/population ratio results in higher estimates of the number of new buildings (400-425 building per year) than have been observed in recent years (on average, 327 buildings were constructed each year between 2005 and 2007), but do match the past 20 year average of 424 buildings per year. Thus, although these forecasts do not properly account for typical real estate fluctuations, they appear to be adequate for longer-term projections.

Spatially, the weighted, stochastically-generated building patterns suggest that the total area of development at suburban densities will increase to encompass 60% of the total private area in the county by 2030, and areas without any buildings within a 564m radius will decrease from 9% at present to less that 3% by 2030 (Figures 8 and 9).

These numbers should be interpreted cautiously as this is only a single forecast scenario. However, recent trends in the subdividing of parcels support this forecast. Between 2002 and 2008, 1800 new buildings were constructed in the county, but over 3800 new parcels smaller than 3 ha were platted, raising the total number of parcels below 3 ha to over 39,000, which combined cover 34% of the total private area of the county. The majority of these small parcels remain undeveloped, but it is very unlikely that they will be used for any purpose besides residential or commercial development, or possibly small-scale forestry. The forecast uncertainty is primarily in the rate in which they will be developed and the rate at which larger parcels will be subdivided.

Discussion

Our analysis highlights several issues important for land use change modeling, land use planning, and ecological services. The primary theme of future development is an increase in the total development footprint as illustrated by the increasing spread of buildings, the increasing building density in all areas, and the growth of subdivision roads, private drives, and long driveways. Emergency response and other services are hindered by long and narrow driveways. Planning programs that promote shorter driveways or increased accessibility may help reduce access costs and improve service.

Several studies have found that water quality and quantity are strongly impacted by roads (Bolstad and Swank 1997; Anderson and MacDonald 1998; Forman and Alexander 1998) and road networks also influence wildlife populations by increasing fragmentation (Lyon 1983; Heilman Jr. et al. 2002). Another ecological service that will be affected by future development is forest area and forest quality. The total forest area in Macon County peaked in the 1980s following recovery from agriculture (This Dissertation, Chapter 1). Over the past two decades, forest area has steadily decreased at the expense of expanding development, and this trend is likely to continue. With smaller parcels, forest management efforts generally decrease (Pomeroy and Yoho 1964; Anderson 1968), which suggests a decrease in the availability and quality of wood products and a possible decline in forest quality as secondary forests over mature.

This research also has implications for research in land use science and rural housing. There have been relatively few studies on forecasting rural growth when compared against the literature on urban growth modeling (Theobald 2005). Other studies of forecasting building density growth in exurban areas relied on a direct extrapolation of spatially-explicit statistical models (Wear and Bolstad 1998; Kline et al. 2003), or models developed with census units as the spatial features (Theobald 2005). In Macon County, Wear and Bolstad (1998) developed models for building projections using a 40-year period between building densities in 1950 and 1990, then ran a single projection to 2030. However, attempting to fit such models for building density changes at more frequent time intervals (e.g., annual or 5 year intervals) results in models with very weak significance at the county scale, largely because new building construction is a highly stochastic and variable process in this loosely-zoned area. We have highlighted significant temporal trends in the general location of new building construction, but this information tells us very little about which specific parcels are likely to be developed. Similarly, although this approach provides a novel interpretation of past and future settlement trends in the county, it ultimately provides little insight into the drivers of development change, a result consistent with other studies that have attempted to identify the processes driving settlement in recreation and second-home areas by examining only the spatial housing patterns (Gustafson et al. 2005). Land use choices in this area are clearly made on a parcel-by-parcel basis, and given the large socio-economic diversity within the county, these choices are highly variable. For example, several small farms are located in areas that have a very high suitability for development, but long-time owners are resistant to subdividing their land. In other instances, developers are building luxury homes in the upper reaches of watersheds that most models would suggest are extremely unsuitable for development.

In this study, we defined development types by building density and used thresholds developed for the entire United States (Theobald 2001). Our primary conclusion of increasing suburbanization of the county is based on this classification scheme. However, alternative definitions of exurbanization may still apply in Macon County. As Crump argues (2003), the perceived growth in exurbia in amenity-rich areas such as the Southern Appalachians may have more to do with social organization than spatial structure. While building density is increasing, most new residential construction is in forested areas, which provide a sense of isolation even if houses are clumped at densities similar to those in more typical suburbs around major urban areas. While provocative, such considerations are beyond the scope of this project.

In tying this research to larger studies of land use change, we found a large change in the settlement patterns over the past 100 years, which inherently alters the land use patterns. Other studies that reported a relatively small amount of land cover change in the region (Loveland et al. 2002; Griffith et al. 2003; Brown et al. 2005) may be underestimating land use changes that are not detectable by moderate scale satellite imagery. It is likely that the emerging patterns of exurban and suburban development in forested, mountainous regions cannot be discerned using traditional remote sensing multispectral classification methodologies applied to moderate resolution satellite imagery such as Landsat (30m cell size) or MODIS (250m-1km). Private roads and driveways are often 3-5m wide, gravel, dirt, or grass-surfaced, and partially covered by tree canopies, so are not strongly detectable by satellite sensors. Similarly, GIS-based approaches that rely on available roads data sets do not capture the large growth in private drives and long driveways. Rather than relying on labor-intensive manual interpretation of aerial photography as we have, automated feature extraction tools or classification of high-resolution satellite imagery may account for these limitations. Another alternative is to focus research on recent and future growth on parcel-based models, which is the primary unit for landowners. However, many of the parcels in Macon County have long been subdivided for residential development, but construction has not taken place. Thus, there is a disconnection or lag between subdivision of the land and development on subdivided sites.

In conclusion, our analysis suggests a transformation of Macon County settlement patterns from a rural area between 1907-1960 to an exurban area between 1960-1975, and increasingly a suburban area since 1975. The trend of suburbanization is forecasted to continue over the next 20 years. Effective planning and community participation may help mitigate any potential negative environmental consequences and cultural strife that might arise with these densifying development patterns.

Table 1: Quantile Regression parameters and significance tests for dependent variables of new building construction from 1965-2005. The independent variable in all cases is time (year).

	Model Fit Parameters		Statistical Tests $^{(1)}$	
Variable	β_0 *(se)*	β_1 *(se)*	T-value *H_0: slope = 0*	F-Value *H_0: slope = slope of median line*
Slope				
Median	-26.1 (13.8)	0.019 (2.74)	2.75	--
75th Percentile	-98.3 (20.9)	0.007 (0.01)	5.59 ***	21.16 ***
95th Percentile	-69.7 (40.1)	0.051 (0.02)	2.52	2.57
Relative Elevation				
Median	-530.0 (125.6)	0.304 (0.06)	4.84 ***	--
75th Percentile	-1460.4 (273.2)	0.821 (0.13)	5.96 ***	20.61 ***
95th Percentile	1475.7 (901.9)	-0.591 (-1.14)	-1.14	3.43
Distance to Primary Markets				
Median	-43590.4 (6346.2)	23.597 (3.20)	7.37 ***	--
75th Percentile	-43482.9 (9960.9)	25.512 (5.02)	5.07 ***	0.21
95th Percentile	-376493.4 (51321)	197.018 (25.96)	7.59 ***	46.4 ***
Distance to Main Roads				
Median	-4854.3 (260.3)	2.509 (0.13)	19.09 ***	--
75th Percentile	-10537.8 (523.5)	5.446 (0.26)	20.61 ***	183.4 ***
95th Percentile	-22812.1 (1572.5)	11.822 (0.79)	14.89 ***	144.6 ***
Previous Year's Building Density				
Median	-14.45 (0.4)	0.007 (0.001)	34.5 ***	--
75th Percentile	-25.91 (1.0)	0.013 (0.001)	27.3 ***	209.5 ***
95th Percentile	-42.35 (4.3)	0.022 (0.002)	10.2 ***	47.9 ***
Previous Year's Forest Density$^{(2)}$				
Median	-10.56 (0.7)	0.006 (0.001)	15.3 ***	--
75th Percentile	-11.15 (0.6)	0.006 (0.001)	19.3 ***	2.15

(1) *, **, *** = Statistical significance at 0.01, 0.001, and < 0.001 levels, respectively

(2) Forest density fit for 95th percentile not included since percentile was at maximum forest density of 100%

Table 2: Validation of forecasting sequence for the period 2003-2007. The quantity of new buildings is forecasted by extrapolating trends in the proportion of buildings in each class. The spatial locations were generated by a single random selection from a weighted distribution.

Variable	Observed 2003-2007	Modeled 2003-2007	Percent Difference (1 - (Observed / Modeled))
Quantity of New Buildings			
Urban	81	63	-28.6 %
Suburban	1214	1066	-13.9
Exurban	368	328	-12.2
Rural	86	77	-11.7
Total	1749	1534	-14.0
Spatial Patterns			
Area within 50m of any building	13157ha	13361ha	1.5
Distance to City			
Median	3392m	4811m	29.5
95th Percentile	20515m	16801m	-22.1
Distance to Main Roads			
Median	168m	184m	-8.6
95th Percentile	887m	665m	-33.5

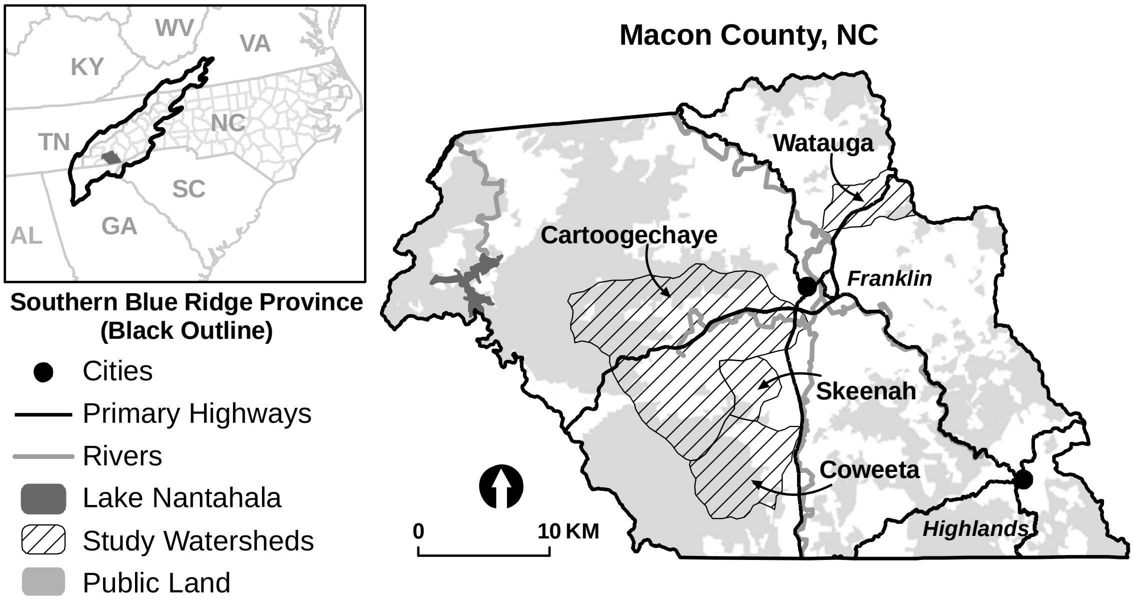

Figure 1: Study area reference map.

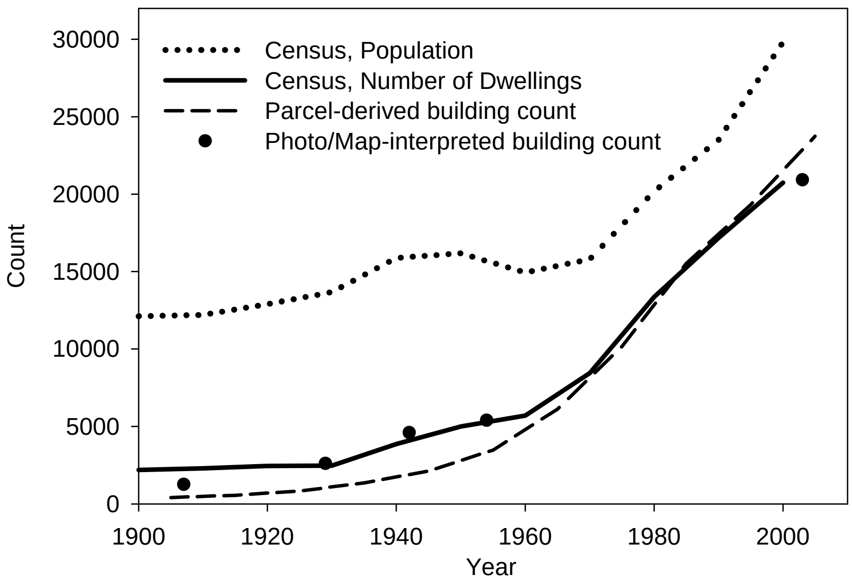

Figure 2: Trends in population and building growth in Macon County, 1900-2007.

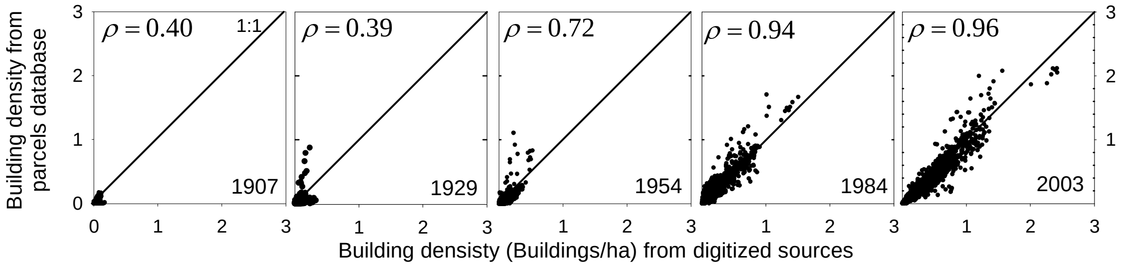

Figure 3: Comparison of building density within the primary watersheds derived from the two primary data sources for representative years. 2000 random points were drawn for each year. The correlation coefficient, ρ, is also given.

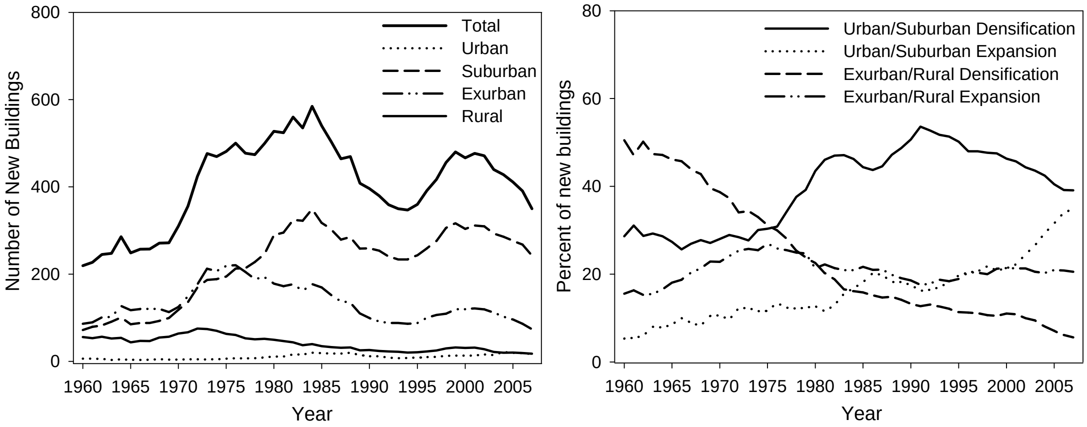

Figure 4: Development type of new buildings in Macon County, NC, 1960-2007. The left graph illustrates the number of new buildings each year, and the right graph depicts the proportion of new buildings each year by development type. Densification indicates new building in areas <70% forested, while expansion denotes new buildings in areas >= 70% forested. All values are 5-year moving averages.

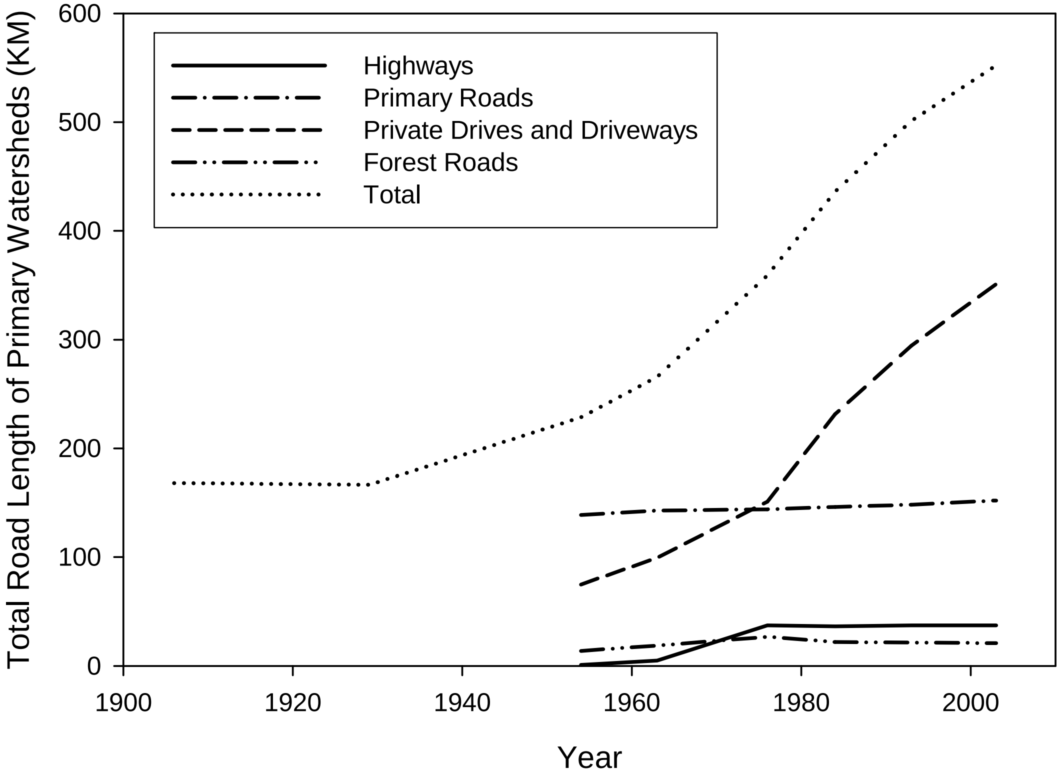

Figure 5: Expansion of the road network by type. For dates prior to 1954, only the total length calculated from historic map sources could be estimated.

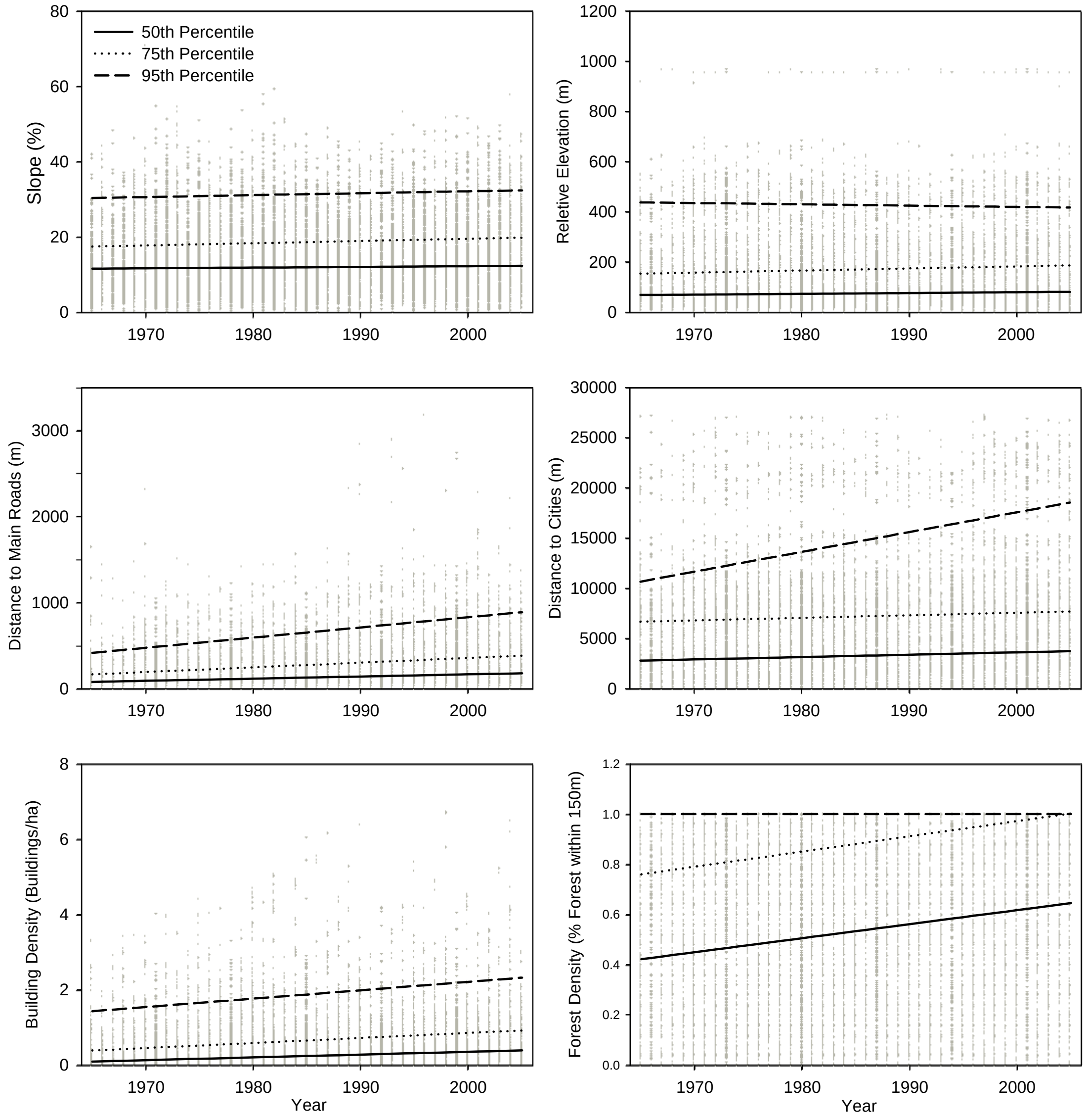

Figure 6: Data points (gray) and regression lines for the quantile regression fits.

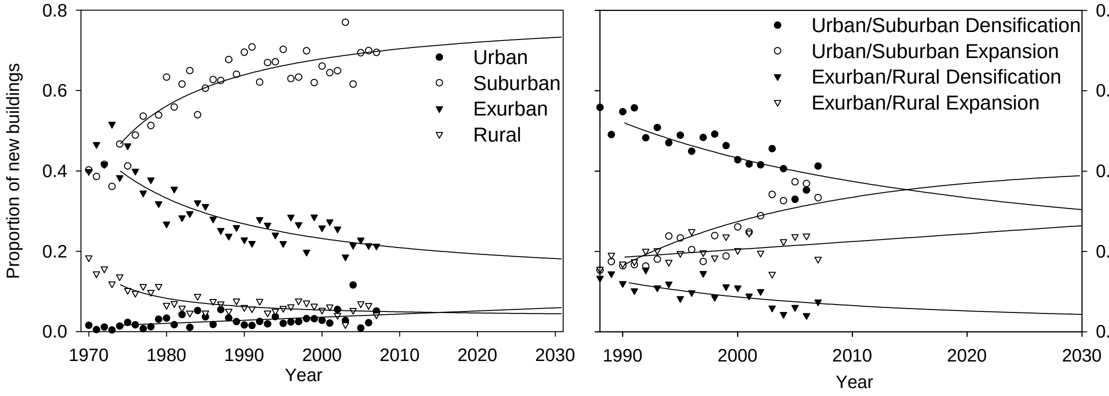

Figure 7: Observed (1975-2007) and extrapolated estimates (through 2030) of the proportion of each type of new development for each year. The left graph extrapolates the development type by building density class, and the right graph extrapolates the combined building density and forest density classifications.

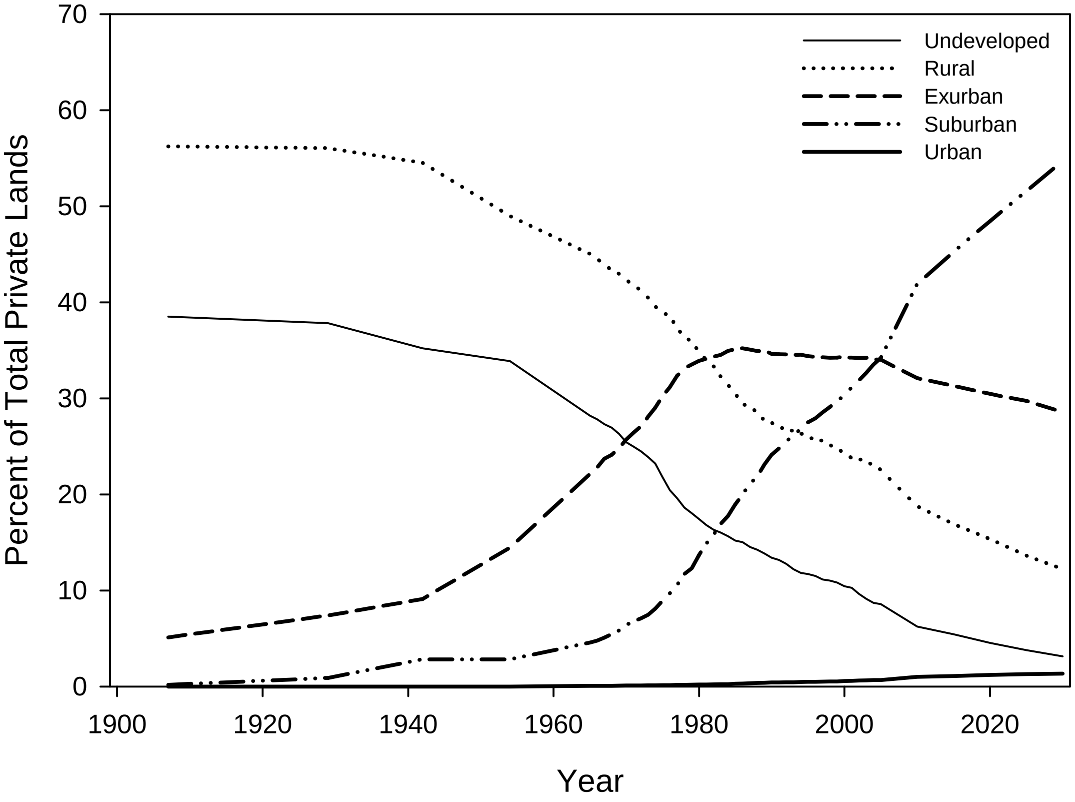

Figure 8: Development type classification as the percentage of all private lands in Macon County, NC, 1907-2005, and forecasted through 2030.

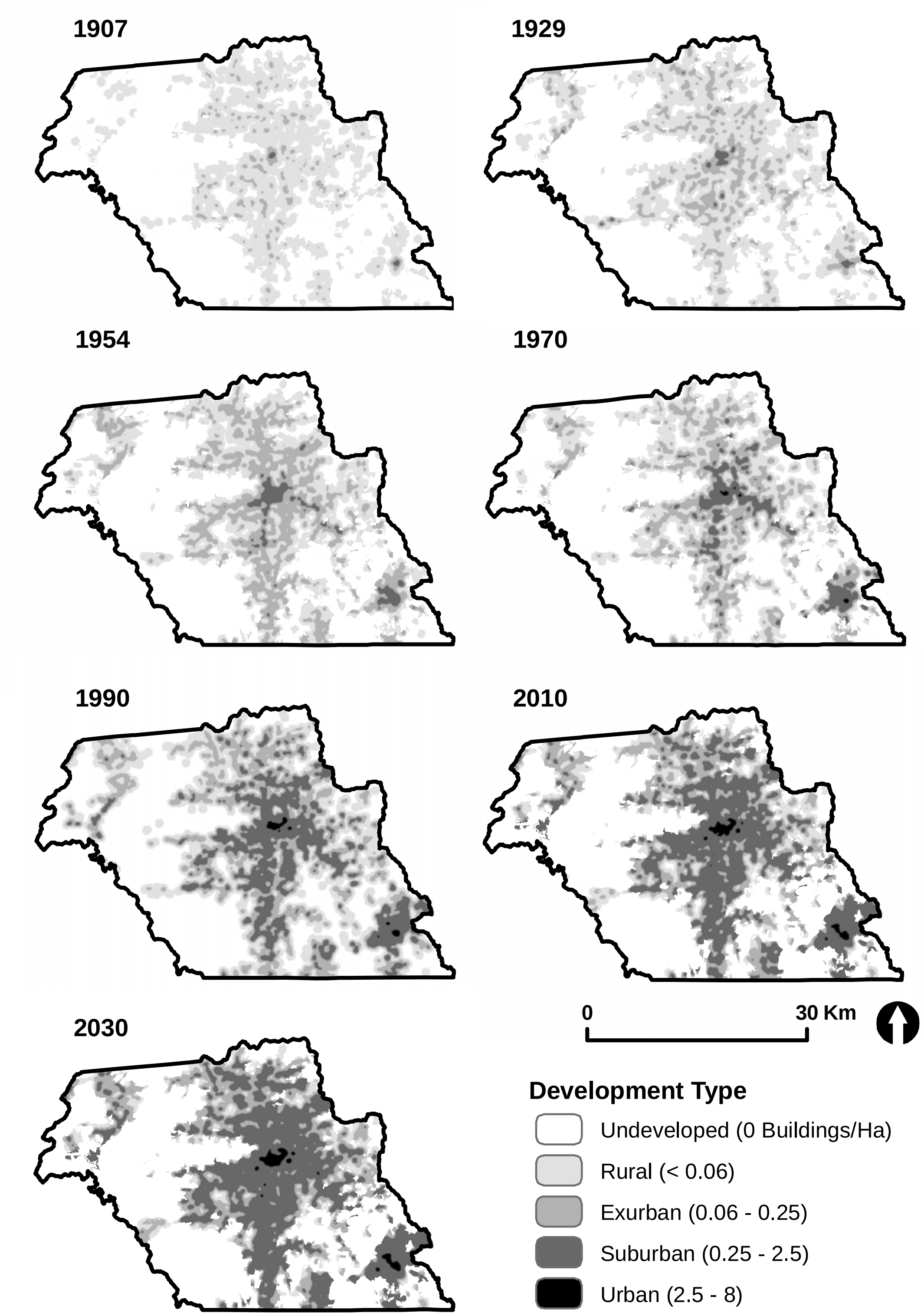

Figure 9: Spatial patterns of building density, Macon County, NC, 1907-2030.

Chapter 3: Spatializing agriculture, forest, and development patterns in Western North Carolina, 1850-2030.

Abstract

The Southern Appalachian region has experienced large and dynamic land use changes since the time of Euro-American settlement. While a common narrative describing the major land use periods of industrial logging, agriculture expansion and abandonment, and recent exurbanization has been developed in the literature, there is limited quantitative information of the timing, magnitude, and spatial patterns of these land use periods. We evaluate these land-use changes by reviewing the literature and available data within a framework of the emerging discipline of land-use science. We develop a spatially- and temporally-consistent general land cover data set across the 21 counties of Western North Carolina between 1850-2030 using a suite of spatial models driven by census data, terrain patterns, and heuristics extracted from the extensive collection of Southern Appalachian research. We estimate that 7,800 km^2, or 34% of the total area in the region, was cultivated at some time, and that the total area footprint of residential and commercial development has doubled since 1970 and tripled since 1950. We forecast that agricultural area will decline 12% by 2030 and the total forest area, which peaked in the 1980s following recovery from widespread agriculture abandonment, will decrease 4.8% as development pressures continue. These data and summary information will be useful for studying past and future human-environment dynamics in the region.

Introduction

Past land-use often affects ecosystem processes and services, and the effects on the landscape may be evident for decades or centuries (DeFries et al. 2004). Studying these effects has important implications for ecological research and conservation planning (Foster et al. 2003). Across the Eastern United States, arguably the largest human impact on terrestrial vegetation since Euro-American settlement has been the expansion of agriculture and subsequent abandonment and afforestation of large areas. In the 31 states that touch or are completely east of the Mississippi River, over 170,000 km^2 of cleared farmland was lost or abandoned between 1910 and 1959, of which only 20-33% was converted to urban uses, with most of the remaining area reverting to forest (Hart 1968; Ramankutty and Foley 1999). This afforestation has resulted in forests notably different than their pre-settlement counterparts. Forested areas that were historically used for agriculture have been shown to contain different canopy and herbaceous species composition (Bellemare et al. 2002; Hall et al. 2002; Fraterrigo et al. 2006), altered cycling and storage of important elements such as carbon (Houghton et al. 1999) and nitrogen (Goodale and Aber 2001), and a lasting influence on the hydrology (Wear et al. 1998; DeFries and Eshleman 2004) and biodiversity of stream ecosystems (Harding et al. 1998; Scott 2006).

The landscape of the heavily forested Southern Appalachian Mountains and its sub-regions has been altered in many, if not most, of the same ways as the larger Eastern US region, but at different rates, intensity, and timing. While the American frontier pressed westward through the major Appalachian valleys, large areas of the most rugged terrain were initially bypassed by most settlers (Salstrom 1995). The combination of steep terrain, relatively few inhabitants, and a unique cultural composition led to a largely self-sustaining, agriculture-based economy through the Civil War and Reconstruction periods. The dominant land use of this period was a "brush fallowing" or "land rotation" style of agriculture, in which patches of forest were cleared and used for cropland or pasture until worn, and left idle or abandoned for up to several decades as the soil recovered (Hart 1977; Otto 1989). In the Blue Ridge Mountains of Western North Carolina (Figure 1), large scale industrial expansion began in the late 1880s and 1890s following the arrival of railroads and the entrepreneurial interest in the Appalachian forests by lumbermen (Eller 1982; Davis 2000). Both agriculture and lumber extraction peaked in the early decades of the 20th century (Van Noppen and Van Noppen 1973; De Vivo 1986). Total Farmland area decreased greatly in the 1910s and 1920s as lumbermen, followed by the US Forest Service, bought up large tracts of forest land (Figure 2). The area of non-woodland farmland, however, decreased only slightly during the period, and it was not until the 1950s that a large net decrease in Improved Farmland (defined as the sum area of cropland, non-woodland pastureland, and farmyards) occurred during the Appalachian out-migration period in the 1950s and 1960s as a large percentage of the rural population relocated to more urban areas (Raitz and Ulack 1984). As part of a nationwide migration turnaround (Brown and Wardwell 1980) rural populations in the Blue Ridge began to rise sharply in the 1970s as second home owners, retirees, and other seeking the amenities of the scenic area migrated to the Southern Appalachians (Raitz and Ulack 1984). This growth has held relatively strong to date and the trend is expected to continue, with the population of the 21 counties in Western North Carolina expected to break 1,000,000 by 2010, and increase 16% by 2030 (North Carolina Office of State Budget and Management 2008).

While this general story of transformations in the use of the Blue Ridge and Southern Appalachians has been widely documented, there is a general lack of extensively quantified and spatially-explicit data beyond the census records from which to evaluate the ecological consequences of these transformations. This is in large part due to the unique challenges of historical land use analysis in the Southern Appalachians. Unlike most of the U.S., there was no single baseline land survey, and only a few isolated land surveys of prime land in the main river valleys (Jurgelski 2004). While a hindrance for modern researchers, these land boundary uncertainties and disputes were a major source of strife for residents, logging and mining companies, and government purchasers (Mastran and Lowerre 1983; Gennett 2007). Reconstructing the trends using other methods, such as photograph interpretation and field sampling, is largely hampered by the extreme gradients of terrain and climate that create a largely heterogeneous landscape. Modern tools such as Geographic Information Systems (GIS) and image processing software provide methods for overcoming these limitations and estimating spatial trends and intensity of land use practices over time.

In this paper, we estimate the magnitude, timing, and spatial patterns of major land use types (forest, non-forest agriculture, and non-forest developed) in Western North Carolina through a combination of a literature review and GIS-based spatial modeling. The study area is the 21-counties that comprise the “Mountains of North Carolina” unit of the US Forest Service Forest Inventory and Analysis (FIA) program (Brown 2002). Two specific objectives are addressed: 1) identify and quantify the major land uses since 1850, and project possible future land use practices over the next 30 years; and 2) quantify and spatialize the extent of the broad land use classes of forest, non-forest developed, and non-forest agriculture. The starting date of 1850 was selected because it coincides with the earliest year of county-level agriculture area estimates in the census records and was the first complete census period following the Treaty of 1835, which resulted in the final attempt at removal of the Cherokee Indians from the region in the episode known as the "Trail of Tears" (Malone 1956; Finger 1991).

As an organized method for evaluating land use trends, we employ the framework of the emerging discipline of land-use science (Veldkamp and Lambin 2001; Agrawal et al. 2002; Parker et al. 2003; Burgi et al. 2004; Rindfuss et al. 2004; Verburg et al. 2004; Manson et al. 2006), which aims to integrate research on land use and land cover changes that have long been studied in a wide variety of disciplines such as geography, economics, and urban and regional planning. Major research themes of land use science include identifying the drivers, rates, trajectories and feedbacks of change (Veldkamp and Lambin 2001; Burgi et al. 2004), linking land use to ecological consequences (DeFries et al. 2004), and addressing a variety of methodological concerns such as scaling across decision-making levels and linking parcel-level land use choices to pixel-level data sets (Rindfuss et al. 2004). In this study, we evaluate the long-term rates and trajectories of change in the Southern Appalachian Mountains and assess the role of biophysical drivers on land-use change.

Database development

To support spatial data modeling, we compiled a database of widely available geospatial data sets within a Geographic Information System (GIS) and developed a variety of historic geospatial datasets. All data sets used in modeling are listed in Table 1. We describe here any processing procedures for newly developed or derived data sets, including disaggregated Census data from 1850-2000, estimated road lines circa 1900, an Agriculture Suitability Index, a forest survey map from 1904, and a baseline 2001 land cover classification derived from the National Land Cover Data set (NLCD). All data were resampled for spatial modeling to a 1 ha raster resolution (2.47 acres, or 100 m cell size) and projected to a UTM Zone 17 coordinate system with a horizontal datum of NAD83.

US Census of Population and Housing and US Census of Agriculture data are used extensively in this research[1]. We compiled data from the decennial US Census reports from 1850-2000 (U.S. Census Bureau 1850-2000) and US Census of Agriculture reports from 1954-2002 (U.S. Department of Agriculture 1954-2002). Using census data in fine-scale, spatially-explicit analysis is often problematic because of aggregated data and changing census boundaries (Peters and MacDonald 2004). We conducted two census disaggregation processes in this study. The first is an estimate of Housing Unit

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[1] This research uses multiple levels of US Census data aggregation, so a brief review is warranted. While the census aims to count vital facts for every person, detailed data of additional statistics are estimated from a smaller sample of the population. In both cases, data are provided to the public in a hierarchy of aggregated units. A Block is the smallest spatial unit for which the 100% enumeration data are available and in this study area the median size of Blocks is 5.6ha (14 acres). Multiple Blocks are organized into Block Groups. A Tract is comprised of multiple Block Groups, and Minor Civil Divisions (MCDs) consist of multiple Tracts. Counties, in turn, consist of multiple MCDs. Much of the pre-1990 data used here was published at the MCD or county level only.

density (HU/ha) used in modeling development patterns between 1940-2000. We spatially disaggregated the 2000 Census Block-level HU estimates to 1 ha cells using the dasymetric method of Theobald (2005), in which road density (km/km^2), derived from a 1998 NCDOT roads layers (NCGICC 2008), was used as ancillary data to spatially disperse the HUs within the privately-owned areas of each Block. For 1940-1990, we use the Block Group-level estimates made possible by the 2000 census “Year Housing Unit Built” sample question, corrected for errors according to the detailed methods of Radeloff et al (2001), and disaggregated using the same dasymetric method (Theobald 2005) constrained by the 2000 Block-level estimates.

The 2nd Census data disaggregation process results from the problem of changing county boundaries in the region, which were not finalized in their present form until 1920. Historic, but largely generalized, county boundary maps (Waisanen and Bliss 2002) were manually reshaped in reference to descriptive histories (Corbitt 1950) and the cartometrically correct current county boundaries as available from the North Carolina OneMap program (NCGICC 2008). In order to match all county-level census variables to the same boundaries, census values for counties whose boundaries changed shape before 1920 were interpolated to present county boundaries using the area of suitable agriculture as the areal interpolation weight. We estimate the spatial location of historically suitable agriculture areas in the region during the mid 19th century by estimating the agriculture areas for the three counties in this study area that have not experienced significant change in their respective county boundaries since 1870 (Clay, Madison, and Wilkes), the census year prior to the beginning of the industrial growth period. For these three counties, we identify the Agriculture Suitability Index threshold (ASI, described below) that results in an area equal to the area of total Improved Farmland reported in the 1870 Census. We assumed the average of these three county threshold values was representative of the entire region, and applied that threshold across all 21 counties to estimate the 19th century extent of suitable agriculture areas. For example, Ashe County in 1850 covered the area that is present-day Ashe and Alleghany counties. While present-day Ashe covers 64% of the historic 1850 Ashe area, present-day Ashe contains only 31% of the suitable farmland within the larger historic boundary. We assume agriculture and population densities were higher in areas with more agriculture lands, so assign 31% of the population from the 1850 census to the present-day Ashe county boundary and the remaining 69% to present-day Alleghany. This ASI-weighted areal interpolation was applied to three census variables: population, HU, and Improved Farmland area. Tables containing the county-level data for each of these variables are included in Appendix A of this dissertation.

As a method of identifying historic agriculture areas, we define an Agriculture Suitability Index (ASI) generalized from the Natural Resources Conservation Service Land Capability Classification of the SSURGO data set (Soil Survey Staff 2008). The LCC provides a categorical estimate of the capability of a given soil unit for growing common crops or pasture grasses, and is based on an assessment of the risks of soil damage (e.g., erosion potential) and limitations on use (e.g., stoniness, shallowness of the rooting zone). At the time of this research, spatial SSURGO data were available for 16 of the 21 counties in the study area (Soil Survey Staff 2008). We address the missing data problem and convert the categorical data to a probability index by creating a logistic function[2] derived from the available SSURGO data with LCC Classes 1 and 2 (slight to moderate limitations) defined as suitable areas, and Classes 3-8 (various types of severe to very severe limitations) defined as unsuitable. We generated a random sample of 10,000 points across the 16-county region with available SSURGO data, and create a logistic function using 8,000 of the sample points. All significant variables ($p < 0.1$), from Table 1 are included in order to maximize spatial variation, resulting in the following model (Pseudo-R^2=0.12):

$$ln(P_{suit}/(1-P_{suit}))) = 0.79 - 0.0013 * ELEV - 0.003 * SLPP + 0.035 * TRMI + 0.00043 * D2STRM \tag{3}$$

where P_{suit} is the probability that a location is suitable for agriculture, *ELEV* is the elevation (m), *SLPP* is the slope (%), *TRMI* is the Topographic Relative Wetness Index (Parker 1982), and *D2STRM* is the straight-line distance to the nearest stream (m). We validate the ASI against the 2,000 sample points excluded from the model and test for significantly larger ASI values for the binary "suitable" classification as well as for the agriculture suitability severity classes of the LCC (Figure 3). In both situations, the model

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[2] Multiple logistic regression models are used in several components of this study. A logistic regression model is more appropriate than general linear regression when the independent data set is binary (e.g, True/False, or 1s/0s). We use the traditional logistic form using a logit link function (Agresti 2002):

$$\ln\left(p_y/(1-p_y)\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \varepsilon \tag{1}$$

where p_y is the probability of location y equaling 1, $ln(p_y/1-p_y)$ is the natural log of the odds of a cell equaling 1, k is the number of independent x variables,$\beta_0 \ldots \beta_k$ are the regression parameters, and ε is the error term. From this model, a probability map is calculated by solving eq. 1 for p_y and applying the function to the appropriate raster data sets:

$$p_y = \frac{e^{(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)}}{1 + e^{(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)}} \tag{2}$$

We report model goodness-of-fit using McFadden's Pseudo-R^2 (McFadden 1974). It should be noted that the Pseudo-R^2 is not directly analogous to a correlation-coefficient R^2 from general linear regression.

fit is highly significant (ANOVA *F*-Test, $F > 500$, $p < 0.0001$). The boxplots in Figure 3 indicate overlap between classes; however, we feel this is acceptable given the scale of analysis and general data limitations.

In addition to these derived data sets, we extracted geospatial data from several historic map sources. A joint USGS/USFS report from 1905 (Ayers and Ashe 1905) was accompanied with a detailed map, generally called the Ayers/Ashe map, which estimated forested areas and forest volume classes. We scanned and georegistered the paper map to a 100 m resolution raster data set using county boundaries as the reference layer. We calculated the distance between 60 mountain peaks, stream intersections, and railroad intersection identifiable on both the Ayers/Ashe map and on current 7.5-minute, 1:24,000-scale USGS topographic maps, and estimate nominal horizontal accuracy of the map to be approximately 500 m. Cleared areas and forest areas (stratified by volume class) were extracted from the map using an iterative feature extraction process to account for the discolorations, contour lines, road lines, and text on the paper map. Each iteration consisted of extracting a separate class, starting with the cleared class and stepping through each progressively larger forest volume class. An unsupervised ISODATA classification (Jensen 1996) was calculated with 20 classes, and each resulting ISODATA class was manually reclassified as being included in one of three categories: in the desired class, in any other forest volume class, or map noise (text, contour lines, etc). The map noise areas were masked out and the other two categories were aggregated using a 9x9 cell moving window majority filter to fill in the map noise areas. The final areas for the specific class iteration were extracted, and the process was repeated for the remaining area and the next volume class. To assess the quality of the feature extraction routine, we compared the final raster layer against a manually digitized version of the Ayers/Ashe Map for Macon County (This Dissertation, Chapter 1). The total area for each class between the two data sets differed by an average of 3%. One other historic data set was created by digitizing line features from georegistered historic maps. A circa 1900s road lines layer was digitized from 30-minute 1:125,000 scale USGS topographic maps dating between 1896-1912 (U.S. Geological Survey 1896-1912), with an estimated horizontal accuracy of 100 m.

The final input data set processed for this study was a baseline estimate of 2001 land cover with four classes (Forest, Agriculture, Developed, and Water/Miscellaneous) generalized from the 2001 National Land Cover Database (Homer et al. 2004) and modified using the spatially disaggregated estimate of Housing Unit density derived from the 2000 census. We feel the 2001 NLCD classification for Western North Carolina significantly underestimates developed areas and overestimates agriculture due to confusion in the automated classification procedure used in the NLCD. As evidence, the NLCD suggests that 12.2% of the 21 county area was in cropland or pasture in 2001, while the 2002 Census of Agriculture reports that only 8.9% of the area was in cropland or non-woodland pasture (U.S. Department of Agriculture 1954-2002)**,** a difference that equates to 76,000 ha. It is clear with visual inspection that large areas of residential lawns, recreational fields, and recently harvested forest stands are misclassified as agriculture on the NLCD. To adjust for this discrepancy, we modified the 2001 NLCD by reducing the amount of agriculture to match the 2002 Census of Agriculture estimates

(U.S. Department of Agriculture 1954-2002). We reclassify the agriculture areas using a logistic regression function developed from a 2003 aerial-photograph interpreted land cover data set for Macon County (This Dissertation, Chapter 1), which to our knowledge is the most detailed land cover classification in the region that properly distinguishes agriculture from non-agriculture lawns and fields. A random sample of 500 points was generated from within all agriculture areas (row crop, hayfields, and pasturelands), and another 500 points from all developed areas (residential, commercial, and park areas). We fit a logistic model that included all significant variables from Table 1 ($p < 0.1$, Pseudo-$R^2 = 0.22$) resulting in the following model:

$$ln(P_{ag}/1-P_{ag}) = -0.22 + 1.77 * BKHU2000 - 0.01 * D2RDS1998 - 2.66 * ASI + 0.01 * ELEV + 0.05 * SLPP \qquad (5)$$

where P_{ag} is the probability of a cell being agriculture, *BKHU2000* is the Housing Unit Density disaggregated from the 2000 Census Block units, *D2RDS1998* is the straight-line distance to the nearest road from the 1998 NCDOT roads layer, *ASI* is the Agriculture Suitability Index value, *ELEV* is the elevation (m) and SLPP is the slope (%).

Starting with the entire 2001 NLCD data set, we extracted the subset of all agriculture classes and then identified the improved delineation of agriculture locations for each county as those areas with the highest likelihood of being agriculture (i.e., largest P_{ag} values) such that the total area is equal to the area of non-woodland farmland in the county as reported on the 2002 Census of Agriculture. All other areas within the subset are identified as being developed if on private land, or else forest harvest sites if on public land.

In order to generalize the modified NLCD categories from 30 m resolution to 100 m resolution for spatial modeling, we applied a rule-based aggregation algorithm as opposed to the more widely-adopted majority-area “winner-takes-all” approach (Bolstad 2008). We used a rule-based approach specifically to reduce the strong influence of roads on the NLCD classification which would otherwise confound model backcasting (described below). Forested areas on the 100 m raster were identified first by creating a 3x3 moving neighborhood window on the input 30 m data, and selecting those cells whose 3x3 neighborhood were at least 50% forested. This helped reduce the roads classification to only major highways, effectively masking out smaller roads from this study. Miscellaneous areas (open water and exposed rock) were identified next using the same 3x3 neighborhood sequence, followed by agriculture. All remaining cells were classified as either forest or developed using a majority-area decision rule between the forest and developed classes. As a final step, all developed cells within 50 m of the 1998 NCDOT Highways layer were reclassified as Miscellaneous, and the Miscellaneous areas were excluded from all modeling in this study. While large areas of highways and pre-reservoir locations where historically available for agriculture, development, and forest harvest, we did not have the appropriate terrain and historic road data to properly account for these historic areas. Combined, these miscellaneous areas account for approximately 1% of study area.

Spatial Modeling and Validation

We developed a sequential 3-phase strategy for modeling developed, agriculture, and forested areas, respectively, for each decade between 1850-2000, and a separate modeling sequence for a single forecast scenario of land cover conditions for each decade from 2010-2030. The type and applicability of data available for the three land use categories varies, as does the typical temporal land-use trajectories associated with the categories. Thus, we employed a variety of different modeling strategies depending on the land use type, availability of data and historical period. This approach confounds validation and error assessment, but follows a general guiding principle of using the best available data and knowledge of the separate land-use change processes, and matching the appropriate modeling strategy with the type of data and extent of knowledge available.

In the first phase we model developed areas, which we define as areas where the land cover is non-forested and used for residential or commercial purposes. While there has been a rise of residential development in predominantly forested areas (This Dissertation, Chapter 1), the primary land cover of these areas at a coarse 100 m resolution is forest. Spatial patterns of developed areas were defined for the 2001 baseline land cover conditions across the region and then backcasted for all previous decades. That is, moving backwards in time, developed areas were "removed" from the landscape each decadal step. The backcasting is divided into two time periods, from 2000 back to 1940 (the dates in which census Block-Group level HU estimates are available), and 1930 back to 1850. We make two general assumptions regarding the quantity and location of historic development. First, we assume that the percentage change in developed cells for each census Block Group area (1940-2000) or county area (1850-1930) each decade is directly proportional to the percentage change in HUs for the same area. This assumption is based on comparison of the 1954 and 2003 land cover data sets for Macon County (This Dissertation, Chapter 1), from which the percentage growth in population between the two dates was 315% and the percentage growth in developed land area was 337%. Second, we assume development is a terminal land cover class in that once a cell has been classified developed, it remains developed for all future periods. This assumption is supported at the regional scale because most causes of abandonment or removal were for reservoir or highway construction. In a case study in Macon County, we found that building removal before 1950 was most associated with farmland abandonment, while removal after 1950 was most related to new construction on the same parcel (This Dissertation, Chapter 2). Historic farmyards were generally much smaller than the 1 ha resolution used in this study, so building loss due to farmland abandonment is captured in the agriculture modeling described below.

Once the total number of developed cells for each decade was determined, the locations of the developed cells for each decade moving backwards in time from the 2000 baseline were identified through deterministic development likelihood indices for two separate periods, 1940-2000 and 1850-1930. These indices consist of a weighted overlay of 3 criteria for the 1940-2000 period (change in Housing Unit density, distance to nearest 1998 roads, and distance to nearest incorporated city or village along the 1998 roads), and two criteria for the 1850-1930 period (distance to nearest 1900s road, and travel distance to the nearest incorporated city or village along the 1900s roads). In both time periods, the variables were each linearly rescaled to a value of between 0-10,000 and summed. This creates a deterministic index where lower values indicate areas where the development was likely to have existed in the previous time step. For example, areas nearer to cities and closer to roads would be more likely to be developed than areas further away from cities or roads. The specific cells to classify as developed were selected as those with the lowest index values, and the process was repeated for the next decade.

Following the modeling of developed lands, the second phase consisted of identifying areas of agriculture, which we define as all non-woodland farm areas. We determine the quantity of agriculture for each county and decade as the total Improved Farmland value extracted from the Census of Agriculture reports (U.S. Census Bureau 1850-1950; U.S. Department of Agriculture 1954-2002). For the 1850-1920 decennial censuses, Improved Farmland was an explicitly reported category. For the 1930-1950 decennial censuses and 1954-2002 quinquennial censuses, Improved Farmland was calculated as Total Land in Farms minus Farm Woodlands and Woodland Pasture. For the 1954-2002 quinquennial censuses, we linearly interpolated Improved Farmland values for the decade breaks using the two nearest census dates (e.g., Total Farmland in 1960 was interpolated from the 1959 and 1964 census estimates).

With these estimates of the quantity of agriculture area, we estimated the location of agriculture for each county each decade as a function of the Agriculture Suitability Index (ASI, defined above) constrained by the developed area classification. For each decade, the total area available for agriculture in each county was identified, and then the locations of agriculture were identified as those areas with the highest ASI values that were not already classified as developed. As expected, the areas with the highest ASI values are found in the fertile valleys and coves, with lower values on steeper slopes, rockier terrain, and drier sites. This method is applied to each decade independently.

The third and final phase of modeling estimated areas of forest, which we assume is all remaining area that is not cleared for development or agriculture and not excluded via the water/miscellaneous mask.

As a measure of forecasting land use through 2030, we estimated the total quantity of each class using similar methods as the backcasting model. First, the total amount of developed area was assumed to be proportional to the expected increase in the number of HUs as determined by the population projections (North Carolina Office of State Budget and Management 2008). Total Improved Farmland was estimated by defining linear trend models for each county between 1980-2000 and extrapolating the trend lines each decade through 2030. Excluding the same Water/Miscellaneous mask, all other areas were classified forest.

Given the broad study area and limited data sources, particularly for historic periods, this multi-modeling strategy is difficult to validate. In order to assess the accuracy of the 3-part land use model, we compared the final backcasting model against four independent data sets. The first is a detailed decadal land cover reconstruction for Macon County (This Dissertation, Chapter 1). The Macon County reconstruction included 3 dates of photo-interpreted land cover (1954, 1993, and 2003) and additional dates were reconstructed using a decision-rule model, terrain data, and ancillary data such as exact building and road locations dating back to 1907. The second independent data set is circa 1950 forest/non-forest classifications developed by Wear and Bolstad (1998) for Madison County and the Cane Creek Watershed in Henderson County. These classifications were based on aerial photograph interpretations. The third independent data set is the 1904 Ayers/Ashe map for the 11 counties of this study area with complete coverage on the Ayers/Ashe map. Finally, we compare the 1990 modeled land cover against a 1991 satellite-derived classification developed using the same automated methodologies as the 2001 NLCD (Coweeta LTER, unpublished data, available at http://coweeta.ecology.uga.edu/).

We evaluate map comparisons using five metrics calculated by the Validate module of the Idrisi software package (Eastman 2006), in which the modeled land cover from this study is validated against the independently generated land cover data sets. “Map agreement” is the percentage of cells on the two maps that have the same classification, and is equivalent to the “overall accuracy” statistic on a standard error matrix (Bolstad 2008). “Quantity disagreement” is an estimate of the percentage of disagreement that is due to differences in the total quantities of each category on the two maps being compared, and “location disagreement” is the percentage of differences due to mismatched pixels. These three “Component of Agreement” metrics sum to 100% of the study area (Pontius Jr. and Suedmeyer 2004). The standard Kappa statistic (Congalton and Mead 1983) is included as a widely applied statistic of the observed agreement between the two maps corrected for chance agreement, although recent research suggests that Kappa-based statistics are misleading for map comparisons in that they do not directly address how much the two maps differ, but rather simply test whether the agreement between the two maps is better than random (Pontius Jr. and Millones 2008). The final metric is the Null Resolution (Pontius Jr. et al. 2004), which is defined as the spatial resolution at which the modeled land cover is better than a Null Model of no change. For the backcasting model applied here, this translates into separately calculating the map agreement statistic between the modeled land cover and two different data sets: 1) the 2001 baseline data set, and 2) the independent reference data set. The data are iteratively coarsened at multiples of the original 100 m raster resolution until the map agreement with the independent data set is higher than the agreement with the 2001 baseline data set. This approach addresses the common problem of having most of the disagreement be a result of location errors rather than quantity errors and gives an indication of the appropriate scale of analysis.

For the final validation step, we compare the modeled forest area estimate against the USFS Forest Inventory and Analysis (FIA) Forest Survey reports since 1938 (Cruickshank 1941; McCormack 1956; Knight and McClure 1966; Cost 1974; Craver 1984; Johnson 1990; Brown 2002) and satellite-based forest/non-forest classifications since 1975 (Homer et al. 2004). The FIA is a periodic national inventory of the forest resource on public and private lands, and is based on a large collection of sample plots which provide a statistical estimate of forest area among other variables.

Results & Discussion

In Western North Carolina, the area of cleared farmland peaked in 1910 and the total non-forest area peaked in 1930 (Figure 5, left side). Following widespread abandonment, the total forest area peaked in 1980, and we estimate that forest area has been lost to development at a rate of 1.1% of total forest area per decade since 1980. Linear extrapolations of agriculture for each county suggest a net 12% decline in agriculture area by 2030, however much of this will likely convert to development rather than forests. With population projected to increase 16% through 2030, we estimate that total forest area will decline by 4.8% during the period as development expands.

The spread and use of agriculture was the dominant land use through at least 1950, after which there is little evidence of widespread brush fallow land rotation practices (Hart 1977; This Dissertation, Chapter 1). The peak total area of cleared farmland occurred between 1900-1940, but agriculture usage on the worst soil conditions and smallest farms peaked in the 1920s and 1930s (Lewis 1931; Taylor 1938), setting the stage for the largest amount of abandonment. By 1938, one author estimated that one-half of Southern Appalachian farms were smaller than 50 acres, and one-half contained no level ground (Taylor 1938). Our model estimated the area of agriculture for each decade independently, so no crop rotation was considered directly. An indirect measure of abandonment, however, is available through the spatial reconstruction. Abandonment for select decades resulted from a decrease in the total area of agriculture, and the spread of development forced agriculture to move to new locations. Combined, we can define a conservative estimate of the total area in the region that was ever cleared for agriculture by calculating the total number of cells that were ever classified as agriculture during the 150 year period. This estimate of 7,800 km^2, or 34% of the region, is larger than the 6,200 km^2 (27%) of cleared agriculture in the peak year of 1910. Incorporating land rotation into the agriculture cycle would likely increase the total area, so this appears to be a lower limit of the total area subjected to agriculture.

Table 2 reports the results of model validation. Model results for all years are an improvement over randomness, and map agreement is greater than 60% for all data sets except for the 1904 Ayers/Ashe map (Figure 3). For the 11 counties with 100% coverage on the Ayers/Ashe map, the Ayers/Ashe map contains 2063.5 km^2 of “Cleared” land, the 1900 modeled classification contains 3032.9 km^2 of “Non-forest” land, and the 1900 Census of Agriculture reports 2901.1 km^2 of “Improved Farmland”. Even considering the different classification types, it appears the Ayers/Ashe map largely underestimates the amount of non-forest area, likely because of the coarse 4 ha nominal minimum mapping unit for the Ayers/Ashe map, errors on the topographic maps used as the basis for mapping by the Ayers/Ashe survey team, and surveyor errors in relying on ocular-estimate mapping procedures. Another possible reason for the large discrepancy is the errors in the Census of Agriculture farmland area estimates on which the 1900 modeled land cover classification is largely based. The Agriculture Census is based on unverified responses of area used by individual farmers.

Table 2 indicates another potential source of error in the total quantity of developed area each decade. In this study, we assumed changes in developed area were proportional to changes in the number of Housing Units. However, compared with the

Macon County land use reconstruction (This Dissertation, Chapter 1), the total quantity of developed area is progressively overestimated going backwards in time. With no readily available alternative basis for determining the amount of historic developed areas and no clearly justifiable basis for creating a sliding scale of HU/development ratios over time, we chose to accept this repeatable and deterministic development heuristic.

Besides evaluating quantitative metrics, it is important to visually compare modeled versus reference data sets. Figure 4 compares modeled classifications against two independently developed data sets, the forest/non-forest 1904 Ayers/Ashe map and the 1954 Macon County aerial photograph-interpreted classification. In general, it is evident that the spatial trends are adequately captured. However, it is apparent that our reliance on the ASI for estimating agriculture areas works well for counties with well-defined central valleys, but the quality breaks down in the eastern counties that transition from the Blue Ridge to the Piedmont physiographic regions. In the higher elevation transitional counties such as Avery and Watauga, the model predicts agriculture on the lower elevation transitional slopes rather than the high elevation valleys where agriculture is primarily constrained. In the predominantly Piedmont counties such as Wilkes and Caldwell, most of the area is classified as relatively suitable for agriculture, so the patterns appear to approach randomness. We explored alternative forms of the ASI model, such as fitting ASI models for individual counties or similar multi-county areas, but these did not improve upon this source of error. For Avery County, this error was largely ameliorated by the large amount of public land in the transitional area.

Figure 5 (right side) compares the modeled forest area against the USFS FIA Forest Survey reports since 1938 and satellite-based forest/non-forest classifications since 1975 (Homer et al. 2004). The FIA surveys indicate a quicker recovery of forest area following agriculture abandonment than our model suggests. This could be due to an overestimation of historic developed areas in our model between 1940-1960, which would otherwise be classified as forest. Since 1990, both the satellite-based classification and our model (which is based on a 2001 satellite-derived classification) report a higher total forest area than the FIA surveys. The 2001 NLCD forest area is 4% higher than the total forestland area of the 2002 FIA report. This difference could be due to definition of forestland in the FIA survey, which in 2002 is defined as areas greater than 0.4 ha (1 acre) in size, at least 10% stocked by forest trees of any size, at least 120 feet wide, and not currently developed (Brown 2002). In Macon County, we estimated that 1100 ha were classified as forested residential in 2003, slightly less than 1% of the county area (This dissertation, Chapter 1). If other counties follow similar trends, then forested residential areas do not fully explain the discrepancy. Another possible explanation is the difference in Minimum Mapping Units (MMU), with the 30 m cells (0.09 ha or 0.22 acre) of the NLCD being smaller than the FIA lower limit of 0.4 ha (1 acre). The percentage of closed-canopy forest area for the Macon County aerial photograph-interpreted land cover in 1954 and 2003, which were developed with a 0.4 ha (1 acre) MMU, were 81.7% and 84.5%, respectively (This dissertation, Chapter 1). The FIA survey estimates of total forest area in Macon County for 1955 and 2002 were 81.6% and 78.6%, respectively. While the 1950s estimates were very close, the 2000s estimates differed by 5.9%, or almost 8,000 ha in one county. The 2001 NLCD estimate of forest area in Macon County is 84.8%, which is rather close to the aerial-photograph interpreted estimate. Thus, the MMU does not appear to be the driving factor. A final possibility for this discrepancy may be increased fragmentation. Smaller and narrower forest strips might be excluded from FIA estimates while being included in satellite and aerial-photograph interpreted estimates. Due to the size of this difference in forest area estimates and the spatial versus sampling-based differences in the methodologies employed, further research is warranted.

We narrowed land cover delineation to the three broadest classes of forest, agriculture, and developed lands, with major highways, water, and bare rock areas excluded from analysis. Other important land uses have had significant roles in the historic and present use of the Blue Ridge. Most notably, identifying areas of forest harvest (e.g., transitional forest) would be extremely useful for studying the long term ecological changes in the region. We evaluated several heuristic-based models based on general descriptions of harvesting patterns (Ayers and Ashe 1905; Glenn 1911; Holmes 1911; Frothingham 1931; Lambert 1961; Clarkson 1976; Eller 1982; Pyle 1988) and explored harvest trends deduced from a National Forest database of forest stand-age history (Hermann 1996) in attempts to define a statistically significant model of the location and rate of harvests, but no significant models were found at the regional scale. Another land cover class notably missing from this analysis is mining. In the mid-1800s, several iron manufacturing operations were located through the region, particularly in Cherokee and Avery Counties (Blethen and Wood 1992), and many other minerals were extracted throughout the region (Stuckey 1965). Many of the these operations required large amounts of wood for use as charcoal for smelting or timber supports in mine shafts, so large areas of agriculture were displaced and forests cleared around these operations.

While this data provides a spatialized representation of historic land cover that provides insights into regional land use patterns and may be useful for a variety of modeling applications, there are several caveats to its use and interpretation. As several authors have noted (Hart 1977; Otto and Anderson 1982; Otto 1989), use of the Appalachian mountain lands has long been and continues to be highly stochastic and heterogeneous. We have by necessity relied on many simplifying assumptions of land use practices based on varying levels of quantitative supporting evidence, and combined those assumptions with deterministic terrain-based models to represent spatial and temporal patterns. Land managers have not had the luxury of selecting the “next best suitable plot of land” across the entire county as we have here in some instances. They simply made choices as best they could given what few (if any) options were available. Spatial accuracy of specific locations is likely very low, but our model validation suggests landscape level trends are reasonably represented, and at a minimum, the quantity matches census-based estimates. This multi-phase deterministic modeling also limits the possibility of landscape pattern analysis (Turner 2005; Iverson 2007) since many of the local spatial patterns are artifacts of the modeling strategy used. For example, between 1850-1940, we identified developed lands moving backwards in time by removing those cells furthest from towns or roads, while the true patterns were likely much more stochastic. The data since 1940, which use a moderately more sophisticated method involving census Housing Unit density estimates, might be more reliable for pattern analysis.

In this research, we reconstructed major land use patterns over a 150 year period in Western North Carolina using a decision-rule modeling strategy built upon sparse spatial data, frequent census data, and terrain-based models. This approach was possible primarily because of the strong influence that the rugged Southern Appalachian terrain has had on historic and present land use. However, it is evident that the relationship between terrain and land use has been dynamic over the past 150 years through changing resource demands and cultural priorities. With the population expected to grow over the next several decades, the human-environment dynamics will likely continue to evolve.

Table 1: General and developed data sets used in this study.

Data Set	Description	Source
General Data Sets		
Ownership	Areas of public lands and protected lands unavailable for development	SAMAB (1996); Land Trust Areas (NCGICC 2008)
2000 Census Block	Polygons of Census Blocks of the 2000 census	NCGICC (2008)
2000 Census Block Groups	Polygons of Census Block Groups of the 2000 census	NCGICC (2008)
2010-2030 Forecasted Partial Block Group Housing Unit Density	Estimated future Housing Unit Density by Partial Block Group	Hammer et al. (2004)
Current County Boundaries (1920-present)	Boundaries for 21 counties in study area	NCGICC (2008)
Historic County Boundaries (1850-1910)	Estimated county boundaries before finalized in present form	Waisanan and Bliss (2002)
Hydrography	Major Streams, Rivers, and lakes	SAMAB (1996)
1998 NCDOT roads	Primary and Secondary roads in NC	NCDOT 1998
2007 NCDOT roads	Primary and Secondary roads in NC	NCGICC (2008)
Elevation	30m resolution Digital Elevation Model (DEM)	USGS (2008)
Slope	Percent slope, derived from DEM	
Terrain Shape Index	Index of landform shape ranging from cove to ridge, derived from DEM	McNab (1989)
Toographic Relative Moisture Index	Index of relative moisture availability, derived from DEM	Parker (1982)
Land Capability Classification (LCC)	Categorical estimate of soils for growing primary crops and pasture grasses; derived from NRCS SSURGO database	Soil Survey Staff (2008)
Developed Data Sets		
1904 Ayers/Ashe forest conditions	Estimated cleared and forested areas from a 1904 joint study between the USFS and USGS	Ayers and Ashe (1904)
1900s roads	Road lines digitized from USGS 30-minute 1:125,000 scale topographic maps dating between 1892-1912	USGS (1892-1912)
Agriculture suitability Index (ASI)	Probability map of agriculture suitability estimated from NRCS Land Capability Classification	

Table 2: Summary of validation comparisons against independent data sets.

Class / Reference Area	Reference Date	Modeled Date	Agreement[*] (%)	Disagreement due to quantity (%)	Disagreement due to location (%)	Kappa	Null Resolution
Macon County comparison against independent land use reconstruction (This Dissertation, Chapter 1)[**]							
All classes	1905	1900	83.8	0.8	15.4	0.458	100m
Forest			*99.6*			*0.478*	
Agriculture			*95.5*			*0.437*	
Development			*66.6*			*0.166*	
All classes	1954	1950	83.7	7.9	8.4	0.437	300m
Forest			*90.9*			*0.394*	
Agriculture			*94.7*			*0.551*	
Development			*78.8*			*0.259*	
All classes	1993	1990	88.4	0.6	11.0	0.491	****
Forest			*99.6*			*0.573*	
Agriculture			*95.7*			*0.301*	
Development			*92.3*			*0.456*	
All classes	2003	2000	88.1	4.9	7.0	0.507	N/A
Forest			*99.4*			*0.589*	
Agriculture			*91.6*			*0.306*	
Development			*98.6*			*0.466*	
Forest/non-forest comparison against independently developed data sets[***]							
Ayers/Ashe Map (11 counties)	1904	1900	71.2	2.7	25.5	0.290	4000m
Madison County	1956	1950	68.3	3.5	28.2	0.361	800m
Cane Creek Watershed	1956	1950	71.3	4.8	24.0	0.429	800m
NLCD (all 21 counties)	1993	1990	82.1	1.0	16.9	0.483	****

[*] For the “all classes” group, the map agreement is the total spatial agreement. For the individual classes, the map agreement is the percent difference in the total quantities irrespective of spatial location.

[**] The 1954, 1993, and 2003 are aerial-photograph interpreted. The 1905 land cover is the result of a decision-rule reconstruction

[***] Source for Ayers/Ashe (Ayers and Ashe 1905), source for Madison and Cane Creek Watershed in Henderson County (Wear and Bolstad 1998), Source for 1991 satellite-based classification (Coweeta LTER, unpublished data)

[****] Indicates no improvement over Null Model at any resolution

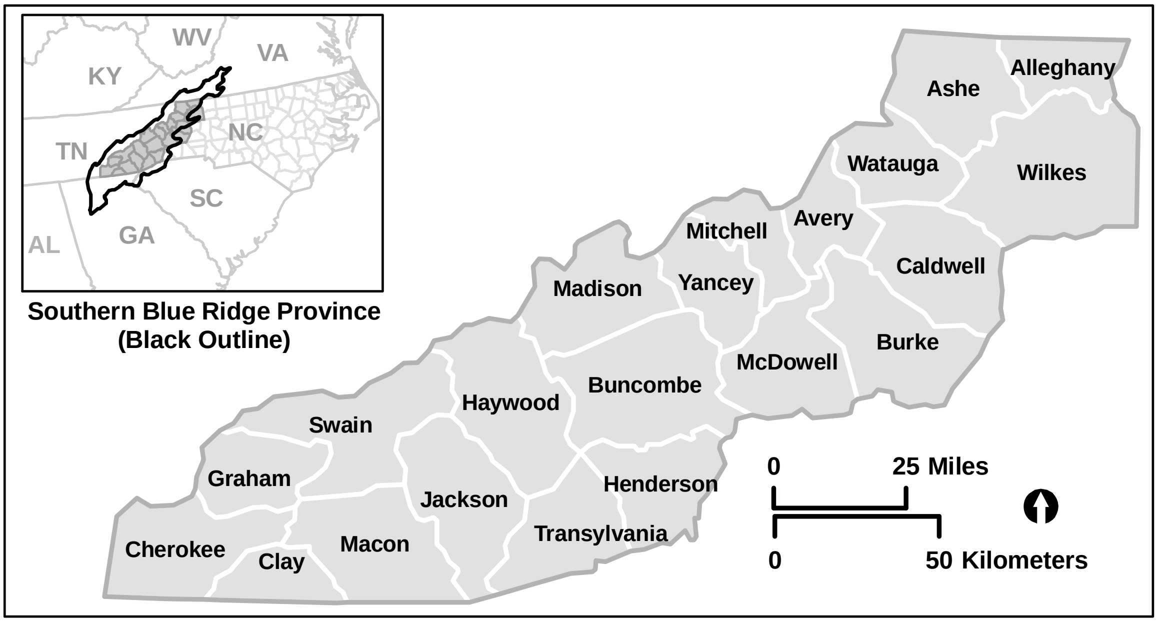

Figure 1: Twenty-one county study area in Western North Carolina.

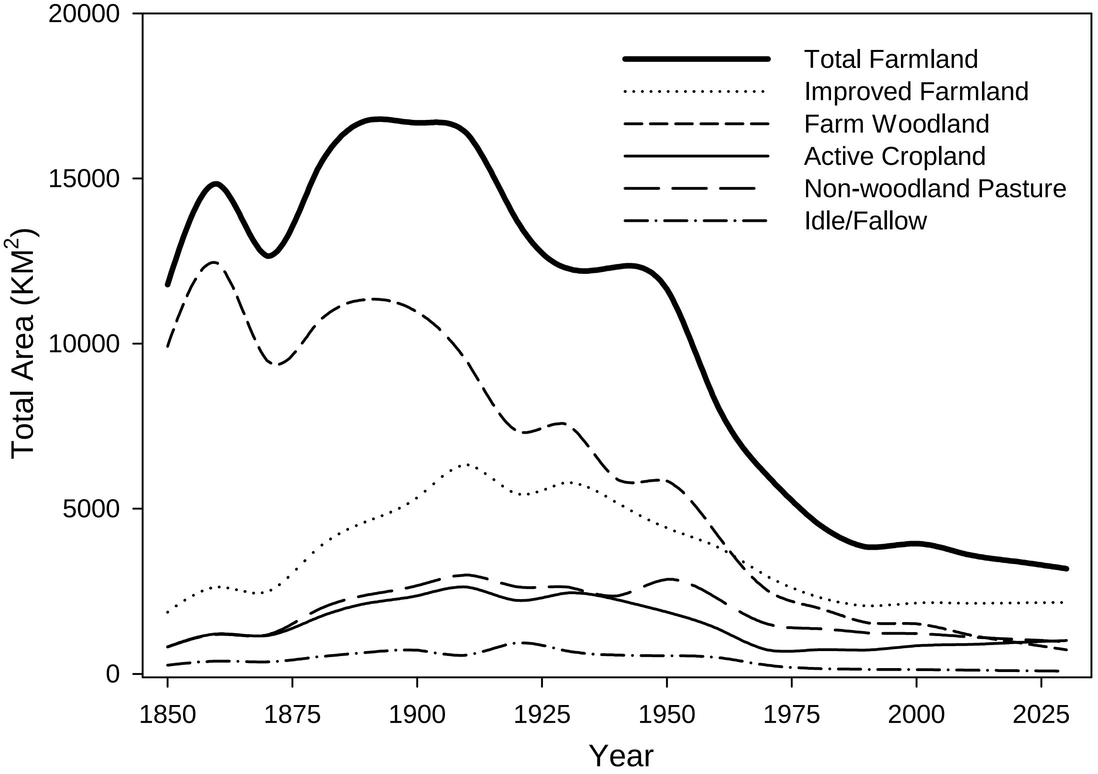

Figure 2: General farm area classes across the 21-county area of Western North Carolina, 1850-2030, estimated from the 1850-2002 Census of Agriculture reports. Improved Farmland for all years is defined as all non-forest farm area. For census years prior to 1920, the Active Cropland, Non-woodland Pasture and Idle/Fallow are estimated by applying the average ratios of each category to Improved Farmland from the 1920-1940 censuses. Farm Woodland prior to 1920 is assumed to be all Unimproved Farmland area as defined by the census. Forecasts from 2010-2030 are the sum of linear extrapolations of the 1980-2000 trends for each county.

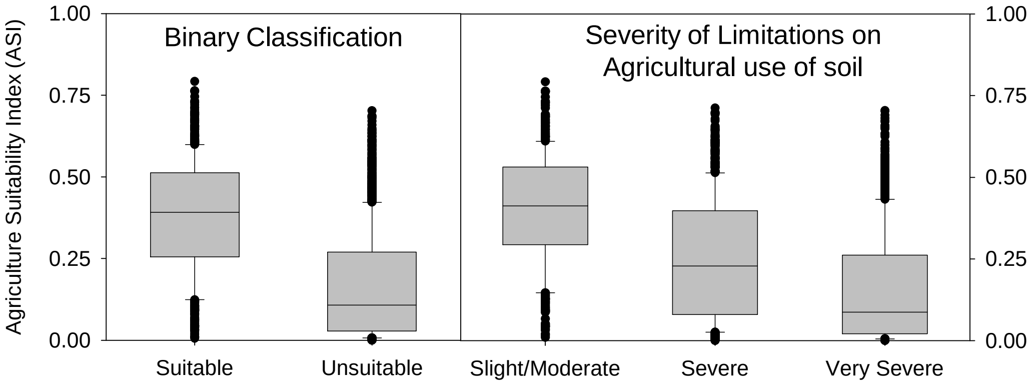

Figure 3: Boxplots of the test data set (*n*=2,000) for the Agriculture Suitability Index derived from the Land Capability Classification. The horizontal boxplot lines show the 25th percentile, mean, and 75th percentile values. The vertical lines extend to the 5th and 95th percentile, and the points represent outliers beyond these limits. The left box illustrates the binary classification of suitable (LCC classes 1 and 2) and unsuitable (LCC classes 3-8) used to develop the logistic regression model. The right box separates the LCC classes by the severity of limitations on agricultural use of the soil. Slight/Moderate (LCC Classes 1 and 2, joined because class 1 covers less than 0.01% of the study area), Severe (LCC classes 3, 5, and 6), and Very Severe (LCC classes 4 and 7).

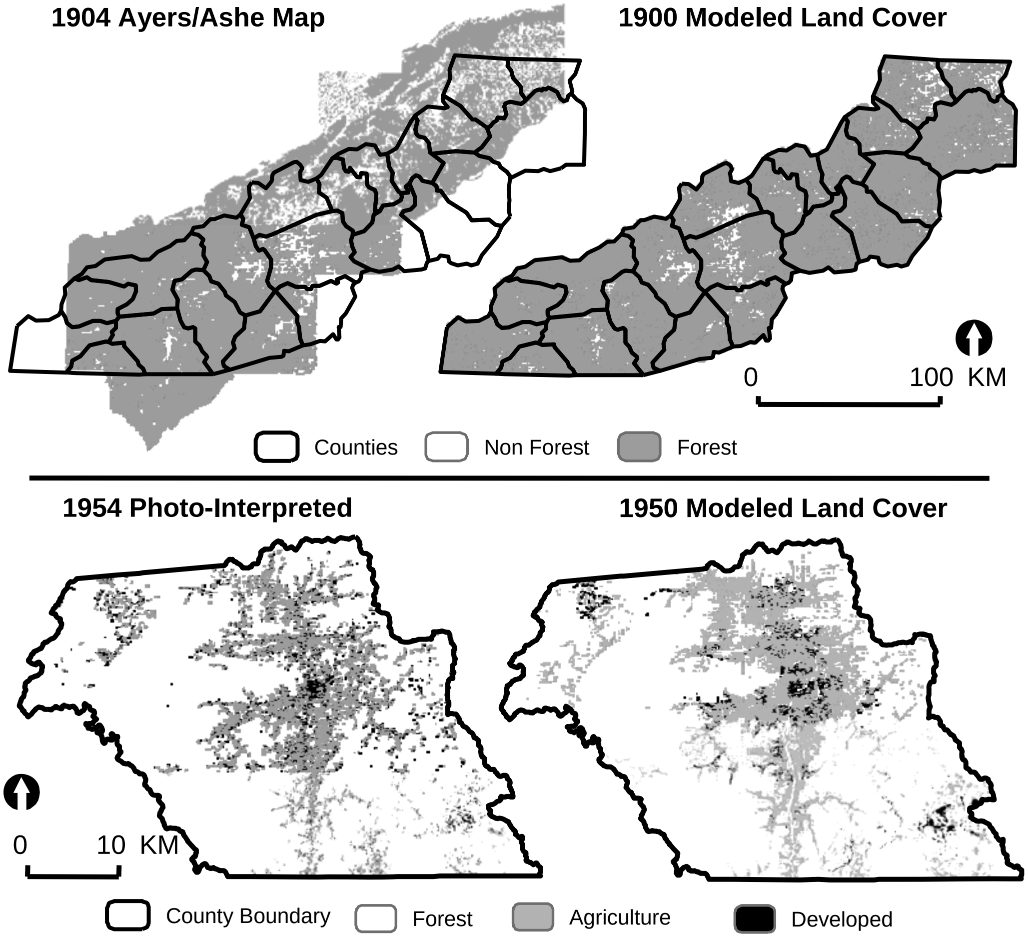

Figure 4: Comparisons of 1904 Ayers/Ashe map and 1900 modeled land cover (top) and Macon County 1954 aerial-photograph interpreted map and 1950 modeled land cover (bottom). Note that the agriculture for the 1954 photo-interpreted includes only active cropland and non-woodland pasture, while the 1950 modeled land cover includes all non-woodland farmland.

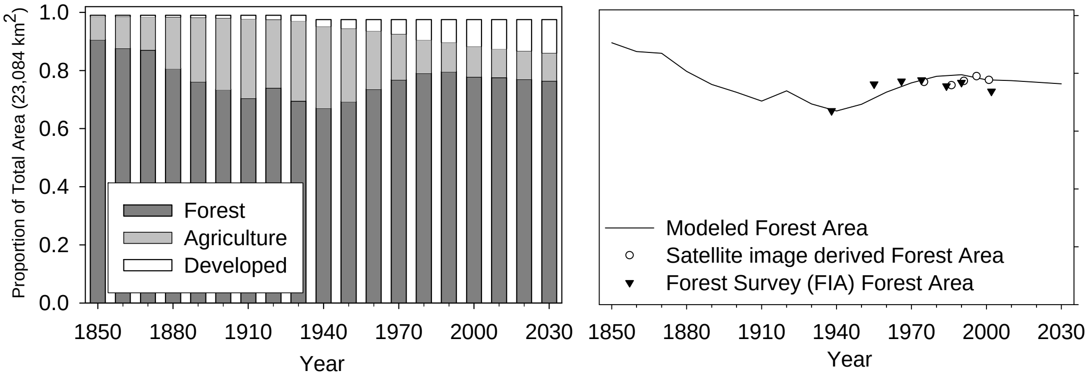

Figure 5: Modeled land cover (left) and comparison of modeled forest area (included abandoned agriculture) against USFS FIA Forest Survey total forest area estimates and land cover classifications derived from various satellite imagery (right).

Chapter 4: Spatially-explicit estimates of temperate hardwood forest carbon accrual in Western North Carolina since 1850 based on a decadal land-use reconstruction.

Abstract

Land-use change is a primary driver of changing carbon pools in terrestrial ecosystems. Throughout the United States, recovery from agriculture expansion and abandonment, increased fire suppression, and reduced timber harvest quantities have resulted in a large net sink of carbon from the atmosphere. However, the rates and magnitudes of this historic sink are uncertain for many regions, and detailed land-use based studies provide opportunities for evaluating the sink. We combine a decadal land-use data set in Western North Carolina from 1850-2030 with terrain-based aboveground forest biomass accrual curves to estimate historic changes in terrestrial carbon storage due to agriculture, development, and forest harvest. We estimate that aboveground biomass in Macon County, NC, decreased from an average of 201 Mg/Ha in 1850 to a low of 40 Mg/Ha in 1930, and has since been recovering at a decreasing rate from 26% per decade during 1940-1970 to 5% per decade since 1990. We forecast that although total forest area in Macon County will decrease 4% from 2000 to 2030 due to expanding development, C accrual in aboveground woody biomass will increase by 10%. Assuming no further change in forest area and no forest harvest or large scale disturbance, we estimate that total aboveground woody biomass would increase 19% by 2050 and 33% by 2100, and would stabilize at approximately 85% of the total 1850 aboveground biomass

pool. Overall, we estimate that industrial logging between 1880-1920 accounted for 84% of the net C loss, while agricultural expansion accounted for 16%.

Introduction

Land use has been identified as a primary control of carbon (C) flux and storage in temperate ecosystems (Birdsey et al. 1993; Houghton 2003). Key uncertainties in the global terrestrial C budget include C dynamics in individual regions (Delcourt and Harris 1980; Wallin et al. 1996; Houghton 2003; Canadell et al. 2007), the role of forest age structure in C cycling (Houghton 2003; Song and Woodcock 2003), the effects of natural disturbance on C budgets (Houghton 2003), and the influence of enhanced forest growth due to global change (Casperson et al. 2000; Schimel et al. 2000) or forest management (Hurtt et al. 2002). Overall, it is still unclear what individual and combined effects these factors have in determining the global C budget. Ultimately, resolving these issues may help in greatly reducing the uncertainty of global change forecasts. Improved historical reconstruction of land use at the regional scale has been identified as a priority for evaluating these potential effects (Houghton 2003; Canadell et al. 2007).

Houghton (2002) identifies six common approaches to inferring C sources or sinks across broad areas (regions to global): 1) Global budgets based on atmospheric data and models, 2) Global budgets based on models of oceanic C uptake, 3) Regional C budgets constructed from forest inventories, 4) Stand-level direct measurement of CO^2 flux (from towers), 5) Physiologically-based process models of ecosystems, and 6) C models based on changes in land use.

Models based on land-use change (number 6 above) typically follow a bookkeeping style approach, in which C is stored in pools and moved through fluxes over discrete time-steps and defined by given rates. Most studies credit the approach to Houghton et al. (1983), although several other studies have used it in various capacities (Plantiga and Birdsey 1983; Heath and Birdsey 1993; Turner et al. 1995; Schroeder 1996; Houghton and Hackler 1999; Mickler et al. 2002; Birdsey and Lewis 2003; Houghton 2003; West and Marland 2003). With this method, C accrues over time in defined component pools (e.g., wood, foliage, soil, crops, etc) at a rate defined by land use history. Land use change is captured by altering C accrual rates (e.g., cultivation lowers soil C accrual) or resetting C pools (e.g., forest harvest resets wood C). A bookkeeping methodology is a simple and flexible approach. Compared with other approaches such as process-based models (Landsberg 2003), criticisms of bookkeeping models include the reliance on aggregated data (often at a county, state, or national scale), and the use of overly simplified definitions of land use change. For example, Houghton (2003) noted that these studies typically only include major anthropogenic land-use change. Natural disturbance (e.g., fire, windthrow, insect, ice storm) and partial disturbances (e.g., silvicultural thinning) are usually not included. Thus, there is a need for more research on spatially-explicit C models that factor land-use change and natural disturbance.

The historic C budget in the Southern Appalachian mountain region is largely uncertain because of a variety of bio-physical and socio-cultural factors that confound quantification. The forests are extremely complex. With more than > 130 species of trees (Braun 1950), the region is considered to be one of the most diverse temperate forest regions in the world (Rohrig and Ulrich 1991). Species composition and C cycling are influenced by strong gradients of temperature, elevation, terrain shape, precipitation, parent material, and soil fertility (Whittaker 1956; Bolstad and Vose 2001). Human disturbance regimes on forests have also been large and variable. Prior to Euro-American settlement in the region, native societies practiced regular burning of the woods for clearing and hunting (Yarnell 1998). In contrast to most of the continental U.S., there was no baseline land survey of the region, although smaller surveys were conducted in many of the main agriculture valleys (Jurgelski 2004). Thus, land ownership was often unclear, and the extensive period of industrial logging between 1880-1920 (Ayers and Ashe 1905; Holmes 1912; Lambert 1961; De Vivo 1986) was sparsely documented at best. The primary logging practice of the era was single-tree selection of the largest trees of marketable species (Staff of the Appalachian Forest Experiment Station 1935; Etheridge and Holmes 1939; Jemison and Hepting 1949), which led to significant structural and compositional changes of the forests (Hardt and Swank 1997; Elliott and Swank 2008). Similarly, the complex, slash-and-burn style agricultural practices left a patchwork mosaic of fields of various stages of abandonment (Hart 1977; Otto and Anderson 1982; Otto 1989).

In many ways, the forests of the Southern Appalachians have recovered from the devastation of peak agriculture and timber extraction in the first half of the 20th century. The federal government purchased large areas of marginal land for National Forests and National Parks in order to protect navigable riverways, reduce degradation of the forests, protect the scenic beauty of the region (Graves 1914; Eller 1982; Mastran and Lowerre

1983). During the same period, conservation-minded citizen groups and some of the earliest professional foresters in the country helped change the management practices (Maughan 1939; Frome 1966). The forests have been aggrading biomass ever since, but there is uncertainty as to the magnitude of this aggradation and how long it will continue until net forest biomass stabilizes.

In this study, we address the research objective of quantifying the effects of land-use change on C accrual in aboveground woody biomass since 1850, and forecast estimates through 2030. We combine a spatially-explicit C accrual model derived from site-yield tables and a terrain-based site classification with decadal land use reconstruction at the spatial scale of both an individual county and across the Blue Ridge physiographic province of Western North Carolina. We focus our analysis on aboveground live biomass accrual in forests. C dynamics in litter, soil, and non-forest land cover type are not considered directly, although we discus implications to the broader C cycle in our discussion. We evaluate trends in C accrual and storage in terrestrial forests using two approaches: a spatially-explicit bookkeeping style model, and aggregate calculations estimated from a variety of government and research reports.

Study Area

Our study area is the 21 counties in Western North Carolina (Figure 1) that comprise the “Mountains of North Carolina” unit of the US Forest Service Forest Inventory and Analysis (FIA) program (Brown 2002). Within the FIA unit, Macon

County is used as an extensive case study. Four watersheds within Macon County were used to identify rates and trajectories of land use change. Collectively, these study areas are located in the Blue Ridge physiographic province of the Southern Appalachian Mountains. The Blue Ridge bedrock is dominated by Gneiss and Schist of the Paleozoic period, and soils are predominantly in the Inceptisol order (Gade and Stillwell 1986). Vegetation cover is predominantly a temperate deciduous forest with mixed conifer species (Braun 1950). The area receives a relatively high amount of precipitation, ranging from 100-180 cm/year. Temperatures are generally cool in the winter (2-4 degrees Celsius) and mild in the summer (20-27^{o} C).

The region is a popular tourist destination, and contains approximately half of the Great Smoky Mountain National Park, the Blue Ridge National Parkway, the Nantahala and Pisgah National forest, approximately 400 km of the Appalachian National Scenic Trail, and over 4,000 km of rivers. The population of the region has doubled since 1940, and is projected to surpass 1,000,000 by 2010 (North Carolina Office of State Budget and Management 2008). The largest city is Asheville, with an estimated 2008 population of over 72,000.

The earliest date of this research is 1850. Euro-American settlement of the region had begun in the late 1700s (Ford 1962), but the Cherokee nation did not cede lands in the westernmost counties until the Treaties of 1819 and 1835 (Malone 1956; Finger 1991; Jurgelski 2004). The 1850 starting date also coincides with the earliest U.S. Census that reported the area of agriculture. Gragson et al. (2008) identify 5 general land use periods in the region since 1850. The Antebellum period, from 1812-1860, was characterized by steady agriculture expansion. During the Civil War and Reconstruction, from 1860-1875, the region experienced a decline of agriculture. The Resource Dependent Period extended from 1875-1945, and consisted of widespread agriculture expansion and extensive industrial logging. From 1945-1970, the Rural Desertion Period, the region experienced a population decline as many people joined the national trend of moving from rural to urban areas (Brown and Hillery Jr. 1962; Raitz and Ulack 1984). Since 1970, the Post-Industrial Residential Period has involved a sharp increase in population and tourism and a decline of resource-based industries. The forests of the region were most heavily affected during the Resource Dependent Period, during which both agriculture area and logging peaked. Figure 2 illustrates the aggregate land-use change for Macon County as well as forest stand age since establishment (This Dissertation, Chapter 1).

Land use database

The primary land use database consists of a detailed reconstruction for Macon County and a generalized reconstruction for the larger 21 county region. The Macon County data consists of a temporally-consistent decadal land cover data set between 1850 that used an iterative, decision-rule model to combine spatial data sets for selected years with aggregate land use estimates provided by U.S. Census of Population and Housing (U.S. Census Bureau 1850-2000), Census of Agriculture (U.S. Department of Agriculture 1954-2002), and periodic U.S. Forest Service forest FIA inventories (Cruickshank 1941; Knight and McClure 1966; Cost 1974; Craver 1984; Johnson 1990; Brown 2002). The spatial data sets consisted of photograph-interpreted land cover for 1954 and 2003, satellite-based classifications since the mid 1970s, soil surveys from 1942 and 1996, road layers since 1886, and building density estimates since 1906. Land use classes of the Macon County data set consist of closed-canopy forest, transitional forest (areas of agriculture abandonment or forest harvest transitioning towards closed-canopy forest), agriculture (row crop plus pastureland), developed areas, and open water. All data development procedures for the Macon County data set are described in detail in Kirk et. al. (This Dissertation, Chapter 1). The Macon County data set separates forest harvest from agriculture clearing and abandonment, so the relative magnitude of the two land use practices are compared.

The regional land use data set estimates forest, agriculture, and developed areas across the 21-county region using a collection of deterministic models applied against a baseline of the 2001 National Land Cover Dataset (Homer et al. 2004). The quantities of Developed area for each decade were calculated as being proportional to the number of Housing Units as defined by the U.S. Census, and the location of Developed areas were identified moving backwards in time by first estimating the Housing Unit densities for Census Partial Block Groups (Radeloff et al. 2005; Theobald 2005), and then selecting cells within these Partial Block Groups as a function of distance to highways and distance to cities. The quantity of agriculture is defined as the total area of non-woodland farmland in the Census of Agriculture, and the location of agriculture was estimated by identifying the non-Developed areas that were the most suitable as defined by a probabilistic agriculture suitability index derived from the Natural Resources Conservation Service Land Capability Classification of the SSURGO data set (Soil Survey Staff 2008). All other areas, with the exception of water and bare rock, were classified as forests. Details of the regional reconstruction are described in Kirk et al. (This Dissertation, Chapter 3). The regional data set does not identify areas of forest harvest separate from agriculture clearings, so regional analysis is limited to evaluating the effects of agriculture and development related pressures on C accrual.

C accrual and Site Class

For modeling C accrual over time, we adopt the Bookkeeping method of Houghton (Houghton et al. 1983; Houghton 1999; Houghton and Hackler 2000; Houghton 2003). With this approach, a maximum forest biomass quantity is estimated, and C accrual from the time of stand establishment is determined as being proportional to the maximum forest biomass. To estimate maximum biomass and the rate of accrual prior to maximum biomass, we adopt an approach similar to Delcourt and Harris (1980) and Birdsey (1996), in which aboveground biomass volume, total biomass volume, and C mass are estimated from timber volume estimates using a multi-step conversion calculation. This approach is common for national or multi-state studies (Delcourt and Harris 1980; Birdsey 1996; Houghton et al. 1999; Birdsey and Lewis 2003). Our approach is unique from these studies in that we apply the method to a smaller geographic area, use a spatially-explicit rather than aggregated model, and estimate timber volume over time from general yield tables rather than from forest inventories.

Our biomass accrual rates are derived from a traditional timber harvest site-yield table (Frothingham 1917; Frothingham 1931), in which timber volume estimates developed through extensive field sampling are stratified by some measure of site quality. The most common form of site-yield table is the Site Index curve, in which site quality is represented by the average height of dominant canopy trees at a reference age (Avery and Burkhart 2002). The Site Index approach is limited in that information about current or past trees on a given site is required. In contrast, we use a site-yield table that defines site quality based on terrain position. In the Southern Appalachian mountains, foresters have used this relatively unique practice of using terrain positions in lieu of Site Index to represent the large heterogeneity of growing conditions and environmental gradients throughout most of the 20th century (Frothingham 1921; Westveld 1949; Smith 1995), and studies have shown a strong relationship between Site Index and terrain features in the region (Trimble Jr. 1956; Dolittle 1957). Terrain position refers to a combination of four primary factors: elevation, slope, aspect, and shape. Terrain shape describes a gradient in concavity or convexity from coves (moist, fertile valley bottoms) to ridges (dry, exposed mountain tops and ridge-lines). Terrain position is strongly linked to forest community type (Braun 1950; Whittaker 1956; Day et al. 1984; Bolstad et al. 1998; Simon et al. 2005), primary productivity (Bolstad and Vose 2001), timber yield (Ayers and Ashe 1905; Zon 1907; Holmes 1911; Frothingham 1931) and biomass accrual potential (Whittaker 1956). The sequence for spatially stratifying terrain position across the region is described in a later section.

The first step in the biomass calculation is to estimate total aboveground volume. We assign a constant fraction of merchantable hardwood timber volume (trees > 5 inches dbh) in ft^3/acre to total aboveground woody volume of 58.8% (Cost 1978), with English units being the more common form in many U.S. publications. This equates to a conversion factor 1.701. This proportion is comparable to other volume and biomass studies in the region. Birdsey (1996) identifies a merchantable-to-total volume conversion factor of 1.793 for hardwoods in southeastern U.S (1.408 for softwoods). Delcourt and Harris (1980) calculated timber volume across all hardwood and softwood species as containing 64% of all aboveground woody volume for 14 southeastern U.S. states, which equates to a conversion factor of 1.562. Total aboveground volume (ft^3/acre) is then converted to total aboveground woody C (lbs/acre) using a conversion factor of 18.23 as calculated for the Oak-Hickory forest type by Birdsey (1996). Finally, C values are converted to Mg/ha.

This merchantable volume to C conversion is applied to all values provided in the Frothingham tables, which contain 5 terrain-based site classes and stand ages from 20-80 years (Figure 3), and are based on a field sample of 350 even-aged mixed-hardwood stands. We fit an asymptotic logistic function for each of the 5 site classes for the available dates, then extrapolate the functions below 20 years and up to 350 years using a 3-parameter sinusoidal logistic function, which is a model form commonly used for C accrual curves in forests (Peet 1981; Henderson and Francesca 1998) and has the form:

$$y = \frac{a}{1+\left(\frac{x}{b}\right)^{c}} \qquad \text{Eq. 1}$$

where y is C mass (Mg/ha), x is age (yrs), and a, b, and c are the three model parameters. Model parameters for the 5 Site Classes are provided in Table 1.

We compare the C accrual curves against two sets of published estimates from sample based studies. One set consists of a series of field-based C budget studies of cove and lower elevation sites at the USFS Coweeta Hydrologic Lab (Monk and Day Jr. 1984; Elliot et al. 2002; Bolstad and Vose 2005), and the second set is from studies of cove sites in the Great Smoky Mountains National Park (GSMNP) (Whittaker 1966; Busing et al. 1993).

Site Class and Terrain Position

The Frothingham site-yield tables identify five classes based on terrain position (Frothingham 1931), or as he describes elsewhere, “habitat” type (Frothingham 1917). Site Class I consists of the “best cove soils.” Site Class II represents “moist slopes and coves.” Site Class III represents “soils of intermediate quality.” Site Class IV represents “better dry slopes and ridges.” Site Class V represents “poorer dry slopes and ridges.” Frothingham’s brief comments on these types are summarized in Table 2. Unfortunately, the descriptions do not fully distinguish the classes beyond these general terms, and separate studies of the relationship between primary productivity and terrain focus on continuous gradients rather than nominal classes (Day and Monk 1977; Bolstad and Vose 2001).

Given these limitations, we spatially stratified the landscape into the Frothingham Site Classes by supplementing Frothingham’s brief descriptions with a combination of deductive inference from several related data sets, most of which were developed in detailed case studies in Macon County (This Dissertation, Chapter1; This Dissertation, Chapter 3). First, we divide the Macon County forested landscape into 3 broad site classes of Cove, Slope, and Ridge by combing area estimates of the 3 classes provided in a 1932 USFS study (Wager and Thomson 1932) with a Terrain Shape Index (McNab 1989) and a 1930 Forest/Non-Forest modeled land cover classification (This

Dissertation, Chapter 1). The Terrain Shape Index (TSI) measures the curvature gradient from cove to ridge, and is calculated as a weighted-average elevation change from the neighboring cells in a raster elevation data set, with negative values representing concavity (coves), positive values representing convexity (ridges), and zero representing flat areas. Wager and Thomson (1932) described the forest area in Macon County as containing 15% cove forest, 80% lower and upper slope forests, and 5% ridge forest. We identify the forested areas from the 1930 land cover classification, then identify the Coves as those forested areas that contain the lowest 15% of TSI values (i.e., most concave), Ridge areas as those with the highest 5% of TSI values (i.e., most convex), and slope type as all others. Limiting analysis to the contemporary forested areas is important since most of the most fertile and broad coves were previously converted to agriculture in the late 19th and early 20th centuries (Frothingham 1931; Wager and Thomson 1932).

Second, we use the Topographic Relative Moisture Index (TRMI) to estimate general moisture availability (Parker 1982). The TRMI estimates the relative moisture content of varying terrain positions based on aspect and slope position, and consists of an ordinal ranking on a scale of 1 to 27, with higher values indicating moister sites.

Finally, we link the Ridge-Slope-Cove classification, TSI values, and TRMI values to Frothingham's forest type description using the forest typic diagram developed by Day et al. (1984) for the Coweeta watershed (Figure 4). This diagram illustrates the relationship between forest type and the terrain variables of elevation, aspect, terrain shape, and relative moisture, and has been used to define generalized forest types for broader regional-scale analysis in multiple previous studies (Bolstad et al. 1998; Wear and Bolstad 1998; Turner et al. 2003). We stratify the landscape into the 5 Frothingham site classes using the following rules. First, Site Classes 1 and 2 are assigned to the “Cove Hardwoods” type as defined by the Day typic diagram. Site Class 1 is defined as the 50% percent of this group with the lowest (i.e., most concave) TSI values, and Site Class 2 to the 50% with the highest TSI values (i.e,. lower slopes). Site Class 3 is defined as all areas of the “Northern Hardwoods” type that are within the Slope class area as defined by the Ridge-Slope-Cove classification of the 1932 USFS report. Site Classes 4 is identified from the remaining area by identifying the 2/3 of the total forest area with the highest (i.e., moistest) TRMI values. This is based on Frothingham’s estimation (1931) that Site Class 4 covered 2/3 of the region’s forest. All remaining areas are assigned as Site Class 5.

To scale this classification to all of Macon County and all of Western North Carolina, we develop a Classification Tree (Brieman et al. 1984) using 10,000 random samples drawn from the 1930 Macon County Site Class as the independent data set, and elevation (m), slope (%), aspect (% deviation from north) (Roberts and Cooper 1989), TSI, and TRMI as the candidate dependent variables. The Classification Tree is a non-parametric recursive partitioning method for classifying a data set into two or more categories using a splitting algorithm. We use a standard Gini splitting function, and use the cross-validate option for tree pruning as implemented in the RPART package of the *R* statistical software (R Development Core Team 2008). The Classification Tree is illustrated in Figure 5.

C Accrual Model

The aboveground woody biomass C accrual model is very simple given the formats of the data sets. For each 100 m cell each decade, the age of the forest since stand establishment is calculated, and the Site Class assigned to the cell defines which Site-Yield equation to apply. We ran the models for combinations of two C accrual methods and three land use definitions. The two C accrual methods consist of the 5 Frothingham Site Class curves (called “Frothingham Tables” in the results section) and the single equation of the S.E. regional Oak-Hickory forest type accrual curve (called “SE Region Average” in the results section) from Birdsey (1996). The two primary land-use definitions consist of the detailed Macon County classification and the generalized regional classifications. A primary difference between the two data sets is that Macon County included areas of forest harvest, while the regional classification did not. In order to compare the two, we created a third land-use data set for Macon County with all forest harvests excluded, which results in older forests. These three data sets are called Macon County land use with logging, Macon County land use with no logging, and Regional land use with no logging.

As comparison data sets, we recreate the aboveground woody C budget for the 21-county region using the 1938-2002 FIA surveys using the regional method of Delcourt and Harris (1980). In addition, we compare the estimated 2000 C pool for Macon County against two independent biomass maps (Kellndorfer et al. 2007-2009; Blackard et al. 2008), which are developed from the extensive FIA database and statistical classification of satellite imagery.

Results and Discussion

The terrain-based Site Class-Yield curves are illustrated in Figure 3, and the parameters are provided in Table 1. The field-based samples in the Coweeta Watershed and Great Smoky Mountain National park fall within the Frothingham curves, with the exception of the largest volume old-growth stands. This is partly explained by the Frothingham equations being developed for second-growth forests.

Overall, we estimate that, considering only land-use change and forest harvest, the total aboveground woody biomass C pool has been aggrading in Macon County since the 1930s, but at a steadily declining rate. Figure 6 illustrates the per Ha average C accrual for Macon County based on the 2 accrual definitions and 3 land-use definitions. The SE Region average curve falls within the Frothingham curves, but when applied across Macon County, the two definitions reproduce markedly different results. For Macon County in 1850, the average total aboveground woody C is estimated to be 219.2 Mg/Ha. The area-weighted average for total aboveground woody C for Macon County in 1850 based on the Frothingham curves is 183.5 Mg/Ha, which is 16% lower than the SE Region average value. When non-harvest land-use change is considered exclusively, this translates into a consistent 15-20% difference in total C between the two accrual definitions. However, when logging is factored, the two C accrual definitions show closer trends. While the SE Region curve estimates a higher initial pool, both methods estimated a minimum average C pool of approximately 40 Mg/Ha in the 1930s. Due to a quicker recovery of aboveground C pools following establishment using the Frothingham curves, the recovery to date is estimated to be larger than for the SE Region Average curve. This is consistent with studies at Coweeta which suggest a fast recovery of aboveground C (Monk and Day Jr. 1984; Elliot et al. 2002; Elliott and Swank 2008).

For the Frothingham curves, we estimate that the 2000 aboveground woody C pool in Macon County is 73% of the 1850 pool. Using the SE Region average, the current C pool is 53% of the 1850 C pool. By 2030, we estimate that, assuming no additional disturbances, total aboveground woody biomass C will increase for Macon County by between 5.6 and 14.4% based on the Frothingham Tables and SE Regional Estimate, respectively, for an average of 9.7%. Assuming no change in forest area or major disturbance, we estimate that total aboveground C storage could, on average, increase 19% by 2050 and 33% by 2100 (Figure 7). Using either C accrual definitions, we estimate that the total C pool would plateau at around 85% of the 1850 level, a result explained by the net loss of lost forest area.

The rates and locations of forest loss have varied over the past 150 years. The net change between 1850 and 2000 has been a loss of 14% of the total forest area. Site Class 1 and Site Class 2 (both cove classes) have been lost to development and agriculture at a higher rate than Site Classes 3-5. In Macon County, 12% of the total Site Class 1 area and 27% of the Site Class 2 area were lost to development or agriculture between 1850 and 2000, with Site Classes 3-5 having a net loss of 2%, 8%, and 4%, respectively. Across the 21-county region, the 5 Site Classes have a net area loss of 14%, 24%, 5%, 18%, and 11%, respectively. Over the past 30 years, the rate of loss is highest on Site Class 2 (coves and lower slopes), and our forecast suggests that this trend will continue. This supports the results of other studies that suggest land-use patterns will affect forest composition in the region (Turner et al. 2003).

This study is a preliminary investigation of a long-term research project on the effects of land-use change on forest C storage and cycling. Our analysis focused on C accrual in aboveground woody biomass. We did not factor key C pools such as soil, foliage, litter, and non-forest ecosystem types. Although these other pools are likely very small in relation to aboveground pools, they may result in significant changes in the total C budget. We also did not directly address several important uncertainties in both forest C cycling and land-use practices. Our definition of forest harvest assumed complete stand removal and uniform establishment and growth of secondary and tertiary forests. Many of the secondary South Appalachian forests were stunted by poor logging practices, severe soil disturbance, and minimal site-preparation practices (Ayers and Ashe 1905; Glenn 1911; Frothingham 1931). Similarly, we did not factor natural succession patterns or disturbance patterns such as forest fires, windthrows, ice storms, disease, or insect outbreaks. The most notable exclusion is the Chestnut Blight, a fungal disease introduced to the United States in at the beginning of the 20th century that killed or stunted nearly all of the Chestnut trees in North Carolina by 1940. Chestnut accounted for approximately one-fourth of all timber volume in the mountains (Slocum and Ross 1945), so the mortality had very large effects on the forest composition and C budget. As Chestnut was a commercially valuable tree, a large percentage of the biomass was salvaged, so C changes due to the Chestnut blight may have been partly accounted for in this analysis. Another area not factored in this analysis is changes in forest logging and management practices. Finally, our analysis did not consider possible changes in climate-change induced alterations of C cycling (Casperson et al. 2000; Schimel et al. 2000; Houghton 2003). As the next step in this research trajectory, we intend to address these limitations by conducting simulation modeling of various disturbance regimes using this land use data set as a foundation. While it is apparent that Southern Appalachian forests are still aggrading C following widespread harvesting and agricultural abandonment, there remain large uncertainties in the spatial rate and patterns in this complex and heterogeneous region.

Table 1: Logistic curves for total aboveground C accrual (Mg/ha) in Southern Appalachian hardwood stands by terrain-defined site class, derived from site-yield tables (Frothingham 1921; Frothingham 1931). The model form is carbon = a / (1 + (age/b)^c). As these are derived from the output of previously developed yield models, all fits are highly significant ($R^2 > 0.99$, $p < 0.0001$). Error estimates were not provided with the original site-yield tables.

Site Class	**a**	**b**	**c**
Site I: “Best Cove Soils”	381.98	35.092	-1.846
Site II: “Moist slopes and coves”	295.44	37.969	-2.216
Site III: “Soils of intermediate quality”	246.36	45.715	-2.208
Site IV: “Better dry slopes and ridges”	153.28	48.081	-3.100
Site V: “Poorer dry slopes and ridges”	102.98	57.630	-3.965

Table 2: Descriptions of terrain-based site quality as provided by Frothingham (1931). The right-most column, % Forest Area, is an estimate of the proportion of the 1930 Macon County forests in each class, and is based on a multi-step decision-rule calculation described in the main text.

Site Class	Elevation	Terrain Position	Forest Type	% Forest Area
Site I: "Best Cove Soils"	2000-4000 ft	Narrow coves; broader coves long since cleared for agriculture	Mixture of species, often dominated by hemlock or yellow poplar	7.5%
Site II: "Moist slopes and coves"	2000-4000 ft	Northerly slopes, lower slopes at about the same elevation as cove forest	Chestnut and several species of oak and hickory dominate	7.5%
Site III: "Soils of intermediate quality"	Up to 5000 ft	Upper moist slopes	Mixture of "Northern Hardwoods"	8.5%
Site IV: "Better dry slopes and ridges"	Unspecified	Found chiefly on southerly or westerly exposures , but often covers east slopes as well around to the northeast	More drought resistant species; estimate 2/3 of total forest area in this class	65%
Site V: "Poorer dry slopes and ridges"	Unspecified	Unspecified	Unspecified	11.5%

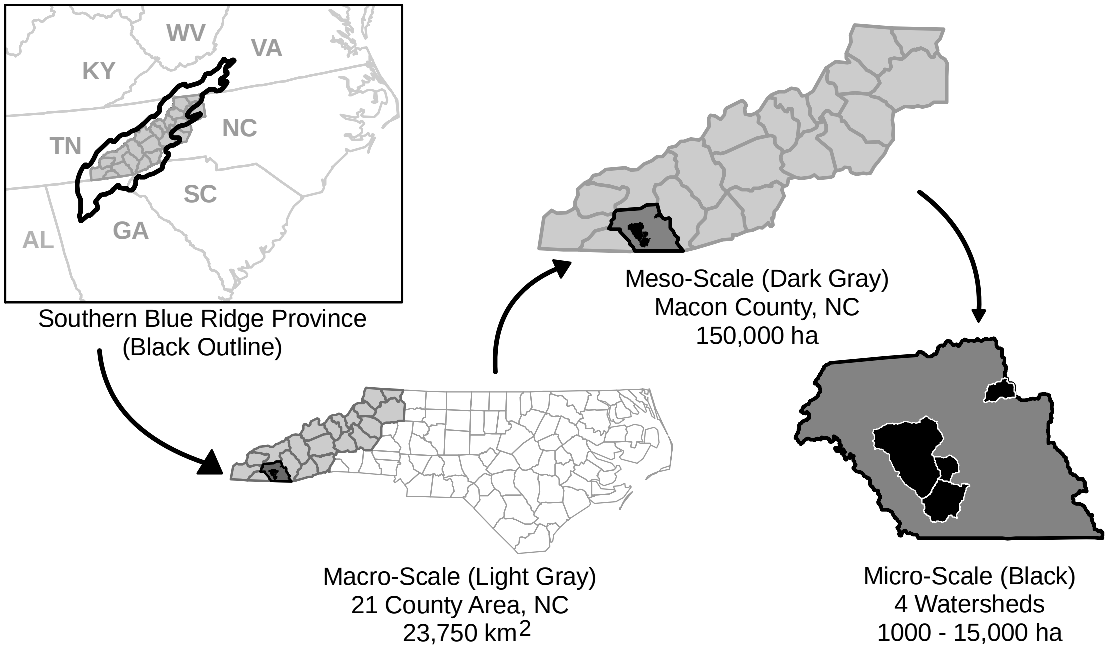

Figure 1: Nested Study areas in Western North Carolina.

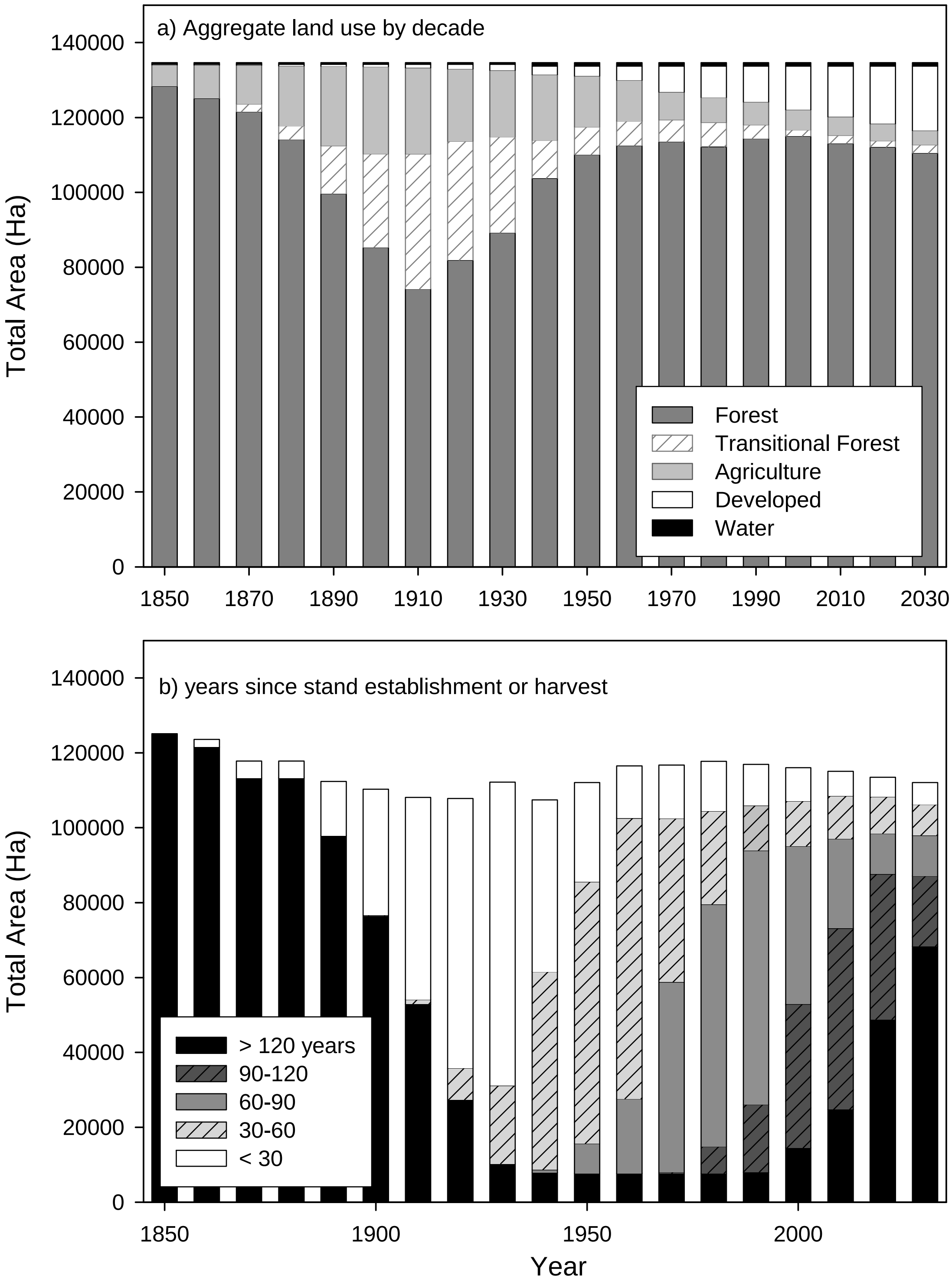

Figure 2: Aggregate land use (top) and forest age since human disturbance (bottom) for Macon County, NC (This Dissertation, Chapter 1). Age since stand establishment or harvest is estimated from the decadal land use reconstruction. The forest area in

the bottom graph is similar to, but no equal to, the sum of forest and transitional forest in the top graph; the difference consists of abandoned agriculture fields that were classified as transitioning towards forest, but had no seedlings established.

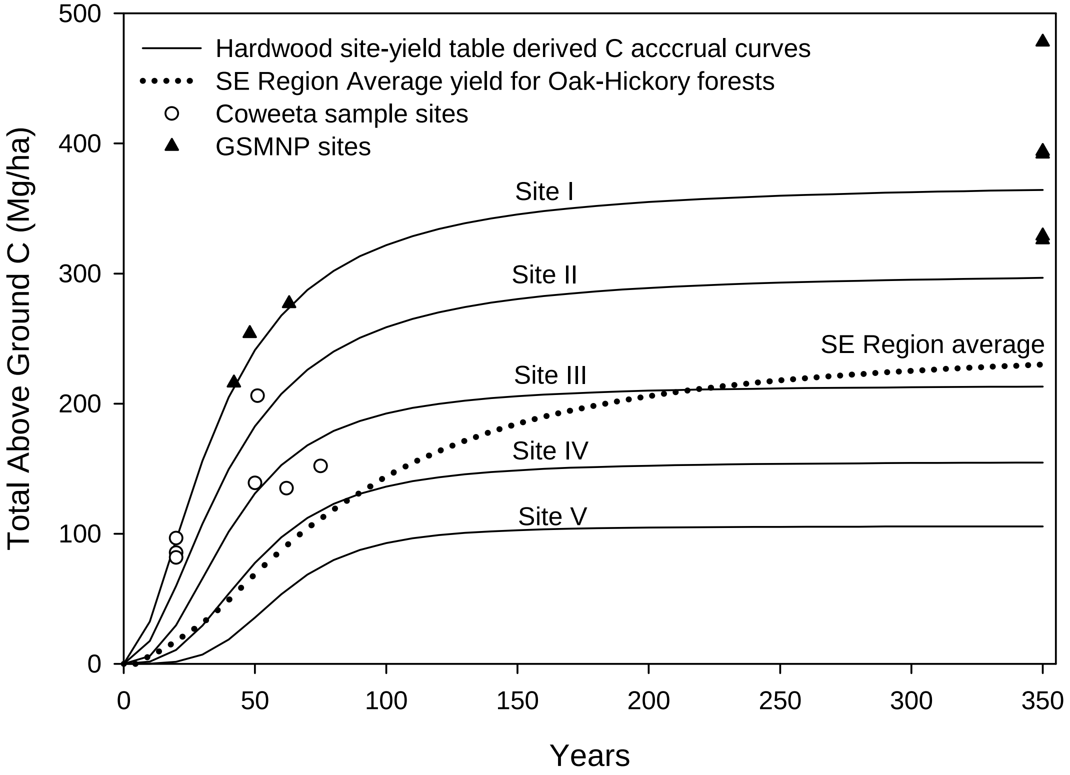

Figure 3: Total Aboveground woody biomass C accrual curves for second growth hardwood stands in the Southern Appalachian region. The 5 site class curves are derived from site-yield tables (Frothingham 1917; Frothingham 1931). The Southeastern US regional C accrual curve is derived from Smith et al. (2006). The points indicate sample site estimates from field-based C budget studies for cove and lower elevation sites at the USFS Coweeta Hydrologic Lab (Monk and Day Jr. 1984; Elliot et al. 2002; Bolstad and Vose 2005) and for cove sites in the Great Smoky Mountains National Park (GSMNP) (Whittaker 1966; Busing et al. 1993). GSMNP old growth sites are estimated to be over 400 years old, but are represented at the upper end of this table as 350 years old

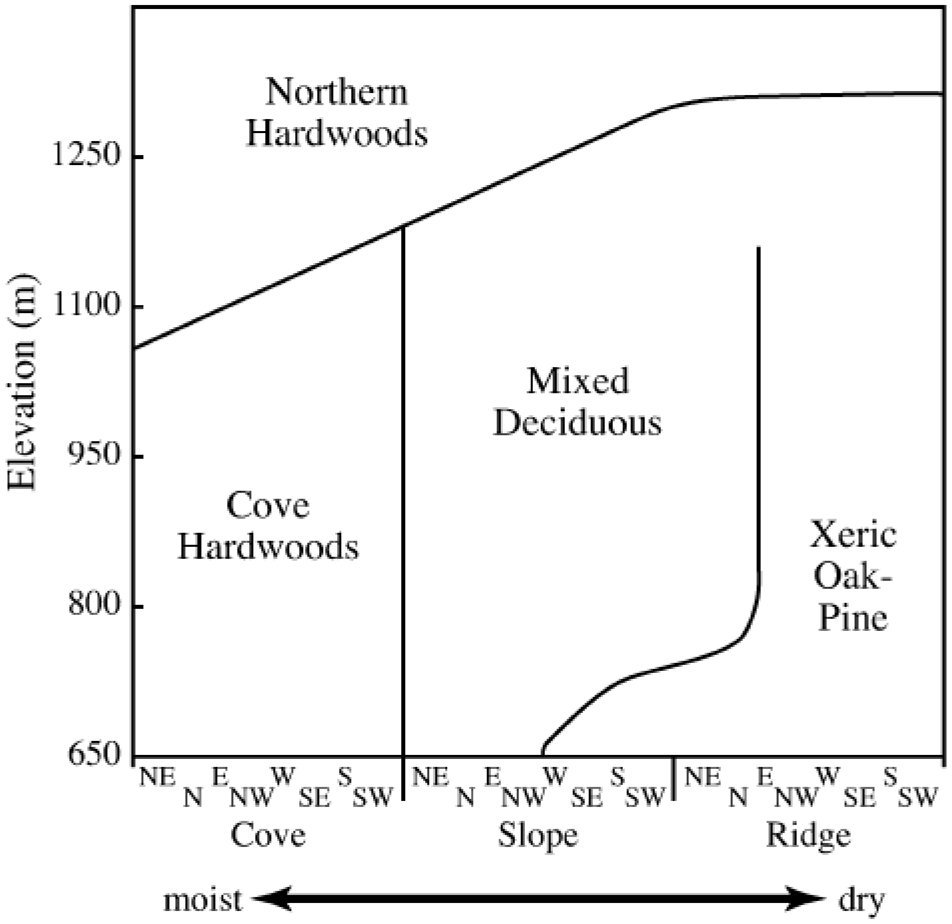

Figure 4: Relationship of forest types to terrain position factors as defined by Day et al. (1984) and redrawn in Bolstad et al.(1998) and Turner et al. (2003).

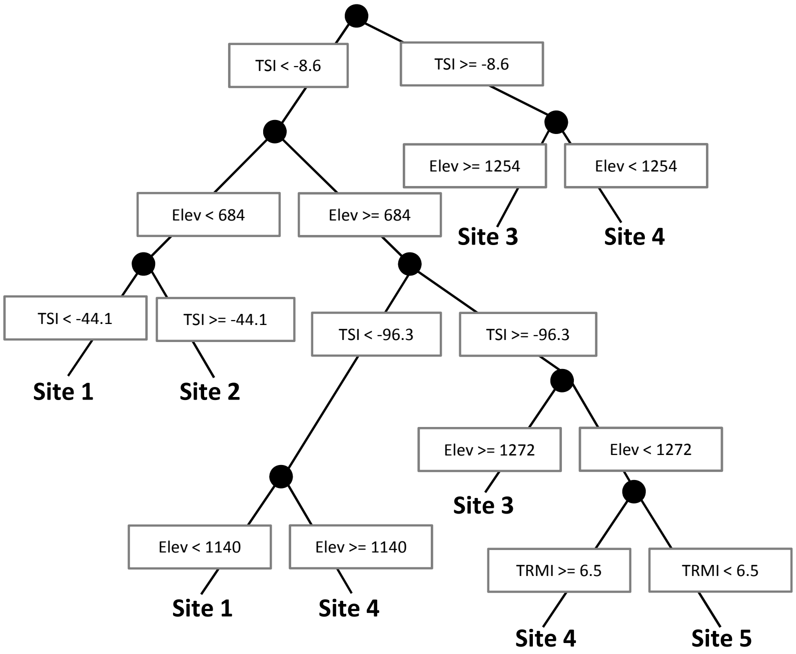

Figure 5: Classification Tree used to scale spatial patterns of the Frothingham Site Class estimates from Macon County to the broader region. The Macon County stratification of Site Classes was estimated from a detailed land-use reconstruction and multiple historic accounts. *TSI* is the Terrain Shape Index , *Elev* is elevation (m), and *TRMI* is the Topographic Relative Moisture Index.

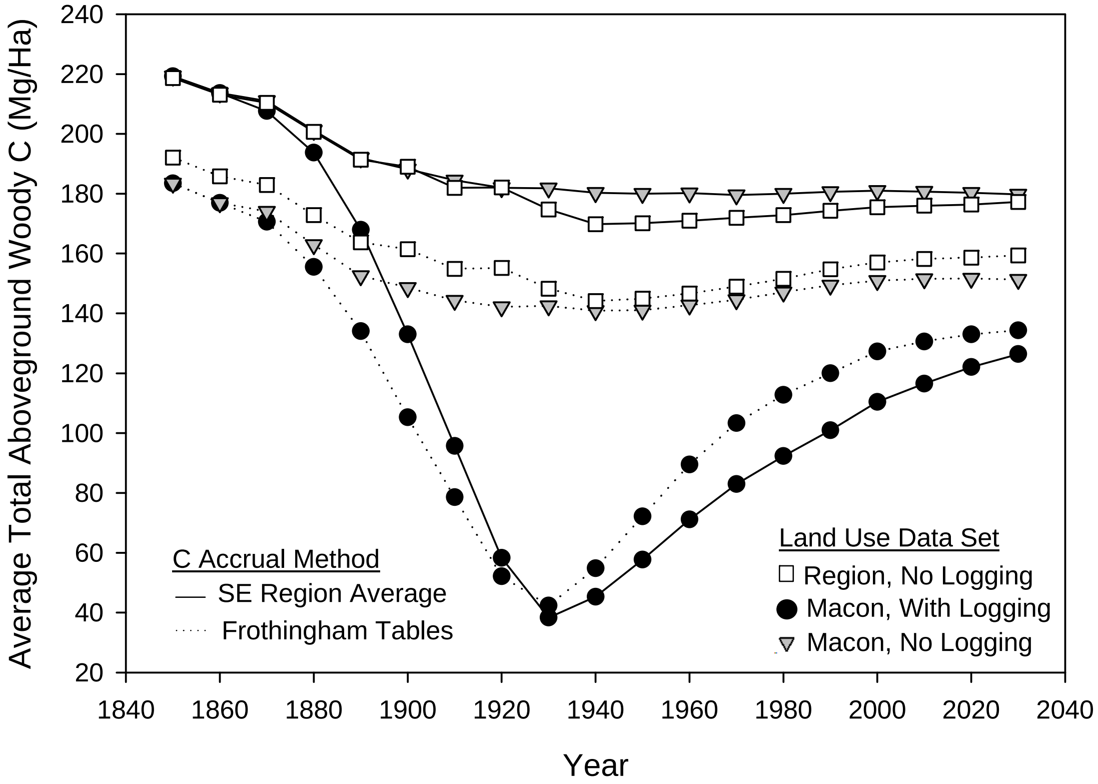

Figure 6: Average total aboveground C in woody biomass for Macon County, 1850-2030. The total area of Macon County is 134,640ha. The six lines represent all combinations of two C accrual methods and three land use data sets. The "Frothingham Tables" method is derived from site-yield tables (Frothingham 1917; Frothingham 1931), while the SE Region Average is the rate defined by a national scale study for Oak-Hickory forests in the SE U.S. (Birdsey 1996). The Macon County land use data set is based on a detailed reconstruction (This Dissertation, Chapter 1), while the "region" data set is a subset of a modeled land cover data set for 21 counties in Western North Carolina (This Dissertation, Chapter 3). The "region" land use data set did not include forest harvest (logging) that was immediately reforested, so a comparable data set was created for Macon County by removing all estimated logged areas.

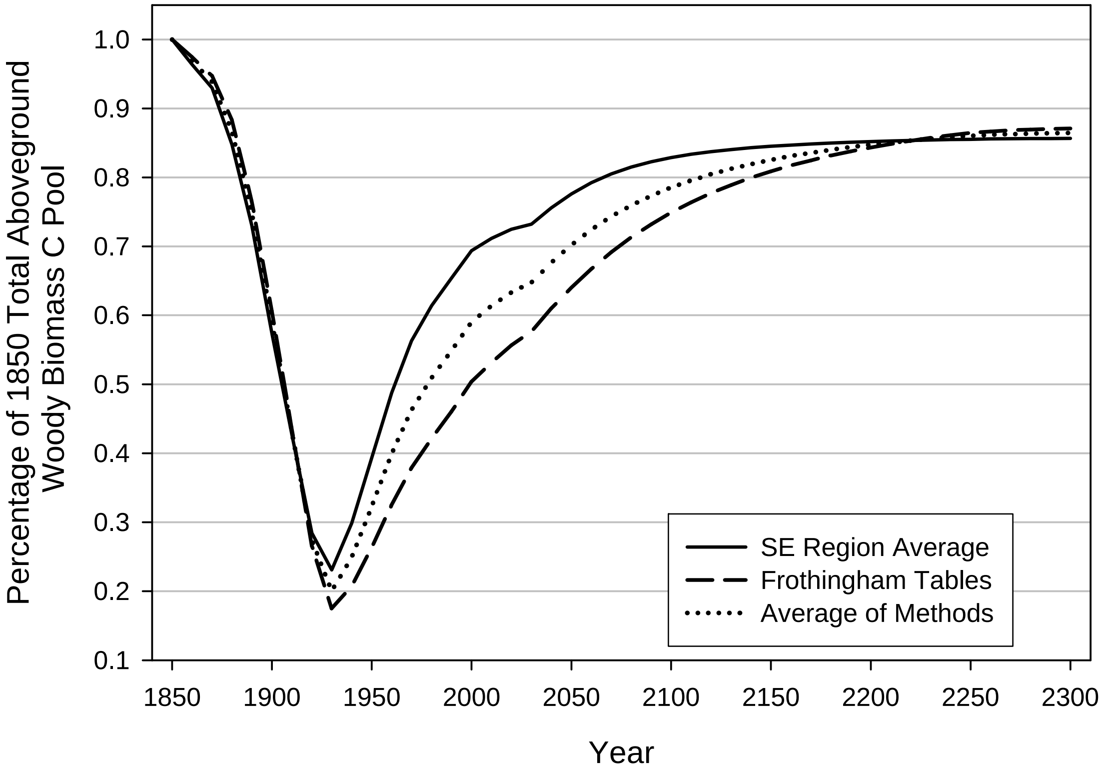

Figure 7: Estimated accrual of total aboveground woody biomass C assuming relative to 1850 C pool, assuming no future change in forest area and no large scale natural disturbance since 1850. In 2000, the pool was approximately 60% of the 1850 pool. Using both methods, the C pool would plateau at approximately 85% of the 1850 pool, and would be reached around the year 2200.

References

Agrawal, C., G. M. Green, J. M. Grove, T. P. Evans and C. M. Schweik. 2002. A review and assessment of land-use change models: dynamics of space, time, and human choice. USDA, Forest Service, Northeastern Research Station General Technical Report NE-297**:** 67.

Agresti, A. 2002. Categorical Data Analysis. New York, Wiley-Interscience.

Anderson, D. M. and L. H. MacDonald. 1998. Modelling road surface sediment production using a vector geographic information system. *Earth Surface Processes and Landforms* 23: 95-107.

Anderson, W. C. 1968. Factors influencing North Carolina landowners to practice forestry. U.S. Department of Agriculture, Forest Service, Southern Forest Experiment Station, Research Paper No. SO-33.**:** 18.

Appalachian Land Ownership Task Force. 1983. Who owns Appalachia? Landownership and its impact. Lexington, The University of Kentucky Press.

Arthur, J. P. 1914. Western North Carolina: A history from 1730-1913. Johnson City, Overmountain Press.

Ashe, W. W. 1893. Notes on the forest resources of North Carolina. *Journal of the Elisha Mitchell Scientific Society* 10: 5-25.

Aspinall, R. 2004. Modelling land use change with generalized linear models - a multi-model analysis of change between 1860 and 2000 in Gallatin Valley, Montana. *Journal of Environmental Management* 72: 91-103.

Avery, T. E. and H. E. Burkhart. 2002. Forest Measurements, 5th ed. New York, McGraw-Hill.

Ayers, H. B. and W. W. Ashe. 1905. The Southern Appalachian Forests. Washington, D.C., U.S. Geological Survey.

Bakker, M. M., G. Govers, C. Kosmas, V. Vanacker, K. van Oost and M. Rounsevell. 2005. Soil erosion as a driver of land-use change. *Agriculture, Ecosystems, and Environment* 105: 467-481.

Bellemare, J., G. Motzkin and D. R. Foster. 2002. Legacies of the agricultural past in the forested present: an assessment of historical land-use effects on rich mesic forests. *Journal of Biogeography* 29: 1401-1420.

Beyer, H. L. 2004. Hawth's Analysis Tools for ArcGIS**:** Available at http://www.spatialecology.com/htools.

Birdsey, R. A. 1996. Carbon storage in United States Forests. Forests and global change, Volume II: Opportunities for improving forest management. R. N. Sampson and D. Hair. Washington, DC, American Forests.

Birdsey, R. A. and G. M. Lewis. 2003. Current and historical trends in use, management, and distribution of U.S. forestlands. The potential of U.S. forest soils to sequester carbon and mitigate the greenhouse effect. J. M. e. a. Kimnle. Boca Raton, Lewis Publications**:** 15-34.

Birdsey, R. A., A. J. Plantiga and L. S. Heath. 1993. Past and prospective carbon storage in United States forests. *Forest Ecology and Management* 58: 33-40.

Blackard, J. A., M. V. Finco, E. H. Helmber, G. R. Holden, M. L. Hoppus, D. M. Jacobs, A. J. Lister, G. G. Moisen, M. D. Nelson, R. Riemann, B. Ruefenacht, D. Salajanu, D. L. Weyermann, K. C. Winterberger, T. J. Brandeis, R. L. Czaplewski, R. E. McRoberts, P. L. Patterson and R. P. Tymcio. 2008. U.S. forest biomass using nationwide forest inventory data and moderate resolution information. *Remote Sensing of Environment* 112: 1658-1677.

Blethen, H. T. and C. W. Wood. 1992. The antebellum iron industry in Western North Carolina. *Journal of the Appalachian Studies Association* 4: 79-87.

Bolstad, P. V. 2008. GIS fundamentals: a first text on Geographic Information Systems, 3rd edition. White Bear Lake, MN, Eider Press.

Bolstad, P. V. and W. T. Swank. 1997. Cumulative impacts of landuse on water quality in a southern Appalachian watershed. *Journal of the American Water Resources Association* 33(3): 519-533.

Bolstad, P. V., W. T. Swank and J. M. Vose. 1998. Predicting Southern Appalachian overstory vegetation with digital terrain data. *Landscape Ecology* 13: 271-283.

Bolstad, P. V. and J. M. Vose. 2001. Forest productivity, leaf area, and terrain in Southern Appalachian deciduous forests. *Forest Science* 47(3): 419-427.

Bolstad, P. V. and J. M. Vose. 2005. Forest and pasture carbon pools and soil respiration in the Southern Appalachian Mountains. *Forest Science* 51(4): 372-383.

Branscome, J. and P. Matthews. 1974. Selling the mountains. *Southern Exposure* 2: 122-129.

Braun, E. L. 1950. Deciduous forest of eastern North America. New York, The Free Press.

Brieman, L., J. Friedman, C. J. Stone and R. A. Olshen. 1984. Classification and Regression Trees. Belmont, Wadsworth International Group.

Brown, D. L. and J. M. Wardwell. 1980. New directions in urban-rural migration. New York, Academic Press.

Brown, D. R., K. M. Johnson, T. R. Loveland and D. M. Theobald. 2005. Rural land-use trends in the conterminous United States, 1950-2000. *Ecological Applications* 15(6): 1851-1863.

Brown, J. S. and G. A. Hillery Jr. 1962. The great migration, 1940-1960. The Southern Appalachian Region: A Survey. T. R. Ford. Lexington, University of Kentucky Press**:** 54-78.

Brown, M. J. 2002. Forest statistics for the Mountains of North Carolina, 2002. USDA, Forest Service, Southern Research Station, Resource Bulletin SRS-87**:** 66.

Burcher, C. L., H. M. Valett and E. F. Benfield. 2007. The land-cover cascade: Relationships coupling land and water. *Ecology* 88(1): 228-242.

Burgi, M., A. M. Hersperger and N. Schneeberger. 2004. Driving forces of landscape change - current and new directions. *Landscape Ecology* 19: 857-868.

Busing, R. T., E. E. C. Clebsch and P. S. White. 1993. Biomass and production of southern Appalachian cove forests reexamined. *Canadian Journal of Forest Research* 23: 760-765.

Cade, B. S. and B. R. Noon. 2003. A gentle introduction to quantile regression for ecologists. *Frontiers in Ecology and the Environment* 1(8): 412-420.

Canadell, J. G., D. E. Pataki, R. Gifford, R. A. Houghton, Y. Luo, M. R. Raupach, P. Smith and W. Steffen. 2007. Saturation of the terrestrial Carbon sink. Terrestrial ecosystems in a changing world. J. G. Canadell, D. E. Pataki and L. F. Pitelka. Berlin, Springer**:** 336.

Carlson, T. and Y. Dierwchter. 2007. Effects of Urban Growth Boundaries on Residential Development in Pierce County, Washington. *The Professional Geographer* 59(2): 209-220.

Casperson, J. P., S. W. Pacala, J. C. Jenkins, G. C. Hurtt, P. R. Moorcroft and R. A. Birdsey. 2000. Contributions of land-use history to carbon accumulation in U.S. forests. *Science* 290(5494): 1148-1151.

Chapin III, F. S., P. A. Matson and H. A. Mooney. 2003. Principles of Ecosystem Ecology. New York, Springer-Verlag.

Cho, S. H. and D. H. Newman. 2005. Spatial analysis of rural land development. *Forest Policy and Economics* 7: 732-744.

Cho, S. H., D. H. Newman and D. N. Wear. 2003. Impacts of second home development on house prices in the Southern Appalachian Highlands. *Review of urban and regional Development Studies* 15(3): 208-225.

Cho, S. H., D. H. Newman and D. N. Wear. 2005. Community choices and housing demands: a spatial analysis of the Southern Appalachian Highlands. *Housing Studies* 20(4): 549-569.

Clarkson, R. B. 1976. Mountain Logging in the Appalachians at the turn of the century. *Southern Lumberman* 227(December): 117-122.

Congalton, R. G. and R. A. Mead. 1983. A quantitative method to test for consistency and correctness in photointerpretation. *Photogrammetric Engineering and Remote Sensing* 49(1): 69-74.

Corbitt, D. L. 1950. The formation of the North Carolina counties, 1663-1943. Raleigh, North Carolina State Department of Archives and History.

Cost, N. D. 1974. Forest Statistics for the Mountain Region of North Carolina, 1974. USDA, US Forest Service, Southern Experiment Station, Resource Bulletin SE-31**:** 40.

Cost, N. D. 1978. Aboveground volume of hardwoods in the mountain region of North Carolina. U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station, Research Note SE-266.**:** 4.

Craver, G. C. 1984. Forest Statistics for the Mountains of North Carolina, 1984. USDA, US Forest Service, Southeastern Forest Experiment Station, Resource Bulletin SE-77**:** 59.

Cruickshank, J. W. 1941. Forest resources of the Mountain Region of North Carolina. USDA, Forest Service, Appalachian Forest Experiment Station Forest Survey Release No. 7**:** 55.

Crump, J. R. 2003. Finding a place in the country: exurban and suburban development in Sonoma County, California. *Environment and Behavior* 35(2): 187-202.

Culbertson, K., D. Case, D. Fowler, H. Morgan and S. Schwellenbach. 2008. Moving to the mountains: amenity migration in the Sierra and Southern Appalachian

Mountains. Political economies of landscape change. J. L. Wescoat and D. M. Johnston. Dordrecht, Springer. 89**:** 217.

Davis, D. E. 2000. Where there are mountains: an environmental history of the southern Appalachians. Athens, University of Georgia Press.

Day, F. P. and C. D. Monk. 1977. Net primary production and phenology on a Southern Appalachian watershed. *American Journal of Botany* 64(9): 1117-1125.

Day, F. P., D. L. Phillips and C. D. Monk. 1984. Forest communities and patterns. Forest Hydrology and Ecology and Coweeta. W. T. Swank and D. A. Crossley Jr. New York, Springer-Verlag. 66**:** 141-149.

De Vivo, M. S. 1986. The deforestation of Western North Carolina: 1900 to 1920. *Pioneer America Society Transactions* 9: 89-94.

DeFries, R. S., G. P. Asner and R. A. Houghton. 2004. Ecosystems and land use change. Geophysical Monograph Series, Geophysical Monograph Union.

DeFries, R. S. and K. N. Eshleman. 2004. Land-use change and hydrologic processes: a major focus for the future. *Hydrological Processes* 18: 2183-2186.

Delcourt, H. R. and W. F. Harris. 1980. Carbon budget of the Southeastern U.S. Biota: Analysis of historical change in trend from source to sink. *Science* 210(4467): 321-323.

Devereux, R. E., E. F. Goldston and W. A. Davis. 1929. Soil Survey of Macon County, North Carolina. U.S. Department of Agriculture, Bureau of Chemistry and Soils**:** 21.

Dolittle, W. T. 1957. Site index of scarlet and black oak in relation to Southern Appalachian soil and topography. *Forest Science* 3(2): 114-124.

Dragicevic, S., D. J. Marceau and C. Marois. 2001. Space, time, and dynamics modeling in historical GIS databases: a fuzzy logic approach. *Environment and Planning B: Planning and Design* 28: 545-562.

Duane, T. P. 1999. Shaping the Sierra: nature, culture, and conflict in the changing west. Berkeley, University of California Press.

Dubin, R. 1995. Estimating logit models with spatial dependence. New directions in spatial econometrics. L. Anselin and J. G. M. Horax. New York, Springer-Verlag**:** 229-242.

Dupouey, J. L., E. Dambrine, J. D. Laffite and C. Moares. 2002. Irreversible impact of past land use on forest soils and biodiversity. *Ecology* 83(11): 2978-2984.

Eastman, J. R. 2006. IDRISI 15: The Andes Edition**:** Clark Labs, Clark University (Worchester, MA).

Efird, C. and R. Moretz. 1980. Appalachian Land Ownership Study, Vol. IV: North Carolina. Boone, Center for Appalachian Studies.

Eller, R. D. 1982. Miners, Millhands, and Mountaineers: Industrialization of the Appalachian South, 1880-1930. Knoxville, The University of Tennessee Press.

Elliot, K. J., L. R. Boring and W. T. Swank. 2002. Aboveground biomass and nutrient accumulation 20 years after clear-cutting a southern Appalachian watershed. *Canadian Journal of Forest Research* 32(4): 667-683.

Elliott, K. J. and W. T. Swank. 2008. Long-term changes in forest composition and diversity following early logging (1919-1923) and the decline of American chestnut (Castanea dentata). *Plant Ecology* 197: 155-172.

ERDAS. 2005. ERDAS Leica Photogrammetry Suite 9.1**:** Leica Geosystems Imaging, LCC (Atlanta, GA: Leica Geosystems, LCC).

ESRI. 2004. ArcGIS version 9.2**:** Environmental Systems Research Institute (Redlands, CA: ESRI Press).

Etheridge, R. B. and J. S. Holmes. 1939. The forest situation in North Carolina. North Carolina Deparment of Conservation and Development, Division of Forestry, Circular No. 23**:** 25.

Fenneman, N. M. 1916. Physiographic Divisions of the United States. *Annals of the Association of American Geographers* 6: 19-98.

Fernandez, L. E., D. L. Brown, R. W. Marans and J. I. Nassauer. 2005. Characterizing location preferences in an exurban population: implications for agent-based modeling. *Environment and Planning B: Planning and Design* 32: 799-820.

Finger, J. R. 1991. The impact of removal on the North Carolina Cherokees. Cherokee Removal: Before and After. W. L. Anderson. Athens, University of Georgia Press**:** 96-111.

Foody, G. M. 1996. Approaches for the production and evaluation of fuzzy land cover classifications from remotely-sensed data. *International Journal of Remote Sensing* 17(7): 1317-1340.

Ford, T. R. e. 1962. The Southern Appalachian region: a survey. Lexington, University of Kentucky Press.

Forman, R. T. T. and L. E. Alexander. 1998. Roads and their major ecological effects. *Annual Review of Ecology and Systematics* 29: 207-231.

Foster, D. R., F. Swanson, J. D. Aber, I. Burke, N. Brokaw, D. Tilman and A. Knapp. 2003. The importance of land-use legacies to ecology and conservation. *BioScience* 53(1): 77-88.

Fraterrigo, J. M., M. G. Turner and S. G. Pearson. 2006. Previous land use alters plant allocation and growth in forest herbs. *Journal of Ecology* 94: 548-557.

Frome, M. 1966. Strangers in high places: the story of the Great Smoky Mountains. Garden City, Doubleday & Company.

Frothingham, E. H. 1917. Ecology and silviculture in the Southern Appalachians: old cuttings as a guide to future practice. *Journal of Forestry* 15(3): 343-349.

Frothingham, E. H. 1921. Site determination and yield forecasts in the Southern Appalachians. *Journal of Forestry* 19(1): 1-15.

Frothingham, E. H. 1931. Timber growing and logging practice in the Southern Appalachian region. U.S. Department of Agriculture, Washington D.C., Technical Bulletin No. 250**:** 89.

Gade, O. and H. D. Stillwell. 1986. North Carolina: People and Environments. Boone, GEO-APP Publishing Co.

Gennett, A. 2007. Sound wormy: memoir of Andrew Gennett, Lumberman. Athens, University of Georgia Press.

Glenn, L. C. 1911. Denudation and erosion in the Southern Appalachian Region and the Monongahela Basin. U.S. Geological Survey, Washington D.C., Professional Paper No. 72.**:** 137.

Goldston, E. F. and W. Gettys. 1956. Soil Survey of Macon County, North Carolina. United States Department of Agriculture, Soil Conservation Service. Series 1944, no. 6.**:** 124.

Goodale, C. L. and J. D. Aber. 2001. The long-term effects of land-use history on nitrogen cycling in northern hardwood forests. *Ecological Applications* 11(1): 253-267.

Gragson, T. L. and P. V. Bolstad. 2006. Land use legacies and the future of Southern Appalachia. *Society and Natural Resources* 19: 175-190.

Gragson, T. L. and P. V. Bolstad. 2007. A local analysis of early 18th century Cherokee settlement. *Social Science History* 31: Need Pages.

Gragson, T. L., P. V. Bolstad and M. W. Devine. 2008. Agricultural transformation of Southern Appalachia. Agrarian landscapes in transition: comparisons of long-term ecological and cultural change. C. L. Redman and D. R. Foster, Oxford University Press.

Graves, H. S. 1914. Purchase of land under the Weeks Law in the Southern Appalachian and White Mountains. US Department of Agriculture, Forest Service, Washington: Government Printing Office, Misc Report.**:** 14.

Griffith, J. A., S. V. Stehman and T. R. Loveland. 2003. Landscape trends in Mid-Atlantic and Southeastern United States Ecoregions. *Environmental Management* 32(5): 572-588.

Gustafson, E. J., R. B. Hammer, V. C. Radeloff and R. S. Potts. 2005. The relationship between environmental amenities and changing human settlement patterns between 1980 and 2000 in the Midwestern USA. *Landscape Ecology* 20: 773-789.

Hale, P. M. 1883. The woods and timbers of North Carolina. New York, E.J. Hale and Son.

Hall, B., G. Motzkin, D. R. Foster, M. Syfert and J. Burk. 2002. Three hundred years of forest and land-use change in Massachusetts, USA. *Journal of Biogeography* 29: 1319-1335.

Hammer, R. B., S. I. Stewart, R. L. Winkler, V. C. Radeloff and P. R. Voss. 2004. Characterizing dynamic spatial and temporal residential density patterns from 1940-1990 across the North Central United States. *Landscape and Urban Planning* 69: 183-199.

Harding, J. S., E. F. Benfield, P. V. Bolstad, G. S. Helfman and E. B. D. Jones III. 1998. Stream biodiversity: the ghost of land use past. *Proceedings of the American Philosophical Society* 95(25): 14843-14847.

Hardt, R. A. and W. T. Swank. 1997. A comparison of structural and compositional characteristics of southern Appalachian Young Second-Growth, and Old-Growth Stands. *Natural Areas Journal* 17: 42-52.

Harris, R. N. S., G. S. Tollley and A. J. Coutu. 1963. Cropland reversion in the South. North Carolina State College, Dept. of Agricultural Economics, Raleigh, Information Series No. 100.**:** 61.

Hart, J. F. 1968. Loss and abandonment of cleared farm land in the eastern United States. *Annals of the Association of American Geographers* 58(3): 417-440.

Hart, J. F. 1977. Land Rotation in Appalachia. *Geographical Review* 67(2): 148-166.

Heath, L. S. and R. A. Birdsey. 1993. Carbon trends of productive temperate forets of the coterminous United States. *Water, Air, and Soil Pollution* 70: 279-293.

Heilman Jr., G. E., J. R. Strittholt, N. C. Slosser and D. A. Dellasala. 2002. Forest fragmentation of the Conterminous United States: assessing forest intactness through road density and spatial characteristics. *BioScience* 52(5): 411-422.

Henderson, R. A. and Z. Francesca. 1998. Ecological numeracy: quantitative analysis of environmental issues. New York, John Wiley and Sons.

Hermann, K. A. e. 1996. The Southern Appalachian Assessment GIS Data Base CD ROM Set. The Southern Appalachian Man and the Biosphere Program. Norris, TN.

Holmes, J. S. 1911. Forest conditions in Western North Carolina. NC Geological and Economic Survey Bulletin No. 23**:** 92.

Holmes, J. S. 1912. Forest Conditions in Western North Carolina. *American Forestry* 18: 384-392.

Homer, C., C. Huang, L. Yang, B. Wylie and M. Coan. 2004. Development of a 2001 National Land-cover Database for the United States. *Photogrammetric Engineering and Remote Sensing* 70: 829-840.

Houghton, R. A. 1999. The annual neet flux of carbon to the atmosphere from changes in land use 1850-1990. *Tellus* 51B(298-313).

Houghton, R. A. 2002. Terrestrial carbon sinks: uncertain explanations. *Biologist* 49(4): 155-160.

Houghton, R. A. 2003. Revised estimates of the annual net flux of carbon to the atmosphere from chagnes in land use and land management 1850-2000. *Tellus, Series B: Chemical and Physical Meteorology* 55(2): 378-390.

Houghton, R. A. 2003. Why are estimates of the terrestrial carbon balance so different? *Global Change Biology* 9: 500-509.

Houghton, R. A. and J. L. Hackler. 1999. Emissions of carbon from forestry and land-use change in tropical Asia. *Global Change Biology* 5: 481-492.

Houghton, R. A. and J. L. Hackler. 2000. Changes in terrestrial carbon storage in the United States. I: The roles of agriculture and forestry. *Global Ecology and Biogeography* 9: 125-144.

Houghton, R. A., J. L. Hackler and K. T. Lawrence. 1999. The U.S. Carbon Budget: Contributions from Land-Use Change. *Science* 285(5427): 574-578.

Houghton, R. A., J. E. Hobbie, J. M. Melillo, B. Moore, B. J. Peterson, G. R. Shaver and G. M. Woodwell. 1983. Changes in the carbon content of terrestrial biota and soils between 1860 and 1980: A net release of CO2 to the atmosphere. *Ecological Monographs* 53(3): 235-262.

Hughes, J. D. 2006. What is Environmental History. Cambridge, Polity Press.

Hurtt, G. C., S. W. Pacala, P. R. Moorcroft, J. P. Casperson, E. Shevliakova, R. A. Houghton and B. Moore III. 2002. Projecting the future of the U.S. carbon sink. *Proceedings of the National Academy of Sciences of the United State of America* 99: 1389-1394.

Huston, M. A. 2005. The three phases of land-use change: implications for biodiversity. *Ecological Applications* 15(6): 1864-1878.

Irwin, E. G., H. J. Cho and N. E. Bockstael. 2007. Measuring the amount and pattern of land development in nonurban areas. *Review of Agricultural Economics* 29(3): 494-501.

Irwin, E. G. and J. Geoghegan. 2001. Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems, and Environment* 85: 7-23.

Iverson, L. R. 2007. Adequate data of known accuracy are critical to advancing the field of landscape ecology. Key topics in landscape ecology. J. Wu and R. Hobbs. Cambridge, Cambridge University Press**:** 11-38.

Jemison, G. M. and G. H. Hepting. 1949. Timber Stand Improvement in the Southern Appalachian Mountains. U.S. Department of Agriculture, Forest Service Miscellaneous Report No. 693.**:** 80.

Jensen, J. R. 1996. Introductory digital image processing: a remote sensing perspective. Upper Saddle River, Prentice Hall.

Johnson, T. G. 1990. Forest statistics for the Mountains of North Carolina, 1990. USDA, US Forest Service, Southeastern Forest Experiment Station, Resource Bulletin SE-118**:** 60.

Jones, J. L. and S. B. Kask. 2000. The fiscal impact of alternative land uses in Macon County, Report for the Land Trust for the Little Tennessee**:** 26.

Jones, K. B., A. C. Neale, M. S. Nash, R. D. Van Remortel, R. D. Wickham, J. D. Riitters and R. V. O'Neill. 2001. Predicting nutrient sediment loadings to streams from landscape metrics: A multiple watershed study from the United States Mid-Atlantic region. *Landscape Ecology* 16(4): 301-312.

Jurgelski, W. M. 2004. New Plow in Old Ground: Cherokees, Whites, and Land in Western North Carolina, 1819-1829. PhD Dissertation, Department of Anthropology, University of Georgia. 320 p.

Kellndorfer, J. M., W. S. Walker, K. M. Kirsch, G. J. Fiske, J. Bishop, E. LaPoint, M. Hoppus and J. Westfall. 2007-2009. The national biomass and carbon dataset 2000 (NBCD 2000): A high resolution baseline for the conterminous U.S. *Remote Sensing of Environment* In Preparation.

Kline, J. D., D. L. Azuma and A. Moses. 2003. Modeling the spatially dynamic distribution of humans in the Oregon (USA) Coast Range. *Landscape Ecology* 18: 347-361.

Knight, H. A. and J. P. McClure. 1966. North Carolina's timber. USDA, Forest Service, Southeastern Forest Experiment Station, Resource Bulletin SE-5**:** 54.

Koenker, R. 2004. Quantreg 4.17: An R package for quantile regression and related methods**:** http://cran.r-project.org (accessed 20 March 2008).

Koenker, R. 2005. Quantile regression. Cambridge, Cambridge University Press.

Koenker, R. and G. Bassett. 1978. Regression quantiles. *Econometrica* 46(1): 33-50.

Lamb, R. F. 1983. The extent and form of exurban sprawl. *Growth and Change* 14(3): 40-47.

Lambert, R. S. 1961. Logging the Great Smokies, 1880-1930. *Tennessee Historical Quarterly* 20(4): 350-363.

Landsberg, J. J. 2003. Modelling forest ecosystems: state of the art, challenges, and future directions. *Canadian Journal of Forest Research* 33: 385-397.

Lewis, C. D. 1931. Government forests and the mountain problem. *Mountain Life and Work* 6: 2-9.

Lewis, R. L. 1998. Transforming the Appalachian Countryside: Railroads, Deforestation, and Social Change in West Virginia, 1880-1920. Chapel Hill, The University of North Carolina Press.

Loveland, T. R., T. L. Sohl, S. V. Stehman, A. L. Gallant, K. L. Sayler and D. E. Napton. 2002. A strategy for estimating the rates of recent United States land-cover changes. *Photogrammetric Engineering and Remote Sensing* 68(10): 1091-1099.

Lyon, L. J. 1983. Road density models describing habitat effectiveness for Elk. *Journal of Forestry* 81(9): 592-613.

Macon County. 2007. Macon County, NC, Online Mapping Service. Available at http://www.maconnc.org/.

Malone, H. T. 1956. Cherokees of the Old South: A People in Transition. Athens, University of Georgia Press.

Manson, S. M., J. Geoghegan and B. L. Turner II. 2006. State of the art in describing future changes in ecosystem service: forecasting changes in land use and land cover. Millenium Ecosystem Assessment: ecosystems and well-being. H. A. Mooney and A. Cropper. Geneva, Island Press. 2**:** 74-76.

Mason, J. E. and G. W. Forster. 1950. Inventory of land use in North Carolina. North Carolina Agriculture Experiment Station, Technical Bulletin No. 93**:** 42.

Mastran, S. S. and N. Lowerre. 1983. Mountaineers and rangers: a history of federal forest management in the Southern Appalachians. USDA, Forest Service, Washington, Miscellaneous Publication FS-280**:** 191.

Maughan, W. E. 1939. A guide to the forestry activities in North Carolina, South Carolina, and Tennessee. Ashevilee, Appalachian Section, Society of American Foresters.

McCormack, J. F. 1956. Forest statistics for the mountain region of North Carolina, 1955. U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station Forest Survey Release No. 46**:** 46.

McGranahan, D. A. 1999. Natural amenities drive rural population change. U.S. Department of Agriculture, Agricultural Economic Report No. 781**:** 27.

McNab, W. H. 1989. Terrain shape index: quantifying effect of minor landforms on tree height. *Forest Science* 35(1): 91-104.

Merchant, C. 2007. American Environmental History: an Introduction. New York, Columbia University Press.

Mertens, B. and E. F. Lambin. 2000. Land-cover change trajectories in southern Cameroon. *Annals of the Association of American Geographers* 90(3): 467-494.

Meyer, W. B. and B. L. Turner. 1994. Changes in land use and land cover: a global perspective. Cambridge, Cambridge University Press.

Mickler, R. A., T. S. Earnhardt and J. A. Moore. 2002. Modelign and spatially distributing net primary production at the regional scale. *Journal of Athe Air and Waste Management Association* 52: 174-185.

Monk, C. D. and F. P. Day Jr. 1984. Biomass, primary production, and selected nutrient budgets for an undisturbed watershed. Forest Hydrology and Ecology and Coweeta. W. T. Swank and D. A. Crossley Jr. New York, Springer-Verlag. 66**:** 151-159.

National Agricultural Statistics Service. 1954-2002. The Census of Agriculture. US Department of Agriculture.

NCGICC. 2008. NC OneMap program. Available at: http://www.nconemap.com/, accessed July 1, 2008.

Nelson, A. C. 1992. Characterizing Exurbia. *Journal of Planning Literature* 6(4): 350-68.

Nelson, A. C. and T. W. Sanchez. 1997. Exurban and suburban households: a departure from traditional location theory? *Journal of Housing Research* 8(2): 249-276.

North Carolina Department of Conservation and Development. 1929. North Carolina: Resources and Industries. Raleigh, State of North Carolina.

North Carolina Department of Transportation. 2006. Standard Specifications for Roads & Structures. NCDOT, Raleigh, NC.

North Carolina Office of State Budget and Management. 2008. North Carolina County Population Projections. Available at http://www.osbm.state.nc.us/ Accessed July 1, 2008.

OrthoMapper. 2004. Image Processing Software Inc. (Madison, WI). Available at http://www.orthomapper.com/.

Otto, J. S. 1989. Forest fallowing in the Southern Appalachian mountains: a problem of comparative agricultural history. *Proceedings of the American Philosophical Society* 133(1): 51-63.

Otto, J. S. and N. E. Anderson. 1982. Slash-and-burn cultivation in the Highlands South: a problem of comparative agricultural history. *Comparative Studies in Society and History* 24(1): 131-147.

Overmars, K. P., G. H. J. de Koning and A. Veldkamp. 2003. Spatial autocorrelation in multi-scale land use models. *Ecological Modelling* 164: 257-270.

Parker, A. J. 1982. The Topographic Relative Moisture Index: an approach to soil-moisture assessment in mountain terrain. *Physical Geography* 32: 160-168.

Parker, D. C., S. M. Manson, M. Janssen, M. J. Hoffmann and P. J. Deadman. 2003. Multi-agent systems for the simulation of land use and land cover change: a review. *Annals of the Association of American Geographers* 93(2): 316-340.

Pearson, S. G., M. G. Turner and J. B. Drake. 1999. Landscape change and habitat availability in the Southern Appalachian highlands and Olympic Peninsula. *Ecological Applications* 9(4): 1288-1304.

Peet, R. K. 1981. Changes in biomass and production during secondary forest succession. Forest succession: concepts and applications. D. C. West, H. H. Shugart and D. B. Botkin. New York, Springer-Verlag**:** 324-338.

Peters, A. H. and H. MacDonald. 2004. Unlocking the census with GIS. Redlands, CA, ESRI Press.

Pinchot, G. and W. W. Ashe. 1897. Timber trees and forests of North Carolina. North Carolina Geological Survey, Bulletin No. 6**:** 227.

Plantiga, A. J. and R. A. Birdsey. 1983. Carbon fluxes resulting form U.S. private timberland management. *Climatic Change* 23: 37-53.

Pollard, K. M. 2005. Population growth and distribution in Appalachia: New Realities. in "Demographic and Socioeconomic Change in Appalachia", Population Reference Bureau**:** 57.

Pomeroy, K. B. and J. G. Yoho. 1964. North Carolina lands: ownership, use, and management of forest and related lands. Washington, The American Forestry Association.

Pontius Jr., R. G. 2000. Quantification error versus location error in comparison of categorical maps. *Photogrammetric Engineering and Remote Sensing* 66(8): 1011-1016.

Pontius Jr., R. G., A. Agrawal and D. Huffaker. 2003. Estimating the uncertainty of land-cover extrapolations while constructing a raster map from tabular data. *Journal of Geographical Systems* 5: 253-273.

Pontius Jr., R. G., D. Huffaker and K. Denman. 2004. Useful techniques of validation for spatially explicit land-change models. *Ecological Modelling* 179: 445-461.

Pontius Jr., R. G. and M. Millones. 2008. Problems and solutions for kappa-based indices of agreement. Studying, Modeling and Sense Making of Planet Earth, Mytilene, Greece.

Pontius Jr., R. G. and B. Suedmeyer. 2004. Components of agreement in categorical maps at multiple resolutions. Remote sensing and GIS accuracy assessment. R. S. Lunetta and J. G. Lyon. Boca Raton, FL, CRC Press**:** 233-51.

Pyle, C. 1988. The type and extent of anthropogenic vegetation disturbance in the Great Smoky Mountains before National Park Service Acquisition. *Castanea* 53(3): 183-196.

R Development Core Team. 2008. R: A language and environment for statistical computing**:** R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http:\\www.R-project.org.

Radeloff, V. C., A. E. Hagen, P. R. Voss, D. R. Field and D. J. Mladenoff. 2000. Exploring the spatial relationship between census and land-cover data. *Society and Natural Resources* 13: 599-609.

Radeloff, V. C., R. B. Hammer and S. I. Stewart. 2005. Rural and suburban sprawl in the U.S. Midwest from 1940 to 2000 and its relation to forest fragmentation. *Conservation Biology* 19(3): 793-805.

Radeloff, V. C., R. B. Hammer, P. R. Voss, A. E. Hagen, D. R. Field and D. J. Mladenoff. 2001. Human demographic trends and landscape level forest management in the Northwest Wisconsin Pine Barrens. *Forest Science* 47(2): 229-241.

Raitz, K. B. and R. Ulack. 1984. Appalachia: A Regional Geography: Land, People, and Development. Boulder, Westview Press.

Ramankutty, N. and J. A. Foley. 1999. Estimating historical changes in land cover: North America croplands from 1850 to 1992. *Global Ecology and Biogeography* 8(5): 381-396.

Riebsame, W. E., H. Gosnell and D. M. Theobald. 1996. Land use and landscape change in the Colorado mountains I: theory, scale and pattern. *Mountain Research and Development* 16(4): 395-405.

Rindfuss, R. R., S. J. Walsh, B. L. Turner, J. Fox, V. Mishra and S. Hanson. 2004. Developing a science of land change: challenges and methodological issues. *Proceedings of the National Academy of Sciences of the United State of America* 101(39): 13976-13981.

Roberts, D. W. and S. V. Cooper. 1989. Concepts and techniques of vegetation mapping. in: Ferguson, D., Morgan, P., Johnson, F.D. (eds.) Land classifications based on vegetation: applications for resource management, pp. 90-96. USDA Forest Service, Intermountain Research Stations, General Technical Report No. INT-257.

Rohrig, E. and B. E. Ulrich. 1991. Ecosystems of the World 7: Temperate Deciduous Forests. Amsterdam, Elsevier.

Sala, O. E., F. S. Chapin III, J. J. Armesto, E. Berlow, J. Bloomfield, R. Dirzo, E. Huber-Sanwald, L. F. Huenneke, R. B. Jackson, A. Kinzig, R. Leemans, D. M. Lodge, H. A. Mooney, M. Oesterheld, N. L. Poff, M. T. Sykes, B. H. Walker, M. Walker and D. H. Wall. 2000. Global biodiversity scenarios for the year 2100. *Science* 287: 1770-1774.

Salstrom, P. 1995. New Appalachia as One of America's Last Frontiers. Appalachia in the Making: the Mountain South in the Nineteenth Century. M. B. Pudup, D. B. Billings and A. L. Waller. Chapel Hill, The University of North Carolina Press**:** 76-102.

Schimel, D., J. Melillo, H. Tian, A. D. McGuire, D. W. Kicklighter, T. Kittel, N. Rosenbloom, S. Running, P. Thornton, D. Ojima, W. Parton, R. Kelly, M. Sykes, R. Neilson and B. Rizzo. 2000. Contribution of increasing CO2 and cliamte to carbon storage by ecosystems in the United States. *Science* 287: 2004-2006.

Schneider, L. C. and R. G. Pontius Jr. 2001. Modeling land-use change in the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems, and Environment* 85: 83-94.

Schroeder, P. 1996. A carbon budget for Brazil: influence of future land-use change. *Climatic Change* 35: 179-197.

Scott, M. C. 2006. Winners and losers among stream fishes in relation to land use legacies and urban development in the southeastern US. *Biological Conservation* 127: 301-309.

Silverman, B. W. 1986. Density estimation for statistics and data analysis. New York, Chapman and Hall.

Simon, S. A., T. K. Collins, G. L. Kauffman, W. H. McNab and C. J. Ulrey. 2005. Ecological zones in the Southern Appalachians: First approximation. USDA, US Forest Service, Southern Research Station, Research Paper No. SRS-41.

Sinclair, A. R. E., D. S. Hik, O. J. Schmitz, G. G. E. Scudder, D. H. Turpin and N. C. Larter. 1995. Biodiversity and the need for habitat renewal. *Ecological Applications* 5(579-587).

Slocum, G. K. and C. R. Ross. 1945. Forest resources appraisal of North Carolina. North Carolina Department of Conservation and Development, Bulletin No. 53**:** 70.

Smith, D. W. 1995. The Southern Appalachian Hardwood Region. Regional Silviculture of the United States, 3rd Edition. J. W. Barrett. New York, John Wiley and Sons, Inc.**:** 173-225.

Smith, J. E., L. S. Heath, K. E. Skog and R. A. Birdsey. 2006. Methods for calculation forest ecosystem and harvested carbon with standard estimates for forest types in the United states. USDA, US Forest Service, Northeastern research station, General Technical Report No. NE-343.

Soil Survey Staff. 2008. Soil Survey Geographic (SSURGO) Database for various North Carolina Counties. Natural Resource Conservation Service, Available online at http://soildatamart.nrcs.usda.gov.

Song, C. and C. E. Woodcock. 2003. A regional forest ecosystem carbon budget model: impacts of forest age structure and landuse history. *Ecological Modelling* 164: 33-47.

Spectorsky, A. C. 1955. The Exurbanites. Philadelphia, Lippincott.

Staff of the Appalachian Forest Experiment Station. 1935. Forest improvement measures for the Southern Appalachians. U.S. Department of Agriculture, Washington D.C., Technical Bulletin No. 476**:** 46.

Starnes, R. 2005. Creating the land of sky: tourism and society in Western North Carolina. Tuscaloosa, University of Alabama Press.

Stuckey, J. L. 1965. North Carolina: Its geology and mineral resources. Raleigh, Department of Conservation and Development.

Taylor, A. W. 1938. Sub-marginal standards of living in the southern Mountains. *Mountain Life and Work* 14: 12-14.

Taylor, S. W. 2001. The New South's New Frontier: a social history of economic development in Southwestern North Carolina. Gainsville, University Press of Florida.

Theobald, D. M. 2005. Landscape patterns of exurban growth in the USA from 1980 to 2020. *Ecology and Society* 10(1): 32.

Theobald, D. M. and T. Hobbs. 1998. Forecasting rural land-use change: a comparison of regression- and spatial transition-based models. *Geographical and Environmental Modelling* 2(1): 65-82.

Trimble Jr., G. R. 1956. Site index of upland oaks in the Northern Appalachians. *Forest Science* 2(3): 162-173.

Turner, D. P., G. J. Koerper, M. E. Harmon and J. T. Lee. 1995. A carbon budget for forests of the conterminous United States. *Ecological Applications* 5(2): 421-436.

Turner, M. G. 1987. Land use changes and net primary production in the Georgia, USA, landscape: 1935-1982. *Environmental Management* 11(2): 237-247.

Turner, M. G. 2005. Landscape ecology: what is the state of the science? *Annual Review of Ecology, Evolution, and Systematics* 36: 319-344.

Turner, M. G., W. E. Gardner and R. V. O'Neill. 2001. Landscape ecology in theory and practice. New York, Springer-Verlag.

Turner, M. G., S. G. Pearson, P. V. Bolstad and D. N. Wear. 2003. Effects of land-cover change on spatial pattern of forest communities in the Southern Appalachian Mountains (USA). *Landscape Ecology* 18: 449-464.

Turner, M. G., D. N. Wear and R. O. Flamm. 1996. Land ownership and land-cover change in the Southern Appalachian Highlands and Olympic Peninsula. *Ecological Applications* 6(4): 1150-1172.

U.S. Census Bureau. 1850-1950. Census of Agriculture. Washington Government Printing Office.

U.S. Census Bureau. 1850-2000. U.S. Census of Population and Housing. Washington: Government Printing Office.

U.S. Census Bureau. 1900-2000. U.S. Census of Population and Housing. Washington: Government Printing Office.

U.S. Department of Agriculture. 1954-2002. Census of Agriculture. Washington Government Printing Office.

U.S. Geological Survey. 1896-1912. Various topographic maps, Western North Carolina**:** 1:125,000. 30 Minute Series. Washington, D.C.: USGS.

U.S. Geological Survey. 1906. Nantahala Quadrangle, North Carolina**:** 1:125,000. 30 Minute Series. Washington, D.C.: USGS.

U.S. Geological Survey. 1907. Cowee Quadrangle, North Carolina**:** 1:125,000. 30 Minute Series. Washington, D.C.: USGS.

Van Noppen, I. W. and J. J. Van Noppen. 1973. Western North Carolina Since the Civil War. Boone, Appalachian Consortium Press.

Veldkamp, A. and E. F. Lambin. 2001. Predicting land-use change. *Agriculture, Ecosystems, and Environment* 85: 1-6.

Verburg, P. H., P. P. Schot, M. J. Dijst and A. Veldkamp. 2004. Land use change modelling: current practice and research priorities. *GeoJournal* 61: 309-324.

Wager, P. W. and R. B. Thomson. 1932. Taxation of forest property in North Carolina. U.S. Department of Agriculture, Forest Service, Progress Report of the Forest Taxation Inquiry No. 17.**:** 132.

Waisanen, P. J. and N. B. Bliss. 2002. Changes in population and agricultural land in conterminous United States counties, 1790 to 1997. *Global Biogeochemical Cycles* 16(4, 1137, doi:10.1029/2001GB001843): 19.

Wallin, D. O., M. E. Harmon, W. B. Cohen, M. Fiorella and W. K. Ferrell. 1996. Use of remote sensing to model land use effects on carbon flux in forests of the Pacific Northwest, USA. The use of remote sensing in the modeling of forest productivity at scales from the stand to the globe. H. L. Gholz, K. Nakane and H. Shimoda. Dordrecht, Kluwer Academic Publishers**:** 219-237.

Wear, D. N. and P. V. Bolstad. 1998. Land-use changes in Southern Appalachian landscapes: spatial analysis and forecast evaluation. *Ecosystems* 1: 575-594.

Wear, D. N., M. G. Turner and R. J. Naiman. 1998. Land cover along an urban-rural gradient: implications for water quality. *Ecological Applications* 8(3): 619-630.

West, T. O. and G. Marland. 2003. Net carbon flux from agriculture: carbon emissions, carbon sequestration, crop yield,and land-use change. *Biogeochemistry* 63: 73-83.

Westveld, R. H. 1949. Applied Silviculture in the United States, 2nd Edition. New York, John Wiley and Sons, Inc.

Whittaker, R. W. 1956. Vegetation of the Great Smoky Mountains. *Ecological Monographs* 26(1): 1-80.

Whittaker, R. W. 1966. Forest dimensions and production in the Great Smoky Mountains. *Ecology* 47: 103-121.

Yarnell, S. L. 1998. The Southern Appalachians: A history of the landscape. USDA, Forest Service, Southern Research Station General Technical Report SRS-18**:** 52.

Zon, R. 1907. Management of Second Growth in the Southern Appalachians. U.S. Department of Agriculture, Forest Service Circular No. 118**:** 22.

Appendix A: Demographic and land use area estimates for 21 counties in Western North Carolina, 1850-2030

Table A-1: Estimate of total population by present county boundary. Census counts are in bold. All non-bold historic values are census estimates corrected for changes in county boundaries using an areal interpolation model weighted on an estimated amount of suitable agriculture area. Future projections are from the NC Office of State Budget and Management (2008).

County	1850	1860	1870	1880	1890	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010	2020	2030
Alleghany	2748	2491	2998	4521	4894	6132	**7745**	**7403**	**7186**	**8341**	**8155**	**7734**	**8134**	**9587**	**9590**	**10677**	11300	11747	12048
Ashe	6038	5473	6586	9932	10752	13471	**19074**	**21001**	**21019**	**22664**	**21878**	**19768**	**19571**	**22325**	**22209**	**24384**	26729	28556	30067
Avery	1032	1853	2551	3632	4870	8408	9429	**10335**	**11803**	**13561**	**13352**	**12009**	**12655**	**14409**	**14867**	**17167**	18455	18912	19007
Buncombe	11716	12788	15698	21909	**35266**	**44288**	**49798**	**64148**	**97937**	**108755**	**124403**	**130074**	**145056**	**160934**	**174357**	**206330**	234800	263660	291569
Burke	7988	9484	10044	**12746**	**14864**	**17608**	**21293**	**23297**	**29410**	**38615**	**45518**	**52701**	**60364**	**72504**	**75740**	**89148**	90604	95342	98962
Caldwell	6191	7348	8308	10087	12054	15694	**20579**	**19984**	**28016**	**35795**	**43352**	**49552**	**56699**	**67746**	**70709**	**77415**	80227	81880	82927
Clay	6259	6178	6977	8182	**9976**	**11860**	**14136**	**15242**	**16151**	**18813**	**18294**	**16335**	**16330**	**18933**	**20170**	**24298**	28246	31500	34148
Cherokee	2186	2032	2461	3316	**4197**	**4532**	**3909**	**4646**	**5434**	**6405**	**6006**	**5526**	**5180**	**6619**	**7155**	**8775**	10961	12827	14367
Graham	1007	955	1078	3401	5179	4223	**4749**	**4872**	**5841**	**6418**	**6886**	**6432**	**6562**	**7217**	**7196**	**7993**	8222	8357	8390
Haywood	3824	4556	7715	**10271**	**13346**	**16222**	**21020**	**23496**	**28273**	**34804**	**37631**	**39711**	**41710**	**46495**	**46948**	**54033**	57974	61874	65295
Henderson	4862	8170	6904	**10281**	**12589**	**13441**	**16262**	**18248**	**23404**	**26049**	**30921**	**36163**	**42804**	**58580**	**69747**	**89173**	107582	125966	144714
Jackson	2921	4445	6092	**7337**	**9512**	**11853**	**12998**	**13396**	**17519**	**19366**	**19261**	**17780**	**21593**	**25811**	**26835**	**33121**	38055	41422	44269
Macon	2754	4042	4869	8064	**10102**	**12104**	**12191**	**12887**	**13672**	**15880**	**16174**	**14935**	**15788**	**20178**	**23504**	**29811**	35208	40521	45630
Madison	5712	5908	8192	12810	**17805**	**20644**	**20132**	**20083**	**20306**	**22522**	**20522**	**17217**	**16003**	**16827**	**16953**	**19635**	20868	21949	22851
McDowell	5918	6746	7296	9917	11034	12680	13677	**16763**	**20336**	**22996**	**25720**	**26742**	**30648**	**35135**	**35681**	**42151**	44911	47390	49673
Mitchell	1571	3126	4076	6506	8831	7701	8725	**11278**	**13962**	**15980**	**15143**	**13906**	**13447**	**14428**	**14433**	**15687**	15975	16250	16330
Swain	1455	1882	2553	2722	4720	8440	**10403**	**13224**	**11568**	**12177**	**9921**	**8387**	**8835**	**10283**	**11268**	**12968**	14387	15932	17354
Transylvania	1853	4745	4124	5340	**5881**	**6620**	**7191**	**9303**	**9589**	**12241**	**15194**	**16372**	**19713**	**23417**	**25520**	**29334**	31572	33130	34140
Watauga	3237	4720	5034	7769	10103	12668	**12799**	**13477**	**15165**	**18114**	**18342**	**17529**	**23404**	**31666**	**36952**	**42695**	45686	47796	49182
Wilkes	**12099**	**14749**	**15539**	**19181**	**22675**	**26872**	**30282**	**32644**	**36162**	**43003**	**45243**	**45269**	**49524**	**58657**	**59393**	**65632**	67670	69152	70258
Yancey	2056	4092	4454	7640	**9490**	**11464**	**12072**	**15093**	**14486**	**17202**	**16306**	**14008**	**12629**	**14934**	**15419**	**17774**	19005	19948	20645
Total	93427	115783	133549	185564	238140	286925	328464	370820	447239	519701	558222	568150	626649	736685	784646	918201	1008437	1094111	1171826

Table A-2: Estimate of number of Housing Units by present county boundary. Census counts are in bold. All non-bold historic values are census estimates corrected for changes in county boundaries using an areal interpolation model weighted on an estimated amount of suitable agriculture area. Future projections are derived from population growth estimates provided by the NC Office of State Budget and Management (2008) using the year 2000 population/Housing Unit ratio for each county.

County	1850	1860	1870	1880	1890	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010	2020	2030
Alleghany	1145	1037	1248	1883	2038	2554	**1468**	**1466**	**1589**	**2181**	**2318**	**2738**	**3413**	**4670**	**5344**	**6412**	6786	7055	7235
Ashe	521	472	568	857	928	1162	**3617**	**3992**	**4196**	**5233**	**5691**	**5892**	**7018**	**9525**	**11119**	**13268**	14544	15538	16360
Avery	195	351	483	688	923	1594	1788	**1932**	**2199**	**2910**	**3490**	**3452**	**4444**	**7075**	**8923**	**11911**	12805	13122	13188
Buncombe	2221	2425	2976	4154	**6687**	**8398**	**9443**	**12310**	**19753**	**28233**	**35616**	**43617**	**51618**	**66131**	**77951**	**99973**	113768	127751	141274
Burke	1514	1798	1904	2417	**2818**	**3339**	**4037**	**4116**	**5184**	**8099**	**11195**	**14501**	**18732**	**27533**	**31575**	**37427**	38038	40027	41547
Caldwell	1174	1393	1575	1912	2285	2976	**3902**	**3908**	**5189**	**8026**	**11082**	**13870**	**18064**	**25557**	**29454**	**33430**	34644	35358	35810
Clay	1186	1171	1323	1551	**1891**	**2249**	**2680**	**2937**	**3064**	**4299**	**4743**	**4897**	**5844**	**8536**	**10319**	**13499**	15692	17500	18971
Cherokee	414	385	466	628	**795**	**859**	**741**	**915**	**1074**	**1483**	**1566**	**1701**	**2059**	**3370**	**4158**	**5425**	6776	7930	8882
Graham	190	181	204	644	**982**	**800**	**900**	**922**	**1069**	**1345**	**1945**	**1962**	**2528**	**3578**	**4132**	**5084**	5230	5316	5337
Haywood	725	863	1463	1947	**2530**	**3076**	**3986**	**4613**	**5613**	**8142**	**10623**	**13108**	**15030**	**20363**	**23975**	**28640**	30729	32796	34609
Henderson	922	1549	1309	1949	**2387**	**2548**	**3083**	**3748**	**5025**	**7540**	**10752**	**14556**	**17502**	**27205**	**34131**	**42996**	51872	60736	69776
Jackson	553	842	1155	1391	**1803**	**2247**	**2464**	**2509**	**3374**	**4214**	**4981**	**5607**	**7254**	**11960**	**14052**	**19291**	22165	24126	25784
Macon	522	766	923	1529	**1915**	**2295**	**2311**	**3252**	**3884**	**5173**	**6745**	**8178**	**10213**	**13946**	**15091**	**18377**	21704	24979	28129
Madison	1083	1120	1553	2429	**3376**	**3914**	**3817**	**2443**	**2716**	**3855**	**5004**	**5702**	**8446**	**13358**	**17174**	**20746**	10333	10868	11314
McDowell	1122	1279	1383	1880	2092	2404	2593	**3882**	**3990**	**5150**	**5156**	**4840**	**5565**	**7167**	**7667**	**9722**	22104	23325	24448
Mitchell	297	592	772	1233	1674	1460	1654	**2157**	**2735**	**3518**	**4024**	**4120**	**4895**	**6055**	**6983**	**7919**	8064	8203	8244
Swain	275	356	484	516	895	1600	**1972**	**2475**	**2232**	**2608**	**2575**	**2781**	**3107**	**4853**	**5664**	**7105**	7882	8729	9508
Transylvania	351	899	782	1012	**1115**	**1255**	**1363**	**1873**	**2038**	**2966**	**4248**	**5199**	**7032**	**10234**	**12893**	**15553**	16740	17566	18101
Watauga	613	895	954	1473	1915	2402	**2427**	**2575**	**3011**	**4146**	**4945**	**5554**	**8595**	**14662**	**19538**	**23155**	24777	25921	26673
Wilkes	2294	2796	2946	3637	**4300**	**5095**	**5742**	**6290**	**6802**	**9283**	**11474**	**12659**	**15906**	**22117**	**24960**	**29261**	30170	30830	31323
Yancey	389	775	844	1448	**1799**	**2174**	**2289**	**2892**	**2920**	**3776**	**4109**	**4061**	**4563**	**6882**	**7994**	**9729**	10403	10919	11301
Total	17706	21945	25315	35178	45148	54401	62277	71207	87657	122180	152282	178995	221828	314777	373097	458923	504024	546844	585686

Table A-3: Estimate of total improved farmland area by present county boundary, in ha. Census counts are in bold. For the quinquennial Census of Agriculture dates between 1954-2002, the values at the decade break are linearly interpolated using the two nearest dates. All non-bold historic values are estimates corrected for changes in county boundaries using an areal interpolation model weighted on an estimated amount of suitable agriculture area. Future projections are estimated by extrapolating exponential trend models developed using the 1970-2000 data.

County	1850	1860	1870	1880	1890	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010	2020	2030
Alleghany	8213	12459	18331	30249	47899	34397	**38696**	**37146**	**37168**	**39576**	**39923**	**22936**	**28561**	**23839**	**21648**	**23437**	22567	22376	22187
Ashe	18043	22178	24341	47419	47899	62554	**66289**	**63961**	**70024**	**74671**	**69782**	**46660**	**45598**	**38556**	**26905**	**28571**	22932	19741	16994
Avery	1964	3979	4274	7323	9350	15596	17809	**14904**	**18871**	**21270**	**19848**	**14473**	**9705**	**5472**	**5081**	**8189**	9138	11179	13676
Buncombe	26572	29660	27257	40308	**48483**	**57580**	**63721**	**52394**	**52895**	**57092**	**48585**	**41342**	**35249**	**23618**	**24575**	**23398**	23636	23526	23416
Burke	12231	13862	13914	17925	**22603**	**26051**	**28796**	**23658**	**31109**	**24285**	**21626**	**22546**	**9676**	**9690**	**8060**	**8399**	7531	7012	6528
Caldwell	10539	16305	16931	18804	24646	28794	**30232**	**24793**	**24690**	**26122**	**22051**	**21220**	**11087**	**9342**	**7899**	**8803**	8161	7922	7690
Clay	9212	12270	9386	12411	**15457**	**16967**	**21114**	**16830**	**26312**	**18758**	**15238**	**13092**	**9763**	**6650**	**5234**	**5613**	4898	4500	4134
Cherokee	3949	4035	5662	7159	**10481**	**9702**	**9949**	**10067**	**11874**	**12631**	**9957**	**8301**	**6644**	**4574**	**4241**	**3909**	3617	3344	3091
Graham	1744	1896	1451	5089	**7757**	**7224**	**9011**	**7065**	**7331**	**5873**	**5613**	**5354**	**3513**	**1914**	**1653**	**1700**	1556	1467	1382
Haywood	7103	10706	14092	21097	**28203**	**34213**	**38664**	**33102**	**41125**	**42910**	**40561**	**30154**	**27852**	**21068**	**19218**	**17373**	15800	14348	13029
Henderson	7638	13759	15401	18391	**23475**	**23784**	**25542**	**21509**	**26060**	**26137**	**24743**	**24833**	**20600**	**17261**	**15928**	**14276**	13046	11865	10790
Jackson	5508	11606	9241	13285	**17204**	**22571**	**23399**	**20144**	**24064**	**26297**	**21781**	**17437**	**7435**	**3959**	**3666**	**4163**	4126	4231	4339
Macon	5659	8884	10366	15932	**21246**	**22494**	**26367**	**20938**	**25172**	**27634**	**22263**	**15346**	**12510**	**6207**	**5855**	**5855**	5631	5469	5312
Madison	11567	13190	13275	27959	**34480**	**40720**	**45920**	**42998**	**47568**	**55806**	**52922**	**42103**	**39794**	**25118**	**20227**	**17865**	14836	12512	10552
McDowell	10864	11074	12250	15812	19761	19357	18602	**13347**	**18386**	**13243**	**15870**	**17785**	**7267**	**4231**	**4995**	**5524**	6381	7291	8331
Mitchell	2998	6743	6518	11880	16181	13630	15399	**17928**	**21032**	**23752**	**20821**	**13290**	**12287**	**6344**	**5140**	**5562**	4963	4647	4351
Swain	2882	4270	4944	4155	5374	11009	**13616**	**11290**	**17217**	**13063**	**7173**	**7510**	**2323**	**1727**	**1131**	**1417**	1152	1043	945
Transylvania	2873	9991	7542	8243	**11502**	**12033**	**11820**	**7844**	**10668**	**10116**	**9925**	**7253**	**4010**	**5692**	**3855**	**4536**	3693	3297	2943
Watauga	6593	9666	10881	26973	25434	33787	**41173**	**34049**	**37478**	**39337**	**37765**	**28151**	**18875**	**12831**	**12785**	**14241**	14727	15515	16345
Wilkes	26435	29586	33226	40530	**50957**	**53543**	**60166**	**44461**	**64058**	**60934**	**47477**	**42646**	**31226**	**27664**	**26933**	**32537**	34040	36916	40036
Yancey	4225	8827	7268	18362	**22065**	**21497**	**26665**	**24926**	**25590**	**30727**	**27489**	**21682**	**20181**	**10520**	**9014**	**8890**	7983	7339	6746
Total	186812	254946	266551	409306	510457	567503	632950	543354	638692	650234	581413	464114	364156	266277	234043	244258	22567	22376	22187

Table A-4: Estimate of total developed area by present county boundary, in ha. The baseline is an aggregated version of the 2001 NLCD data set corrected for agriculture-overestimation. Historic values from 1940-1990 and forecasts from 2010-2030 are estimated via disaggregation of Census Block Group estimates using the method of Theobald (2005). Historic values from 1850-1930 are extrapolated from exponential fit models developed using the 1940-2000 data. Future projections are estimated by extrapolating linear or exponential trend models (depending on the county) developed using the 1950-2000 data.

County	1850	1860	1870	1880	1890	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010	2020	2030
Alleghany	169	208	259	322	402	503	631	791	994	1204	1511	2007	2570	3533	3903	4526	4790	4979	5107
Ashe	330	397	479	578	698	845	1023	1241	1506	1751	2190	2733	3353	4437	4791	5455	5979	6388	6726
Avery	173	211	260	322	400	497	619	771	962	1224	1505	1795	2201	3164	3803	4379	4707	4824	4848
Buncombe	1501	1828	2222	2711	3313	4049	4949	6050	7398	8727	10866	13710	17088	21982	24510	28409	32329	36303	40145
Burke	566	728	941	1220	1584	2058	2675	3483	4534	5571	7552	10233	13388	19553	22043	25972	26396	27776	28831
Caldwell	484	628	814	1062	1385	1810	2366	3093	4048	4737	6949	9526	12664	18011	20460	23136	23976	24470	24783
Clay	216	267	334	417	525	662	836	1057	1336	1663	2227	2640	3310	4652	5522	6885	8004	8926	9676
Cherokee	83	104	130	166	213	274	353	458	595	758	1038	1310	1606	2506	2924	3692	4611	5397	6045
Graham	89	107	128	156	191	234	289	357	442	480	725	858	1097	1478	1592	1809	1861	1891	1899
Haywood	565	677	811	972	1166	1401	1683	2023	2432	2772	3427	4397	5269	6742	7281	8168	8763	9353	9870
Henderson	408	522	670	859	1108	1430	1845	2387	3087	4018	5049	6656	8394	12320	14644	17911	21609	25301	29066
Jackson	211	267	340	433	554	711	910	1170	1505	1994	2483	3013	4008	5989	6722	8716	10014	10900	11650
Macon	220	279	358	459	594	770	998	1298	1687	2250	2813	3499	4704	7082	8572	10009	11820	13605	15320
Madison	450	523	610	712	831	970	1133	1325	1550	1780	2133	2459	2905	3655	3892	4556	4842	5093	5302
McDowell	281	360	462	595	768	995	1291	1676	2175	2685	3578	4860	6531	9238	10090	12676	13506	14251	14938
Mitchell	306	361	426	503	596	708	842	1002	1189	1285	1683	2123	2533	3187	3404	3633	3700	3763	3782
Swain	138	166	200	243	296	362	443	544	667	823	1011	1190	1440	2115	2344	2692	2986	3307	3602
Transylvania	193	243	307	388	493	627	799	1018	1299	1576	2147	2700	3471	4899	5729	6622	7127	7479	7707
Watauga	181	227	286	362	459	583	742	945	1205	1633	1913	2257	3048	4630	5504	6227	6663	6971	7173
Wilkes	588	751	962	1234	1584	2034	2614	3360	4323	5171	6993	9407	12555	17756	19489	22281	22972	23476	23851
Yancey	202	240	289	349	423	513	622	756	920	1074	1391	1675	1950	2733	3013	3465	3705	3888	4025
Total	7354	9094	11288	14063	17583	22036	27663	34805	43854	53176	69184	89048	114085	159662	180232	211219	230360	248341	264346

Table A-5: Estimate of total forestland area by present county boundary, in ha. These data are the residuals of the county area after developed areas, improved farmland, water bodies, and bare rock areas have been subtracted.

County	1850	1860	1870	1880	1890	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010	2020	2030
Alleghany	51938	47653	41730	29749	12019	25420	20993	22383	22158	18887	18233	34724	28536	32295	34116	31704	32310	32312	32374
Ashe	92019	87817	85572	62395	61795	46993	43080	45190	38862	33339	37789	60368	60810	66768	78065	75735	80850	83632	86042
Avery	61615	59562	59218	56107	54002	47659	45324	48077	43919	39211	40352	45437	49799	53069	52821	49137	47860	45703	43182
Buncombe	141773	138358	140367	126827	118050	108217	101176	111402	109553	103492	109860	114259	116974	123711	120226	117504	113347	109483	105751
Burke	117182	115389	115124	110834	105792	101870	98508	102838	94336	101860	102538	98937	108652	102473	101613	97345	97789	96929	96358
Caldwell	110882	104972	104160	102039	95874	91301	89307	94019	93167	91569	93428	91682	98677	95075	94069	90489	90291	90036	89955
Clay	108733	105624	108441	105333	102179	100532	96211	100274	90513	97113	100069	101802	104461	106232	106778	105036	104633	104109	103725
Cherokee	51739	51632	49979	48446	45077	45795	45469	45246	43302	42767	45161	46545	47906	49076	48991	48555	47928	47416	47020
Graham	74031	73861	74285	70619	67916	68406	66564	68442	68091	70209	70224	70350	71952	73170	73317	73053	73146	73205	73282
Haywood	135544	131829	128309	121143	113843	107598	102865	108087	99655	91676	93370	102807	104237	109548	110859	111817	112795	113658	114459
Henderson	88515	82280	80490	77311	71978	71347	69174	72665	67414	62566	62929	61232	63727	63140	62149	60534	58067	55556	52865
Jackson	121337	115183	117475	113338	109298	103774	102747	105742	101487	93553	97580	101394	110401	111896	111456	108965	107704	106713	105856
Macon	127879	124595	123034	117367	111918	110494	106393	111522	106899	101730	106538	112769	114400	118325	117187	115750	114163	112540	110983
Madison	104462	102766	102594	87808	81168	74789	69426	72156	67361	55221	57752	68245	70108	84034	88688	90386	93129	95203	96953
McDowell	103266	102977	101699	98004	93882	94059	94518	99388	93850	97358	93838	90641	99488	99817	98201	95086	93400	91744	90018
Mitchell	53850	50050	50210	44771	40377	42816	40913	38224	34933	29419	31952	39043	39636	44925	45912	45261	45794	46046	46324
Swain	133960	132544	131836	132582	131310	125609	122921	125146	119096	122816	128518	128002	132939	132860	133227	132593	132564	132352	132155
Transylvania	94716	87548	89933	89151	85787	85122	85163	88920	85815	84524	84144	86263	88735	85625	86632	85058	85396	85441	85567
Watauga	73844	70725	69451	53283	54725	46248	38703	45624	41935	37265	38557	47827	56312	60774	59946	57767	56845	55750	54717
Wilkes	168226	164912	161061	153485	142708	139672	132469	147428	126868	125749	137384	139801	148073	146434	145432	137036	134842	131462	127967
Yancey	76457	71817	73327	62173	58396	58874	53597	55202	54374	47069	49990	55513	56739	65617	66843	66515	67183	67644	68100
Total	2091968	2022094	2008295	1862765	1758094	1696595	1625521	1707975	1603588	1547393	1600206	1697641	1772562	1824864	1836528	1795326	1790027	1776923	1763641