ABSTRACT

FISHER, MANSFIELD. Land Use and Forest Type Change in the U.S. South. (Under the direction of Dr. Bob Abt and Dr. Walter Thurman).

Currently, there are few econometric land use models that recognize the heterogeneity of forestland, which makes it difficult to understand how demand for new forest products affects the distribution of forest types. I construct an econometric land use change model to examine how changing market forces could affect forest types in twelve states in the U.S. South. There is broad concern about the effects of increasing wood pellet export demand on forests in the southeastern U.S. Total wood pellet exports from the U.S., measured in metric tons, is used as an independent variable to empirically test for effects of increased wood pellet export demand on the shares of land uses and forest types. Seven land use categories are modeled: five forest types, agriculture land, and developed land. Using different sets of geographic dummy variables, two econometric land use models are estimated using Seemingly Unrelated Regression (SUR) analysis. Results indicate that different forest types are affected differentially by drivers of land use change, highlighting the importance of developing land use change models that capture forest type dynamics. I find that demand for wood pellet exports has a positive marginal effect on the share of pine plantations, oak-pine forests, natural pine forests, and bottomland hardwood forests, but a negative marginal effect on the share of upland hardwood forests. The shares of all forest types and land uses demonstrate an inelastic relationship to wood pellet exports. Pine plantations are the most sensitive forest type to changes in wood pellet exports followed by natural pine forests. Although this is an important first step in understanding the effects of increased demand for wood pellet exports, future analyses should use a county-level fixed effects model that completely controls for cross-sectional variation and therefore provides a better

empirical test of whether or not increased demand for wood pellet exports affects southern forests.

Land Use and Forest Type Change in the U.S. South

by
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DEDICATION

This thesis is dedicated to my wife, Caroline, and family. Without their love and support I could not have completed my graduate degree.

BIOGRAPHY

Mansfield Fisher is a candidate for the degree of Master of Science in Economics and Forestry at North Carolina State University.

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CHAPTER 1: POLICY BACKGROUND

1.1: INTRODUCTION

Since the inception of plantation forests in the U.S. South in the 1950s, there has been concern over the conversion of natural forests to planted or managed forests. Over the last decade, the rise of the wood pellet industry has reinvigorated the concern about the loss of natural forests in the U.S. South. In Section 1.2, I examine the policy decisions and initial conditions that led to the establishment of the wood pellet export industry in the Southeast U.S. Section 1.3 briefly discusses the working forest landscape of the Southeast U.S. and why land use in this region is especially sensitive to market influences. In Section 1.4, I discuss the importance of forest heterogeneity in understanding the ecosystem services forests provide. To accurately understand the implications of market changes on forests in the U.S. South, land use change models that account for heterogeneity in forests are necessary.

1.2: THE RISE OF WOOD PELLETS

According to Bennet of Forest2Market (2019), wood pellet markets have existed for decades, but the market remained small as wood pellets were primarily used for heating homes or small-scale electricity generation in the Pacific Northwest and Northeast U.S. U.S. production of wood pellets remained small until the European Union passed the 2009 Renewable Energy Directive which induced a rapid expansion of demand for wood pellets produced in the U.S. South (Directive 2009/28/EC, 2009).

The Renewable Energy Directive of 2009 is a European Union (E.U.) policy which mandated that by 2020 the E.U. must obtain 20% of total energy consumption from renewable energy sources. Contained within this directive, is the declaration that biomass fuels are considered a renewable energy source (Directive 2009/28/EC, 2009). In December 2018, the

E.U. passed a revised version of the original Renewable Energy Directive that established a new renewable energy target of 32% by 2030 and reaffirmed the important role that biomass plays as part of the renewable energy portfolio (Directive 2018/2001, 2018). E.U. member states have the autonomy to decide how to reach these targets and are required to submit their own national renewable energy plans.

The United Kingdom (U.K.) was not alone in pursuing biomass, Peska et al. (2007) noted that as of the early 2000s, Sweden, Denmark, Germany, and Austria had highly developed pellet markets. However, the U.K. played a critical role in the development of the U.S. wood pellet export industry. The large increase in wood pellet consumption in the U.K. is primarily the result of two factors. The first factor was a result of E.U. policies that required the U.K. to meet E.U. renewable energy targets. The second factor was the disposition of the U.K.'s current energy portfolio, which relied heavily on coal. These two factors prompted the United Kingdom to aggressively embrace bioenergy through subsidies for the conversion of coal-fired energy plants to wood pellet-fired plants (Fanous & Moomaw, 2018; Goh et al., 2013; Sikkema et al., 2011; Watt, 2007). As of 2017, the U.K. was the largest consumer of wood pellets in the E.U., consuming 8.5 million metric tons, a 14.3% increase from 2016 (Calderon et al., 2019). Considering the U.K.'s limited ability to produce wood pellets, only 350,000 metric tons in 2015, the U.K. needed a large and stable source of wood pellets (Thrän et al., 2017). The established shipping capabilities of the Eastern seaboard and the abundance of working forests allowed the U.S. South to assert itself as a primary exporter of wood pellets to Europe and more specifically the U.K. In 2017, 80% of US wood pellet exports were sent to the U.K. (Ireland, 2018). Figure 1.1 shows the percentage of total wood pellet exports from the U.S. by export destination. Figure 1.2 shows the total wood pellet exports from the U.S. by export destination.

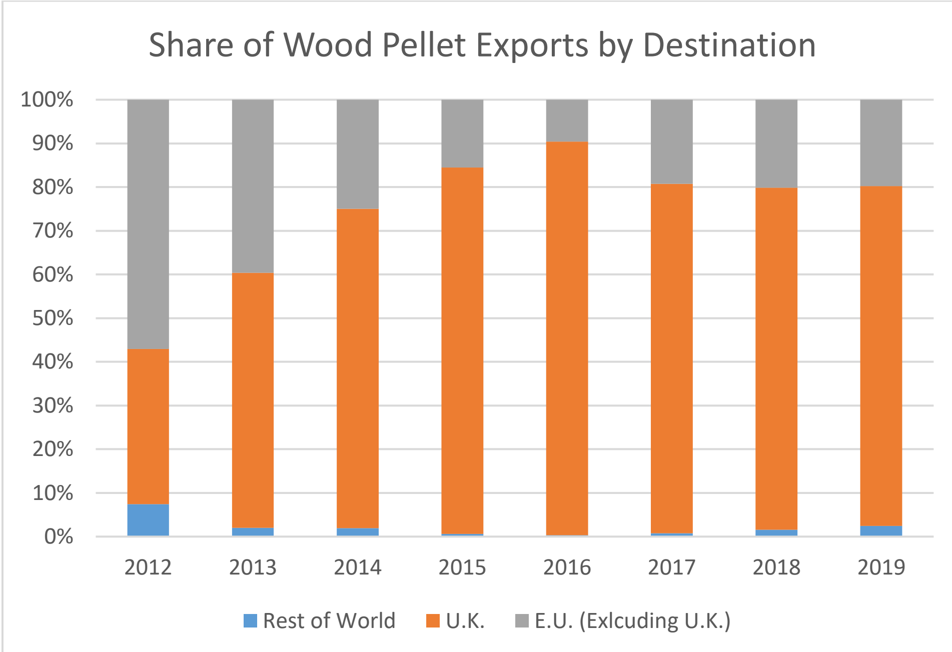

Figure 1.1: The share of total wood pellet exports from the U.S. by export destination (United States, 2020).

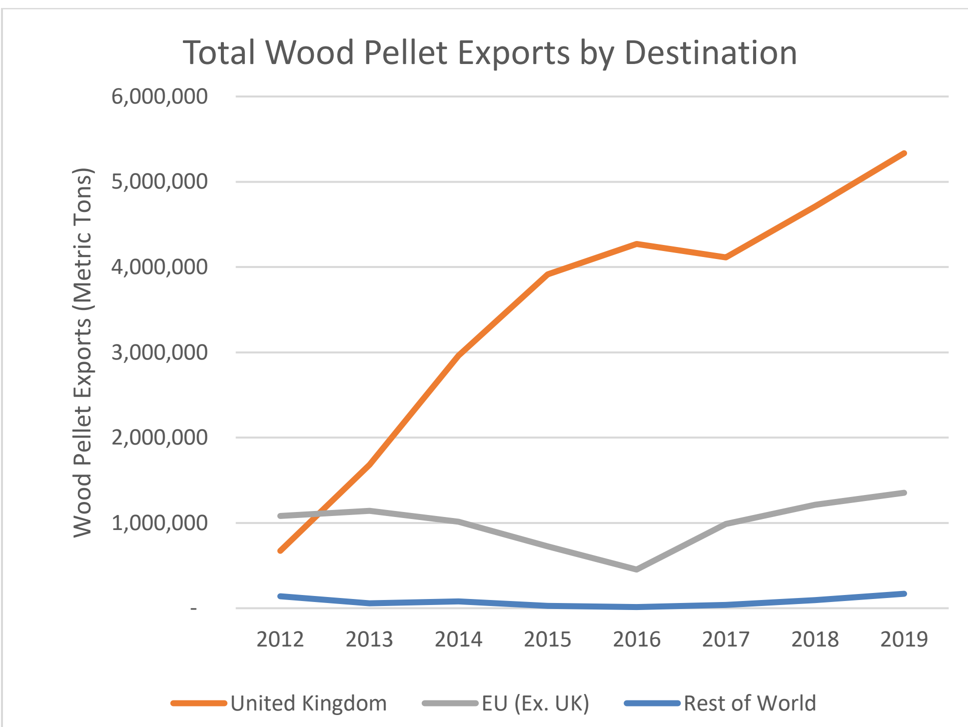

Figure 1.2: Total wood pellet exports by export destination (United States, 2020).

1.3: SOUTHERN WORKING FORESTS

Previous research has demonstrated that forests in the U.S. South can provide a reliable and stable timber supply, evidence that private forest owners respond to scarcity signals (Kim et al., 2018; Wear & Prestemon, 2004). Although this may seem obvious now, this was an important finding because private land ownership is especially high in the U.S. South. The majority of the U.S. South is privately owned, about 85% of total land (Butler & Wear, 2013). The U.S. Southeast is heavily forested with forest densities ranging from 40% to 80%, except in parts of Texas and Oklahoma. Also, southeastern forests grow quickly compared to other regions in the U.S., due to its subtropical climate (Butler & Wear, 2012). Since 1986 no other country has produced more timber than the Southeastern U.S. High forest densities, a climate that results in high timber growth rates, and high levels of private ownership make the Southeastern U.S. a predominantly working forest landscape (Wear & Greis, 2013). Because the Southeast is dominated by private forestland it is important understand how different types of forestland respond to market forces.

1.4: FOREST TYPES AND ECOSYSTEM SERVICES

Although the area of plantation forests has leveled off in many states, concern over the conversion of natural forests to plantation forests persists. The development of the U.S. Southeast as a primary exporter of wood pellets to the E.U. has reinvigorated concern about the conversion of natural forests to pine plantations and the potential loss of ecosystem services. (Schlesinger, 2018). Ecosystem services are the benefits that people derive from ecosystems. Carbon sequestration, water filtering services, and soil stabilization are all examples of ecosystem services provided by forests.

Private forest land in the US South primarily falls into two categories, naturally regenerated forests and managed plantation forests. Managed plantation forests occupy 24% of the southern forest landscape and are often managed using genetically improved seedlings, site preparation, and application of fertilizers and herbicide to maximize timber output (Fox et al., 2004). Naturally regenerated forests tend to be passively managed with occasional harvesting.

An important concern of many advocating for the protection of natural forests is the loss of biodiversity when natural forests are converted to plantation forests. In general, natural forests are thought to sustain a higher level of biodiversity than plantation forests (Brockerhoff et al., 2013). Carnus et al. (2006) highlighted four different components of biological diversity: genetic, species, structural, and functional diversity. A principal critique of plantation forests is that they are monocultures at the forest level and have an even-aged structure at the stand level, which ultimately results in a lower level of biological and structural diversity than natural forests. However, Carnus et al. (2006) concluded that planted forests can have a positive or negative impact on biodiversity levels depending on the level of interest (tree, stand, landscape) and the surrounding landscape context in which the plantation forest is situated. This finding emphasizes the need to contextualize changes in plantation forest acreage with changes in other forest types.

Duden et al. (2018) specifically investigated the effects of increased wood pellet demand on biodiversity. The researchers simulated increases in wood pellet demand using a partial equilibrium model, SRTS, and generated projections of five different forest type areas through 2030. Next, the researchers used the forest type area projections to create spatially explicit land use projections and overlayed these projections with species richness maps to gauge the effect the increased wood pellet demand on biodiversity. Ultimately, they concluded that whether biodiversity is projected to increase or decrease depends on the location and taxonomic group of interest. Results from Duden et al. (2018) emphasize the importance of developing land use and forest type change models that show how specific forest types are affected by economic forces in order to accurately understand their impacts on biodiversity. Put simply market forces affect forest types differentially and influence the portfolio of ecosystem services they provide across the landscape.

Beyond supporting biodiversity, forests provide a variety of other ecosystem services such as nutrient cycling, filtering services that enhance water quality, air quality maintenance, erosion control, and carbon sequestration (Brockerhoff et al., 2013). Brockerhoff et al. (2013) cited the empirically tested link between biodiversity and ecosystem productivity as one reason why natural forests, in general, provide higher levels of ecosystem services than plantation forests. Similarly, Meyer et al. (2015) concluded that land with higher levels of "naturalness" provide higher levels of ecosystem services. However, Brockerhoff et al. (2013) concluded that comparisons between natural and planted forests need to be contextualized by the surrounding ecological landscape, level of management intensity, species composition of plantation forests, and other factors. Because different forest types provide different levels of ecosystem services, it is important to understand how different forest types are affected by drivers of land use change.

1.5: CONCLUSION

Evidence from Section 1.2 indicates that the substantial increase in wood pellet production in the U.S. South is a result of E.U. renewable energy policy decisions, the U.K.'s existing energy infrastructure, the abundance of forestland in the U.S. South, and the existing trans-Atlantic shipping infrastructure along the eastern seaboard. Section 1.4 highlights the fact that not all forests are equal in their ability to supply ecosystem services. As a result, to better understand how market and other forces affect the supply of ecosystem resources, we must first understand how market forces affect different forest types and land uses.

CHAPTER 2: LITERATURE REVIEW

2.1: INTRODUCTION

The current chapter explores important drivers of land use change and research investigating the effects of the new export driven wood pellet industry on southern forests. Section 2.2 introduces the location and land quality theories of von Thünen and Ricardo that underpin models of land use change. Section 2.2 continues by describing the two different approaches that researchers have used in their treatment of forestland in econometric models of land use change. In Sections 2.3-2.5, I describe results primarily related to forestland from the land use change literature with a focus on highlighting results from these two different modeling approaches. Each section discusses one of three groups of land use change drivers that have been previously identified by Jeuck et al. (2014) as important determinants of land use change. The three groups are market, socioeconomic, and site quality forces. Of specific relevance to my analysis is whether previous research found evidence that drivers of land use change affect distinct forest types differently. In Section 2.6, I examine the results of several studies that investigated how increased demand for wood pellet exports could affect southern forests.

2.2: MODELS OF LAND USE CHANGE

In general, econometric land use models are based on the land quality and location theories developed by Ricardo and von Thünen (Bell et al., 2006, Chapter 6). Ricardian theory posits that biophysical characteristics, i.e. land quality, determine land use rents. In the Ricardian model of land use, land rents increase with land quality increases. Von Thünen contends that land rents and ultimately land use are a function of market access, i.e. proximity to markets. In von Thünen's land use model, land rents decrease as the distance from a central market increases. Both Ricardian and von Thünen theories rely on the assumption that landowners allocate a parcel of land to the land use that provides the highest economic return (Randall and Castle, 1985). Land use change models commonly model only private land dynamics because public land is often subject to non-economic forces. Many determinants used in land use change models today are derived from the theories of Ricardo and von Thünen.

Of specific interest in this analysis, models of land use change differ distinctly in their treatment of forestland. The majority of econometric land use change models treated forestland as a homogenous land use category. The studies that use a single forestland category rely on the assumption that land use change drivers affect different types of forestland similarly. There is a much smaller set of land use change studies that recognize the heterogeneity of forestland and disaggregated forestland into broad forest type groups. These studies allowed for the possibility that forest types could be affected differently by land use change drivers. Because I am interested in understanding how drivers of land use change, e.g. increased demand for wood pellet exports, affect southern forests it is necessary to examine the implications of treating forestland as heterogeneous or homogenous.

2.3: DRIVERS OF LAND USE CHANGE: MARKET FORCES

There is strong empirical evidence that economic rents are important determinants of land use (Jeuck et al., 2014). Previous models of land use change utilized a variety of variables to capture the effects of market forces such as measures of risk and uncertainty, but almost universally incorporated were land use economic rents. Due to the prevalence of rent variables in models of land use change, I focus the discussion of results on these determinants.

The expectation in the literature is that increasing economic returns to a specific land use results in an increase in the share of that land use on the landscape. This hypothesis is supported by empirical evidence from land use change models that treat forestland as a homogenous land use. For example, Ahn et al. (2002) constructed a land use change model for the South-Central U.S. that treated forestland as a homogenous land use category. The researchers used their estimated model to project the future extent of three land use categories: forest, agriculture, and developed/urban. Their results indicated that both agriculture and forest rents were important drivers of agriculture and forestland area. Specifically, they found that increasing forest rents increased the share of forestland and decreased the share of agriculture land. Conversely, increasing agriculture returns increased the share of agriculture land and decreased the share of forestland. Although Lubowski (2002) used a slightly different approach and modeled land use change across the entire U.S., his results supported the hypothesis that increasing economic returns to a given land use increase the share of that land use. His results indicated that economic returns to different land uses were important determinants in the probability of conversion to and from other land uses. Specifically related to forestland dynamics, he found that increasing returns to forestland increased the probability of other land uses converting to forestland.

However, evidence from the land use change literature that disaggregates forestland by forest type suggests that forest types are affected differentially by market drivers. For example, Sohngen and Brown (2006) included economic rents for each forest type in modeling forest-agriculture conversion dynamics. They estimated the rental value of each forest type in their analysis: the rental value for planted pine, natural pine, and upland hardwood. The researchers found that the rental value for pine plantations and natural pine forests were statistically significant and had a positive effect on the share of their respective forest type. However, the rental value for upland hardwood forests was not statistically significant in the upland hardwood regression equation.

For forest types other than pine plantations, it is often impossible to associate a specific management regime with a broad forest type, which makes it difficult to estimate economic returns. As a result, many land use change studies that disaggregate forestland used timber price time series as proxies for returns to different forest types (Nagubadi & Zhang, 2005). Nagubadi and Zhang (2005) estimated a land use change model that included three forest type groups and two land uses: softwood forests, mixed hardwood-softwood forests, hardwood forests, agriculture land, and urban land. Pine sawtimber and oak sawtimber price series were included as proxies for economic returns for the different forest types. The authors found that pine sawtimber prices had a positive marginal effect on the share of softwood forests and a negative marginal effect on the share of mixed hardwood-softwood forests and hardwood forests. Oak sawtimber prices had a negative marginal effect on the share of softwood forests and a positive marginal effect on the share of mixed hardwood-softwood and hardwood forests. These results generally support the hypothesis that increased returns to a specific land use or forest type increases the share of that land use or forest type on the landscape. However, softwood forests were almost twice as sensitive to changes in oak sawtimber prices and more than four times as sensitive to changes in pine sawtimber prices than the other forest types. Similar to land use change models that treat forestland as a homogenous land use category, studies that disaggregate forestland by forest type found that rents are important determinants of forest type shares. Further, the empirical evidence from studies that disaggregated forestland indicated that different forest types had varying levels of sensitivity to economic rents. These findings suggest that distinct types of forestland are affected differently by their respective economic rents.

Land use change studies that disaggregated forestland found that forest types also responded differently to agriculture rents. Sohngen and Brown (2006) found that agriculture rents had a statistically significant and negative effect on the share of all the forest types included in their analysis. This finding is consistent with findings from land use change studies that used a homogenous forestland group. However, based on the agriculture rent coefficient, the three forest types showed varying levels of sensitivity to changes in agriculture rents. Nagubadi and Zhang (2005) found that agriculture rents had a statistically significant and negative marginal effect on the share of softwood forests but did not have a statistically significant effect on the share of mixed and hardwood forest types. Zhang and Nagubadi (2005) also found that the share of softwood forests decreased as agriculture rents decreased but both mixed and hardwood forests were unaffected by changes in agriculture rents.

Based on the evidence from studies of land use change that recognize the heterogeneity of forestland, different forest types do not necessarily respond similarly to changes in economic rents. Forest types showed varying levels of sensitivity and in some cases were not affected by economic rents. Therefore, to accurately model how forestland is affected by changes in economic rents it is necessary to disaggregate forestland.

2.4: DRIVERS OF LAND USE CHANGE: SOCIOECONOMIC FORCES

Many models of land use change include socioeconomic variables. These variables often captured population dynamics, income dynamics, and levels of educational attainment (Jeuck et al. 2014). I highlight findings related to population density and per capita income, because they were two of the most commonly used socioeconomic variables. Some researchers included population density and per capita income explicitly as proxies for urban economic rents (Ahn et al., 2002; Mauldin et al., 1999; Platinga et al., 1999). However, others did not explicitly state that these measures were proxies for urban rents but cited that they captured the effects of population pressure (Nagubadi & Zhang, 2005; Zhang & Nagubadi, 2005). Irrespective of the authors' motivations for including population density and per capita income as drivers of land use change, the expectation was that as population density and per capita income increased more land would be dedicated to urban and developed uses.

Results from land use change models that treated forestland as homogenous generally find that increasing population pressure, measured by population density and per capita income, increased the share of urban land and decreased the share of forestland and agriculture land. For example, Plantinga et al. (1999) used population density as a proxy for returns to urban land uses and found that it had a statistically significant and positive effect on the share of urban land and a negative effect on the shares of agriculture land and forestland. Ahn et al. (2002) found that population density had a positive marginal effect on the share of urban land and a negative marginal effect on the share of forestland.

Results from land use change studies that treated forestland as heterogeneous found that forest types had the same general relationship; increasing population pressure led to smaller shares of all the forest types. However, results also indicated that some forest types are more negatively affected than others by increasing population pressure. For example, Nagubadi and Zhang (2005) found that average per capita income had a negative marginal effect on the share of all three forest types but softwood forests were twice as sensitive as mixed hardwood-softwood forests and almost five times as sensitive as hardwood forests to changes in per capita income. Their results also indicated that softwood and mixed forests were roughly five times more sensitive to changes in population density than hardwood forests.

The land use change literature that treated forestland as a single land use category established a clear empirical relationship between changes in population density and per capita income and the shares of agriculture, forestland, and urban land. Results from land use change models that disaggregate forestland demonstrated that forest types vary in their sensitivity to changes in population pressure. Consequently, to accurately understand how socioeconomic factors affect forestland it is necessary to use disaggregated forestland categories.

2.5: DRIVERS OF LAND USE CHANGE: SITE QUALITY

Jeuck et al. (2014) concluded that measures of site quality are especially important determinants of land use decisions between forestry and agriculture. Because site quality is a critical component in the productivity of timber and crop production, it is not surprising that site quality is an important determinant of land use. Site quality was commonly measured using the Land Capability Classification (LCC) system. LCC classes are based on the risk of soil damage and soil limitations. There are eight LCC classes (I-VIII) with I representing the best site quality and VIII representing the worst site quality (Klingebiel & Montgomery, 1961). Evidence from land use change models that treated forestland as homogenous generally found that as land quality increased, the share of agriculture land increased compared to other rural land uses. For example, Lubowski (2002) found that as land quality increased, the probability of agriculture converting to another rural land use decreased and the probability of other rural land uses converting to agriculture increased. Likewise, Nagubadi and Zhang (2005) found that counties with a higher percentage of land in the two best LCC classes, classes I and II, had larger shares of agriculture land and smaller shares of forestland.

Site quality was also an important group of determinants of land use in models using forest type categories; however, results suggested that the share of all forest types are not negatively affected by increases in site quality. Nagubadi and Zhang (2005) used the LCC system to capture site quality in their study. Specifically, they included the share of land that is in the two best LCC classes and the average LCC class within a county. Both site quality variables had a positive marginal effect on the share of hardwood forests, but a negative marginal effect on the share of softwood and mixed hardwood-softwood forests. Softwood forests were more sensitive than the other forest types to changes in the share of land in the two best LCC classes; however, hardwood forests were more sensitive to changes in the average LCC class. Results from Zhang and Nagubadi (2005) indicated that mixed hardwood-softwood forests were the most sensitive to changes in the share of land in the two best LCC classes and the share of softwood forests was not affected by changes in site quality. To account for site quality differences between counties, Sohngen and Brown (2006) used a dummy variable that represented counties with more than 50% of land dedicated to agriculture. Their results indicated that the share of all forest types was smaller in counties when more than 50% of the county land was in agriculture; however, the magnitude of the coefficient estimates for the forest types were different. Clearly forest types are not affected uniformly by changes in site quality.

Sections 2.3-2.5 revealed that forest type groups are affected differently by market, socioeconomic, and site quality factors. Many of the determinants of land use change showed varying levels of statistical significance, varying levels of sensitivity, and unexpected relationships with respect to the different forest type groups. Due to the limited number of studies that disaggregated forestland, it is difficult to highlight empirically robust relationships between many of the drivers of land use change and forest type groups. However, it is evident that to accurately understand the market, socioeconomic, and site quality influences on forestland it is necessary to use disaggregated forestland groups. Based on these conclusions, I construct a land use change model that disaggregates forestland into five different forest type groups and includes agriculture and developed land uses. Based on a review of the literature, variables that capture market, socioeconomic, and site quality effects are important determinants of land uses.

2.6: EFFECTS OF INCREASED DEMAND FOR WOOD PELLETS

In this section, I present results from key studies related to how increased wood pellet demand could affect southern forests. However, none of the studies discussed below use a land use change model to assess how increased demand for wood pellet exports could affect the share of different forest types and land uses. [To my knowledge, the land use model constructed in my analysis is the first land use change model to explicitly include wood pellet exports as a potential driver of land use/forest type change.] Although these studies used different empirical methods, their results are still relevant to my analysis because they investigated the effects of increased wood pellet demand on forests in the U.S. South. They also provide an avenue to demonstrate how the results of my research could be used and integrated into other models.

The first three studies discussed, Duden et al. (2017), Costanza et al. (2015), and Costanza et al. (2017), used similar methodological approaches to examine how increased demand for wood pellet exports affects the share of different forest types. All three studies relied on the SubRegional Timber Supply (SRTS) model developed by Abt et al. (2002). The SRTS model integrates economic theory with growth dynamics of southern forests to provide a platform to model timber supply and demand changes. Because I am interested in forest type area change, I focused specifically on this aspect of the SRTS model, but for more information on the SRTS model refer to Abt et al. (2002). The SRTS model allows forest types to respond to price changes based on their relative timber price elasticities. To model how increased demand for wood pellets affects the areas of different forest types, the researchers first inputted scenarios of increased demand for wood pellets into the SRTS model. The SRTS model forecasts how timber prices respond to the inputted demand scenarios and based on the relative price sensitivity of each forest type, the SRTS model outputs how the area of each forest type is affected. The

SRTS model outputs how the resulting price changes affected the share of five different forest types: pine plantation, oak-pine forests, natural pine forest, upland hardwood forests, and bottomland hardwood forests. Duden et al. (2017) used the new projected areas of the five forest types as inputs for a spatial allocation model which spatially assigned the changes in the different forest types to geographic locations. Costanza et al. (2015, 2017) converted the forest type area outputs from the SRTS model into annual transition targets that represented annual conversions among forest types. These annual transition targets were used as inputs for a state-and-simulation model (ST-Sim), which resulted in outputs of land use transitions. Although their methodological approaches are not identical, all three studies relied on the SRTS model to estimate the effects of increased wood pellet demand on forest type area.

As explained, the SRTS model bases its estimates of forest type area on their relative sensitivity to timber prices. The default settings in the SRTS model are based on a heuristic that pine plantations are twice as price responsive as natural pine, oak-pine, and upland hardwood forests. Bottomland hardwood forests are half as price responsive as natural pine, oak-pine, and upland hardwood forests. Land use change models that disaggregate forestland into forest type groups can estimate how sensitive the different forest types are to changes in timber prices. These empirically based timber price elasticities could improve forest type acreage change estimates from models like the SRTS model.

The results discussed below are relevant for my study because they investigated the effects of increased wood pellet demand on southern forests, a primary goal of my research. The results from these four studies serve as a point of comparison for the results from my analysis. Duden et al. (2017) defined four scenarios of future wood products demand. These four scenarios were characterized by varying levels of wood pellet and housing demand. The researchers used a forecasting horizon of 20 years, 2010 to 2030. Their results indicated that increased wood pellet demand led to an overall larger share of forestland area; however, the increase in forestland was primarily driven by increasing pine plantation acreage. The researchers found that increased wood pellet demand led to more conversions of natural forests to pine plantations. Mixed pine and natural pine forests were the natural forest types that lost the largest amount of acreage to pine plantations. Duden et al. (2017) also spatially assigned the increases or decreases in the various forest types and land uses. Projections from the spatial land use allocation model showed that conversions of natural forests to pine plantations primarily occurred in the coastal regions of Virginia, North Carolina, South Carolina, Georgia, Alabama, and Mississippi.

Constanza et al. (2015) investigated the effects of wood pellet demand on land use and forest dynamics in North Carolina. The researchers defined two bioenergy scenarios using the same level of wood pellet demand but varied the portion of harvest residuals that were used as feedstock to meet the increased wood pellet demand. Consistent with evidence provided by Duden et al. (2017), Costanza et al. (2015) concluded that increased wood pellet demand led to a larger share of forestland. Although there was a larger share of forestland, the forestland in the wood pellets scenarios was subject to a higher degree of management e.g. more thinning and harvesting. Their results also showed that increased demand for wood pellets led to a smaller share of agriculture land.

Costanza et al. (2017) continued their previous work by expanding the demand scenarios to incorporate biofuels other than wood pellets. They defined five different demand scenarios that include various levels of demand for liquid biofuel from purpose-grown crops and wood pellets. As another dimension to the demand scenarios, restrictions were imposed on where purpose-grown crops could be farmed, from either marginal agriculture land or marginal forestland. These restrictions mandated a certain amount of conversion of either marginal agriculture land or marginal forestland. The researchers' results substantiated evidence from previous studies; increased demand for wood pellets increased the share of forests relative to a baseline scenario that included no demand for wood pellets. Results related to the shares of different forest types showed that the shares and total area of both pine plantations and oak-pine forests increased as a result of increased demand for wood pellets. The share and total area of bottomland hardwood forests decreased in all three scenarios that included demand for wood pellets. Although the share of upland hardwood and natural pine forests decreased in all three wood pellet scenarios, the total area of these forest types increased in two of the three scenarios. Like Duden et al. (2017), Costanza et al. (2015, 2017) found that increased demand for wood pellets does affect forest type composition and structure and the effects are spatially heterogeneous.

Dale et al. (2019) used a fundamentally different approach than the previous studies discussed in this section. The researchers utilized the Forest Inventory and Analysis (FIA) Program dataset to test if forest characteristics and conditions from a pre-wood pellet and post-wood pellet period were significantly different. The study area was comprised of two different geographic areas, which the researchers called fuelsheds, surrounding the Port of Savannah and Port of Norfolk. These fuelsheds were chosen because these two ports shipped over half of the total wood pellets exported from the United States. The study used a 120-kilometer radius around the ports to define the two fuelshed areas. Four groups of forest characteristics were compared: total volume of timber inventory in naturally regenerated stands and plantations, the number of dead trees per hectare, stand age structure, and carbon stocks. The wood volume in natural forests increased in the Savannah fuelshed but remained unchanged in the Chesapeake fuelshed. The carbon content of soil and leaf litter, live harvestable material, and dead non-harvestable material increased in the Savannah fuelshed and increased or remained the same in the Chesapeake fuelshed. Ultimately, the researchers concluded that increased demand for wood pellets were not affecting forests in the Southeast, evidence contrary to the conclusions of Duden et al. (2017) and Costanza et al. (2015, 2017). An important limitation of this study is that it did not include analysis of forest type acreage changes in the study areas, which makes it difficult to compare their results with results of the other studies discussed in this section. However, this study is important because it showed that depending on the forest characteristics of interest, conclusions as to whether increased demand from wood pellet exports affects southern forests can vary. Further, the researchers acknowledge that effects from increased wood pellet demand on southern forest may not have yet been realized.

Previous research on the effects of increased demand for wood pellets on southern forests found evidence that increasing demand for wood pellets led to increases in pine plantation area that comes from the conversion of natural timberland and agriculture land. However, forest types are affected differentially by increased demand for wood pellets with some forest types being more affected than others. Results from Dale et al. (2018) found that increased demand for wood pellets were not affecting southern forests, demonstrating that increased demand for wood pellets may affect some forest characteristics but not others.

In conclusion, Sections 2.2-2.5 discussed market, socioeconomic, and site quality factors that affect the distribution of land uses and influence land use change. These sections underscored the importance of disaggregating forestland by forest type, as the evidence suggests that many drivers of land use change affect distinct forest types differently. Based on these conclusions, I disaggregate forestland into different forest types and include several of the previously discussed drivers of land use change in the land use model constructed in my analysis. Section 2.6 presented results from previous research on how increased demand for wood pellets could affect southern forests. These results serve to contextualize the results from my land use change model with the expanding body of research investigating the effects of increased wood pellet demand on southern forests.

Chapter 3: Data and Methods

3.1: INTRODUCTION

In Chapter 3, I describe the data utilized in my analysis to construct an econometric land use model with heterogeneous forestland. The discussion of the data highlights the sources and methods used to construct the dataset. In Sections 3.2 and 3.3, I describe the inventory data used to construct the dependent variable in the land use model, which is based on the share of different forest types and land uses within a county. Sections 3.4-3.8 discuss the independent variables used in my analysis.

3.2: FIA DATA FOR LAND USES AND FOREST TYPE ESTIMATES

In this analysis, I constructed a land use share model in which the dependent variables are based on estimates of land use area. The Forest Inventory and Analysis (FIA) database serves as the source for land use and forest type acreage estimates, which were developed for each county within the study area. The Forest Inventory and Analysis program of the USDA Forest Service is a national forest inventory system designed to determine "the extent, condition, volume, growth, and use of trees on the Nation's forestland" (Burrill et al., 2018, p. Preface-3).

In the early 2000s, the USDA Forest Service (USFS) switched from a ten-year periodic survey to a continuous annual survey system. Depending on the state and year, the entire state is surveyed on a 5-year cycle or 7-year cycle. A 5-year cycle consists of 5 panels, each panel represents 20% of the total inventory plots within a cycle. A single panel consists of all inventory plots that are sampled within the same year. Similarly, a state using a 7-year cycle samples 14.3% of inventory plots each year. Each panel contains sample inventory plots that are randomly distributed across the entire state. Figure 3.1 demonstrates the implementation of a 5-year continuous annual survey system.

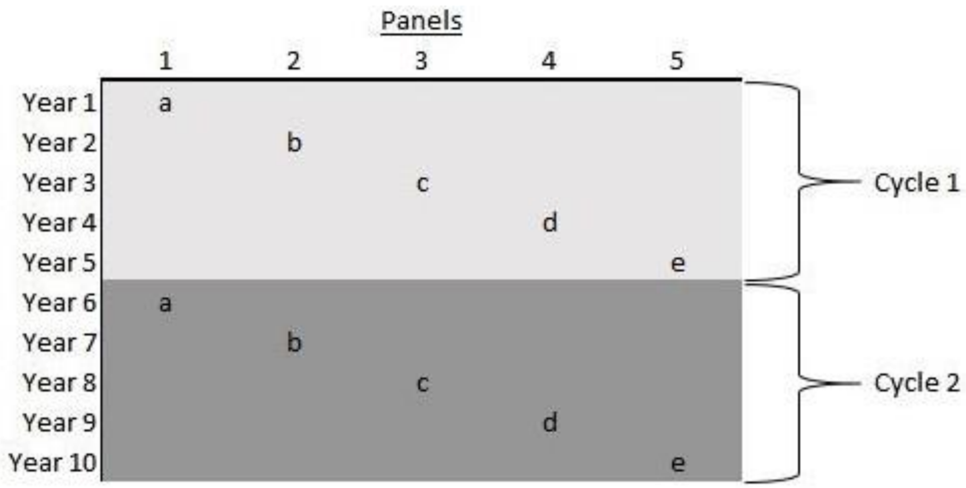

Figure 3.1: 5-year rotating annual panel sampling design of the FIA program (Westfall et al., 2013).

The FIA sampling and stratification methodology consists of three phases. I focus on the descriptions of Phase 1 and Phase 2 because they are the basis for estimating forest type acreages. Phase 1 uses remote sensed data to classify land into various groups, which is then used to develop strata i.e. grouped plots with similar characteristics. Stratification is a statistical technique that reduces the variance of estimates from the inventory data. USFS staff visit Phase 2 inventory plots and conduct on-the-ground sampling. Phase 2 inventory plots are designed to cover a 1-acre sample area and are sampled according to a national standard of fixed radius plots. Each plot consists of four subplots. Figure 3.2 shows the nationally standardized fixed-radius plot design. Each inventory plot represents approximately 5,900 acres of land (Burrill et al., 2018). More information on the FIA sampling methodology can be found in Beechtold and Patterson (2005).

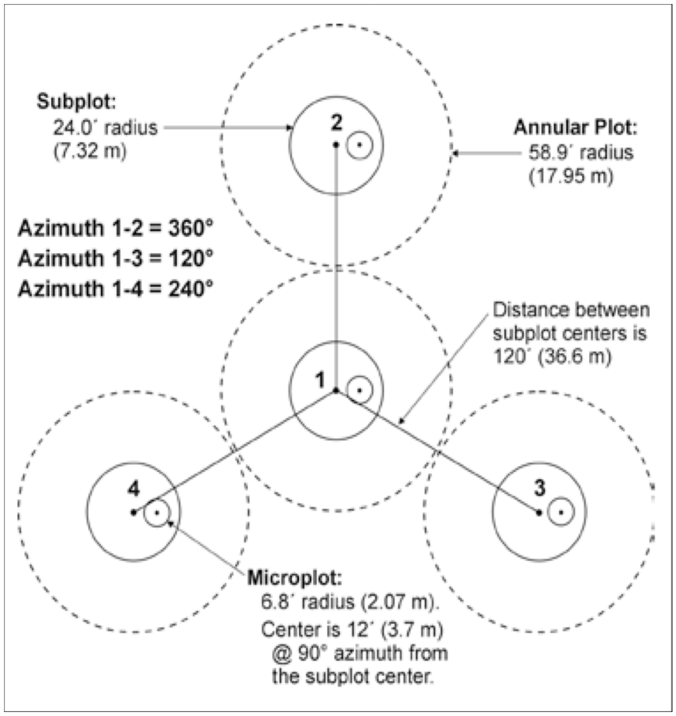

Figure 3.2: FIA Phase 2 sampling plot design (Burrill et al., 2018).

3.3 LAND USE AND FOREST TYPE DEFINITIONS

In Section 3.3, I describe the forest type and land use definitions used in my analysis. A combination of FIA variables was used to construct these definitions. Table 3.1 describes how the FIA variables were used to construct the forest type and land use definitions.

Table 3.1: Forest type and land use definitions used in the analysis as defined by a combination of variables from the FIA Database.

Forest Type/land use	FIA Variables Used to Define Forest Types	Definition of Forest Type/Land Use
Pine Plantations	Owner Group Code, Forest Type Code, Stand Origin Code	Loblolly, slash pine, loblolly/hardwood, slash pine/ hardwood, or non-stocked forest types that are artificially regenerated.
Bottomland Hardwood Forests	Owner Group Code, Forest Type Code, Stand Origin Code	Oak/Gum/Cypress group, Elm/Ash/Cottonwood group, Tropical Hardwood groups, or Topical Pines group and can be naturally or artificially regenerated.
Upland Hardwood Forests	Owner Group Code, Forest Type Code, Stand Origin Code	Oak/Hickory group, Maple/Beech/Birch group, Aspen/Birch group, Other Hardwoods group, or Exotic Hardwoods Group.
Oak-Pine Forests	Owner Group Code, Forest Type Code, Stand Origin Code	Eastern white pine/northern red oak/white ash, Eastern red cedar/hardwood, longleaf pine/oak, shortleaf pine/oak, Virginia pine/southern red oak, other pine/hardwood, slash pine/hardwood that was naturally regenerated, loblolly pine/hardwood that was naturally regenerated.
Natural Pine Forests	Owner Group Code, Forest Type Code, Stand Origin Code	White/red/jack pine group, Spruce/fir group, longleaf pine, shortleaf pine, Virginia pine, Sand pine, Table mountain pine, Pond pine, Pitch pine, Spruce pine, Other Eastern softwoods group, Fir/spruce/mountain hemlock group, Exotic Softwoods group, Other Softwoods group, slash pine that was naturally regenerated, loblolly pine that was naturally regenerated.
Agriculture Land	Land Use SRS	Cropland and Pasture.
Developed Land	Land Use SRS	Developed Land

The seven land uses and forest types used in this analysis do not include all land uses within a county. On average across the dataset, these seven land use/forest type categories represented 90.2% of total land within a county. There are two reasons why this occurs. First, only private forestland is used in the analysis. Second, there are eight land use categories that were dropped from the analysis. The rangeland land use category is not included in the analysis because the majority of counties do not have rangeland. Because the empirical model requires that each county have some land dedicated to each land use/forest type category, counties with no land classified as rangeland could not be used in the analysis. The inclusion of the rangeland land use category would have significantly reduced the number of counties used in the analysis. Rangeland, as defined by the FIA program, is "land primarily composed of grasses, forbs, or shrubs. This includes lands vegetated naturally or artificially to provide plant cover managed like native vegetation and does not meet the definition of pasture" (Burrill et al., 2018, p. 2-59). Based on this definition it did not seem appropriate to include rangeland in the agriculture land use category. Ultimately, because it was not feasible to include a separate rangeland category and it did not seem appropriate to included rangeland in the agriculture land category, rangeland was excluded from the analysis.

There are seven other land use categories that were not included in the analysis: Other, Non-vegetated, Wetland, Beach, Non-forest, Census Water, Noncensus Water, and Nonsampled. These land use categories were not included in the analysis because there was no clear way to incorporate them into the land use categories that were used in the analysis and many of them are not influenced by humans. For example, census and noncensus water cannot be converted to another land use.

Because the total amount of land in each county was not modeled, it was possible that the total number of acres of land in the seven land use categories included in the analysis could change over time. Across the dataset, the total amount of land from each county that was in the seven different modeled land uses/forest types was relatively stable, indicating that conversion from one land use to another primarily occurred between one of the seven land uses/forest types that were used in the analysis. On average the total land within the seven land use/forest type categories within a county changed 0.4% across the study period. The largest change in the total area modeled within a county over the study period was 12.25%.

I constrained forest type acreage estimates to private land ownership because public land use decisions are assumed to be governed by non-economic factors. However, the FIA program does not distinguish between private and public land for agriculture and developed land uses, so these two land use categories included both private and public land. The Owner Group Code is used to select only private forestland. Two different variables from the FIA database were combined to categorize the forest types used in this analysis. These variables are the Forest Type Code and the Stand Origin Code from the Condition Table. The Land Use SRS Code, also found in the Condition Table, was used to identify land uses that were not forest e.g. agriculture and developed land (Burrill et al., 2018). I defined the natural pine, oak-pine, upland hardwood, and bottomland hardwood forest types using previous forest type groupings found in Sheffield (1997). Although most of the forest type groupings have straight forward definitions, pine plantations can be described in various ways. Unlike Sheffield (1997), who defined pine plantations as any pine or softwood forests that have been artificially regenerated, I used a more restrictive definition of pine plantations. Because I wanted the pine plantation definition to reflect a forest type that is principally focused on timber production, I defined pine plantations as any loblolly pine, slash pine, loblolly pine-hardwood, or slash pine-hardwood forest that was artificially regenerated. Loblolly and slash pine are the primary species planted on tracts where managers seek to maximize financial returns and are likely to be subject to increased management intensity (Fox et al., 2004). Importantly, this definition excluded longleaf pine stands that have been artificially regenerated.

Because many longleaf plantings are implemented for restoration purposes and not timber production, it was necessary to exclude them from the pine plantation forest type. The longleaf pine ecosystem was once a dominant forest type on the landscape, originally thought to cover 90 million acres, but it has been reduced to cover only 3 million acres (Jose et al., 2007, p. 3). In 2005, state, federal, and private cooperators began to formally organize with the express goal of restoring longleaf habitat (America's Longleaf Restoration Initiative). As of 2017, America’s Longleaf Restoration Initiative (ALRI) estimated that roughly a million acres of longleaf plantings had occurred in the southeast (Boyd, 2017).

County-level acreage estimates of all forest types/land uses from 2005 to 2015 for 12 states in the US South were estimated using FIA inventory data. The 12 states included in my study are Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia. County-level forest type and land use acreage estimates were used to construct the dependent variables in the estimated system of equations. Table 3.2 shows the average number of acres within a county in each land use and forest type category by state. It also displays the coefficient of variation of the acreage in each land use and forest type within an average county in each state. The coefficient of variation was used to show the temporal variation of land use and forest type areas in an average county. Because the standard deviations of the acres within a county and forest type/land use group are normalized using the average acreage of each land use/forest type within a county, the coefficient of variation allows for more meaningful comparisons across states and land use/forest type groups.

Table 3.2: Average acreage and coefficient of variation within an average county for each state.

	Oak-Pine		Upland Hardwood		Natural Pine		Bottomland Hardwood		Pine Plantation		Agriculture		Developed	
States	**Mean**	**Coeff. of Var.**	**Mean**	**Coeff. of Var.**	**Mean**	**Coeff. of Var.**	**Mean**	**Coeff. of Var.**	**Mean**	**Coeff. of Var.**	**Mean**	**Coeff. of Var.**	**Mean**	**Coeff. of Var.**
Alabama	34,721	0.168	99,944	0.079	56,625	0.144	38,525	0.137	102,501	0.092	71,904	0.063	52,706	0.064
Arkansas	23,878	0.220	71,365	0.079	48,062	0.169	33,594	0.114	67,255	0.138	93,829	0.062	39,195	0.096
Florida	21,468	0.230	51,213	0.171	42,083	0.165	48,921	0.107	89,322	0.078	63,233	0.078	64,140	0.059
Georgia	15,739	0.231	36,966	0.144	29,282	0.149	27,137	0.114	58,451	0.098	43,374	0.107	27,078	0.084
Louisiana	21,779	0.147	51,847	0.143	43,991	0.168	62,022	0.081	102,702	0.056	97,818	0.068	59,716	0.079
Mississippi	20,585	0.281	65,205	0.127	37,481	0.207	36,094	0.150	73,639	0.110	65,524	0.082	36,856	0.112
North Carolina	22,358	0.247	49,608	0.150	42,750	0.164	30,553	0.144	44,004	0.160	85,311	0.057	53,238	0.059
Oklahoma	110,133	0.149	222,938	0.048	112,221	0.139	30,760	0.306	261,379	0.092	161,218	0.025	55,444	0.122
South Carolina	26,150	0.265	58,231	0.135	57,882	0.132	47,329	0.139	63,808	0.089	68,678	0.068	60,733	0.074
Tennessee	13,858	0.285	133,608	0.056	9,771	0.267	26,760	0.116	25,220	0.114	107,504	0.045	42,251	0.062
Texas	32,225	0.228	72,180	0.136	63,426	0.130	42,901	0.140	81,619	0.115	123,249	0.058	78,585	0.067
Virginia	15,233	0.315	77,104	0.085	14,039	0.307	10,268	0.161	40,365	0.117	50,359	0.078	30,667	0.121
Average of All States	29,844	0.230	82,517	0.113	46,468	0.178	36,239	0.142	84,189	0.105	86,000	0.066	50,051	0.083

As previously mentioned, an entire state is surveyed over a 5 or 7-year period. Therefore, it was difficult to impose a specific year on county-level estimates of land use and forest types area. I used the midpoint year of the survey period for all land use share estimates during a given survey cycle. For example, if the survey period was from 2003-2007, then the land use share estimates during this survey period were coded with the year as 2005. There were also gaps in the FIA data for some years and states. If there was a gap in the FIA data, which made it impossible to estimate a land use share for a particular year, then linear interpolation was applied to ensure a continuous time series.

Not all counties in each state were included in the analysis for several reasons. The principal reason was due to the formulation of the empirical model, which precludes the use of counties that have zero acres of a land use or forest type. Following Hardie and Parks (1997) and developed further in Chapter 4, the empirical model follows Equation 1. The numerator, y_{ikt}, represents the share of land in land use/forest type (k) within county (i) at time (t). This analysis included five different forest types and two land uses, a total of seven different forest types/land uses, thus K equals seven. This results in a system of six equations where the omitted forest type/land use is y_{i7t}. If a county had zero acres of any of the land uses or forest types, then the dependent variable would be undefined and therefore dropped from the analysis.

$$(1)\ \ln\left(\frac{y_{ikt}}{y_{i7t}}\right) = \beta_k X_{it} + \varepsilon_{ikt} \text{ for } k = 1, \ldots\ldots, K-1, i = 1, \ldots\ldots, I, t = 1, \ldots\ldots, T$$

The final dataset had 4,543 observations. Appendix A contains detailed maps and charts that show the average number of acres in each forest type and land use group for counties used in the analysis. Appendix A also shows total acreage estimates of each forest type and land use category by state. This set of charts show estimates based on the entire state, not just the counties used in this analysis.

The time series dimension of the dataset varies by state because the FIA inventory program is administered by states. State budget constraints affect the number of years it takes to complete a full panel. Some states operate on a 5-year panel design while others use a 7-year panel design. Additionally, the new annual panel inventory design was implemented by the FIA program in 1999, but states did not adopt the new inventory design in the same year. Figure 3.3 shows the number of counties and the time series length from each state used in the analysis.

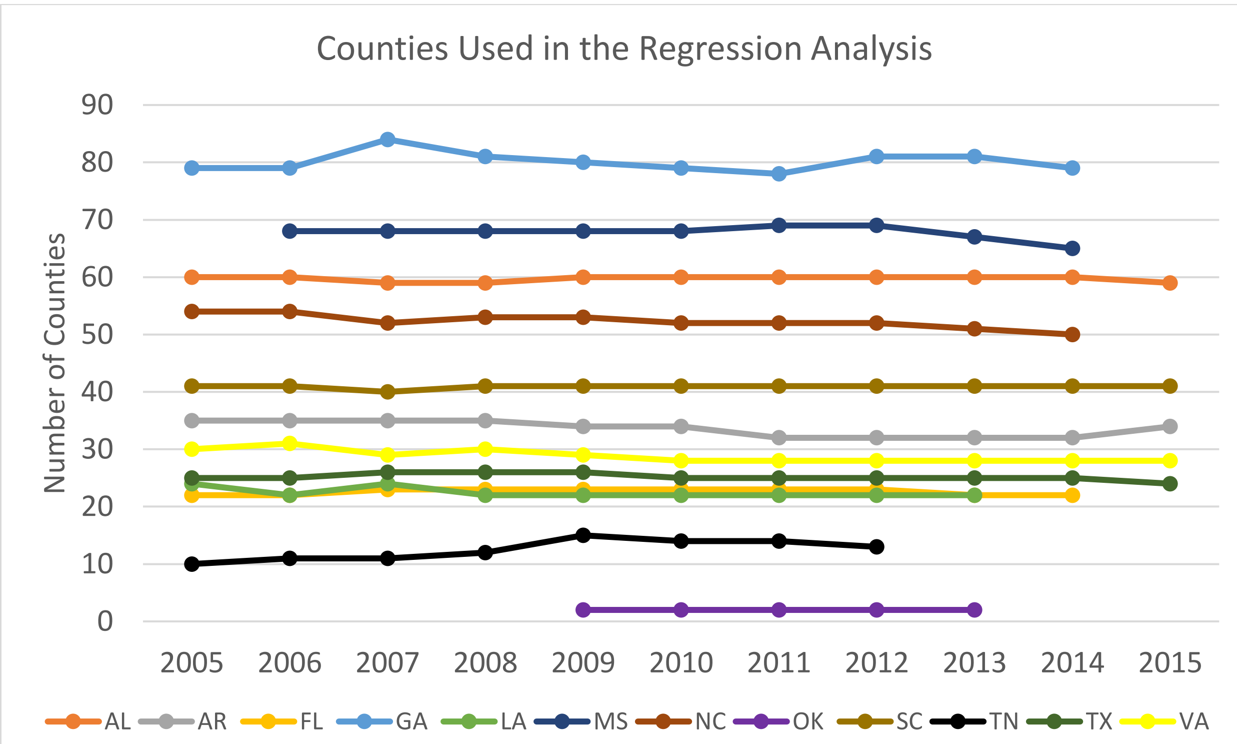

Figure 3.3: The number of counties from each state used in the analysis.

Occasionally counties were included in the analysis for one year but not another. This occurred in counties where there were relatively small portions of a given forest type or land use. As previously stated, each FIA inventory plot represents roughly 5,900 acres. Any land use or forest type acreage estimate within a county that is small may only be based on a single inventory plot. Ultimately, this means that small changes on an inventory plot could force counties to be excluded from the analysis for certain years and cause them to be included in other years.

Furthermore, some counties were excluded from the final dataset due to missing independent variable data. The Forest2Market timber price dataset is limited to certain counties within some states. Florida, Oklahoma, and Texas all have counties for which price data is unavailable. Because these price series were used to estimate pine plantation forest rents, counties with missing price data were excluded from the analysis. Other counties were excluded because of missing data in the per capita income and population datasets.

3.4: AGRICULTURE AND FOREST TYPE ECONOMIC RENTS

Table 3.3 presents the sample size, mean, range, and standard deviation of the continuous independent variables used in the regression models. Tables 3.4 and 3.5 show the sample size, mean, range, and standard deviation for the different sets of geographic dummy variables used in the state and ecoregion regression models.

Table 3.3: Summary statistics of the independent variables used in both regression models.

				Range	
Independent Variable	*n*	*Mean*	*SD*	*Min*	*Max*
Value_Pine_Plantation	4543	1342.89	456.62	184.32	2525.57
Annual_Net_Rev_Ag	4543	42.28	72.70	-167.5	772.54
Pop_Density	4543	0.1506	0.2307	0.0061	3.87
Per_Capita_Income	4543	29863.96	6258.68	14615	89158
Pellet Exports (Million tons)	4543	1.01	1.57	0	4.67
LCC12	4543	0.2278	0.1307	0.0032	0.6319

Table 3.4: Summary statistics of the state dummy variables used in the state regression model.

State Dummy Variables	*n*	*Fraction of Total Counties by State*	*Range* *Min*	*Max*
AL	4543	0.14462	0	1
AR	4543	0.08144	0	1
FL	4543	0.04975	0	1
GA	4543	0.17632	0	1
LA	4543	0.04446	0	1
MS	4543	0.13427	0	1
NC	4543	0.11512	0	1
OK	4543	0.0022	0	1
SC	4543	0.09905	0	1
TN	4543	0.02201	0	1
VA	4543	0.06978	0	1

Table 3.5*:* Summary statistics of the ecoregion dummy variables used in the ecoregion regression model.

Ecoregion Dummy Variables	*n*	*Fraction of Total Counties by Ecoregion*	*Range* *Min*	*Max*
PP	4543	0.00947	0	1
Pied	4543	0.57517	0	1
EBLO	4543	0.01673	0	1
EBLC	4543	0.02751	0	1
LMR	4543	0.02399	0	1

The value of an acre of pine plantations ($Value\_pine\_plantation_{it}$) were estimated at the county level and were obtained from Elise Kaya, a PhD candidate at NC State University. A brief overview of the estimation procedure is described below, but for more information see Kaya (2020).

The value of an acre of pine plantation variable for each county is a composition of three inputs: stumpage price data, timber yields, and establishment costs. Pine sawtimber, chip-n-saw, and pulpwood prices were obtained from Forest2Market as a bi-monthly price time series for 39 micromarkets, a collection of counties. For this analysis, yearly price time series were necessary; therefore, a simple yearly average was calculated. Pine plantation timber yields were estimated using data from FIA sample inventory plots. Yield curves were estimated for coastal and non-coastal regions. The two different yield curves capture climatic and physiographic differences across these regions. Pine plantation establishment costs were obtained from Nielsen et al. (2014). Finally, county-level value of an acre of pine plantations were estimated as the net present value of an infinite stream of forest revenue based on the optimal rotation age. Optimal rotation age was calculated using the Faustmann formula with a 5% discount rate. Figure 3.4 shows the average value of an acre of pine plantation for each county for the study period, 2005-2015. The estimates of the value of an acre of pine plantation were inflated to 2018 dollars, using the producer price index for all commodities

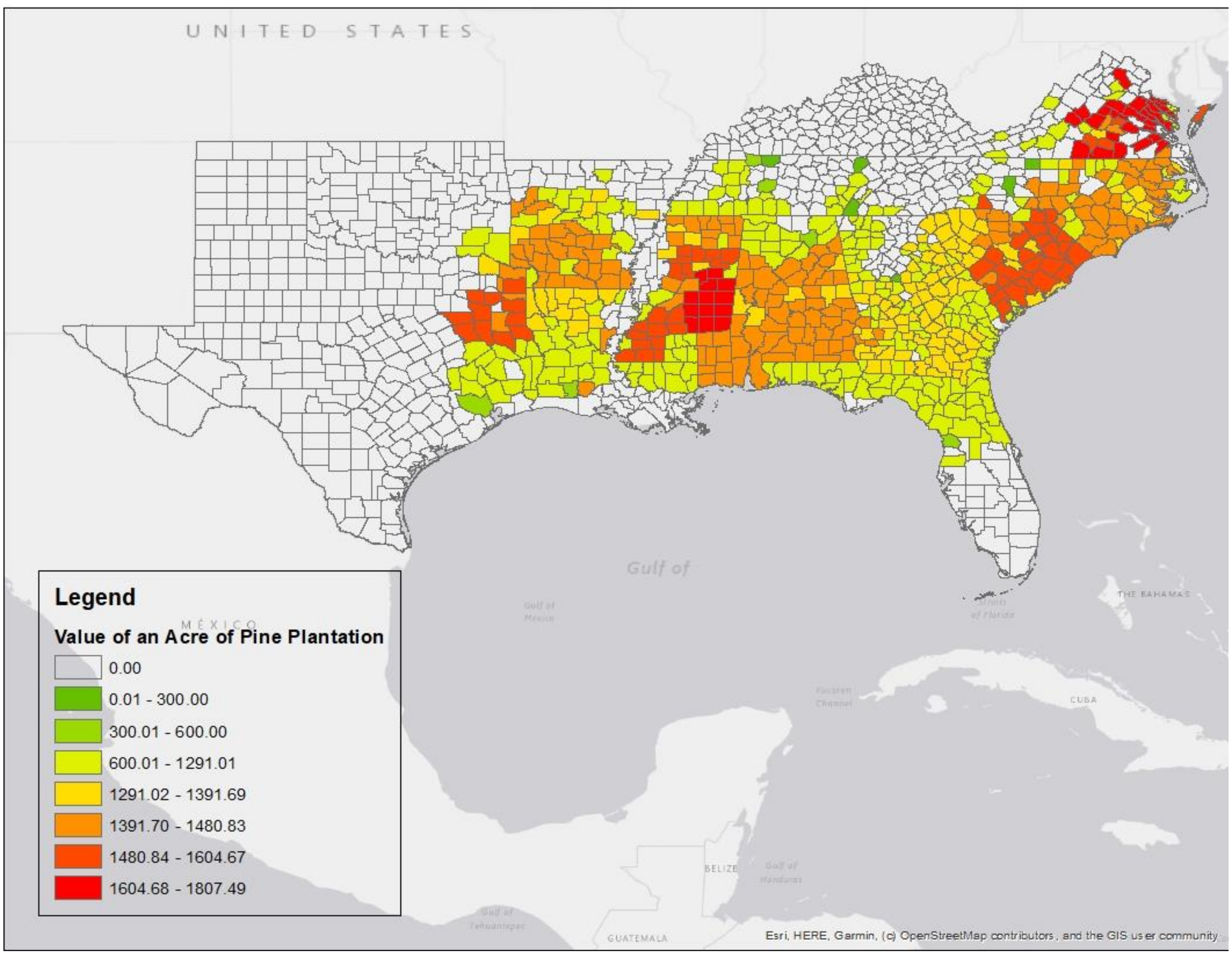

Figure 3.4: Per acre value of pine plantations by county (Kaya, 2020).

Because management practices for forest types other than pine plantations are highly variable, it is difficult to estimate county-level forest rents for other forest types. The aggregation of different forest types into broader forest type categories further complicates forest type specific rent estimates, because this aggregation can result in significant intra-forest type species variation. Management practices are also highly variable across forest types other than pine plantations due to landowner preferences, access to capital, and regional timber markets. For these reasons, I did not include economic rents for forest types other than pine plantations. Similar to county-level estimates of the value of an acre of pine plantations, estimates of annual net revenue from agriculture land were obtained from Kaya (2020). I provide a brief overview of the estimation process, but for more information see Kaya (2020). To estimate county-level annual net revenue from agriculture land, crop revenues, livestock revenues, total crop cash receipts, and total livestock cash receipts were collected for each county from the Regional Economic Information System (REIS) of the Bureau of Economic Analysis (BEA). However, county-level expenditures were not differentiated by product, which made it impossible to allocate the expenditures to crop or livestock production. Therefore, an adjustment was made to estimate crop and livestock net revenue. The ratio of crop sales to total cash receipts from crops were calculated and then multiplied by total net income. The same procedure was applied to livestock revenues and total cash receipts from livestock. The new scaled versions of net income for both categories were added together and used as a proxy for annual net revenue from agriculture land. Per acre annual net revenue from agriculture ($Annual\_Net\_Rev\_Ag_{it}$) was calculated by dividing county level annual net revenue from agriculture by the total number of acres within a county. Per acre annual net revenue from agriculture estimates were inflated to 2018 dollars, using the producer price index for all commodities. Figure 3.5 shows average annual net revenue from agriculture by county for the study period, 2005-2015.

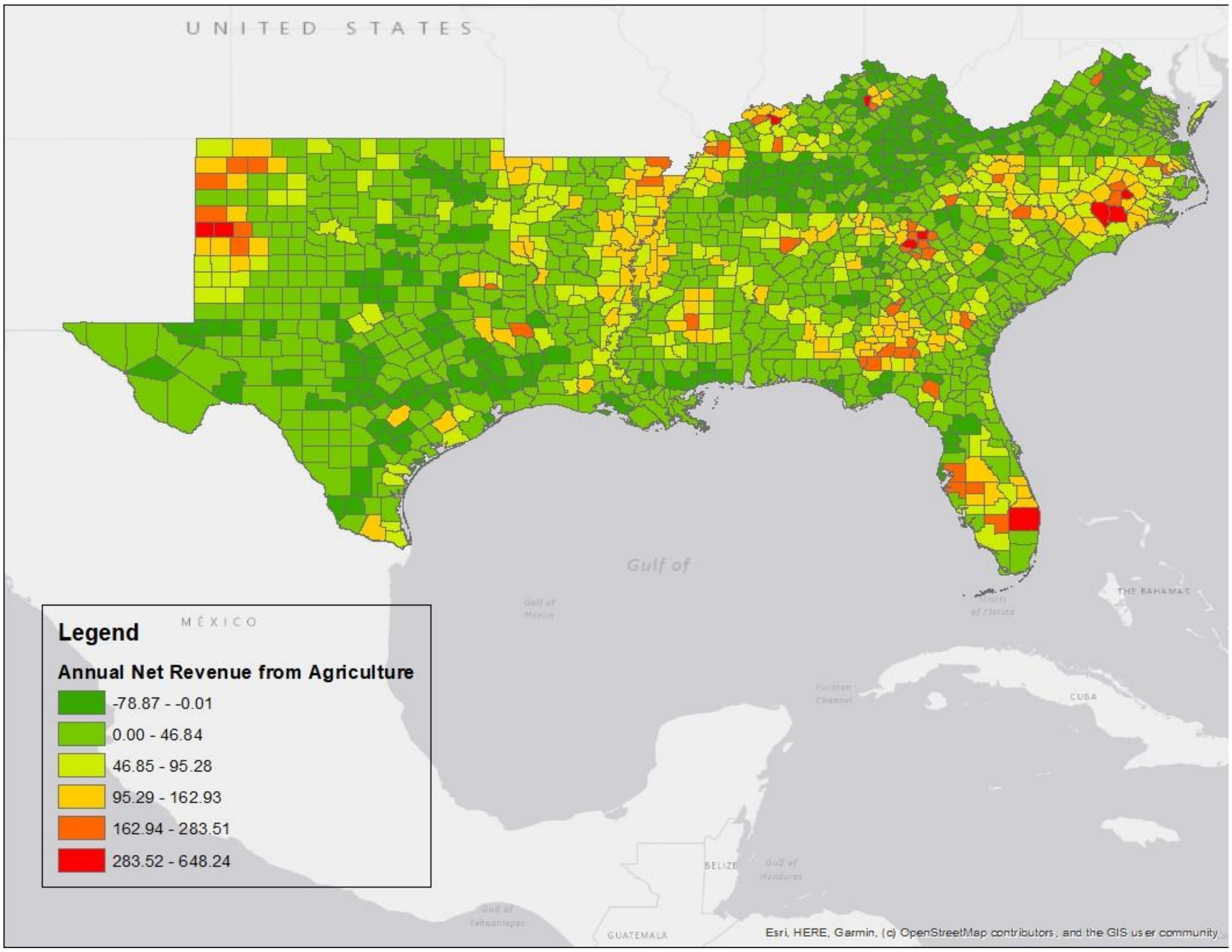

Figure 3.5: Per acre annual net revenue from agriculture by county (Kaya, 2020).

As can be seen in Table 3.3, there is a large discrepancy in the variables that represent returns to pine plantations and agriculture land. This is primarily due to the formulation of these two variables. The value of an acre of pine plantations represents the net present value of an infinite stream of revenue and costs from pine plantations; however, the annual net returns to agriculture land only presents a single year of net revenue from agriculture land. The value of an acre of pine plantations is substantially larger because it accounts for the future revenue from pine plantations whereas the annual net revenue from agriculture land only represents net revenue from a single year.

3.5: PROXIES FOR URBAN RENTS

In this analysis, per capita income and population density were calculated for each county and year. These variables were included as proxies for urban development pressure or urban economic rents. Previous land use change research used population density as a proxy for urban rents. The researchers hypothesized that increasing population leads to more development pressure and ultimately higher urban rents (Plantinga et al., 1996). County-level per capita income ($per\_capita\_income_{it}$) data were obtained from the BEA. Per capita income estimates were adjusted to a 2018 base year using the Consumer Price Index. Population estimates for each county were obtained from the BEA. County-level population density ($pop\_density_{it}$) was calculated as the number of people per acre of total land area within a county.

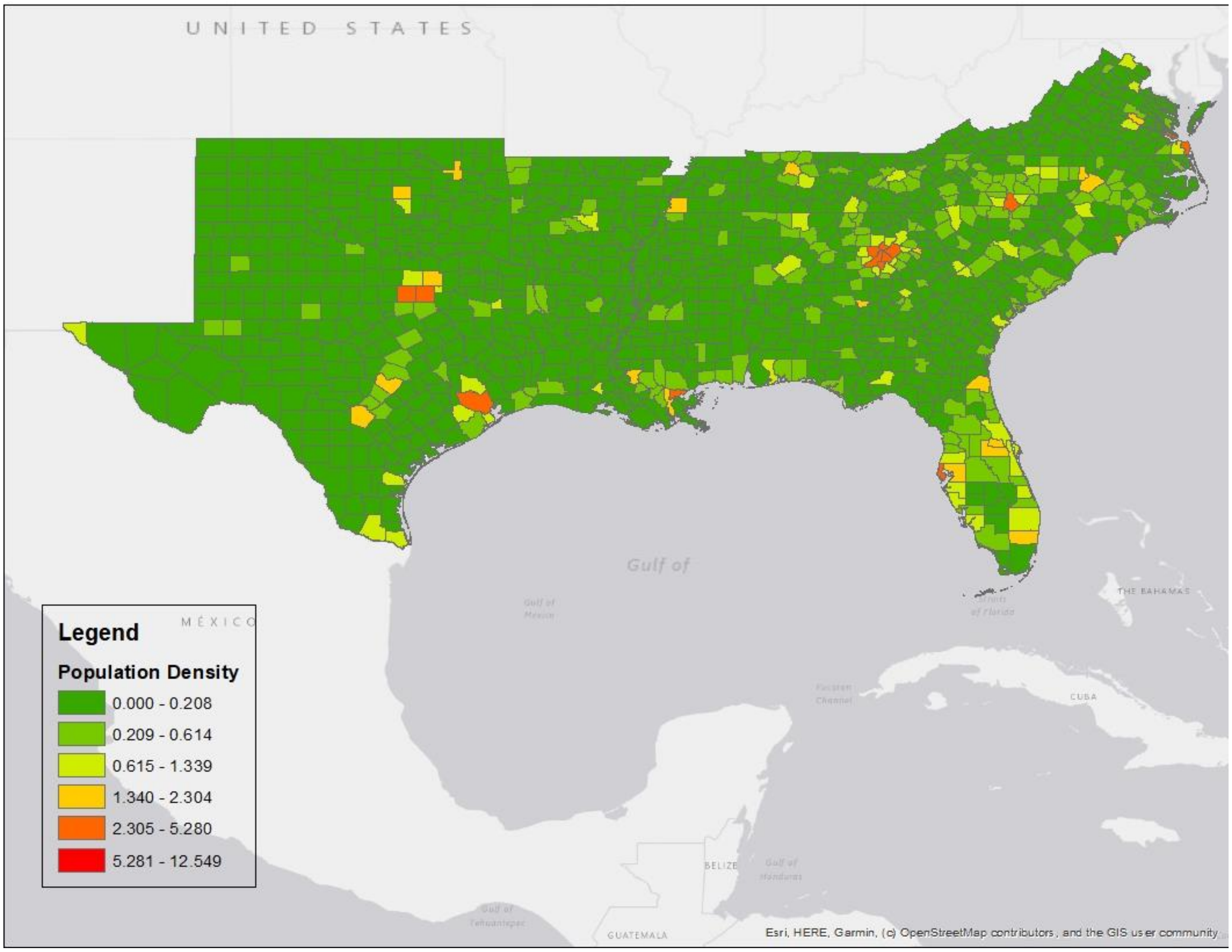

Figure 3.6: Average population density by county.

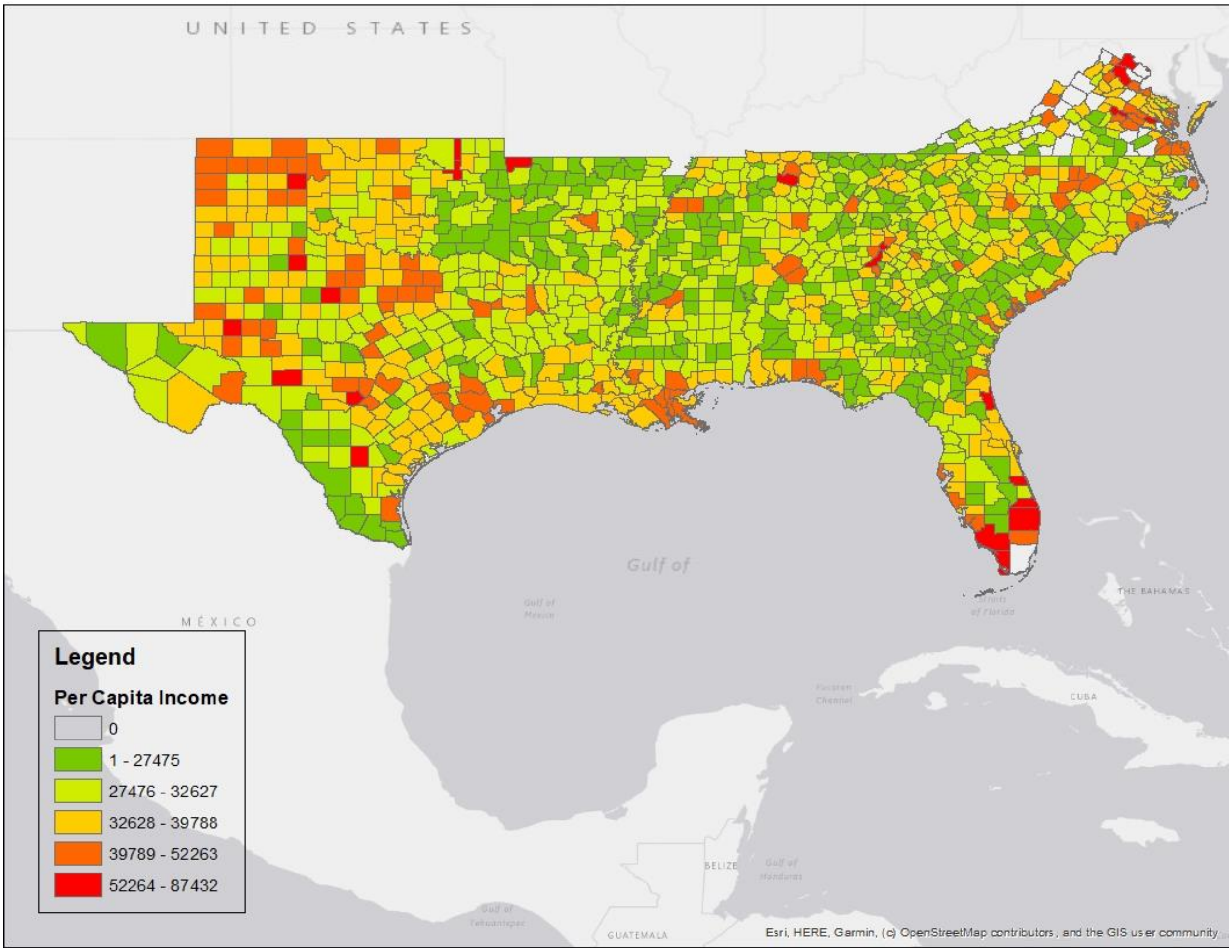

Figure 3.7: Average per capita income by county.

3.6: WOOD PELLET EXPORTS

Total wood pellet exports from the U.S. by year (*pellet_exports*$_t$) presented in Figure 3.8 was obtained from the U.S. International Trade Commission website using the Harmonized System (HS) Code for wood pellets, 440131 (Harmonized System (HS) Codes, 2020; United States, 2020). As evidenced in Section 1.2, wood pellet exports from the U.S. are driven by European Union policy changes, an exogenous force. Due to the exogeneity of total U.S. wood pellet exports, the use of this variable provided an empirical way to test if wood pellet exports are affecting southeastern forests. Figures 3.7 and 3.8 demonstrate that the majority of export wood pellets are shipped to the European Union, specifically the United Kingdom. Due to other variable time series limitations, which limited the temporal aspect of the data to the period from 2005 to 2015, I used total wood pellet exports from 2012-2015 in this analysis.

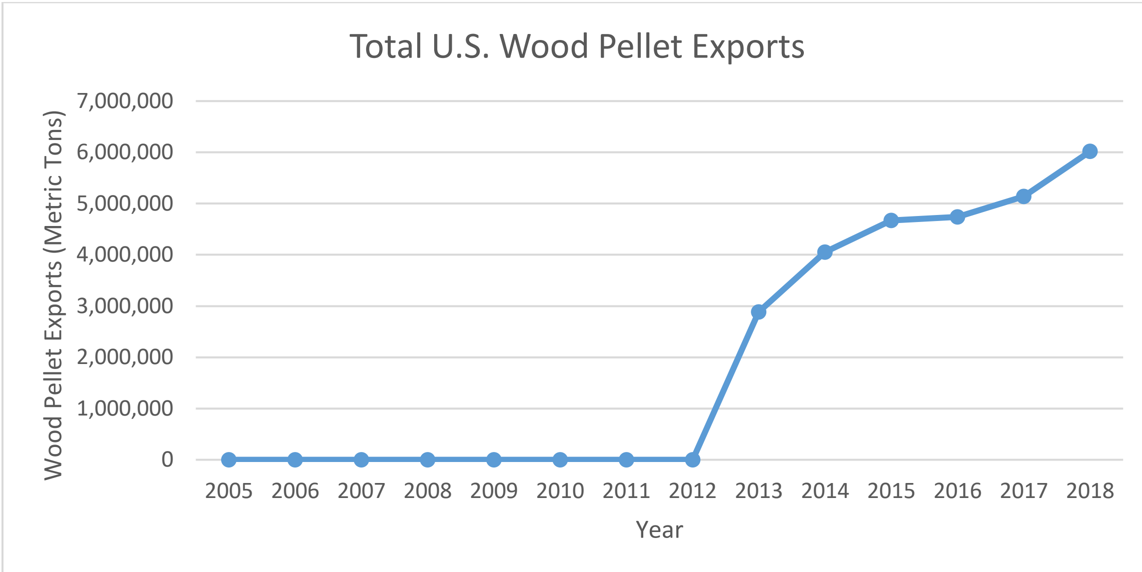

Figure 3.8: Total wood pellet exports from the U.S.

3.7: LAND CAPABILITY CLASSIFICATION SYSTEM

The Land Capability Classification system was designed with a focus on the suitability of land for agriculture. The LCC system classifies land based on the risks of soil damage or limitations that the soils exhibit. There are eight LCC classes (I-VIII). As you move from LCC class I to LCC class VIII, the risks of soil damage and soil limitations increases (Klingebiel & Montgomery, 1961). I included the share of land within a county that was in the two best LCC classes ($LCC12_{it}$), classes I and II, as an independent variable in the land use model. $LCC12_{it}$ was expressed as a number between zero and one. Data on the area of LCC classes from each county were obtained from the National Resource Inventory.

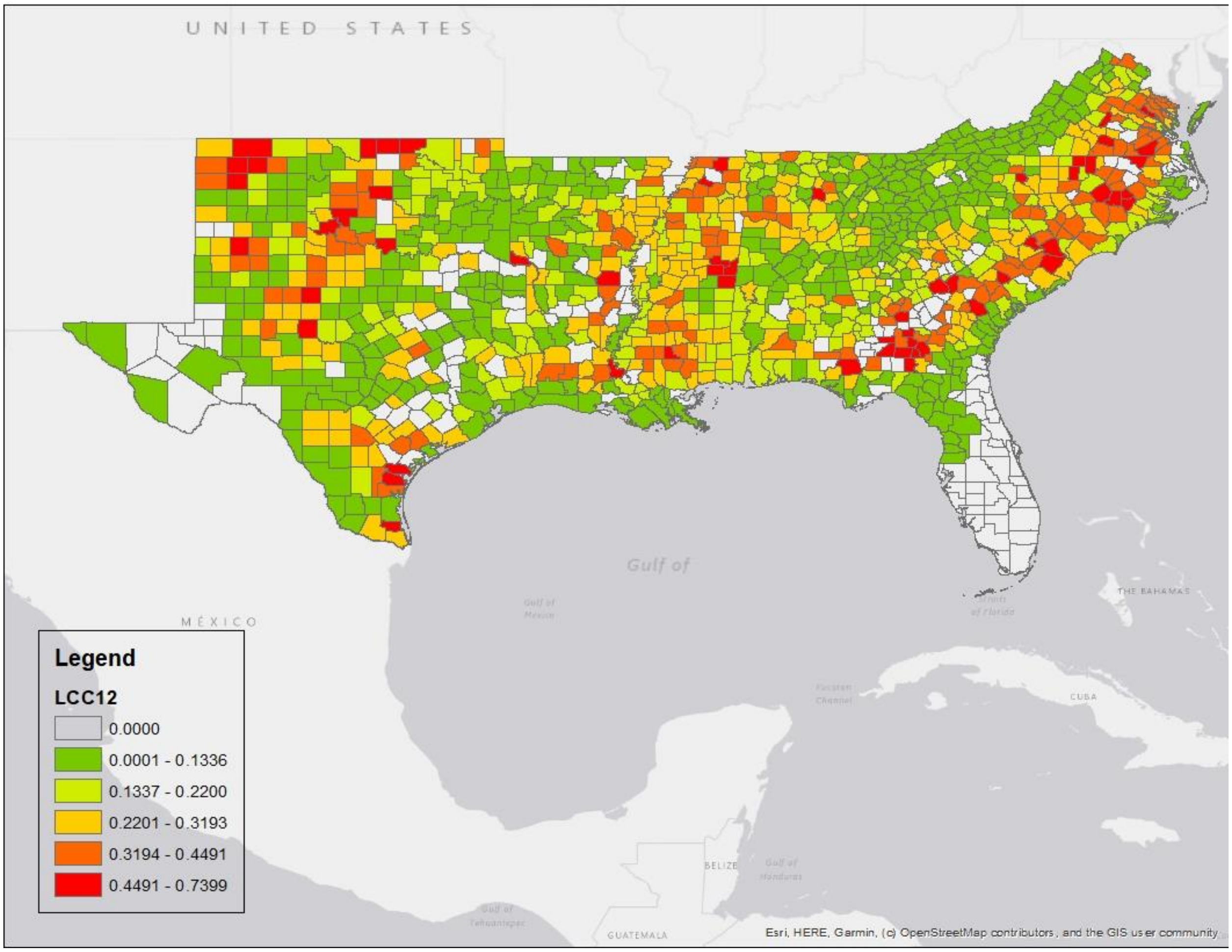

Figure 3.9: Share of land within a county in the two best LCC Classes, Classes I and II.

3.8: SPATIAL FIXED EFFECTS

I estimated two different models in this analysis using different sets of geographic dummy variables. State and ecoregion dummy variables were included to capture cross-sectional variation in the modeling region. In the state model, Texas was used as the base state, so interpretation of the state dummy variables reflects the difference with this base state. The set of state dummy variables captures spatial heterogeneity related to state-level policies that may affect land use change and forest type change, such as property tax structures or incentive programs.

State dummy variables fail to capture the spatial heterogeneity of many land characteristics that are similar across multiple states but vary within states. Some examples include soil properties, climate, and land-surface form. For example, the Coastal Plain spans multiple states but was formed under similar geological processes and therefore has similar soil types and structure. However, soils in the mountains of North Carolina and soils in the Coastal Plain of North Carolina are inherently different. I used ecoregion dummy variables to control for spatial characteristics that are similar across multiple states but vary within a state. The ecoregion classifications were obtained from the from the USFS (Bailey, 1995). The USFS provides three different ecoregion classifications that vary in their level of spatial detail: domains, divisions, and provinces. Because ecoregion provinces provided the highest level of detail and therefore the most variation across the modeling region, ecoregion provinces were used in the analysis. The modeling region included six different ecoregion provinces (ecoregions): Outer Coastal Plain Mixed Forest Province, Southeastern Mixed Forest Province, Eastern Broadleaf Forest Oceanic Province, Eastern Broadleaf Forest Continental Province, Lower Mississippi Riverine Forest Province, and Prairie Parkland Subtropical Province. Figure 3.10 shows a map of the ecoregions that were used in this analysis. In the ecoregion model the Coastal Plain was the reference category, so interpretation of the ecoregion dummy variables reflects the difference from the Coastal Plain.

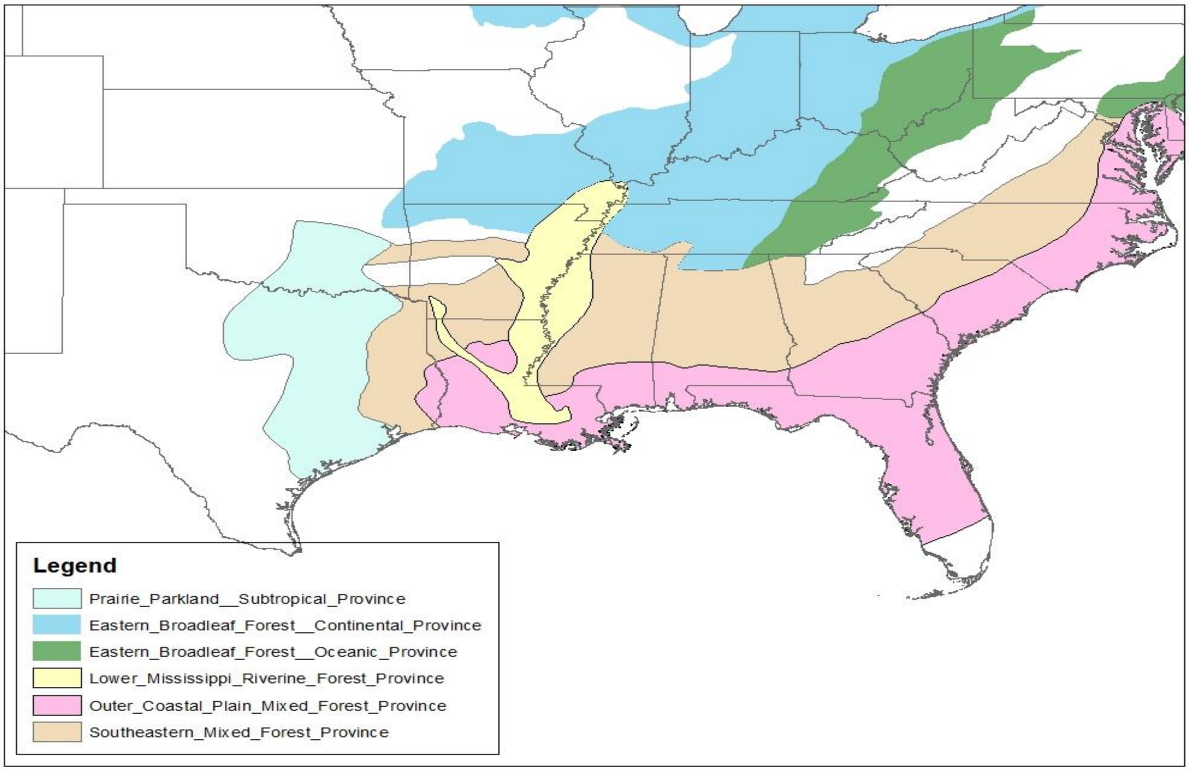

Figure 3.10: Map of ecoregion provinces used in the analysis (Bailey, 1995).

Chapter 4: Methodology

4.1: INTRODUCTION

This chapter describes the analytical framework used to investigate the drivers of land use and forest type change in the U.S. South. In Section 4.2, I describe the empirical model used in the analysis. Section 4.3 explains how marginal effects and elasticities were estimated. Marginal effects and elasticities were used to aid in the interpretation of the model results. 4.4 investigates potential econometric issues and discusses the methods used to test for multicollinearity and heteroskedasticity. Finally, sections 4.5-4.7 presents results from the estimated models.

4.2: EMPIRCIAL MODEL FORMULATION

In my analysis, I utilized the empirical land use model using aggregate county-level data developed in Hardie and Parks (1997). The ability to model land use decisions using aggregate data is important because observing the individual land use choices of private landowners is often impossible. However, aggregate data is readily available from a variety of sources. The level of aggregation can vary, but it is most common to aggregate land use shares and explanatory variables to the county level. Although the model presented by Hardie and Parks (1997) was previously used in many empirical applications, their work presents an organized theoretical structure and formalized model assumptions. The model formalized by Hardie and Parks (1997) relies primarily on the Ricardian model of land rents, in which land use depends on differences in land quality. A functional form is chosen that constrains the sum of all modeled land use shares to one. Equation 1 shows a commonly used multinomial logistic formulation of the empirical model. p_{ikt} represents the expected land use share (*k*), in county (*i*), at time (*t*);

β_k represents a parameter vector for land use *k*; X_{it} represents a vector of exogenous explanatory variables for county (*i*) at time (*t*).

$$1)\ p_{ikt} = \frac{\exp(\beta_k X_{it})}{\sum_k exp(\beta_k X_{it})}$$

Normalizing Equation 1 with one of the land use shares, Equation 1 can be written as Equations 2 and 3. I use developed land use, p_{i7t}, to normalize equation 1. p_{iKt} represents optimal land use proportions.

$$2)\ p_{ikt} = \frac{\exp(\beta_k X_{it})}{1+\sum_{s=1}^{6} \exp(\beta_s X_{it})}\ k = 1,2,3,4,5,6$$

$$3)\ p_{i7t} = \frac{1}{1+\sum_{s=1}^{6} \exp(\beta_s X_{it})}$$

The optimal land use proportions are not observable due to random factors and are replaced with actual land use proportions. The logarithmic transformation results in the expression of actual land use shares as the natural logarithm of the ratio of expected land use shares, (y_{ikt}/y_{iKt}), as is shown in Equation 4.

$$4)\ \ln\left(\frac{y_{ikt}}{y_{iKt}}\right) = \beta_k X_{it} + \varepsilon_{ikt} \text{ for } k = 1, \ldots\ldots, K-1$$

As stated previously, I modeled seven different land uses/forest types: developed land, agricultural land, pine plantations, natural pine forests, oak-pine forests, upland hardwood forests, and bottomland hardwood forests. The use of seven land use/forest type categories results in a system of six equations which are shown in Equations 5-10. Each land use/forest type category is normalized on the developed land use category, y_{i7t}. The other land use/forest type categories are represented by y_{i1t} - y_{i6t}. The system of equations is estimated using a Seemingly Unrelated Regression model.

$$5)\ \ln\left(\frac{y_{i1t}}{y_{i7t}}\right) = \beta_1 X_{it} + \varepsilon_{i1t}$$

$$6)\ \ln\left(\frac{y_{i2t}}{y_{i7t}}\right) = \beta_2 X_{it} + \varepsilon_{i2t}$$

$$7)\ \ln\left(\frac{y_{i3t}}{y_{i7t}}\right) = \beta_3 X_{it} + \varepsilon_{i3t}$$

$$8)\ \ln\left(\frac{y_{i4t}}{y_{i7t}}\right) = \beta_4 X_{it} + \varepsilon_{i4t}$$

$$9)\ \ln\left(\frac{y_{i5t}}{y_{i7t}}\right) = \beta_5 X_{it} + \varepsilon_{i5t}$$

$$10)\ \ln\left(\frac{y_{i6t}}{y_{i7t}}\right) = \beta_6 X_{it} + \varepsilon_{i6t}$$

Expected land use shares can be recovered by solving Equations 11 and 12.

$$11)\ y_{ikt} = \frac{\exp(\beta_k X_{it})}{1+\sum_{s=1}^{6}\exp(\beta_s X_{it})}\ k = 1,2,3,4,5,6$$

$$12)\ y_{i7t} = \frac{1}{1+\sum_{s=1}^{6}\exp(\beta_s X_{it})}$$

4.3: INTERPRETTING MODEL RESULTS: MARGINAL EFFECTS AND ELASTICITIES

When using this approach, the regression coefficients are difficult to interpret directly due to the functional form of the regression equations. To aid in the interpretation of the regression coefficients, the marginal effects of the independent variables are estimated following Equation 13 (Greene, 1993, p.666). Marginal effects of the independent variables on the share of oak-pine forests, natural pine forests, pine plantations, upland hardwood forests, bottomland hardwood forests, and agriculture land are estimated using Equation 13. Marginal effects are estimated at the mean value of all independent variables. Because marginal effects are calculated at the mean of all the independent variables, the marginal effect represents the effect of an independent variable on the "average" county from the data set. The marginal effect of an independent variable for a specific county could be smaller or larger than the marginal effect for the "average" county.

$$13)\ \frac{\partial y_{ikt}}{\partial x_{ikt}} = y_{ikt}(\beta_{kx} - \sum_{k=1}^{K-1} y_{ikt}\beta_{kx}) \text{ for k} = 1, \dots, \text{K} - 1$$

Because the shares of all land uses must sum to one, the marginal effects of an independent variable on the share of all land uses must sum to zero. Therefore, the marginal effect of an independent variable on the share of developed land can be estimated using Equation 14.

$$14)\ \frac{\partial y_{ikt}}{\partial x_{ikt}} = 0 - \sum_{k=1}^{K-1} \frac{\partial y_{ikt}}{\partial x_{ikt}} \text{ for k} = 1, \dots, \text{K} - 1$$

Elasticities are calculated using mean values of the independent variables and the marginal effects of the independent variables using Equation 15. y_{iKt} represents the share of an individual forest type or land use for an "average" county in the dataset.

$$15)\ e_{iKt} = \frac{\%\Delta y_{iKt}}{\%\Delta x_{iKt}} \text{ for k} = 1, \dots, \text{K}$$

4.4: TESTING MODEL VALIDITY

This section describes the methods and results used to investigate potential econometric issues. Specifically, I tested for multicollinearity and heteroskedasticity.

Multicollinearity arises when two or more independent variables are highly correlated (Woolridge, 2013, p. 91). As a first step, I looked at the correlation matrix of independent variables for the ecoregion model, which is presented in Figure 4.1. Figure 4.1 demonstrates that wood pellet exports and the value of an acre of pine plantations are the only variables that have a correlation larger than 0.5, indicating a high degree of correlation. There are three pairs of variables that have correlation values greater than 0.3, indicating a moderate degree of correlation: per capita income and population density, per capita income and wood pellet exports, and the Prairie Parkland ecoregion and population density.

Table 4.1: Correlation Matrix of independent variables for the Ecoregion Model.

Variable	1	2	3	4	5	6	7	8	9	10	11
1: Value_Pine_Plantation	-										
2: Pop_Den	0.12	-									
3: Per_Cap_Income	0.29	0.42	-								
4: Pellet_Exports	0.59	0.01	0.33	-							
5: LCC12	0.08	0.07	0.01	0.01	-						
6: Annual_Net_Rev_Ag	0.01	0.04	0.07	0.08	0.28	-					
7: PP	0.01	0.32	0.06	0.01	0.11	0.04	-				
8: Pied	0.01	0.02	0.07	0.05	0.18	0.07	0.11	-			
9: EBLO	0.05	0.07	0.05	0	0.14	0.02	0.01	0.15	-		
10: EBLC	0.08	0.05	0.07	0.05	0	0.03	0.02	0.2	0.02	-	
11: LMR	0.02	0.06	0.06	0.03	0.05	0.02	0.02	0.18	0.02	0.03	-

Considering there are multiple independent variables with at least a moderate degree of correlation, I calculated the Variance Inflation Factor (VIF) for all the coefficients of the independent variables. Equations 1 and 2 demonstrate how to calculate the VIF for the independent variable X_1. Equation 1 shows the regression of all the k-1 independent variables on the independent variable X_1. Using the R-squared value from the regression the VIF for X_1 was calculated following Equation 2.

$$1)\ x_1 = \alpha_0 + \alpha_2 x_2 + \ldots + \alpha_k x_k + e$$

$$2)\ VIF_{x1} = \frac{1}{1 - R_1^2}$$

Although setting a cut-off point for what qualifies as a VIF that is “too high” is arbitrary, cutoff points of five and ten are commonly used (Woolridge, 2013, p.94). All the independent variables have a VIF of less than two. Ultimately, I concluded that none of the independent variables should be excluded from the analysis due to multicollinearity in the ecoregion model.

Applying the same steps to the state model, Figure 4.2 shows the correlation matrix of the independent variables for the state model. The only variables that are different in the state model are the set of state dummy variables. Of the variables that are different, there are only two instances of moderate correlation, a correlation value greater than 0.3 and less than 0.5. The NC state dummy variable is moderately correlated with annual net revenue from agriculture and the VA state dummy variable is moderately correlated with per capita income. The VIF estimates for the state model were all below three. Similar to the ecoregion, I concluded that none of the independent variables should be excluded from the analysis because of multicollinearity.

Table 4.2: Correlation Matrix of independent variables for the State Model.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1: Value_Pine_Plantation	-																
2: Pop_Den	0.12	-															
3: Per_Cap_Income	0.29	0.42	-														
4: Pellet_Exports	0.59	0.01	0.33	-													
5: LCC12	0.08	0.07	0.01	0.01	-												
6: Annual_Net_Rev_Ag	0.01	0.04	0.07	0.08	0.28	-											
7: AL	0.01	0.32	0.06	0.01	0.11	0.04	-										
8: AR	0.03	0.02	0.07	0.05	0.18	0.07	0.11	-									
9: FL	0.12	0.07	0.05	0	0.14	0.02	0.01	0.15	-								
10: GA	0.05	0.05	0.07	0.05	0	0.03	0.02	0.2	0.02	-							
11: LA	0.02	0.06	0.06	0.03	0.05	0.02	0.02	0.18	0.02	0.03	-						
12: MS	0.05	0.1	0.08	0.01	0.14	0.02	0.16	0.12	0.09	0.18	0.08	-					
13: NC	0	0.09	0.07	0.04	0.16	0.34	0.15	0.11	0.08	0.17	0.08	0.14	-				
14: OK	0.05	0.03	0.02	0	0.07	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	-			
15: SC	0.08	0.09	0	0.05	0.08	0.11	0.14	0.1	0.08	0.15	0.07	0.13	0.12	0.02	-		
16: TN	0.08	0.01	0.02	0.07	0.04	0.06	0.06	0.04	0.03	0.07	0.03	0.06	0.05	0.01	0.05	-	
17: VA	0.11	0.01	0.3	0.03	0.16	0.14	0.11	0.08	0.06	0.13	0.06	0.11	0.1	0.01	0.09	0.04	-

Homoskedasticity is the assumption that the error term conditioned on the explanatory variables is the same for all combinations of values of the explanatory variables (Woolridge, 2013 p. 269). Because county size, land use legacy, and other factors are different across counties, it is likely that heteroskedasticity is present. I used the White's test (Woolridge, 2013 p. 269) and the Breusch-Pagan test (Woolridge, 2013 p. 267) to test for the presence of heteroskedasticity.

The White's test and Breusch-Pagan test were applied to each regression equation in both the state and ecoregion models. In all twelve regression equations, both the White's test and Breusch-Pagan test return a P-value less than 0.0001. Therefore, I rejected the null hypothesis of homoskedasticity and concluded that heteroskedasticity is present. Although the presence of heteroskedasticity does not result in inconsistent or biased estimates of the coefficients, it does cause the variance of the coefficient estimates to be biased. Since variance estimates are used to construct confidence intervals and determine statistical significance, the statistical significance of the independent variables may no longer be reliable. [However, I did not correct for heteroskedasticity, but this should be addressed in future analyses.]

4.5: RESULTS OF THE STATE MODEL

Tables 4.3 and 4.4 display the coefficients, level of statistical significance, and the standard errors of the state SUR regression model. Excluding the state dummy variables, the majority of variables in all six regression equations are significantly different from zero at the 5% level.

Table 4.3: Regression results from the State Model.

	Ln(Oak-Pine/Dev)		Ln(Upland HW/Dev)		Ln(Natural Pine/Dev)	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept[1]	-0.2265*	(0.11316)	1.83761**	(0.10835)	0.55318**	(0.11432)
Value_Pine_Plantation [2]	0.00035**	(0.00004)	0.00001	(0.00004)	0.00039**	(0.00004)
Pop_Den	-1.76931**	(0.06289)	-1.2356**	(0.06022)	-1.68035**	(0.06353)
Per_Cap_Income	-0.00002**	(0.000003)	-0.00004**	(0.000003)	-0.00002**	(0.000003)
Pellet_Exports (Million Tons)	0.07074**	(0.01074)	0.03226**	(0.01029)	0.12241**	(0.01085)
LCC12	-0.18984	(0.10939)	-0.76839**	(0.10475)	0.08099	(0.11051)
Annual_Net_Rev_Ag	-0.00128**	(0.0002)	-0.00036	(0.00019)	-0.00202**	(0.0002)
AL	0.08608	(0.06073)	0.41867**	(0.05815)	-0.24726**	(0.06135)
AR	-0.07742	(0.06751)	0.3125**	(0.06464)	-0.22086**	(0.0682)
FL	-0.48433**	(0.0764)	-0.60967**	(0.07315)	-0.63852**	(0.07718)
GA	0.01293	(0.06059)	-0.06678	(0.05802)	-0.0584	(0.06121)
LA	-0.68768**	(0.07913)	-0.42943**	(0.07577)	-0.5362**	(0.07994)
MS	-0.16707**	(0.06304)	0.30253**	(0.06036)	-0.38279**	(0.06369)
NC	-0.14332*	(0.06603)	-0.21719**	(0.06322)	-0.18616**	(0.0667)
OK	1.00509**	(0.27198)	0.71785**	(0.26042)	0.30299	(0.27476)
SC	-0.28662**	(0.06585)	-0.23121**	(0.06306)	-0.21097**	(0.06653)
TN	-0.57054**	(0.10042)	0.9278**	(0.09615)	-1.62913**	(0.10145)
VA	-0.22103**	(0.0743)	1.00207**	(0.07115)	-1.0576**	(0.07506)
System Weighted Adjusted R-Square	0.2471					

[1]** Statistically significant at the 1 percent level.
[2]* Statistically significant at the 5 percent level.

Table 4.4: Regression results from the State Model (Continued).

	Ln(Bottomland HW/Dev)		Ln(Pine Plantation/Dev)		Ln(Agriculture/Dev)	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept[1]	0.57409**	(0.14178)	0.94013**	(0.13388)	1.66209**	(0.11065)
Value_Pine_Plantation [2]	0.00023**	(0.00005)	0.00056**	(0.00004)	-0.00006	(0.00004)
Pop_Den	-1.8226**	(0.07879)	-2.725**	(0.0744)	-1.20965**	(0.06149)
Per_Cap_Income	-0.00004**	(0.000003)	-0.00004**	(0.000003)	-0.00003**	(0.000003)
Pellet_Exports (Million Tons)	0.0798**	(0.01346)	0.16352**	(0.01271)	0.00126	(0.01051)
LCC12	1.69815**	(0.13706)	0.96627**	(0.12942)	2.08569**	(0.10697)
Annual_Net_Rev_Ag	-0.00029	(0.00025)	-0.00168**	(0.00023)	0.00251**	(0.00019)
AL	-0.50519**	(0.07609)	0.08222	(0.07185)	-0.5354**	(0.05938)
AR	-0.35298**	(0.08458)	-0.28779**	(0.07987)	-0.08365	(0.06601)
FL	-0.00931	(0.09571)	0.18702*	(0.09038)	-0.90583**	(0.0747)
GA	-0.25677**	(0.07591)	0.2589**	(0.07168)	-0.77308**	(0.05925)
LA	0.15156	(0.09914)	0.00892	(0.09362)	-0.5674**	(0.07738)
MS	-0.26358**	(0.07898)	-0.01048	(0.07458)	-0.63832**	(0.06164)
NC	-0.61442**	(0.08272)	-0.47835**	(0.07811)	-0.6264**	(0.06456)
OK	-0.52052	(0.34075)	1.04207**	(0.32177)	0.20799	(0.26595)
SC	-0.34996**	(0.08251)	-0.30329**	(0.07791)	-0.72201**	(0.06439)
TN	-0.42506**	(0.12581)	-0.84941**	(0.1188)	-0.08116	(0.09819)
VA	-1.05345**	(0.09309)	-0.22752**	(0.0879)	-0.20885**	(0.07266)
System Weighted Adjusted R- Square	0.2471					

[1]** Statistically significant at the 1 percent level.
[2]* Statistically significant at the 5 percent level.

Due to the logarithmic transformation of the model, direct interpretation of the regression coefficients on the expected land use/forest type shares is difficult. Tables 4.5 and 4.6 display the marginal effects and elasticity estimates of each independent variable on the land use and forest type shares. The marginal effects of the independent variables represent the change in the share of a forest type or land use for a one unit increase in the independent, holding all other variables constant. The elasticity estimates show the percentage change in the forest type/land use share for a 1% increase in the independent variable. For example, the pine plantation rent elasticity with respect to the share of oak-pine forests was 0.233, which means a 1% increase in the value of an acre of pine plantations increases the share of oak-pine forests by 0.233%.

Table 4.5: Estimated marginal effects of independent variables from the State Model.

				Marginal Effects			
Variable	**Oak-Pine**	**Upland HW**	**Natural Pine**	**Bottomland HW**	**Pine Plantation**	**Agriculture**	**Developed**
Value_Pine_Plantation	0.000010	-0.000033	0.000027	0.000004	0.000069	-0.000054	-0.000023
Pop_Den	-0.017730	0.046915	-0.026341	-0.027793	-0.225884	0.059096	0.191736
Per_Cap_Income	0.000001	-0.000002	0.000001	-0.000001	-0.000002	0.000000	0.000004
Pellet_Exports (Million Tons)	0.000513	-0.005943	0.007598	0.001399	0.018271	-0.013744	-0.008094
LCC12	-0.048508	-0.277432	-0.068609	0.084865	0.061403	0.329791	-0.081510
Annual_Net_Rev_Ag	-0.000067	-0.000040	-0.000234	-0.000010	-0.000274	0.000603	0.000021
AL	0.010403	0.101001	-0.019970	-0.032945	0.030810	-0.100870	0.011569
AR	-0.000506	0.075915	-0.019147	-0.022475	-0.039437	-0.003330	0.008980
FL	-0.004884	-0.041285	-0.029773	0.031087	0.106171	-0.113736	0.052419
GA	0.010774	0.020176	0.013829	-0.007011	0.076944	-0.136624	0.021913
LA	-0.022560	-0.024069	-0.028692	0.036398	0.057192	-0.058473	0.040203
MS	-0.000131	0.093030	-0.027460	-0.007810	0.027817	-0.106930	0.021485
NC	0.012385	0.026730	0.020832	-0.020802	-0.022858	-0.062090	0.045804
OK	0.033954	0.056415	-0.016560	-0.075549	0.109487	-0.051137	-0.056610
SC	0.002882	0.020669	0.015636	-0.001179	0.005723	-0.087394	0.043663
TN	-0.018502	0.236330	-0.172576	-0.013093	-0.106276	0.040292	0.033825
VA	-0.006102	0.223031	-0.118337	-0.073971	-0.019648	-0.020412	0.015439

Table 4.6: Elasticity estimates of selected independent variables from the State Model.

				Elasticities			
Variable	**Oak-Pine**	**Upland HW**	**Natural Pine**	**Bottomland HW**	**Pine Plantation**	**Agriculture**	**Developed**
Value_Pine_Plantation	0.233	-0.224	0.290	0.067	0.511	-0.319	-0.239
Pop_Den	-0.045	0.035	-0.031	-0.053	-0.189	0.039	0.222
Per_Cap_Income	0.263	-0.334	0.263	-0.334	-0.334	-0.035	0.861
Pellet_Exports (Million Tons)	0.009	-0.030	0.061	0.018	0.102	-0.062	-0.063
LCC12	-0.186	-0.318	-0.124	0.244	0.078	0.333	-0.143
Annual_Net_Rev_Ag	-0.047	-0.008	-0.079	-0.005	-0.064	0.113	0.007

The pine plantation rent variable is statistically different than zero at the 5% level for all the regression equations except the upland hardwood and agriculture equations. The value of an acre of pine plantations had a positive marginal effect on the share of oak-pine forests, natural pine forests, pine plantations, and bottomland hardwood forests. Pine plantations were the most sensitive to changes in the pine plantation rent variable. For an average county, a 1% increase in the value of an acre of pine plantations results in a 0.51% increase in the share of pine plantations. Bottomland hardwood forests were very inelastic to changes in the value of an acre of pine plantations. A 1% increase in the value of an acre of pine plantations results in a .06% increase in the share of bottomland hardwood forests.

Annual net revenue from agriculture had a statistically significant effect on the share of oak-pine forests, natural pine forests, pine plantations, and agriculture. Annual net revenue from agriculture had a positive marginal effect on the share of agricultural land and a negative marginal effect on the shares all three forest types. The share of agriculture land was the most sensitive to changes in annual net revenue from agriculture. Annual net revenue from agriculture affected oak-pine forests, natural pine forests, and pine plantations similarly. Agriculture land was about twice as sensitive as the other three forest types to changes in annual net revenue from agriculture.

Both population density and per capita income were statistically different than zero at the 5% level in all six regression equations. Increases in population density increased the share of upland hardwood forests, agriculture land, and developed land, whereas, it decreased the share of oak-pine forests, natural pine forests, bottomland hardwood forests, and pine plantations. The positive marginal effect of population density on the share of upland hardwood forests was surprising as previous Zhang and Nagubadi (2005) found the opposite effect. However, the effect of increasing population density on the share of upland hardwoods is relatively small, a 1% increase in the population density results in only a 0.04% increase in the share of upland hardwood forests. Developed land was the most sensitive to changes in population density. But excluding developed land, pine plantations were three to five time more sensitive to population density than the other forest types/land uses. With the exception of developed land and pine plantations, the forest types and land uses were very inelastic with respect to changes in population density.

Per capita income was statistically significant all the regression equations. Both population density and per capita income were included as proxies for developed land use rents; therefore, it was surprising that these two variables had different marginal effects on the share of oak-pine forests, upland hardwood forests, natural pine forests, and agricultural land. Per capita income had a positive marginal effect on the share of oak-pine forests, natural pine forests, and developed land. The share of developed land was the most sensitive to changes in per capita income. The share of agricultural land was significantly less sensitive to changes in per capita income than any of the other forest types or land uses. The per capita income elasticities demonstrated that oak-pine forests and natural pine forests are affected similarly by changes in per capita income. My results demonstrated that the shares of pine plantations, bottomland hardwood forests, and upland hardwood forests were similar in their sensitivity to changes in per capita income.

Total wood pellet exports from the U.S. was statistically significant in all the forest type regression equations. The wood pellet export variable was converted to millions of metric tons and the average across the data set is 1.01 or 1,010,000 metric tons. Consequently, a one unit increase in the wood pellet export variable is equivalent to an additional 1 million metric tons of wood pellet exports. The marginal effect of the wood pellet export variable exhibited the same pattern of positive and negative marginal effects as the pine plantation rent variable. Unlike the pine plantation rent variable, the export wood pellet variable was statistically significant in the upland hardwood regression equation. Wood pellet exports had a positive marginal effect on the share of oak-pine forests, natural pine forests, pine plantations, and bottomland hardwood forests. Conversely, it had a negative marginal effect on the share of upland hardwood forests, agricultural land, and developed land. Although all land use and forest types shares demonstrated an inelastic relationship to wood pellet exports, oak-pine, upland hardwood, and bottomland hardwood forests had the most inelastic relationships. The share of pine plantations was the most sensitive land use/forest type to changes in wood pellet exports.

The LCC12 variable was not the statistically different than zero at the 5% level in the oak-pine and natural pine regression equations. The LCC12 variable had a positive effect on the share of agricultural land, bottomland hardwood forests, and pine plantations and a negative elasticity with respect to developed land, oak-pine forests, upland hardwood forests, and natural pine forests. Agriculture land was the most sensitive to changes in LCC12; however, bottomland hardwood and upland hardwood forests were almost as sensitive to changes in the LCC12 variable. Pine plantations were the least sensitive to changes in the share of land in the two best LCC classes within a county.

4.6: RESULTS OF ECOREGION MODEL

The system weighted adjusted R-Squared value for the ecoregion model indicates a slightly better fit than the state model. The majority of the continuous independent variables were statistically different from zero at the 5% level for all six regression equations. Tables 4.7 and 4.8 present coefficient estimates, statistical significance, and standard errors for the independent variables in ecoregion regression model. Tables 4.9 and 4.10 show the marginal effects and elasticity estimates of the independent variables from the ecoregion model.

Table 4.7: Regression results from the Ecoregion Model.

	Ln(Oak-Pine/Dev)		Ln(Upland Hardwood/Dev)		Ln(Natural Pine/Dev)	
Variable	**Coefficient (SE)**		**Coefficient (SE)**		**Coefficient (SE)**	
Intercept[1]	-0.32542**	(0.092767)	0.4927**	(0.082116)	0.93238**	(0.096432)
Value_Pine_Plantation [2]	0.00034**	(0.000035)	0.00016**	(0.000031)	0.00031**	(0.000037)
Pop_Den	-1.84089**	(0.065027)	-1.76408**	(0.057561)	-1.51324**	(0.067596)
Per_Cap_Income	-0.00002**	(0.000002)	-0.00003**	(0.000002)	-0.00004**	(0.000003)
Pellet_Exports (Million Tons)	0.07746**	(0.010481)	0.0473**	(0.009277)	0.127**	(0.010895)
LCC12	-0.13699	(0.104367)	0.46793**	(0.092384)	-0.37002**	(0.10849)
Annual_Net_Rev_Ag	-0.00085**	(0.000182)	-0.00107**	(0.000161)	-0.0011**	(0.000189)
CP	0.43172**	(0.140078)	1.55814**	(0.123995)	0.16415	(0.145612)
Pied	0.22687**	(0.027744)	0.9946**	(0.024558)	-0.03129	(0.02884)
EBLO	0.39085**	(0.101424)	1.71288**	(0.089779)	-0.58573**	(0.105431)
EBLC	-0.25852**	(0.079715)	1.17057**	(0.070563)	-1.15413**	(0.082864)
LMR	-0.65684**	(0.084052)	0.3007**	(0.074402)	-0.38342**	(0.087373)
System Weighted Adjusted R-Square	0.2731					

[1]** Statistically significant at the 1 percent level.
[2]* Statistically significant at the 5 percent level.

Table 4.8: Regression results from the Ecoregion Model (Continued).

	Ln(Bottomland Hardwood/Dev)		Ln(Pine Plantation/Dev)		Ln(Agriculture/Dev)	
Variable	**Coefficient (SE)**		**Coefficient (SE)**		**Coefficient (SE)**	
Intercept[1]	1.25994**	(0.111528)	1.73779**	(0.107838)	0.40512**	(0.089669)
Value_Pine_Plantation [2]	0.00009*	(0.000042)	0.00041**	(0.000041)	0.00003	(0.000034)
Pop_Den	-1.82443**	(0.078178)	-2.71051**	(0.075591)	-1.56938**	(0.062855)
Per_Cap_Income	-0.00004**	(0.000003)	-0.00005**	(0.000003)	-0.00002**	(0.000002)
Pellet_Exports (Million Tons)	0.06402**	(0.0126)	0.14664**	(0.012183)	0.00732	(0.010131)
LCC12	0.77762**	(0.125474)	0.294*	(0.121322)	2.14882**	(0.100881)
Annual_Net_Rev_Ag	-0.00047*	(0.000219)	-0.00192**	(0.000211)	0.00229**	(0.000176)
PraPark	0.80405**	(0.168407)	-0.33216*	(0.162835)	1.99095**	(0.1354)
Pied	-0.63183**	(0.033354)	-0.23512**	(0.032251)	0.28234**	(0.026817)
EBLO	-1.191**	(0.121936)	-1.51569**	(0.117901)	-0.01401	(0.098037)
EBLC	-0.8448**	(0.095837)	-1.52472**	(0.092665)	0.8668**	(0.077053)
LMR	0.64654**	(0.101051)	-0.3435**	(0.097708)	0.99743**	(0.081246)
System Weighted Adjusted R-Square	0.2731					

[1]** Statistically significant at the 1 percent level.
[2]* Statistically significant at the 5 percent level.

Table 4.9: Estimated marginal effects from the Ecoregion Model.

	Marginal Effects						
Variable	**Oak-Pine**	**Upland HW**	**Natural Pine**	**Bottomland HW**	**Pine Plantation**	**Agriculture**	**Developed**
Value_Pine_Plantation	0.000012	-0.000003	0.000015	-0.000010	0.000042	-0.000032	-0.000024
Pop_Den	-0.014415	-0.022365	0.014982	-0.019025	-0.194963	0.015036	0.220750
Per_Cap_Income	0.000001	0.000000	-0.000001	-0.000001	-0.000004	0.000002	0.000004
Pellet_Exports (Million Tons)	0.000976	-0.003066	0.007317	0.000001	0.015080	-0.011702	-0.008604
LCC12	-0.054298	-0.026326	-0.113991	0.017358	-0.057920	0.317358	-0.082181
Annual_Net_Rev_Ag	-0.000039	-0.000139	-0.000091	-0.000016	-0.000293	0.000537	0.000042
PraPark	-0.024593	0.144529	-0.070449	0.003485	-0.201267	0.251889	-0.103594
Pied	0.005957	0.155975	-0.020450	-0.081088	-0.069331	0.028397	-0.019460
EBLO	0.037730	0.338082	-0.053032	-0.110870	-0.253042	0.023770	0.017362
EBLC	-0.009650	0.237879	-0.119476	-0.075103	-0.255355	0.204832	0.016872
LMR	-0.060261	0.023309	-0.064712	0.049370	-0.094390	0.170033	-0.023350

Table 4.10: Elasticity estimates from the Ecoregion Model.

	Elasticities						
Variable	**Oak-Pine**	**Upland HW**	**Natural Pine**	**Bottomland HW**	**Pine Plantation**	**Agriculture**	**Developed**
Value_Pine_Plantation	0.213	-0.024	0.173	-0.122	0.309	-0.206	-0.240
Pop_Den	-0.030	-0.018	0.019	-0.027	-0.161	0.011	0.247
Per_Cap_Income	0.270	-0.029	-0.328	-0.328	-0.626	0.270	0.867
Pellet_Exports (Million Tons)	0.014	-0.017	0.064	0.000	0.084	-0.057	-0.065
LCC12	-0.170	-0.033	-0.224	0.038	-0.072	0.350	-0.139
Annual_Net_Rev_Ag	-0.023	-0.032	-0.033	-0.007	-0.068	0.110	0.013

The value of an acre of pine plantations was statistically significant in all of the regression equations except the agriculture equation. The value of an acre of pine plantations demonstrated the same positive and negative marginal effects on the shares of the forest types/land uses as the state model except, except for bottomland hardwood forests. The value of an acre of pine plantations had a positive marginal effect on the share of bottomland hardwood forests in the state model but a negative marginal effect in the ecoregion model. Oak-pine forest, natural pine forest, and pine planation shares increased as the value of an acre of pine plantations increase, whereas, upland hardwood forest, bottomland hardwood forest, agriculture land, and developed land shares decreased as the value of an acre of pine plantations increased. Similar to the state model, the share of pine plantations was most sensitive to changes in the value of an acre of pine plantations. Upland hardwood forests were the most inelastic of all the land use/forest type categories to changes in the value of an acre of pine plantations.

The marginal effect of annual net revenue from agriculture had the same sign for all land uses/forest types as the state model. Annual net revenue from agriculture were statistically significant in all the regression equations. Annual net revenue from agriculture had a positive marginal effect on the share of agriculture and developed land and a negative marginal effect on the share of all the forest types. The agricultural land use share was most sensitive to changes in annual net revenue from agriculture and demonstrated a similar elasticity between the ecoregion and state models. In the ecoregion model, pine plantations were more sensitive to changes in annual net revenue from agriculture; however, natural pine forests were slightly more sensitive to changes in annual net revenue from agriculture than pine plantations in the state model. The share of bottomland hardwood forests was the least sensitive to changes in annual net revenue from agriculture in both the state and ecoregion models.

Like the state model, population density was statistically different from zero at the 5% level in all six regression equations. Population density had a positive marginal effect on the share of agricultural land, developed land, and natural pine forests, but a negative marginal effect on the other forest types. Population density had the largest effect on the share of developed land. Similar to the state model, the share of pine plantations was more sensitive to changes in population density compared to the shares of agriculture land and the other forest types. The share of pine plantations were 5-14 times more sensitive to population density than the share of agriculture land and the other forest types. Comparing the state and ecoregion models, population density had a different marginal effect on the share of natural pine and upland hardwood forest. However, in both models the share of natural pine and upland hardwood forests were very inelastic to changes in population density.

Per capita income was statistically significant in all six regression equations. Per capita income had a positive marginal effect on the share of developed land and developed land was the most sensitive to changes in per capita income. Per capita income also had a positive marginal effect on the share of agriculture land and oak-pine forests. The per capita income elasticity estimates for the share of oak-pine forests and developed land were similar in magnitude between the state and ecoregion models. The marginal effect of per capita income on the share of agriculture land and natural pine forests exhibited different signs between the state and ecoregion models. Pine plantations were almost twice as sensitive to changes in per capita income than the other forest types. Upland hardwood forests were the least sensitive land use/forest type group to changes in per capita income. This was different than the state model where upland hardwood forests were one of the most sensitive forest types to changes in per capita income.

Like the state model, the wood pellet exports variable was statistically significant in all the forest type regression equations. The relationship between wood pellet exports and the share of forest the forest types was the same across both models. Wood pellet exports had a positive marginal effect on the share of pine plantations, oak-pine forests, upland hardwood forests, and bottomland hardwood forests; and a negative marginal effect on the share of developed land, agricultural land, and upland hardwood forests. The share of all land uses and forest types demonstrated an inelastic relationship to changes in wood pellet exports. Pine plantations were the most sensitive and bottomland hardwood forests were the least sensitive to changes in wood pellet exports.

The LCC12 variable was statistically significant in all the regression equations except the oak-pine regression equation. LCC12 had a positive effect on the share of agriculture land and bottomland hardwood land and negative effect on the shares of all other land uses/forest types. LCC12 elasticity with respect to pine plantations demonstrated a different sign between the state and ecoregion models. The share of agricultural land was the most sensitive to changes in the LCC12 variable. Of all the forest types, the share of natural pine forests was the most sensitive to changes in the LCC12 variable. Upland hardwood and bottomland hardwood forests were the most inelastic to changes in the share of land in the two best LCC classes.

4.7: ANALYSIS OF FIXED EFFECTS

As stated previously, the ecoregion model had a slightly better fit than the state model. The system weighted adjusted R-squared value for the ecoregion and state models were 0.2731 and 0.2471, respectively. In this section, I focus specifically on the analysis of the ecoregion fixed effects because analysis of the state specific factors that influence land use and forest type shares has been addressed by other researchers. Previous research has analyzed how state policies such as property taxes, agricultural policies, and cost share programs influence different land uses (Plantinga, 1996; Polyakov & Zhang, 2008).

In the ecoregion model, the Coastal Plain (*CP*) ecoregion is the reference category for the interpretation of the ecoregion dummy variables. Counties located in the Coastal Plain had a larger share of pine plantations than all other regions, which was demonstrated by the negative marginal effects of all the ecoregions. All the ecoregions also had a smaller share of natural pine forests than the Coastal Plain. The five ecoregion dummy variables had a positive marginal effect on the share upland hardwood forests and agriculture, implying counties in these ecoregions had a larger share of upland hardwood forests and agriculture land than the Coastal Plain. The Piedmont (*Pied)* and Eastern Broadleaf Forest Oceanic (*EBLO*) ecoregions had a larger share of oak-pine forests than the Coastal Plain. Conversely, the Prairie Parkland Subtropical (*PraPark*), Eastern Broadleaf Forest Continental (*EBLC*), and Lower Mississippi Riverine Forest (*LMR*) ecoregions had a smaller share of oak-pine forests than the Coastal Plain. Both the Prairie Parkland Subtropical and Lower Mississippi River Forest ecoregions had a larger share of bottomland hardwood forests than the Coastal Plain, whereas, the other regions had a smaller share of bottomland hardwood forests. The Prairie Parkland Subtropical, Piedmont, and Lower Mississippi Riverine ecoregions had a smaller share of developed land than the Coastal Plain.

4.8: CONCLUSION

The results from both the state and ecoregion models indicated that forest types do respond differently to drivers of land use change, evidenced by different relationships and varying levels of statistical significance with respect to the independent variables. My results indicated that increasing values of an acre of pine plantations increased the share of forest types with pine as a dominant species in their species composition and decreased or did not affect the share of forests that are dominated by hardwood species. Further, increasing annual net revenue from agriculture decreased the share of all forest types, but had the largest impact on the share of natural pine forests and pine plantations. The effects of increasing site quality had an ambiguous effect on the share of pine plantations. Oak-pine forests were unaffected by changes in site quality. Increases in site quality decreased the share upland hardwood and natural pine forests and increased the share of bottomland hardwood forest. Per capita income and population density had the most conflicting effects on the share of the different forest types between the two models. However, bottomland hardwood forests and pine plantations appear to be the forest types that were most susceptible to increasing population pressure. Across both models, pine plantations were the most sensitive to changes in population pressure, as measured by per capita income and population density. Similar to the pine plantation rent variable, the shares of three forest types with pine as a significant part of their species composition increased as wood pellet exports increased. Surprisingly, increased wood pellet exports increased the share of bottomland hardwood forests. The share of upland hardwood forests was unaffected by increases in wood pellet exports but was negatively affected in the ecoregion model.

Chapter 5: Discussion

5.1: INTRODUCTION

There were two objectives of this research project. The primary objective was to build an econometric model of land use change to better understand how land use drivers affect different forest types. A discussion of the results as they relate to this question is presented in section 5.2. The second objective was to use this model to understand how wood pellet exports impacts land use/forest type shares in the U.S. South. Section 5.3 examines results related to the wood pellet export variable. Section 5.4 discusses possible ways the results from this study could be integrated into different kinds of research and concludes by examining the limitations of this study and provides suggestions on how it could be improved.

5.2: DRIVERS OF LAND USE AND FOREST TYPE CHANGE

This study found that values of an acre of pine plantations, annual net revenue from agriculture, and the proxies for developed rents, per capita income and population density, are important variables for determining the share of forest types and land uses. These findings are consistent with previous research that found land use/forest type rents to be important determinants of land use and forest type change (Ahn et al., 2002; Hardie et al., 2000; Kim et al., 2018; Lubowski, 2002; Zhang & Nagubadi, 2005). Furthermore, the different economic rent elasticities confirm previous research findings that forest types respond differently to economic rents (Nagubadi & Zhang 2005; Sohngen & Brown 2005; Zhang & Nagubadi 2005).

Although economic rents for each forest type were not estimated, the value of an acre of pine plantations had different effects on the individual forest types. My results from both the state and ecoregion models indicated that the value of an acre of pine plantations had a positive marginal effect on the share of oak-pine forests, natural pine forests, and pine plantations. It may seem surprising that the value of an acre of pine plantations had a positive marginal effect on the share of oak-pine and natural pine forests. However, because both forest types have a significant portion of pine in their species composition, it is reasonable to expect that higher rents for pine plantations could also incentivize the retention of these forest types, especially if pine plantation rent increases are due to rising prices for pine timber. Zhang and Nagubadi (2005) found a similar result; pine timber prices had a positive marginal effect on the share of softwood and mixed hardwood-softwood forests. I expected that the value of an acre of pine plantations would have a negative marginal effect on the share of upland hardwood forests. In the state model, the share of upland hardwood forests was unaffected by the value of an acre of pine plantations, but in the ecoregion model the value of an acre of pine plantations had a negative marginal effect on the share of upland hardwood forests. Previous literature generally supports the latter finding that increases in economic returns to pine forests has a negative marginal effect on the share of hardwood forests (Nagubadi &Zhang, 2005; Sohngen & Brown, 2006; Zhang & Nagubadi, 2005). I hypothesized that pine plantations rents would either not be statistically significant in determining the share of bottomland hardwood forests or would have a negative marginal effect on the share of bottomland hardwood forests. Unexpectedly, results from the state model showed that the value of an acre of pine plantations had a statistically significant and positive marginal effect on the share of bottomland hardwood forests. In the ecoregion model, the value of an acre of pine plantations had a statistically significant and negative marginal effect on the share of bottomland hardwood forests, which is the expected sign. In both models, bottomland hardwood forests are relatively inelastic to changes in the value of an acre of pine plantations compared to the other forest types. This is not surprising considering bottomland hardwood forests are often not compatible with successful conversion to pine plantations. Although none of the studies reviewed included bottomland hardwood forests as a forest type category, their results demonstrated that hardwood forest types are more inelastic to changes in softwood rents than softwood forest types (Nagubadi &Zhang, 2005; Zhang & Nagubadi, 2005).

I expected that the value of an acre of pine plantations would be statistically significant and have a negative marginal effect on the share of agriculture land. My results indicate that the value of an acre of pine plantations are not statistically significant in explaining the ratio of the share of agriculture land to the share of developed land. However, the marginal effect of the value of an acre of pine plantations has a negative marginal effect on the share of agriculture land. Results from previous land use change literature supports my original hypothesis that the value of an acre of pine plantations would have a statistically significant and negative marginal effect on the share of agriculture land (Ahn et al., 2002; Nagubadi & Zhang, 2005; Zhang & Nagubadi, 2005).

Annual net revenue from agriculture appear to be a robust variable for explaining land use and forest type shares. The results from my study showed that in ten of twelve regression equations annual net revenue from agriculture were statistically different than zero at the 5% level. In the literature reviewed, there was not a clear consensus on how annual net revenue from agriculture affected many of the forest types (Nagubadi &Zhang, 2005, Sohngen & Brown, 2006; Zhang & Nagubadi, 2005). The agriculture rent elasticities indicated that the forest types varied in their sensitivity to changes in annual net revenue from agriculture. Pine plantations were the most sensitive to changes in annual net revenue from agriculture in the state model and the second most sensitive in the ecoregion model. Excluding developed land, agriculture and pine plantations are likely to derive the largest net returns. As a result, landowners who focus exclusively on maximizing economic rents from their land, may be ultimately more responsive to changes in the relative returns of pine plantations and agriculture. Results from my analysis show that natural pine forests were more sensitive to changes in annual net revenue from agriculture compared to the remaining forest types. The relatively large agriculture rent elasticities with respect to natural pine forests and pine plantations could be explained by physiographic characteristics. If natural pine forests, pine plantations, and agriculture land are all better suited for a specific set of overlapping physiographic characteristics, then it would not be surprising that pine plantations and natural pine forests are less inelastic to changes in annual net revenue from agriculture than the other forest types. Results from Nagubadi and Zhang (2005) and Zhang and Nagubadi (2005) found that softwood forests were most sensitive to changes in annual net revenue from agriculture. My results indicate that the share of bottomland hardwood forests was either not affected by annual net revenue from agriculture or very inelastic to changes in annual net revenue from agriculture. This could be a product of federal and state restrictions regarding the conversion of wetlands to other land uses. In the state model, upland hardwood forests were not affected by annual net revenue from agriculture but in the ecoregion model, annual net revenue from agriculture had a statistically significant and negative marginal effect. There is little consensus among previous land use change studies regarding how annual net revenue from agriculture affect hardwood forests. However, my results support the previous results that forest types are affected differently by annual net revenue from agriculture and emphasizes the need to recognize forest heterogeneity in modeling land use change (Nagubadi &Zhang, 2005, Sohngen & Brown, 2006; Zhang & Nagubadi, 2005).

In both models used in my analysis, population density and per capita income were statistically significant in all the regression equations, which provides evidence that development pressure affects all forest types and land uses. The population density and per capita income variables had the expected marginal effect on the share of developed land, pine plantations, and bottomland hardwood forests in both models. Results from previous research demonstrated that both population density and per capita income had a negative effect on the share of all forest types (Nagubadi & Zhang, 2005; Sohngen & Brown, 2006). My results show that pine plantations are significantly more sensitive to changes in population density than the other forest types. Similarly, pine plantations are one of the forest types most sensitive to changes in per capita income. Based on these results I conclude that pine plantations are more sensitive to urban rents than the other forest types. Because other studies that reported elasticity estimates did not use pine plantations as a forest type category, it is impossible substantiate this finding.

For oak-pine, natural pine, and upland hardwood forests, I find that per capita income and population density had conflicting effects and that these effects were not consistent across both models, which makes it impossible to highlight empirically robust relationships. For example, I find that population density has a negative marginal effect on the share of natural pine forests, but per capita income had a positive marginal effect on the share of natural pine forests in the state model. However, the relationships between population density and per capita income and the share of natural pine forests are reversed in the ecoregion model. No previous studies that reported elasticities used these forest types so it is difficult to contextualize these mixed results.

Unexpectedly, the results from both models used in this study indicate that population density has a positive marginal effect on the share of agriculture land. Per capita income has a positive marginal effect on the share of agriculture land in the ecoregion model, but a negative marginal effect in the state model. Although results are mixed, I conclude that population density and per capita income do not have a negative effect on the share of agriculture land. Results from previous land use change studies regarding the relationship between agriculture land and population pressure are also mixed. For example, Nagubadi and Zhang (2005) found that both population density and per capita income had a negative marginal effect on the share of agriculture land; however, Ahn et al. (2002) found that population density had a positive marginal effect on the share of agriculture land. Zhang and Nagubadi (2005) also found that population density and per capita income had a positive marginal effect on the share of agriculture land.

The Land Capability Classification system is primarily focused on the suitability of land for agriculture. The LCC variable used in this analysis, LCC12, is the share of total land within a county that is in LCC classes I and II, the two best LCC classes. Based on the description of how the LCC system was constructed, I expected that as the LCC12 variable increased the share of agriculture would increase. Considering there is little temporal variation in the LCC12 variable within a county, a more appropriate expectation was that counties with a larger share of land in the two best LCC classes would have a larger share of agriculture land than counties with a smaller share of land in the two best LCC classes. The results from the state and ecoregion models support this hypothesis. The share of land in LCC classes I and II was statistically significant in the agriculture regression equation and had a positive effect on the share of agricultural land. Although this was the most common result in the literature (Nagubadi & Zhang, 2005; Plantinga et al. 1999; Zhang & Nagubadi, 2005), some results suggested that the share of agriculture land decreased as LCC12 increased (Ahn et al., 2002). Across both models, the LCC variable was statistically significant in nine of the twelve regression equations. In the state and ecoregion models, I find that the share of land in LCC classes I and II has a negative marginal effect on the share of oak-pine forests, upland hardwood forests, natural pine forests, and developed land. Conversely, LCC12 had a positive marginal effect on the share of bottomland hardwood forests. Although there were exceptions, results from previous studies generally demonstrated that all forest types are negatively affected by increases in the share of land in the two best LCC classes. The share of land in LCC classes I and II has a positive marginal effect on the share of pine plantations in the state model, but a negative marginal effect in the ecoregion model. Even though the LCC system is primarily defined in terms of suitability of land for agriculture, some soil properties that are better suited for agriculture will undoubtedly overlap with soil properties that are better suited for pine plantations. Therefore, from a theoretical standpoint, it is difficult to determine the expected effect of the LCC12 variable on the share of pine plantations. Clearly, the different fixed effects used to control for spatial heterogeneity played a role in the conflicting results.

To summarize these results, both the state and ecoregion models demonstrate that forest types respond differently to determinants of land use change. The value of an acre of pine plantations have the largest positive marginal effect on the share of pine plantations but increases in the value of an acre of pine plantations also increases the share of oak-pine forests and natural pine forests. Upland hardwood forests were the only forest type whose share is negatively affected by increases in the value of an acre of pine plantations. Annual net revenue from agriculture have a negative marginal effect on the share of all forest types. Pine plantations and natural pine forests appear to be the most sensitive to changes in annual net revenue from agriculture. Population density and per capita income have contradictory effects on the shares of many forest types across both models. The share of land within a county in the two best LCC classes has the largest positive marginal effect on the share of agriculture. Both oak-pine and natural pine forests are negatively affected by increases in the share of land within a county that is in the two best LCC classes. There was no discernable relationship between the share of pine plantations and the share of land in the two best LCC classes within a county. Due to limited number of land use models that disaggregate forestland, it is difficult to synthesize my results with previous findings. Although my results provide evidence of certain empirical relationships between drivers of land use change and different forest type groups, there were many results that were not robust and warrant further investigation.

5.3: WOOD PELLET EXPORTS AND FOREST TYPE CHANGE

The second goal of this study is to test whether wood pellet exports affected the share of forest types and land uses. In both the state and ecoregion models, the wood pellet export variable is statistically significant in all the regression equations except the agriculture regression equation. Previous work on the effect of increased wood pellet demand on the southeastern forests has shown that wood pellet demand will impact the acreage of many forest types and land uses (Costanza et al., 2015, 2017; Duden, 2017). As stated previously, the major studies that I compared my results to all used the SRTS model to determine how forest types respond to changes in demand for wood pellets. The SRTS model uses a heuristic to determine how sensitive the forest types are to changes in timber prices. The assumption in the SRTS model is that pine plantations are twice as sensitive to price changes as oak-pine, natural pine, and upland hardwood forests and bottomland hardwood forests are half as price sensitive as oak-pine, natural pine, and upland hardwood forests.

The marginal effects of wood pellet exports on the share of forest types and land uses is consistent across both models used in this analysis. Wood pellet exports have a positive marginal effect on the share of pine plantations, oak-pine forests, natural pine forests, and bottomland hardwood forests, but a negative marginal effect on the share of upland hardwood forests, agriculture land, and developed land. I expected that if wood pellet exports had a statistically significant effect on the share of pine plantations that this effect would be positive. Evidence from my study that increased demand for wood pellet exports increases the share of pine plantations supports conclusions from previous research (Costanza et al., 2017; Duden et al., 2017).

Results from my analysis show that wood pellet exports had a positive marginal effect on the share of oak-pine and natural pine forests; however, Duden (2018) found that pine plantation expansion due to increased wood pellet demand is primarily the result of conversion of oak-pine and natural pine forests, which is evidence that conflicts with my findings. Costanza et al. (2017) found that under all three demand scenarios that include increased demand for wood pellets, mixed-pine hardwood forests increased in acreage in projections to 2050 compared to the baseline. The researchers also found that natural pine forest acreage increased in two of the three demand scenarios that included increased demand for wood pellets compared to a baseline. My results support the findings from Costanza et al. (2017) that increasing wood pellet demand does not necessarily result in smaller shares of mixed pine and natural pine forests. Similar to evidence provided by Costanza et al. (2017) and Duden et al. (2018), I find that wood pellet exports have the largest positive effect on the share of pine plantations and the second largest positive effect on the share of natural pine forests. Results from the state model indicate that natural pine forests are almost half as sensitive to changes in wood pellet exports as pine plantations, but in the ecoregion model natural pine forests are only slightly more inelastic to wood pellet exports than pine plantations. However, oak-pine forests are significantly more inelastic to changes in wood pellet exports than natural pine forests and pine plantations.

Costanza et al. (2017) found that the share of upland hardwood forests decreased in acreage in all three scenarios that included increased demand for wood pellets, although the decrease in share was small. This result is consistent with the results of both models used in my analysis, which indicated that wood pellet export demand has a negative marginal effect on the share of upland hardwood forests. Furthermore, I found evidence that upland hardwood forests are very inelastic to changes in wood pellet demand. Surprisingly, I find that wood pellet exports are statistically significant in determining the share of bottomland hardwood forests and had a positive marginal effect on the share of bottomland hardwood forests. These results were unexpected and contradicted findings by Costanza et al. (2017), which showed that bottomland hardwood forest area decreased under all three wood pellet scenarios. From my perspective, there is no justification for a causal relationship that increased demand for wood pellets would cause the share of bottomland hardwood forests to increase.

My results suggest that increasing wood pellet demand does not affect the share of agriculture land. However, Costanza et al. (2015) found that increased demand for wood pellets led to decreases in the share of agriculture land. Similarly, Coastanza et al. (2015) found that increasing demand for wood pellets did increase conversions of agriculture land to forestland. From my analysis it is impossible to determine if wood pellets exports are a statistically significant determinant of the share of urban land because the urban land use category is the residual land use category. This problem could be addressed in the future by estimating the statistical significance of the marginal effects and elasticities.

Results from my analysis indicate that wood pellet exports do impact southeastern forests. My results provide more evidence that increasing demand for wood pellet exports increases the share of pine plantations. My results suggest that the share of oak-pine and natural pine forests increases as a result of increased demand for wood pellet exports. Furthermore, I find evidence that upland hardwood forests are negatively impacted by increasing demand for wood pellet exports. Although, my results suggest that bottomland hardwood forest are positively impacted by increases in wood pellet demand, in the absence of an explanation of the causal relationship, this result is tenuous. Overall, the share of all forest type groups is very inelastic to changes in wood pellet exports. Contrary to findings from previous research, I find evidence that wood pellet exports do not have a statistically significant effect on the share of agriculture land.

5.4: LIMITATIONS AND FUTURE RESEARCH

There are several improvements that could enhance this study. As identified in Section 4.5 heteroskedasticity was present and no correction was made. Heteroskedasticity can affect the statistical significance of the independent variables and steps will need to be taken to correct for this in future studies.

Because this study utilizes a panel dataset, it is necessary to completely control for the cross-sectional variation to accurately capture the temporal relationship between independent and dependent variables. Although attempts are made to control for cross-sectional variation through the inclusion of state and ecoregion dummy variables, evidence from Ahn et al. (2000[b]) suggests that a county-level fixed effects model more effectively controls for cross-sectional variation than an Ordinary Least Squares (OLS) model. Therefore, a next step for future analyses is to construct a county-level fixed effects model and compare the results to those of my study.

A limitation of the wood pellet export variable, used in this analysis, is that it ignores the possibility of spatially heterogeneous effects of increased wood pellet demand on forest type shares. It is reasonable to assume that increased demand for wood pellet exports may have a different effect on the share of forest types and land uses depending on the location of wood pellet export mills. For example, I would expect the closer a county is to a wood pellet mill the more influence the mills procurement decisions would have on the size of the various forest type and land use shares. In future studies, this issue could be addressed by calculating total wood pellet exports by port and using a distance function to determine how to assign wood pellet export quantities to specific counties.

Section 1.4 illustrated that there are many factors that influence the provisioning of ecosystem services from forests. The inclusion of disaggregated forest type categories in models of land use change, provide a finer level of detail about how forestland responds to drivers of land use change. These results can be linked to models that model ecosystem services from forests. Through this linkage, researchers can better understand how market forces and other drivers of land use change affect ecosystem service provided by forestland.

The results from my study provide insight as to how different forest types respond to the value of an acre of pine plantations, annual net revenue from agriculture, and urban rent proxies. However, there is the potential to include forest type specific rents or rent proxies such as timber prices for different species and estimate price elasticities with respect to the different forest types. These estimated price elasticities results could replace the heuristic in the SRTS model that determines how forest types respond to timber prices. Using the estimated price elasticities, forest type area change estimates from SRTS would be directly linked to an empirical evidence.

My results indicate that distinct forest types respond differently to drivers of land use change. As a result, if forestland is of specific interest to the researcher, disaggregating forestland by forest type provides a better understanding of how drivers of land use change affect forestland. While there appear to several empirically robust relationships between different forest types and drivers of land use change, there were many instances in which no robust relationship could be determined. My results indicate that wood pellet exports have a statistically significant effect on the share of all forest types. However, wood pellet exports do not have a negative effect on the shares of all natural forest types. Increased demand for wood pellet exports increases the share of oak-pine forests and natural pine forests but decreases the share of upland hardwood forests.

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APPENDIX

Appendix A

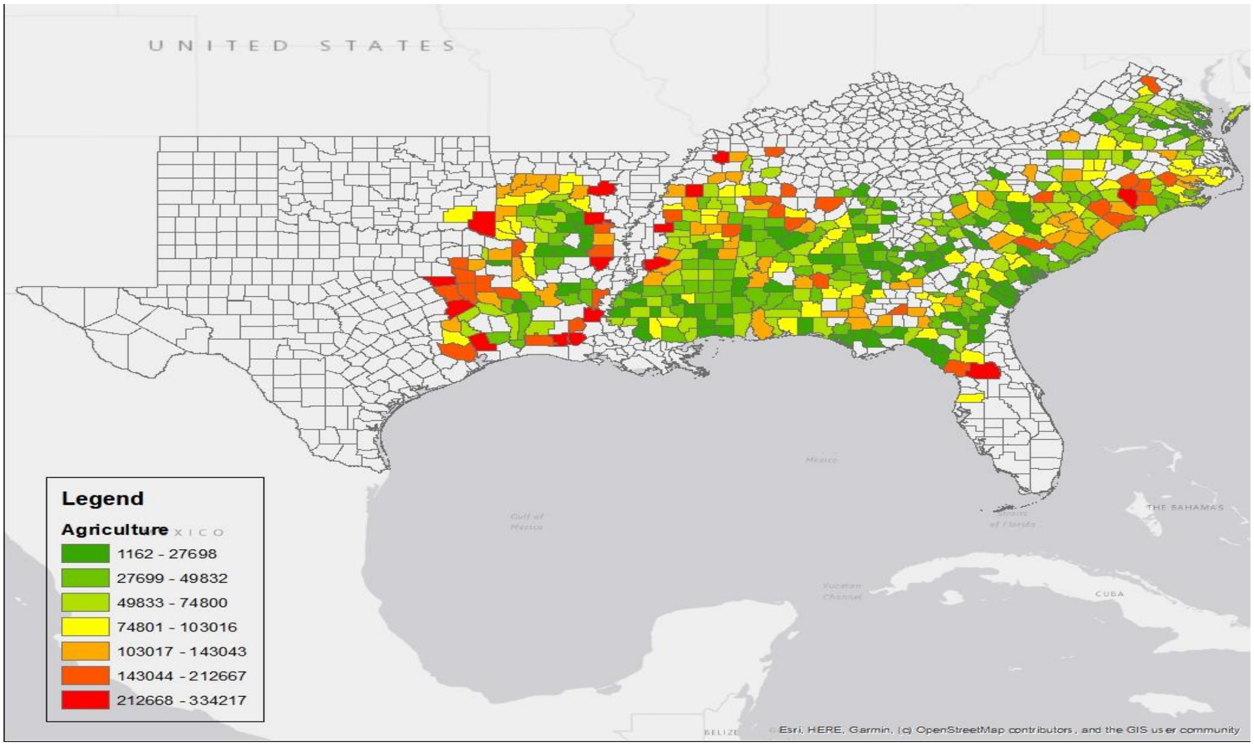

Figure 1: Agriculture acreage for counties used in the land use models.

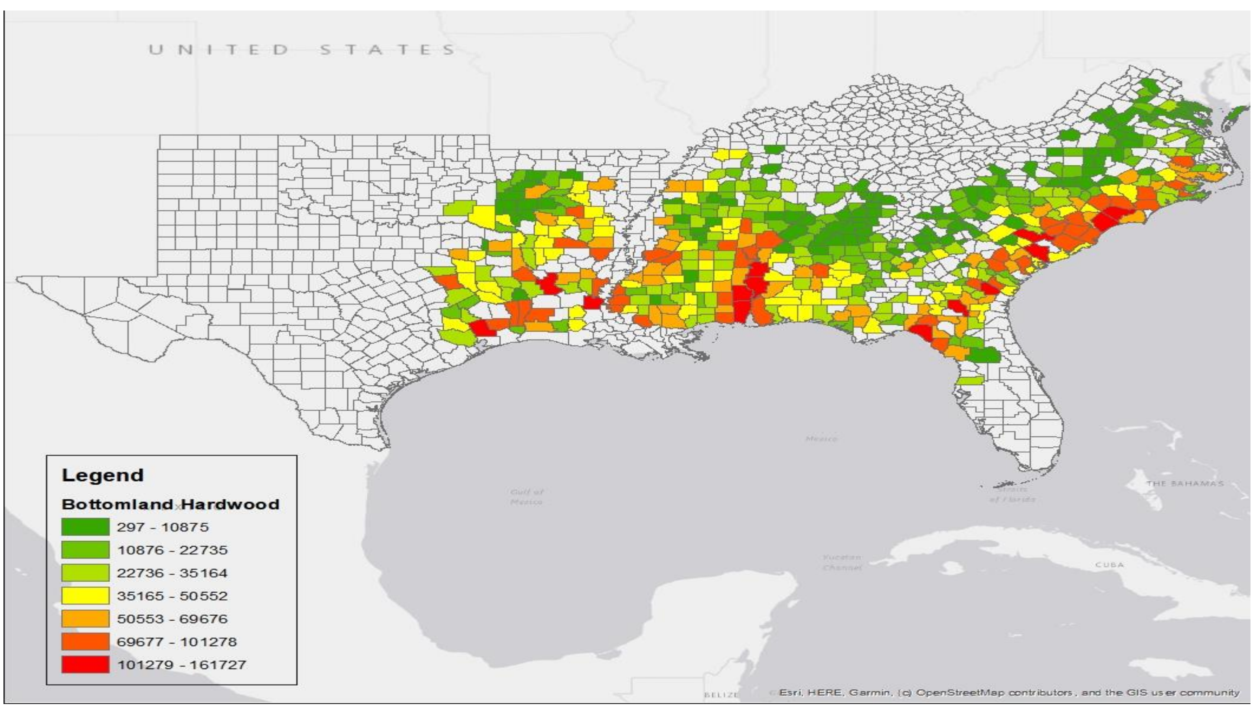

Figure 2: Bottomland hardwood forest acreage for counties used in the land use models.

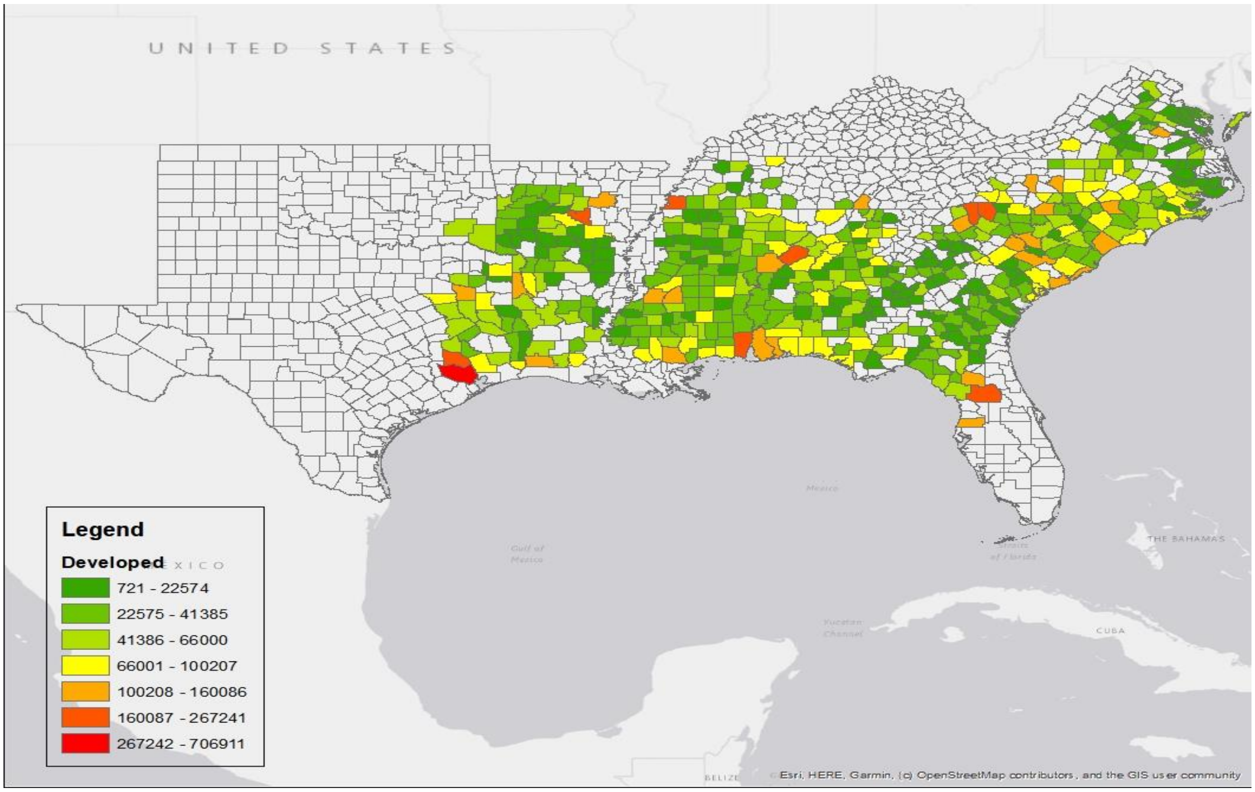

Figure 3: Developed land acreage for counties used in the land use models.

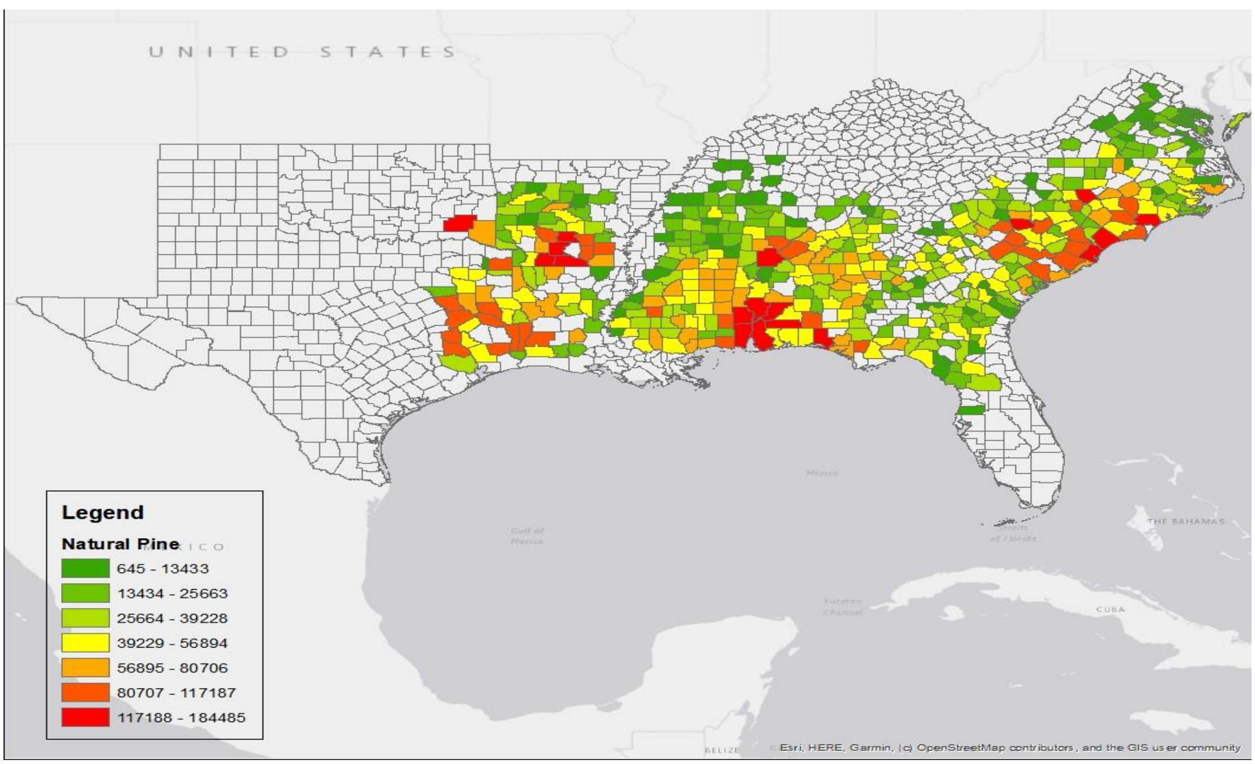

Figure 4: Natural pine forest acreage for counties used in the land use models.

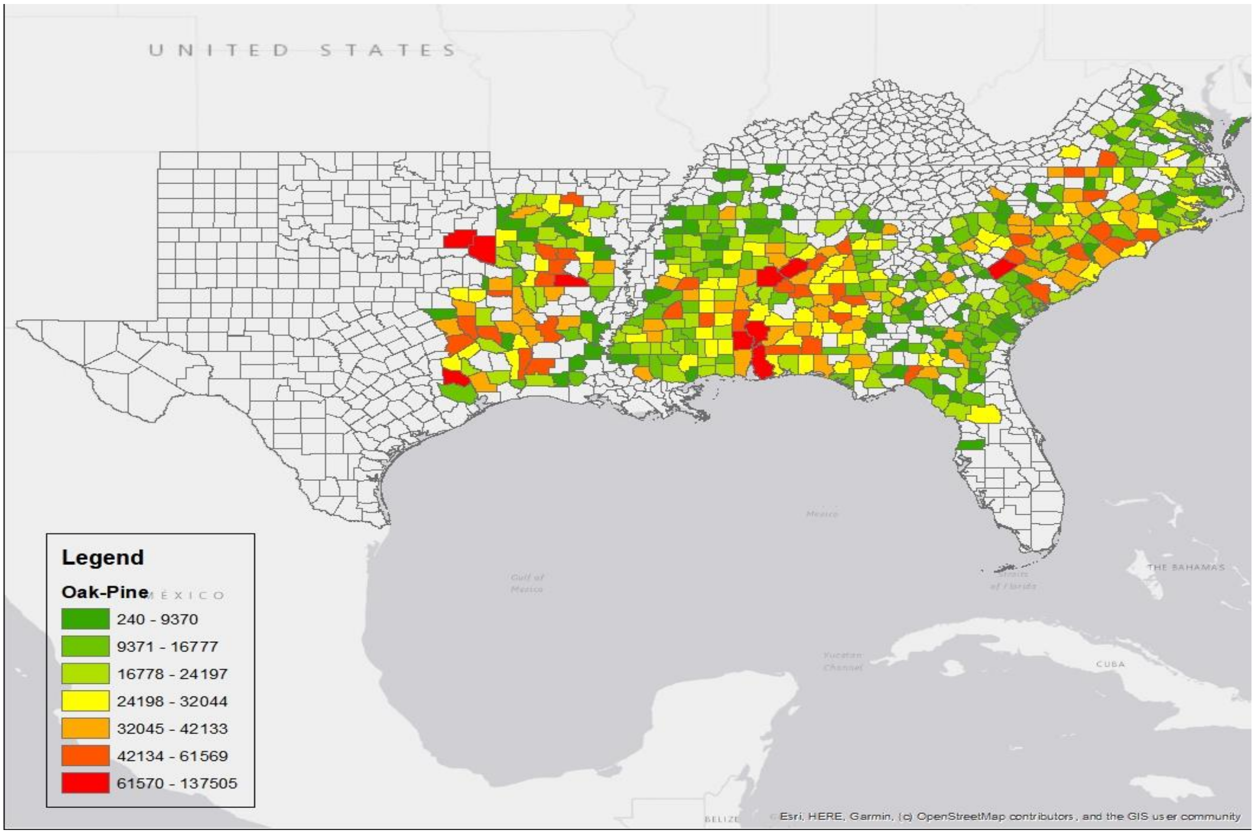

Figure 5: Oak-pine forest acreage for counties used in the land use models.

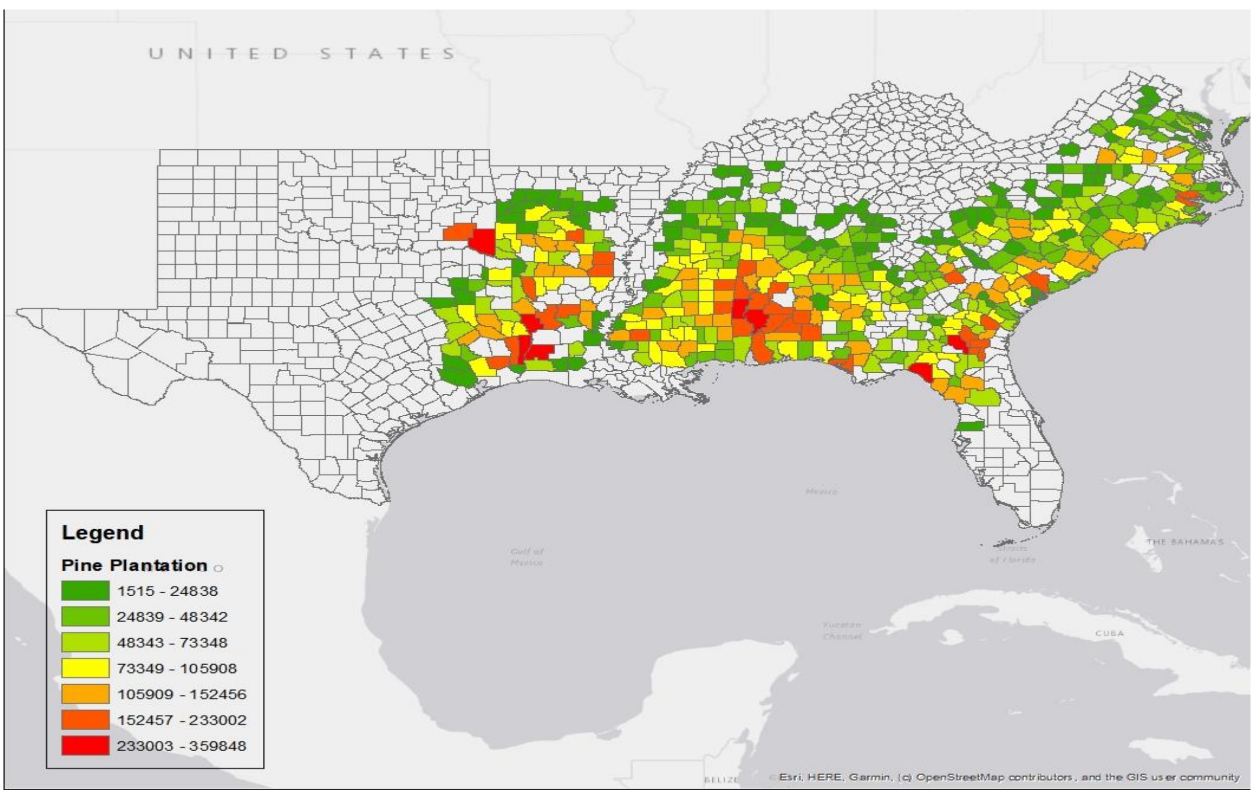

Figure 6: Pine plantation acreage for counties used in the land use models.

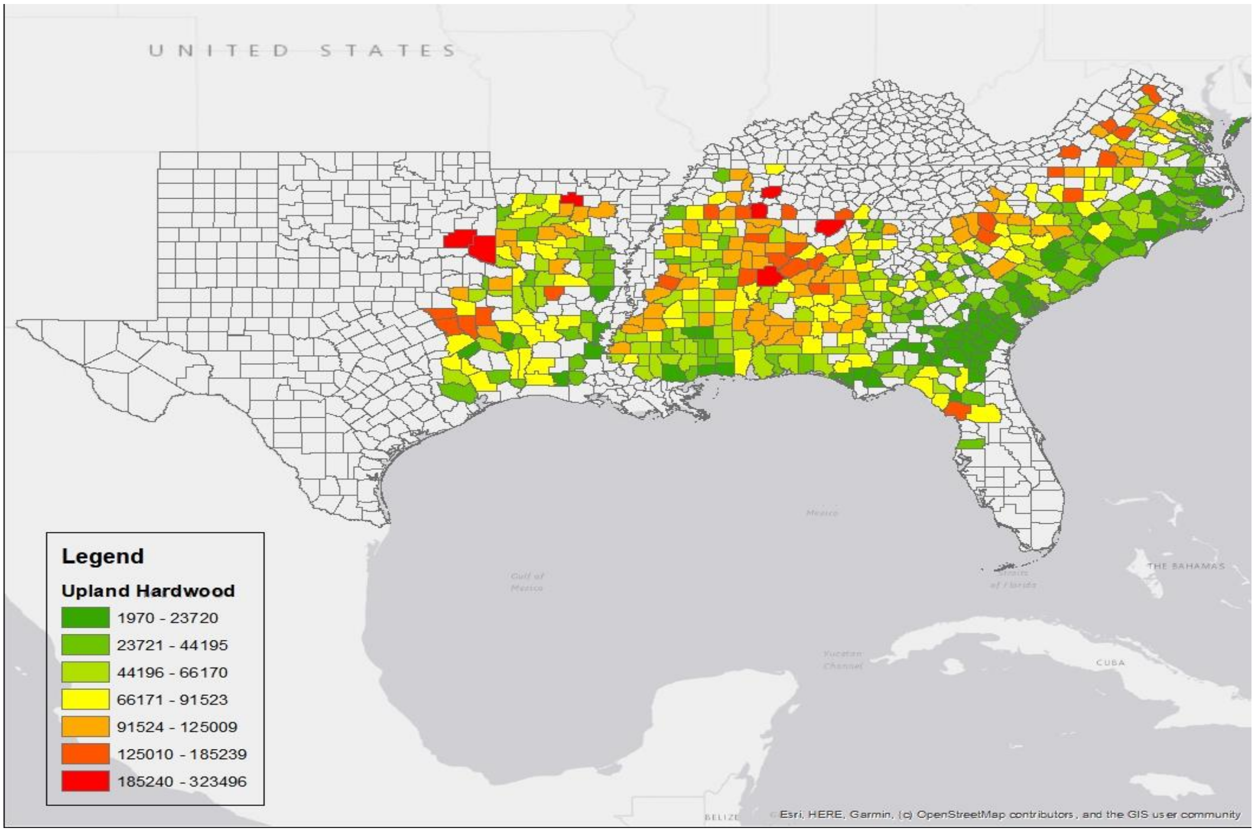

Figure 7: Upland hardwood forest acreage for counties used in the land use models.

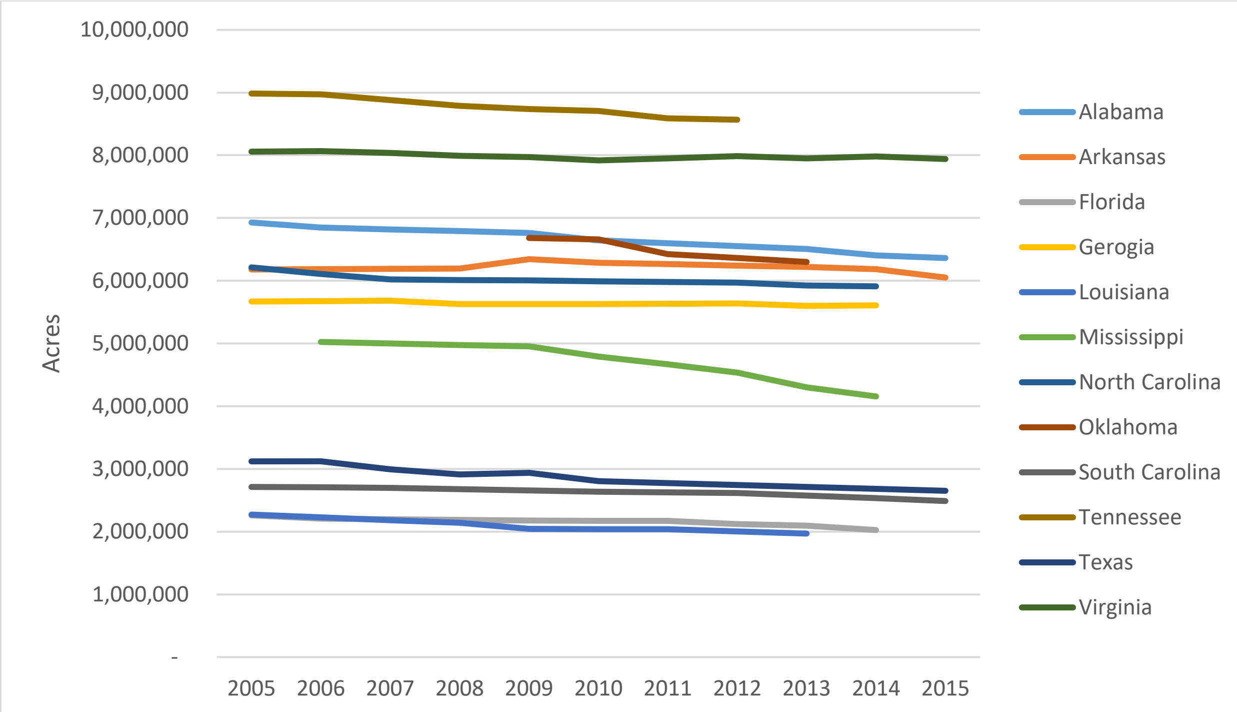

Figure 8: Area of agriculture land for all counties in the state, except Texas, which only includes eastern Texas.

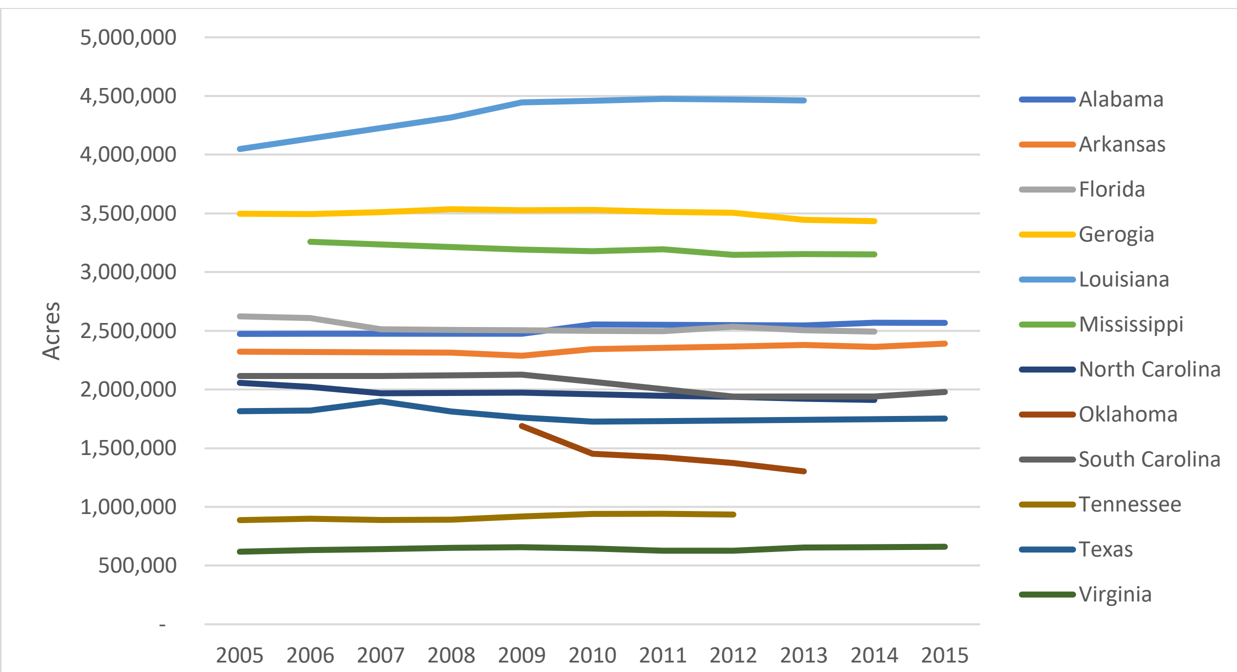

Figure 9: Area of bottomland hardwood forests for all counties in the state, except Texas, which only includes eastern Texas.

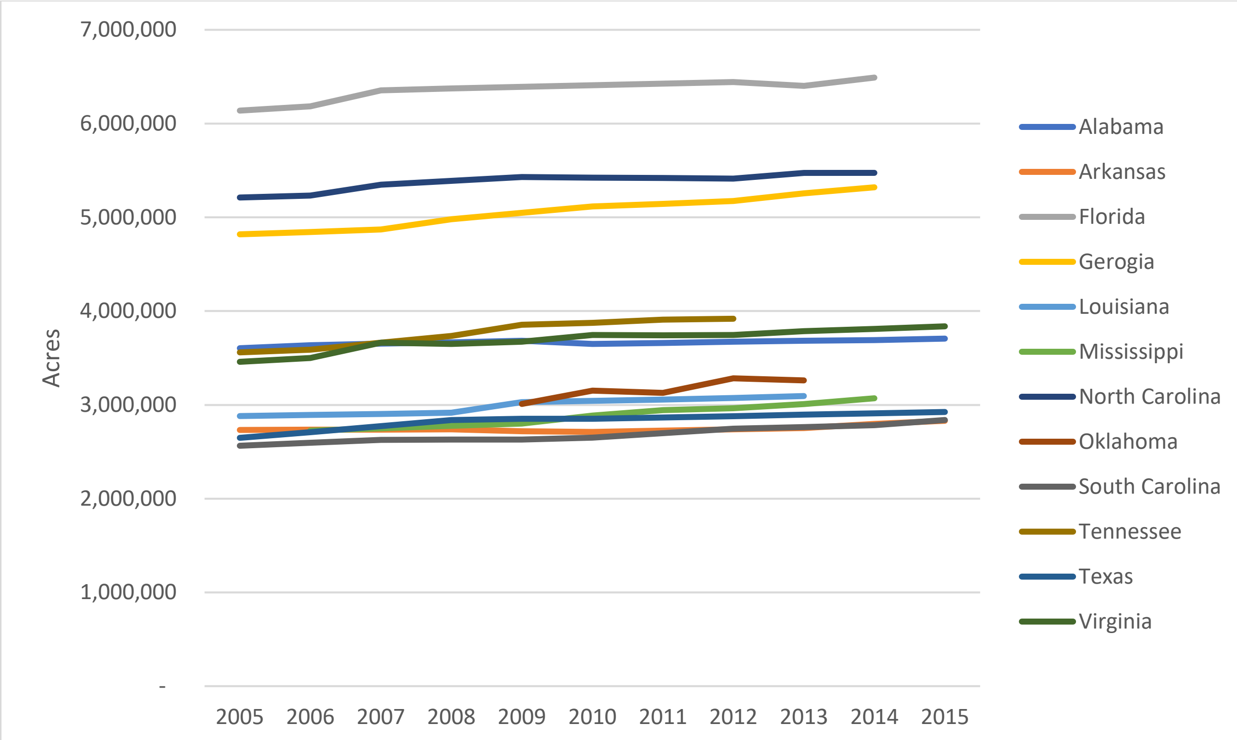

Figure 10: Area of developed land for all counties in the state, except Texas, which only includes eastern Texas.

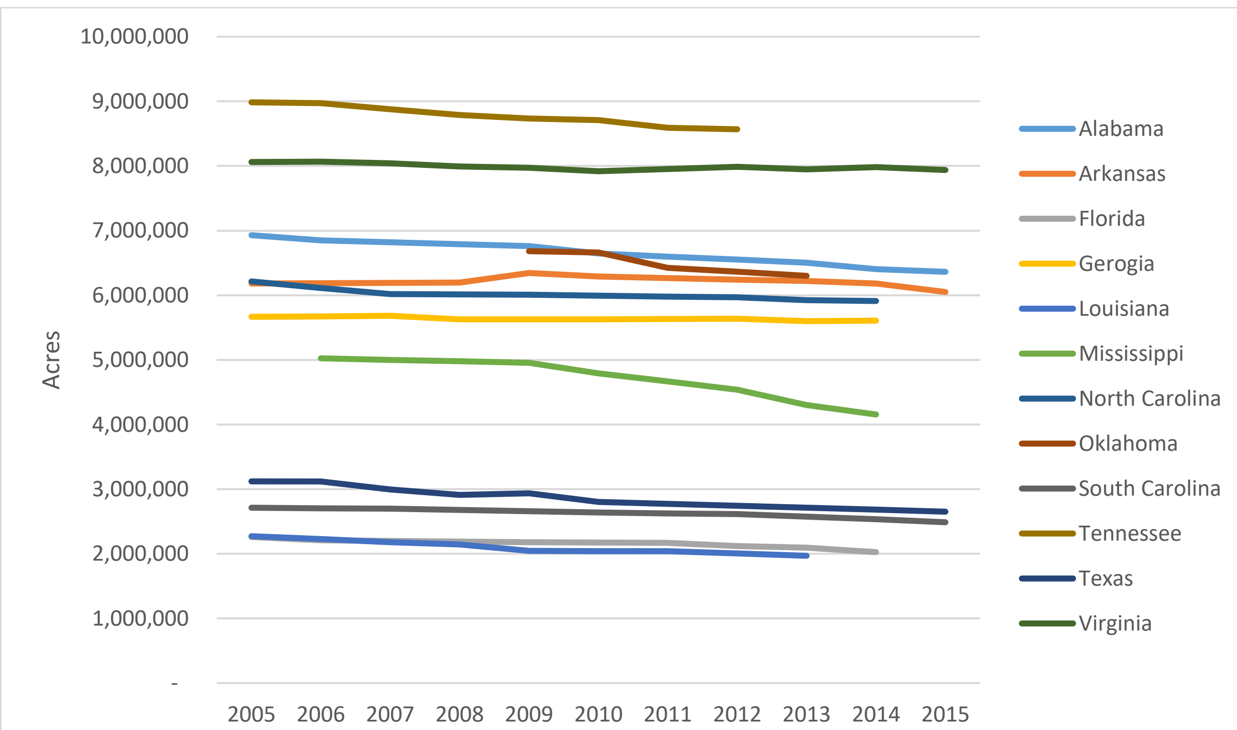

Figure 11: Area of natural pine forests for all counties in the state, except Texas, which only includes eastern Texas.

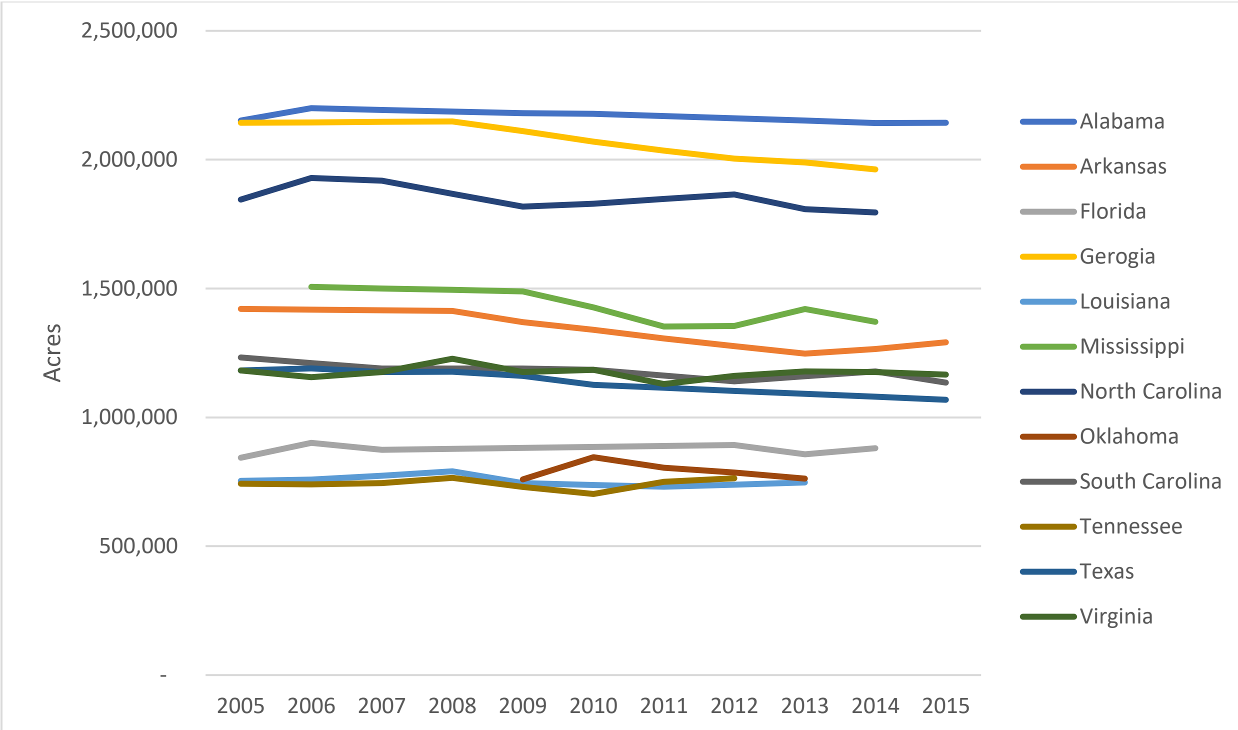

Figure 12: Area of oak-pine forests for all counties in the state, except Texas, which only includes eastern Texas.

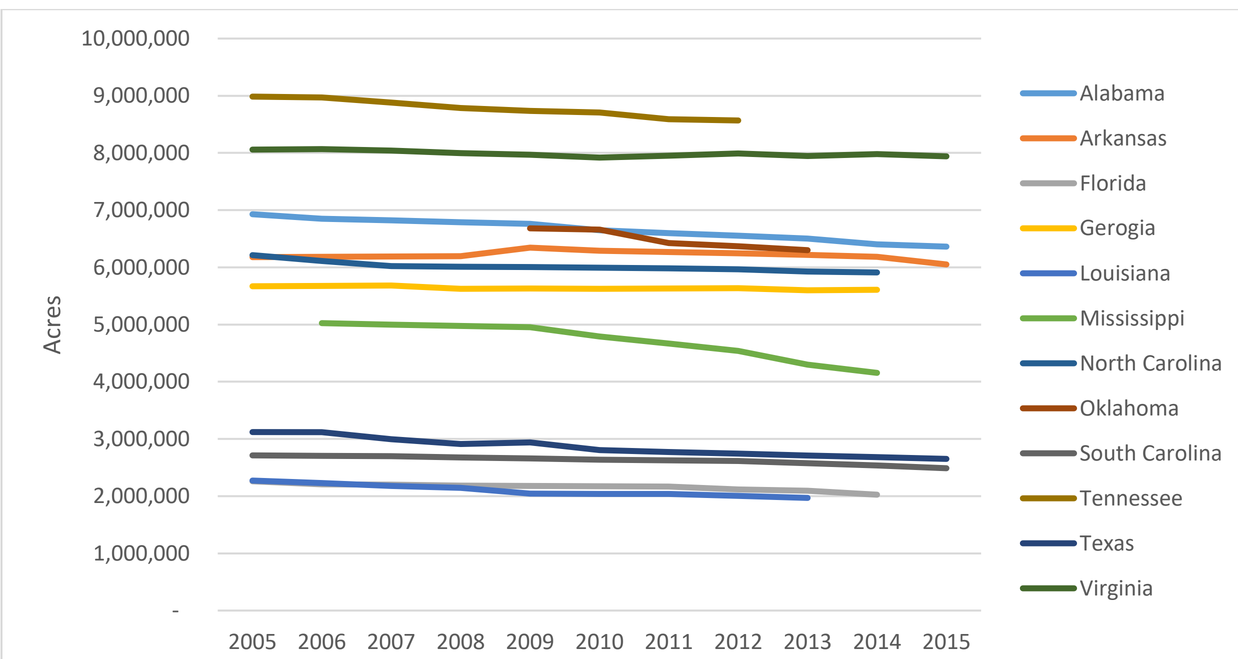

Figure 13: Area of pine plantations for all counties in the state, except Texas, which only includes eastern Texas.

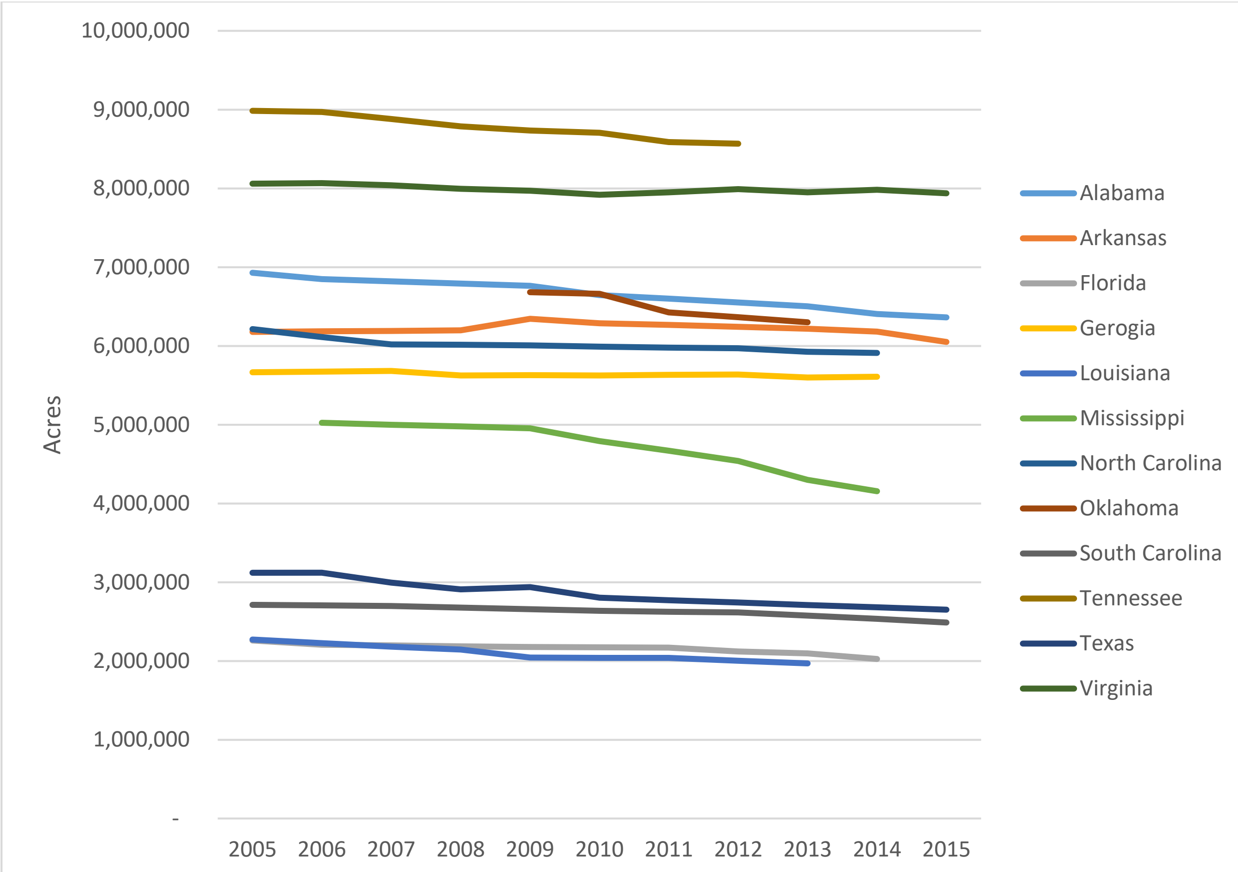

Figure 14: Area of upland hardwood forests for all counties in the state, except Texas, which only includes eastern Texas.