ABSTRACT

MOTHERSHEAD, PARKER TULL. Geo-spatial Analysis of Socioeconomic Risk Factors Affecting Wildfire Arson Occurrence in the Southeastern United States. (Under the direction of Bob Abt, Jeffrey Prestemon, and Fred Cubbage.)

Wildfires are not only detrimental to valuable timber assets, manmade structures, human health, and the safety of communities in the wildland urban interface (WUI) but they also negatively impact water quality, recreation, tourism, grazing, and biodiversity. Out of all wildfires in the Southeastern United States, approximately 25% are started intentionally by individuals attempting to burn someone else's land. Because firesetting is an illegal act, it is theorized that woodsburners can be expected to follow an expected utility theory whereas firesetting will continue as long as the individual's expected benefits exceed his or her expected costs. The majority of these costs can be measured using socioeconomic variables which will affect the amount of fires an individual starts. This study uses a negative binomial count model to determine the effects of socioeconomic variables across different spatial regions in Georgia, North Carolina, and South Carolina in order to determine high risk areas of wildfire arson. Results show that wildfire arson follows the expected utility theory of crime. Wildfire arson decreases as income, employment, and percentage of the economy in farming increase. Results also show statistical evidence that areas with high White and Native American Populations could be expected to have higher levels of wildfire arson. From these results, wildfire prevention specialists can better target high risk areas of wildfire arson in order to decrease the losses from illegal wildfires.

Geo-spatial Analysis of Socioeconomic Risk Factors Affecting Wildfire Arson Occurrence in the Southeastern United States

by
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TABLE OF CONTENTS

LIST OF TABLES iv
LIST OF FIGURES v
LIST OF EQUATIONS vi
Introduction 1
Terminology 2
History of Firesetting 3
  European Settlement to the 19th Century 3
  The 20th Century 4
Who Starts Fires and Why? 5
  Normative Woodsburners 5
  Criminal Woodsburners 6
Economic Model of Firesetting 8
Recent Literature 14
Socioeconomic Model of Southern wildfire Arson ignitions 1
  Data 1
  Model 9
  Variable Selection 11
  Results 16
    Goodness of Fit 17
    Multicollinearity 20
    Parameter Estimates 40
Discussion 41
Conclusion 45
References 47
Appendices 51
Appendix A 52
Appendix B 54
Appendix C 55
Appendix D 58
Appendix E 62

LIST OF TABLES

Table 1) Variables Selected in Model and their Units 16
Table 2) Goodness of fit Statistics 17
Table 3) Parameter Estimates for Ecoregion Models 21
Table 4) Parameter Estimates for Pooled and State Models 22
Table 5) Elasticity for all models and variables (red denoted significance <0.1) 39
Table 6) Data Statistics for all Models 52
Table 7) Correlation Matrices for all models (highlighted values <-0.5, and > 0.5) 58

LIST OF FIGURES

Figure 1) Expected Utility function and budget constraints of Woodsburners 12
Figure 2) Expected Utility function and budget constraints of individuals with extreme utility curves 13
Figure 3) Incendiary start locations by year for section of Robeson County, NC 2
Figure 4) Histogram of incendiary wildfire counts per county in GA, NC, and SC from 1990-2009... 4
Figure 5) Total Wildfire Ignitions by year for GA, NC, and SC 5
Figure 6) Total wildfire ignitions by state (1990-2009) 5
Figure 7) Total wildfire ignitions by Cause (1990-2009)... 6
Figure 8) Average N3 anomaly and inverse Incendiary fire count 1990-2009 7
Figure 9) Incendiary Wildfire Ignitions by ecoregion, 1990-2009... 8
Figure 10) Incendiary fires by ecoregion between 1990-2009 9
Figure 11) Frequency distribution of actual counts and Predicted Counts by model............. 18
Figure 12) Actual wildfires per county (1990-2009) and Predicted Values for all Models ... 19
Figure 13) Scatterplot of Native American Population and Incendiary Counts 43
Figure 14) Rainfall Rankings for 2003 54
Figure 15) Temperature Rankings for 2003.. 54
Figure 16) Total Fire Density between 1990-2009... 62
Figure 17) Incendiary Fire densities for years 1990-1994.. 63
Figure 18) Incendiary Fire densities for years 2005-2009.. 64
Figure 19) Ecoregion Boundaries in Study Area 65
Figure 20) Difference between model predictions and actual fire counts from 1990-2009 ... 66

LIST OF EQUATIONS

Equation 1) Completeness Axiom……………………………………………………………….9
Equation 2) Transitivity Axiom……..……………………………………………………...9
Equation 3) Independence Axiom……..…….……………………………………………..9
Equation 4) Continuity Axiom……………………….………………………………...…10
Equation 5) Becker's Utility Function………………..………………………………...10
Equation 6) Derivative with respect to probability………………………………………… 11
Equation 7) Derivative with respect to Punishment…………………………………………11
Equation 8) Expected Utility Function………………………………………...……….11
Equation 9) Poisson distribution…………………………….…………………………25
Equation 10) Poisson Variance and Mean……………………..………………..………25
Equation 11) Negative Binomial Distribution……………………………………………26
Equation 12) Negative Binomial Mean and Variance……………………………….……26
Equation 13) Negative Binomial Regression……………………………………………...27
Equation 14) Exponent Negative Binomial Regression…………………………………… 27
Equation 15) Poisson autoregressive model……………………………………..……..27
Equation 16) Model Form for Study……………………………………………..…….….31

Introduction

In 2011, the United States had 74,126 individual wildfires that burned approximately 8,711,307 acres of land. Human caused fires in the southeastern United States accounted for 53% of all national wildfires started and 33% of total acres burned (39,329 ignitions and 2,835,762 acres) (NIFC). Wildfire arson is the second leading cause of wildfire in the Southeast and accounts for 25% of all human caused fires (Prestemon and Butry, 2010; Hall, 2007; Tridata, 1997). The National Fire Protection Association estimates that 12% of direct property damage is attributed to outdoor fire setting. The direct and indirect damages caused by wildfires in the Southeast total in the billions of dollars every year. The Big Turnaround complex fire in southern Georgia alone cost almost $28,000,000 in suppression costs (Raikar, 2007). Wildland arson not only creates damages to timber, manmade structures, human health, and the safety of communities in the wildland urban interface (WUI) but also negatively impacts water, recreation, tourism, grazing, and biodiversity.

Unlike most wildfires, arson wildfires are more common in high population areas such as the WUI. These areas have higher valued structures and the proximity to inhabitants can lead to increased costs per fire. Cohen (2000) found that WUI wildland fires have a higher likelihood of causing property damage than fires originating within structures. It is because of these damages that wildland managers and law enforcement agencies seek to forecast wildfire arson occurrence and would benefit from new information that would help to better manage lands and combat arson occurrence.

Despite the high percentage and damage of wildland arson, there have been very few economic studies on the factors influencing ignition rates. The majority of the literature focused specifically the natural environmental underpinnings of arson-e.g., biotic, atmospheric, and spatial dispersion factors. The main purpose of this study is to more closely examine the non-ecological factors affecting arson wildfires, specifically social and economic, affecting wildfire ignition rates in order to give wildland managers and law enforcement officials the tools to target high risk areas of wildfire arson. The objectives of this study are to: (1) review the literature on wildfire arsonists, (2) explain how economic theory can be used to explain wildfire arsonist's behavior, (3) assemble a spatial database of physical and socioeconomic variables associated with wildfires, (4) develop and estimate a model based on economic theory to better understand the influences of socioeconomic factors on wildfire arson, and (5) compare results to other studies and regions.

Terminology

Before examining the specifics of wildfire arson, here is an explanation of the terminology and inclusivity of the term "wildfire arson". The term "arson" is commonly defined as "malicious burning to destroy property" and thus has a very negative connotation much akin to other criminology terms such as robbery or murder. In contrast, wildfire arson is sometimes defined quite differently. Historically wildfires were, more often than not, intentionally started for non-malicious reasons (Doolittle and Lightsey, 1979). For this study, arson wildfires are defined as incendiary fires. An incendiary fire is defined by the United States Forest Service as:

> "A wildfire willfully ignited by anyone to burn, or spread to, vegetation or property with knowledge that the fire should not be ignited and/or without consent of the land owner or his/her agent."

Dollitle and Lightsey's (1979) study of Southern wildfires acknowledged this difference and designated a more inclusive term "firesetting" to mean any person who sets an unauthorized or technically illegal fire with or without malicious intent. For the purpose of this study, "firesetting" will be used in this manner, and anyone starting a fire will be classified as a "woodsburner". It is impossible to determine the intent of individual woodsburners from the available data and because of this, no differentiation can be made in most analyses.

Another key point in classifying "incendiary" fires is that they do not include fires started by children. It can be assumed that children do not intentionally start fires with malicious intent as well as have little or no knowledge of their illegality. Because of this, any fire started by a minor (generally under 15 years of age) is classified under the cause "children" and is not included in this study.

History of Firesetting

European Settlement to the 19th Century

Well before the settlers first came to North America, firesetting was a common cultural tool for modifying the environment. Recent studies have found that early hominids used fire as long as one million years ago for simple tasks such as cooking food (Berna et al., 2012). Humans learned early that firesetting could be used as a tool to collect both plants and animals and soon after began setting fire to vegetation. These prehistoric uses are similar to modern fire management. Fire was used to remove dense vegetation, corral game species, improve pastureland, and increase crop yields (Kuhlken, 1999). As agricultural practices developed, burning became an important tool for clearing undeveloped land for agropastoral systems. This is especially true in the pre-settlement South where Native Americans commonly used fire to clear underbrush to facilitate crop growth and increase game populations.

As colonial settlers arrived, they soon discovered the same benefits of fire use. Large clearing of fertile land and pine savannahs, caused by reoccurring natural fires, were used as both agricultural and pastoral land because of their fertile soil. This inherent benefit from fire created a culture of firesetting, especially in the Southeast where traditional Native American practices were observed. Otto and Anderson (1982) noted that “More than any other region of the U.S., this amalgamation persisted in the South, giving it an incendiary tradition without parallel in America.” This tradition continued to increase with the growth in the “free range cattle complex,” which took advantage of the large amount of forage in the expansive pine savannahs of the Southeast. Land was abundant and most settlers followed the European tradition of common pastoral land in which everyone had the rights to use forestland for grazing.

As the new colonies developed, most of the South was given away by the British Crown in large land grants to wealthy and influential colonists. These grants were often haphazardly drawn together, noncontiguous, and spanned hundreds of thousands of acres. This made it difficult for new landowners to properly patrol or enforce their land rights. Because of this, many cattle owners still followed common grazing practices and assumed rights to both grazing and annual firesetting (Bertrand and Baird, 1974).

The 20th Century

The mid-century brought about a drastic change in the southern forestland. As the country developed, the need for timber increased and most of the forestland, commonly used as agropastoral land, began to shift ownership from family estates to large corporate timber companies. The changes to corporate ownership also lead to a change in management strategies. Fire was no longer seen as a tool but rather as a destructive force degrading the valuable timber supply. Thus, fire suppression became a leading management tenant of corporate land owners as well as the newly created national forest system. In the 1920s, the American Forestry Association sent a group of anti-fire activists called the “Dixie Crusaders”. These individuals went throughout the South preaching the “evils” of fire in attempt to change the mindset of the southern woodsburner (Wilson, 2010; Bennett, 2007).

This change threatened the existence of backwoods subsistence farmers who relied on fire use to manage “their” land. From this fear arose a new practice of retaliatory arson. “Burning the Big Man” became a common practice to get back at large corporate landowners (Kerr, 1958; St. Petersburg Times, 1958). The mentality of “If I can’t use it, no one can” became commonplace, especially in rural areas with little or no law enforcement. By the 1930’s, wildfire arson became so rampant that the Forest Service hired teams of sociologists to conduct research into its causes, focusing on the “sociocultural environment within which acts of wood-burning take place” (Dunkleberger and Altobellis, 1975). This time period represents the largest amount of forestland burned in American history. Six million acres a year, an area larger than the state of New Jersey, were burned in the Southeast alone. It is also estimated that 80% of the fires started in the South were attributed directly to spiteful wildfire arson (Kerr, 1958). With the passage of time, the amount of malicious wildfire arson began to shrink with increasing law enforcement and the lack of results attributed to spiteful burning. Many Southerners, who saw arson as their last form of protest against the encroachment of the new industrial complex, began to accept the status quo and accepted the presence of corporate landowners (Kuhlken, 1999).

Who Starts Fires and Why?

Despite the decrease in wildfire arson, the dominant practice of firesetting has persisted to the present day and remains a problem for forest managers. It is assumed that all firesetting is done to accomplish a specific goal by the individual. These benefits, whether perceived or actual, are what motivate woodsburners to partake in illegal activity. These benefits can be used to divide woodsburners into two major categories: normative and criminal burners[1].

Normative Woodsburners

Normative (or socially acceptable) wood burning has been, perhaps until recent years, the most common form of firesetting in the southeastern U.S. Normative firesetting is not driven by malicious intent but instead by a desire to change or manipulate the landscape for personal benefit. This type of firesetting was common up through the mid-20th century in the South but is likely to have decreased in importance (although this is a conjecture worth investigating), due to increases in the rates of legally sanctioned prescribed burning and more vigorous enforcement of arson laws . In the epoch of widespread normative firesetting, community members saw these activities as having a positive impact on the land and thus viewed woodsburners positively. A study by Doolittle and Lightsey (1979) found that in their sample of rural southern communities, woodsburners were seen favorably by 54% of residents. The common reasons described for this type of firesetting included (1) clearing undergrowth to improve aesthetics and to reduce fuel for large destructive fires, (2) eliminating pests such as ticks, chiggers, and snakes and their habitat, (3) enabling the production of new food source for both cattle (new green grass shoots) and game species (mast and legume growth for foraging animals such as deer, quail, and turkey), and (4) increasing the productivity of timber operations by killing off deciduous growth and ridding the land of wood boring insects (Daniel, 2007; Doolittle and Lightsey, 1979).

While there has been evidence that some of these reasons do contribute benefits to timber land, it is generally concluded that individuals overestimate their actual value. For example, Bertrand and Baird (1975) found that fire had very minor short term effects on pest

[1] It is important to note that a third type of woodsburner exists; the Psychotic woodsburner. These individuals suffer from neurological disorders and are drawn to firesetting through delusions and hallucinations instead of

populations. The perceived value of firesetting is therefore a more important factor than the actual value. These perceived benefits are disseminated from generation to generation through folklore and thus, the tradition continues. Woodsburners have often justified their activity to outsiders or law enforcement by pointing to the favorably perceived actions of their predecessors.

The sociological research on wildfire setting discovered two major groups of normative woodsburners (Doolittle and Lightsey, 1979; Bertrand and Baird, 1975; Kuhlken, 1999). The first and most active group of woodsburners was younger, white males of age 20 to 25. Most of these individuals were unemployed or working part-time. They had a very low education level with most having just finished high school or having dropped out with 2 to 3 years left. These individuals were typically locals who had lived in the area their whole life with leave only for military service. They lived at fairly low economic standards, typically lower middle class, but had a relatively average standard of living compared to the community in which they lived. These younger woodsburners were often described as loners who only associated with close family members and one or two good friends. They described their favorite pastime as hunting (specifically, deer) (Doolittle and Lightley, 1979).

The second, and larger, group was older white males who were no longer as active in firesetting activities. They were typically in their mid-forties (average 46) and not as well educated as the younger group. They were also predominantly local but experienced a slightly higher standard of living. Most of these burners had retired from active firesetting but were seen as patriarchs who encouraged and approved of the younger groups activities. This group was also possibly responsible for setting the social norms of the community, thus leading to increased firesetting from the younger generation.

Criminal Woodsburners

Criminal woodsburners differ from normative woodsburners in that they ignite fires with malicious intent for profit, employment, thrill seeking, or to harm people and property. Criminal firesetting can be categorized into three main groups: vindictive, instrumental, and cathartic (Barker, 1994).

Vindictive fires are set with the intent to harm a certain aggressor. In the South, these are commonly referred to as revenge, jealousy, spite, or grudge fires. These fires tend to occur in areas where historic land rights change hands. Such woodsburners harbor deep resentment when land they have been using for years is fenced off, roads are gated, or rent is charged for access. These instances normally arise from perceptions that "faceless" outside organizations had taken control of forestland that was formerly viewed as available to all. The aggressor's only tool for showing disapproval is to set fire to the resource and potentially destroy what they are no longer allowed to use. Doolittle and Lightsey (1979) found that areas with the most restrictions were more likely to be burned. The lands with the highest fire rates tended to be owned by corporate timber companies or absentee private landowners (hunting clubs). Land managed by the Forest Service was less likely to be burned due to fewer restrictions (especially on hunting).

The least common land type to be burned was state-owned forest land due to hunting availability[2] and strong local community ties. Most regions have a local state forest manager who is seen as part of the community and is present most of the year. On the other hand, corporate and federally owned land managers are seen by woodsburners as impersonal "office people". This translates into the belief that local communities are being exploited for profit or political gain. Corporations are seen in an especially negative light by local residents because they possess power, wealth, and influence, everything the residents do not (Doolittle, 1978). This sense of "exploitation" provides many woodsburners with enough rationale to light a fire.

Instrumental fires are those designed as a tactic to achieve an end goal. While uncommon, instrumental fires are usually set by firefighters to fulfill "hero" ambitions. A study in South Carolina by Cabe (1996) found that firefighter arson is more common than one would believe. The individuals who ignite fires are usually new volunteers who have gone through basic firefighter training and are eager to see some action but the call never comes in. These woodsburners were described by noted arsonist researchers Lewis and Yarnell (1951) as "men with grandiose social ambitions whose natural equipment dooms them to insignificance. No activity is too bizarre, if it brings them attention, for they are like adolescents who dream of becoming courageous supermen." South Carolina, which saw an average of 50 wildfires per year attributed to firefighter arson in the early 1990s, is not alone

[2] Hunting is allowed on most all state owned forests and game lands.

in this problem. The experiences in South Carolina in the early 1990s led some agencies to screen new recruits for typical arsonist behavior, presumably leading to a decrease in the frequency of firefighter arson (Cabe, 1996).

Cathartic is the final category of criminal firesetting. These fires are set as an expression of an emotion such as anger, tension, or despair. These fires are usually described as vandalism, boredom, or tension relieving fires. More often than not these fires are set by youths in rural areas that start setting small fires as children. As they grow older, their firesetting tends to slowly increase in size until they must ignite large open areas in order to fulfill their desires. Cathartic individuals are usually described as "pyromaniacs" and are often well known to local enforcement agencies. These individuals are more likely to have a criminal background and disregard for the safety of others in the community.

Economic Model of Firesetting

It is possible to use this detailed understanding of why individuals start fires to develop an economic model to understand woodsburners' behavior. Criminology studies have found that most illegal behavior can be modeled effectively by determining the perpetrators expected utility of committing a crime (Becker, 1968; Neilson, 1997). Utility, or overall satisfaction of an event, can be calculated by weighing the costs against benefits. It can be expected that an individual will continue any activity as long as the expected benefits (monetary or psychological) are greater than the expect costs. Thus, when the expected costs from firesetting exceed the benefits, the individual will not set a fire. But this begs the question; what exactly are the costs to individual firesetters?

Costs of firesetting can be either direct or indirect. Direct costs include items such as lighter fluid, matches, or gasoline used to actually ignite the fire. Because these are usually common household items, the costs are generally very low and provide few barriers to entry. This is true for most other crimes. For example, a robber's direct cost could be as limited as the cost of a knife or bullets for a gun. Because of their small monetary value, direct costs are usually not the most important factor in committing a crime.

Indirect costs, on the other hand, can be very large. An indirect cost can generally be thought of as the opportunity cost of committing a crime. These opportunity costs usually include the time and income lost while committing a crime. One can assume that this cost would also be very low for a single crime, but one must also include the foregone costs. These include the income and time costs if an individual is caught in the act. If an individual is caught and convicted of a crime, they will be forced to pay a fine. This fine could be a simple monetary payment or be a function of wages lost while incarcerated. This cost can be much larger considering the fact that incarceration could be anywhere from months (for simple arson charges) to an entire lifetime (for murder charges). Because of this difference, the probability of being caught is important to include in crime models (Blumstein, 1978).

Before delving into the woodsburners utility model, it is important to first understand some key assumptions included in all utility maximizing crime models. These assumptions, or axioms, were first postulated by Von Neumann and Morgenstern (1947) in their book "Theory of Games and Economic Behavior". These key axioms cannot be proven true, but in order for any probability theory to hold true, they must be assumed. The four axioms all relate to the rational behavior of individuals, which is key to any economic model. The first axiom of utility is that of "Completeness" where for every A and B either:

$$\boldsymbol{A \geq B \text{ or } A \leq B} \tag{1}$$

This axiom assumes that every individual has preference, and given the choice can always decide between two alternatives. The second axiom is that of "transitivity" where given the choice between A, B, and C:

$$\boldsymbol{\text{if } A \geq B \text{ and } B \geq C, \text{then } A \geq C} \tag{2}$$

According to the completeness axiom, an individual can always decide between two alternatives. The transitivity axiom states that given more than two alternatives an individual can choose between them and also chooses consistently. The third axiom is that of "independence," where given a choice between three lotteries A, B, and C with a probability $p\epsilon(0,1)$, if A ≥ B:

$$\boldsymbol{pA + (1 - p)C \geq pB + (1 - p)C} \tag{3}$$

This axiom states that, given the choice between two lotteries mixed with a third, the same preferences identified between the original shall hold true. By solving the equation using a p value of one, we find that A ≥ B and conversely if the p is zero we find C ≥ C. The fact that C could be represented in this axiom as greater than itself is a point of much criticism in the decision making literature (Mongin, 1997). Despite this controversy, the third axiom can be assumed to be true in most instances.

The fourth and final axiom is that of "Continuity" where given a choice between three lotteries A, B, and C with A ≥ B ≥ C there exists a certain p where:

$$\boldsymbol{pA + (1-p)C = B, or\ pA + (1-p)C \geq B \geq (1-p)A + pC} \tag{4}$$

This axiom assumes that there exists a certain probability for a given lottery (A and C) that would make an individual indifferent between it and a third outcome (B). This assumption shows how the exact probability matters in individual's choice. If a probability of an outcome reaches a certain threshold, then the outcome will be just as advantageous as the next best thing. This axiom applies to firesetting in that at there is a certain probability of arrest in which an individual will be just as likely to ignite a fire as they would be to not ignite.

By using the Von Neumann and Morgenstern axioms, it is assumed that individuals are acting in a rational matter and their preferences can be represented by a utility maximizing function[3]. Using these assumptions, an economic model of utility can be created where the expected utility of a woodsburner can be expressed as a function of probability, punishment, and other factors. This form of utility function was made popular by Becker's (1968) approach:

$$\boldsymbol{O_i = O_i(p_i, f_i, u_i)} \tag{5}$$

Where O_i is the number of offenses committed by person i, p_i is the probability of being caught, f_i is the cost of being caught or the punishment, and u_i is an all-inclusive term which represents all other factors which influences the offence. An increase in either p_i or f_i

[3] Another key assumption not included in the axioms is that all individuals are risk-averse. In this case, they would refuse a fair gamble or when the expected utility is equal to zero. This risk aversion can also be seen in the concave shape of an individual's utility function.

would decrease the individuals utility because they would have not only a higher probability of being caught but also a higher punishment or "cost". This can be shown by the first derivatives of p_i and f_i which are both negative (Becker, 1968):

$$\boldsymbol{O_{ip}} = \frac{\partial \boldsymbol{O_i}}{\partial \boldsymbol{p_i}} < \mathbf{0} \tag{6}$$

$$\boldsymbol{O_{if}} = \frac{\partial \boldsymbol{O_i}}{\partial \boldsymbol{pf_i}} < \mathbf{0} \tag{7}$$

Using Becker's approach, the model can be further developed by including costs functions and probability of arrest. The woodsburner's expected utility from successfully starting a wildfire can be described as:

$$\boldsymbol{E}[\boldsymbol{U_i}\,(\boldsymbol{O_i})] = \boldsymbol{p_i U_i}\big(\boldsymbol{g_i} - \boldsymbol{c_i} - \boldsymbol{f_i}(\boldsymbol{W_i}, \boldsymbol{w_i})\big) + (\mathbf{1} - \boldsymbol{p_i})\boldsymbol{U_i}(\boldsymbol{g_i} - \boldsymbol{c_i}) \tag{8}$$

Where E is the expectations operator, U_i is the firesetter's utility, O_i is the number of fires ignited, p_i is the probability the woodsburner will be caught by law enforcement, g_i is the expected benefits (psychological and monetary) from firesetting, c_i is the direct cost of production, and f_i is the expected punishment if caught expressed as a function of forgone income[4]. f_i is determined by the employment status, W_i, and wage rate w_i (Prestemon and Butry, 2005; Gould et al. 2002; Burdett and Wright, 2003; Becker 1968). Expected utility implies that individuals will continue to set fires as long as the expected marginal psychological and monetary benefits exceed the marginal costs of production and expected loss from being caught. It can also be assumed that the first derivatives for p_i and f_i are negative (similar to Equations 6 and 7).

This expected utility function can be displayed graphically (Figure 1) to show the budget constraints and utility curves of a woodsburner. The Y-axis represents the amount of fires set and the X-axis represents all other goods purchased (AOG). The number of fires set can be considered a good for this individual and thus is a function of income similar to all

[4] It could be assumed that higher income could give an individual access to better representation in court and thus a better chance of no conviction. Due to the difficulty of measuring this factor it will not be included in the study and it will be assumed that on average everyone has equal representation.

other goods. First consider an individual with a budget constraint B_0 and a utility curve U_0. Given this individual's preferences, he will choose point A to maximize his utility and will set F_0 fires and consume Q_0 of all other goods. Assume this same individual has a decrease in his overall income. This decrease could be from a change in employment or wages received. From this shift, the individual's budget constraint will shift from B_0 to B_1.

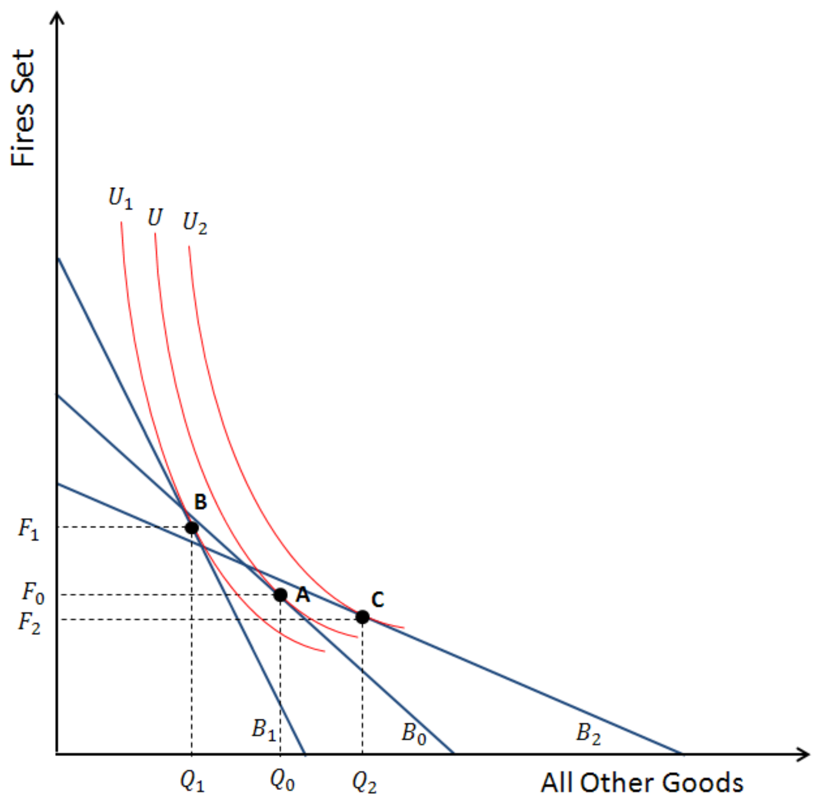

Figure 1 Expected Utility function and budget constraints of Woodsburners

According to economic theory, one could expect the budget constraint to maintain the same slope and shift outward. This would lead the individual to be able to have more of both goods (fire and AOG). However, firesetting follows the economic theory of household production (Allgood, 2009) where an increase/decrease in income changes the overall costs of other goods. This applies to firesetting in that a decrease in income (F(W,w)) also decreases the overall cost of firesetting as seen in Equation 8. As costs decrease, the amount of a good that can be purchased increases. This explains the change in slope from B_0 to B_1. In other words, the expected punishment for setting a fire becomes less when an individual has less income, thus leading the individual to set more fires. This can be seen by point B, where the individuals overall utility decreases from a decrease in income. But, because the slope of the budget constraint has increased (negatively), the individual now gains more utility from increasing the amount of fires set and decreasing the amount of AOG purchased. Conversely, the same choices can be seen if an individual experiences an increase in income. This increase would cause a shift in the budget constraint from B_0 to B_2, thus allowing the individual to purchase more AOG and increasing the cost of firesetting. This would move the individual's decision point to C, where he is maximizing his utility given the choices he is given. This leads to a decrease in amount of fires set and an increase in amount of AOG purchased.

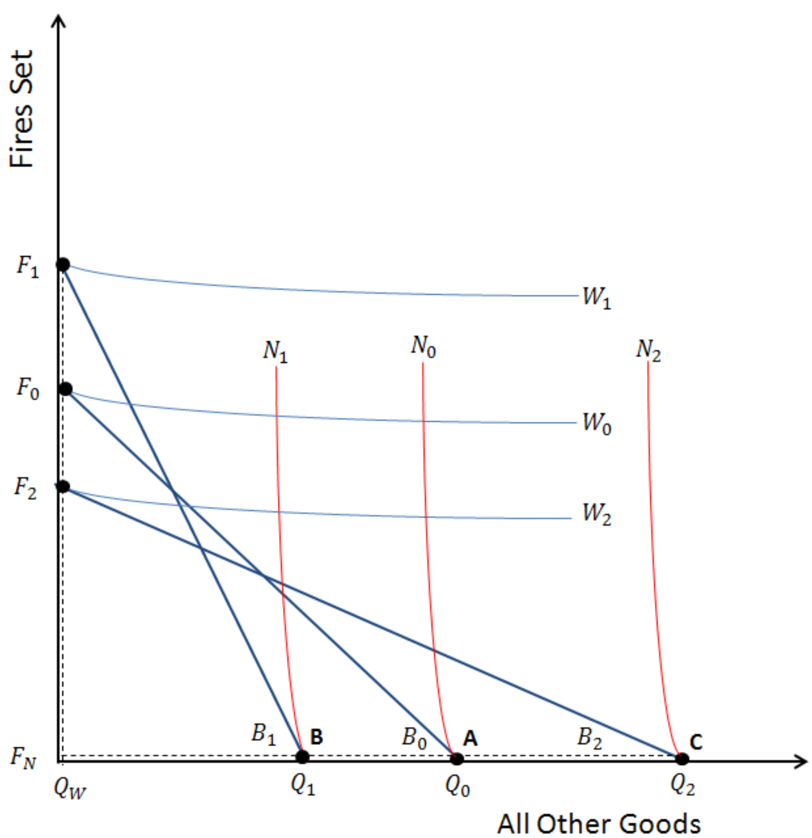

Figure 2 Expected Utility function and budget constraints of individuals with extreme utility curves

Next, consider the utility maximizing function of extreme individuals (Figure 2). This includes individuals who have little if any benefit from setting fires (normal individuals) and those who experience the greatest benefit (serial and psychotic individuals). If we assume the same changes in the budget lines as in Figure 1, we can see dramatically different choices by these two individuals. The normal individual, with no desire to set fires, has a utility curve that looks almost vertical (curve N). If one were to zoom in on the tangency point, one would see that the curve does exist but only at very low values. For example, this individual might have the desire to light a small campfire or burn debris. Because of the shape of the utility curve, the normal individual will always choose a bundle of goods where almost all income is spent on AOG and there is only a small or nonexistent amount of fires being set (Points A, B, C). The serial or psychotic woodsburner, on the other hand, derives a huge benefit from igniting fires. No matter his income level (and costs), he will choose to set as many fires as possible. This is seen by utility curves W, which appear to be horizontal.

As shown by Figure 1 and 2 the tradeoff between fires set and AOG greatly depends on the individual's utility curve. The expected utility model assumes all individuals have concavity in their utility curves because of the four axioms and thus are expected to behave rationally. It can be assumed that most individuals have utility curves shaped like curve N (Figure 2) and thus do not ignite any fires. Despite this, the expected utility theory implies that one will see aggregate changes of firesetting within a population as economic variables change due to the effects of woodsburners within the population.

Recent Literature

While there has been little reference to wildfire arson in the literature, there has been a fair amount of research conducted on non-wildfire arson. Important lessons have been learned from these studies and the few relate specifically to wildfire which will be discussed below.

Murrey et al. (2001) developed a linear model to determine the effects of over 180 socioeconomic variables affecting arson rates in Seattle, St. Petersburg, Charlotte, and San Diego. Using a correlation matrix to remove independent variables with high correlation to the dependent (>.5) and stepwise selection, they were able to discover five significant variables effecting arson count. These significant variables were (1) change in producer prices (2) Canadian CPI (3) homeowner's insurance premiums (4) total forgery loss ratio[5] and (5) vacancy rate in rental housing units. Only variable 2 and 4 had positive parameter estimates. The main finding of the study was that arson rates are higher in areas with signs of a depressed local economy. This study was intended to be only exploratory in nature and assumes fires were a continuous variable, thus a linear model was used. A loglinear model would help to improve these findings in future studies.

Corrigan and Siegfied (2011) studied the rate of urban arson rates to determine if there was a significant relationship between arson and the unemployment rate, mortgage rate, and housing price index. The study found a negative relationship between the housing price index (-0.523) and a positive relationship with the mortgage rate (8.565). The unemployment rate had a negative relationship but was not statistically significant. This study also used a linear model to estimate relationships.

Thomas *et al.* (2010) used more statistically consistant economic methods to estimate the effects of economic variables on wildland and non-wildland arson fires. The study's purpose was to test the effects of the "Broken Windows Theory" on wildfire arson. The theory postulates that the presence of visible signs of rundown property or infrastructure ("broken windows") will lead to higher incidences of crime. The study used a zero inflated Poisson count model and found that house vacancy rates and temperature were significant and positively related to wildfire counts. Dumping sites on nearby federal land, social disorder[6], police per capita, and precipitation were negatively correlated. The study also found that unemployment was positively related to arson count but was not significant. The study concluded that there was some evidence of the "Broken Window" theory in wildfire occurrence.

The most extensive modern research in wildfire arson has been completed by the USDA Southern Research Station on wildfire arson rates in Florida, California, and Michigan. Three major studies, focused on Florida, have been conducted estimating the

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[5] Amount of money lost to forgery, such as insurance fraud, divided by population

[6] Social disorder was classified by the amount of part II (FBI uniform crime report statistics) crimes committed in the area.

effects of economic and spatial variables. Mercer and Prestemon (2005) studied the effects of economic variables on wildfire arson rates in the wildland-urban interface. The study used three models to estimate the effects on ignition count, fire extent, and an intensity-weighted aggregate extent. The study found that socioeconomic variables were significant in all three models. The results showed that, at the county level, increases in poverty rate and population levels corresponded to increase in amount of wildfire area and intensity-weighted extent burned while increases in unemployment corresponded to decreases in all three models. The results also showed that the poverty rate was negatively related to ignition counts. The results showed that forestland managers should be aware of socioeconomic variables and consider them in their management decision and that the data tended to follow patterns of the expected utility theory.

In the second study (Prestemon and Butry, 2005), authors estimated models of daily and annual arson wildfire ignition counts. The daily model employed a Poisson autoregressive model for six high frequency arson areas in Florida, while Poisson type annual arson count models were specified for all Florida counties. Estimates of the daily models demonstrated highly significant arson ignition autocorrelation. The study also showed that a pooled model of daily counts for all six areas had similar autocorrelation results as the individual location daily count models but also showed influences of wage rate and poverty. The third study (Butry and Prestemon, 2005) was very similar to the second in that it used a Poisson autocorrelation model and focused on spatio-temporal as well as temporal autoregressive relationships in daily arson counts in Census Tracts in Florida. The model results indicated that spatio-temporal dummy variables accounting for previous days’ arson ignitions in surrounding Census Tracts did partially explain counts within a Tract. This confirmed hypothesis that fine time scale and fine spatial scale firesetting has both spatio-temporal as well as temporal; autoregressive components that could be used for predictive purposes.

Socioeconomic Model of Southern wildfire Arson ignitions

Although recent literature shows different impacts, there is evidence that socioeconomic variables do affect wildfire arson. The purpose of this study is to create a model to determine the effects of socioeconomic variables on wildfire arson in Georgia, North Carolina, and South Carolina as well as to explore the differing socioeconomic effects of wildfire arson between varying southern ecoregions[7]. While the study is similar to those done by Prestemon and Butry (2010), it differs by considering a larger scope and by focusing on specific geospatial ecoregions. These ecoregions may help to explain both the effects of different cultural attitudes to firesetting as well as the effects of successful wildfire ignitions.

Data

The data for this study were collected from all 305 counties in Georgia, North Carolina, and South Carolina from 1990 through 2009 containing 6,100 individual observations. The dependent variable, fire count data, was collected from the National Fire Incident Reporting System and aggregated by the USDA Southern Research Station in Asheville, North Carolina. During the study period, the NFIRS reported 365, 782 wildfire ignition in the study area. Of these ignitions, 84,277 were classified as incendiary fires (23%) burning over 588,000 acres of forestland in total. These data were aggregated to obtain the study's dependent variable, count of incendiary wildfire ignitions for each county by year. Count data was used instead of burn area because area burned is affected more by weather and suppression efforts and less by socioeconomic variables.

One factor to consider is the validity of the dependent fire count data. Data reported to the National Fire Incident Reporting System is reported by local fire departments and law enforcement and varies greatly among regions. This variability could include whether or not fire departments report all fires, the cause they attribute to each fire, and the location of the fire. The only one of these possible reporting problems that can be checked with this study's data is the fire location reporting problem. This can be seen by looking at the Latitude and Longitude coordinates reported to the NFIRS. Figure 3 shows the difference in report

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[7] Map of Ecoregions can be found in Appendix D (Figure 19), and descriptions (Griffin, 2010) can be found in Appendix C

locations between the 1990s and 2000s. In the early 1990s, there was not widespread use of GPS systems by local fire departments due to their high cost. Because of this, fire start locations were reported using hard maps and approximate coordinates. This leads to the clear grid pattern shown in Figure 3. This is in contrast to values in the late 2000's where GPS costs became very low and their use became widespread. Because of this technology development, newer report locations are much more accurate.

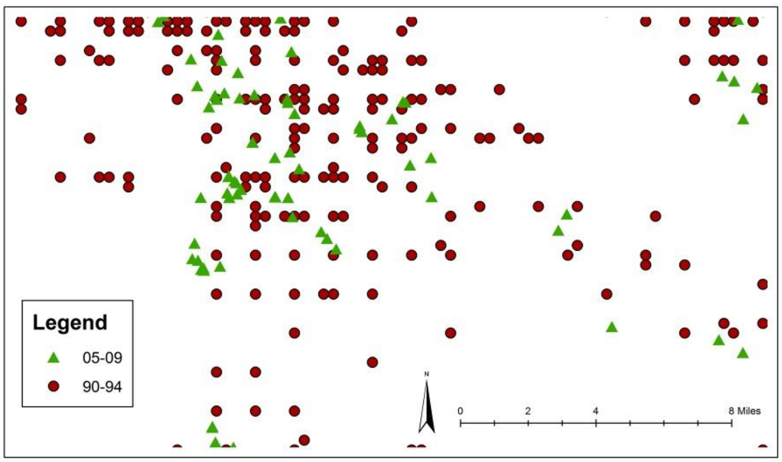

Figure 3 Incendiary start locations by year for section of Robeson County, NC

In addition to the to the dependent fire count data, a one year lagged dependent variable was created to be used as an independent variable. The purpose of this variable was to account for any factor that could be correlated to wildfires from one year to the next. This could include things such as normative firesetting beliefs, the presence or absence of one or more serial arsonists, the amount of forestland, persistent levels law enforcement, etc. Thus, if there was a high (low) count of arson fires the previous year, it could be expected that the count for the next year would also be high (low).

Compiling county level independent variables from different government sources was more time-consuming. Data were collected for five separate variable categories: (1) income, (2) employment, (3) poverty, (4) population, (5) geographic, and (6) weather. Income data for counties included per-capita personal income, aggregate personal income, nonfarm proprietor's income[8], farm proprietor's income[9], net earnings, average earnings per job, and median household income. This data was collected from the Bureau of Economic Affair's (BEA) regional economic accounts database and the U.S. Census Bureau. Employment data was collected from the St. Louis Federal Reserve (FRED) and BEA. These data included county unemployment rates, state unemployment rates, federal unemployment rates, and total employment. Poverty data was collected from the U.S. Census Bureau's small income and poverty estimates. The data included number of individuals living under the poverty line and the poverty rates (total, under the age of 18, and between the ages of 5 to18). Population data were collected from the US Census bureau's intercensal estimates. Not only was total population data collected but also demographic data. Data included population estimates by race, sex, and Hispanic origin (African American, Native American or Alaskan native, Asian or Pacific Islander, and White). Geographic data was collected from GIS database files provided by the Environmental Protection Agency and the United States Geological Survey's National Atlas. The data collected included level III ecoregions (Appendix E, Figure 19), county area, and highway locations. Finally, weather data was collected from the National Oceanic and Atmospheric Administration's National Climatic Data Center. This data included El Niño anomaly reading (regions 3, 3.4, and 4), precipitation, temperature, and Palmer drought index.

Before discussing model selection, it is important to understand the frequencies and spatiotemporal trends of the dependent variable. Figure 4 shows the frequencies of incendiary fires in the study area. Just like most count data, the distribution is skewed to the left with the greatest counts at lower values[10]. This distribution shows the need for a nonlinear regression model to best fit the data.

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[8]Nonfarm Proprietors' Income consists of the income that is received by nonfarm sole proprietorships and partnerships and the income that is received by tax-exempt cooperatives

[9] - Farm proprietors' income consists of the income that is received by the sole proprietorships and the partnerships that operate farms. It excludes the income that is received by corporate farms

[10] Values over 95 were omitted due to chart size. The maximum wildfire count of 350 was in Williamsburg County in 1994.

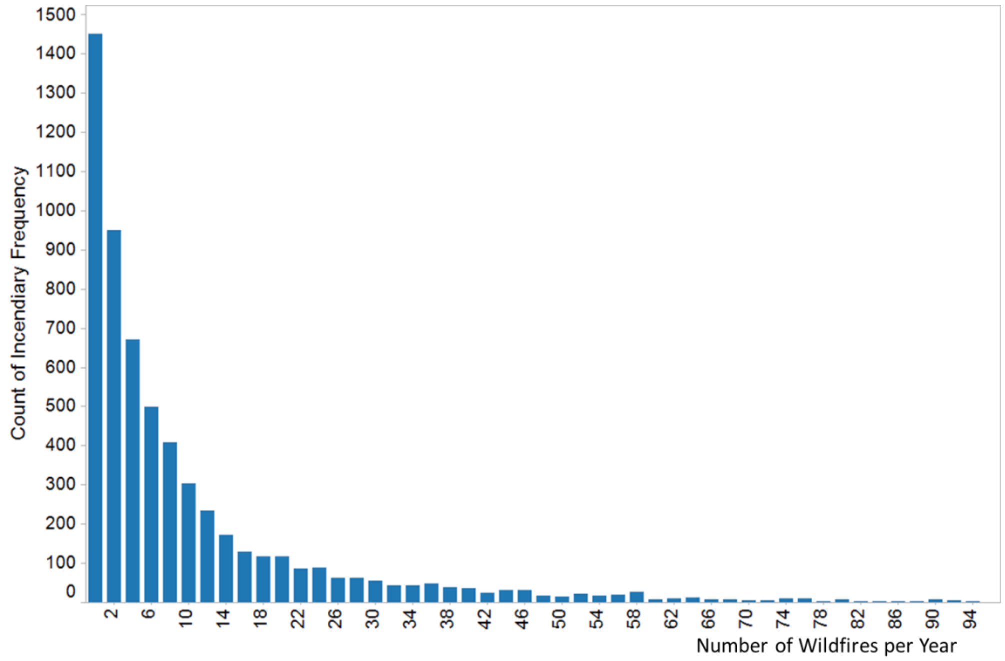

Figure 4 Histogram of incendiary wildfire counts per county in GA, NC, and SC from 1990-2009

Overall, wildfires have been decreasing over time in most of the United States. This is no different in the study region where wildfires have trended downward in all regions from 1990-2009 (fig 5, 6). But this trend does not hold true when wildfires are broken down into their causes. Figure 7, which plots all wildfires in the study region from 1990-2009 by cause, shows that fires caused by equipment use and "Miscellaneous" have increased over this time. Another very important trend to discuss is the trough present in 2003. The year 2003 was one of the wettest and coldest on record for most of the eastern United States (NCDC, 2004)[11]. North Carolina had its wettest year on record in 2003. The increase precipitation and humidity and lower than normal temperatures made wildfire ignition much more difficult. This change in weather patterns can be seen changes in what I refer to as the N3 ("Niño 3 Sea Surface Temperature Anomaly") over this time span.

[11] Appendix B (Figures 13 and 14) shows temperatures and precipitation trends for 2003.

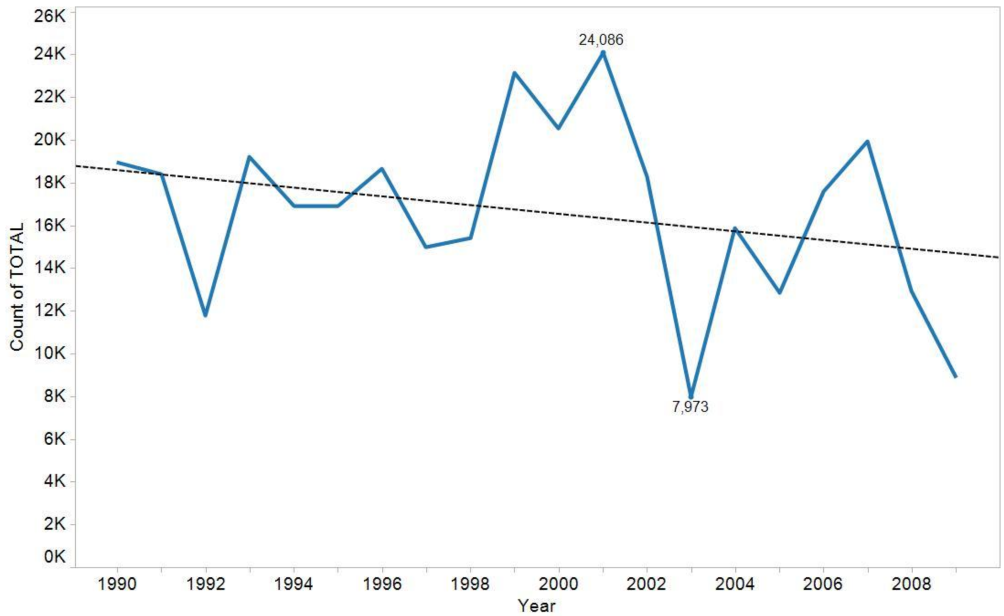

Figure 5 Total Wildfire Ignitions by year for GA, NC, and SC

Figure 6 Total wildfire ignitions by state (1990-2009)

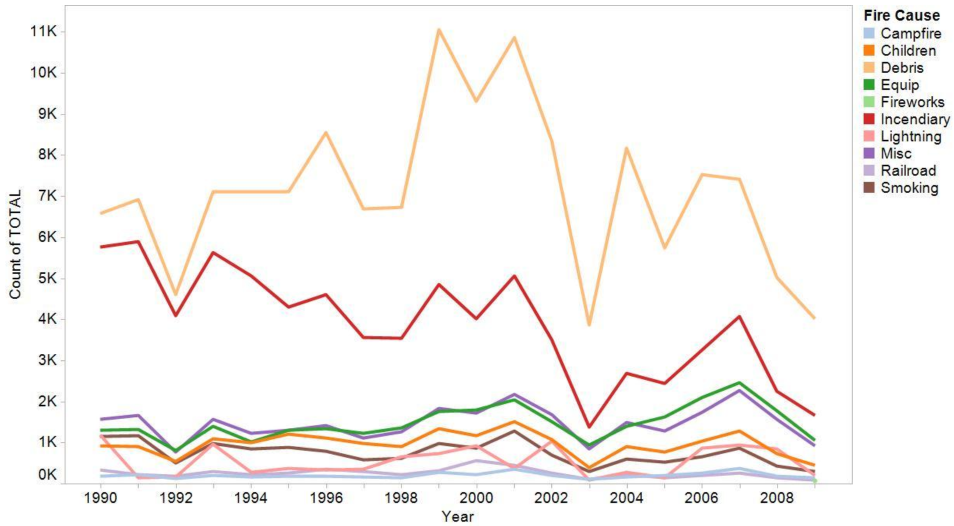

Figure 7 Total wildfire ignitions by Cause (1990-2009)

The N3 measures the El Niño/La Niña Southern oscillation anomaly, or ENSO[12]. The El Niño climatic pattern typically occurs every two to seven years in the tropical waters of the east Pacific Ocean. The phenomenon causes variation in water temperature and air pressure which result in climactic effects in the contiguous United States. The oscillation anomaly is measured in the difference between normal and current sea surface temperatures (SST). When the SST is high (low), the measure is positive (negative). There have been a multitude of studies conducted in the recent past to determine the relationship between typical El Niño conditions and wildfire occurrence in the southeastern United States (Simard, 1985; Barnett and Brenner, 1992; Brenner, 1992; Stevens,1991). The majority of these studies have found that wildfire risk and El Niño conditions are negatively correlated in the southeastern US. For the study area of Georgia, North Carolina, and South Carolina, Barnett and Brenner (1992) found correlations of -.24, -.39, and -.39, respectfully. This relationship can also be seen in the study area by plotting N3 alongside the inverse incendiary fire counts (Figure 8).

[12] The three measures of the El Niño effect are Niño 3 Niño 3.4, and Niño 4 anomalies. The difference between the three corresponds with their latitude and longitude coordinates in the Pacific Ocean. The Niño 3 Region is bounded by 90°W-150°W and 5°S- 5°N. The Niño 3.4 Region is bounded by 120°W-170°W and 5°S-5°N. The Niño 4 region is bounded by 160°E-150°W and 5°S- 5°N.

The reason this occurs has to do with the pressure systems created by El Niño conditions. As SSTs rise in the eastern tropical Pacific Ocean anomalous convection sets up over the dateline in the fall and winter. The resulting heating disrupts the long wave structure of the middle northern hemisphere causing lower than normal pressure in the winter and spring. This lower than normal pressure system creates higher than normal rain fall and lower than normal temperatures in the Southeastern United States (Barnett and Brenner, 1992).

Figure 8 Average N3 anomaly and inverse Incendiary fire count 1990-2009

One of the major purposes of this study is to see how the effects of economic variables change over the landscape. While county level data would provide the highest spatial resolution, much of the physiographic variation can be captured using the ecoregions. The regions present in Georgia, North Carolina, and South Carolina are the Blue Ridge, Middle Atlantic Coastal Plain, Piedmont, Ridge and Valley, Southeastern Plains, and Southern Coastal Plains. These regions are divided based on climate, vegetation, hydrology, terrain, wildlife, and land use/human activity (See Appendix C for ecoregion descriptions). Because of these differing environmental and ecological conditions, each ecoregion can be expected to have a different extent of wildfire arson. Figure 9 shows how wildfire frequency is separated between ecoregions with Southeastern Plains and Middle Atlantic Coastal Plains representing the majority of ignitions. These regions make up what is commonly referred to as the Coastal Plain. This area not only has a low population density but also a distinct culture where normative firesetting was historically common.

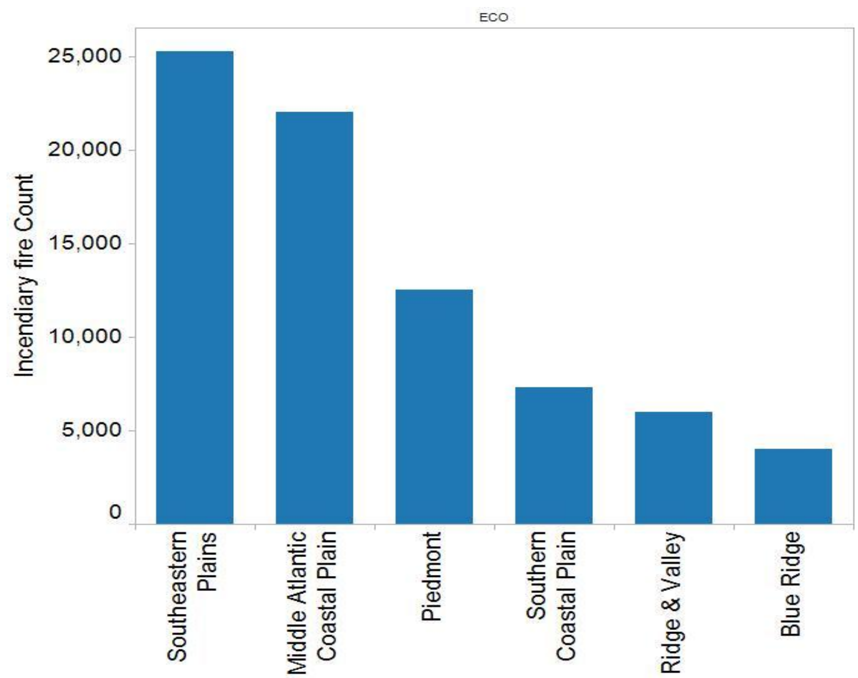

Figure 9 Incendiary Wildfire Ignitions by ecoregion, 1990-2009

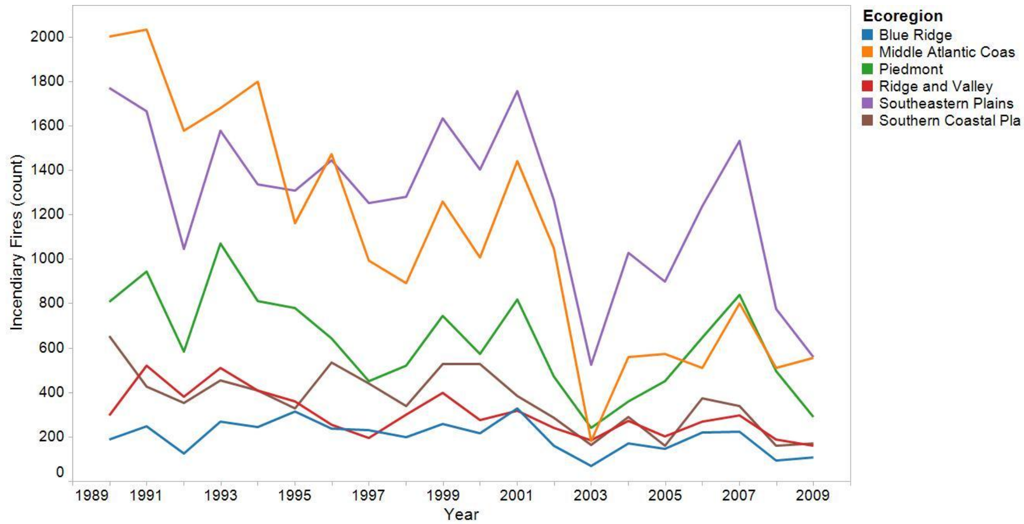

Figure 10 Incendiary fires by ecoregion between 1990-2009

Model

A linear regression model is unfit for this data due to its high skew to the left (Figure 4). Because of this, a loglinear model should be used in order to take into account the higher counts at low values. The most common loglinear model used is a Poisson regression model (Hubbard, 2005). A Poisson regression assumes that the independent variables can be interpreted as a linear regression when the dependent variable is transformed by its log (Hubbard, 2005). This regression will also follow a Poisson distribution with parameter λ if it takes integer values $y = 0,1,2 \ldots$ with a probability:

$$\mathbf{Pr}(\boldsymbol{Y} = \boldsymbol{y}|\boldsymbol{\lambda}) = \frac{\boldsymbol{e^{-\lambda}\lambda^{y}}}{\boldsymbol{y}!} \quad \textbf{(9)}$$

for $\lambda > 0$. The second major assumption is that the mean and the variance of the distribution can be shown to be:

$$\boldsymbol{E(Y) = var(Y) = \lambda} \quad \textbf{(10)}$$

This second assumption that the mean is equal to the variance is where most Poisson models fail. In real-world data, this is sometimes not the case, and the variance is different than the mean. This failure does not affect the parameter estimates of a Poisson regression but simply leads the standard errors to be biased and too small. Small standard errors will result in parameter estimates being considered significant when in actuality they are not. This difference between the variance and mean is called the dispersion (variance-to-mean ratio), or the degree to which values of a frequency are scattered. To correct for dispersion, one can run a negative binomial regression (Hubbard, 2005; Quintanilha and Ho, 2006)). A negative distribution is different from a Poisson in that it has two parameters: λ which is the expected value or mean, and α which is the over-dispersion parameter. This leads to a distribution having the probability:

$$\mathbf{Pr}(\boldsymbol{Y}|\boldsymbol{\lambda},\boldsymbol{\alpha}\,) = \frac{\boldsymbol{\Gamma}(\boldsymbol{y}+\boldsymbol{\alpha}^{-1})}{\boldsymbol{y}!\boldsymbol{\Gamma}(\boldsymbol{\alpha}^{-1})}\left(\frac{\boldsymbol{\alpha}^{-1}}{\boldsymbol{\alpha}^{-1}+\boldsymbol{\lambda}}\right)^{\boldsymbol{\alpha}^{-1}}\left(\frac{\boldsymbol{\lambda}}{\boldsymbol{\alpha}^{-1}+\boldsymbol{\lambda}}\right)^{\boldsymbol{y}} \quad \textbf{(11)}$$

Where Γ is the gamma distribution. In essence, what this distribution does is take into account the over-dispersion (α) of the model. As α approaches zero, the distribution becomes more like a Poisson, until the point where α = 0 there is no over-dispersion and the distribution is the same as a Poisson model. From this comes a mean and variance for a negative binomial distribution of:

$$\boldsymbol{E}(\boldsymbol{Y}) = \boldsymbol{var}(\boldsymbol{Y}) = \boldsymbol{\lambda} + \boldsymbol{\alpha}\boldsymbol{\lambda}^{\mathbf{2}} \quad \textbf{(12)}$$

When α > 0. Using this distribution one can calculate a negative binomial in a similar way to a Poisson. By taking the over dispersion into account, one can correct for the small standard errors and thus obtain more robust parameter significance (Hubbard,2005). The formula for a negative binomial distribution is the same loglinear form as a Poisson (but results are different due to different distribution). This equation is:

$$\log(Y) = intercept + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n \tag{13}$$

This implies that Y is the exponential function of independent variables:

$$\mathbf{Y} = exp(intercept + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n) \tag{14}$$

The model for this study was created in SAS using the GENMOD procedure with a negative binomial distribution (Beal, 2005). Exploratory data analysis was used to create preliminary model runs in conjunction with correlation matrix to decrease the amount of independent variables in the model, overcome multicollinearity, and address outliers.

Variable Selection

In order to make a statistically stronger model, there was a need to remove the lagged dependent variable and some of the variables from each of the six categories (income, employment, poverty, population, geographic, and weather).

A lagged dependent variable was added to the model during early calculations but because of the model form, it could not be included. The lagged variable caused a great deal of misspecification at high incendiary fire count because of the model's loglinear form. This means that as count values increases, the lagged variable will cause expected counts to increase exponentially. For this reason, the lagged dependent variable was not included. One way of including the lagged dependent variable would be to create a Poisson autoregressive model (Prestemon and Butry, 2005)[13]. This model would allow for the lagged dependent variable to be excluded from the exponent form as shown in equation 15.

$$\mathbf{Y} = \boldsymbol{\beta}_1 \mathbf{Lag}(\mathbf{y}) + \mathbf{exp}(\boldsymbol{\beta}_2 \mathbf{X}_2 + \boldsymbol{\beta}_3 \mathbf{X}_3 \ldots + \boldsymbol{\beta}_n \mathbf{X}_n) \tag{15}$$

[13] A Poisson autoregressive model was run with the help of Jeffrey Prestemon but due to the data the model would not converge after multiple iterations, unlike the negative binomial model, and thus could not be used.

When the lagged dependent variable was added into the negative Binomial Models, it showed a positive relationship which was significant for all ten models but because of its exponential effects on larger count counties, it was removed.

Early data analysis found that much of the data had problems of multicollinearity. From the larger dataset, a Pearson's correlation matrix was created. From this matrix, highly correlated variables were run in separate models to determine which had the greatest effect on ignition counts and lowest standard error. Along with this, early model runs were conducted including all variables to determine variables to remove based on statistical significance and standard errors. There was also a major problem of outliers within the dataset. While this can be assumed normal for economic variables, it still created problems for data analysis. The major outliers were large urban counties. These counties not only had much higher income and employment values but also had relatively few incendiary wildfire ignitions due to the small amount of woodland present in the urban landscape. The three major areas of concern were Charlotte (Mecklenburg County), Raleigh/Cary (Wake County) and Atlanta (Cobb, Fulton, DeKalb, and Gwinnett County). These counties were removed from the dataset because they would have skewed model results and contributed little to our expected utility model of incendiary wildfire. Because of this, the study's results are not applicable to major urban areas.

A trend variable accounts for a multitude of unquantifiable variables, including things such as changes over time in technology, attitudes towards fire setting, and law enforcement. This variable (YEAR) was created by subtracting 1900 from the year to create a variable which had an average around 100. This was done so that final elasticity could be interpreted as per year (if year had been changed to 1-20 then the elasticity would show the difference in .1 years).

The majority of the income variables had problems with multicollinearity. Much of this correlation could be attributed to median household income (MHI) and personal income (PI). MHI was not only highly correlated to other income variables but also to the poverty and demographic variables. PI, which was the total personal income per county, was clearly correlated with per capita personal income and population as well as the poverty variables.

With the removal of these two variables, much of the multicollinearity was corrected. This left five variables to be included in the model: non-farm income (NFI), farm income (FI)[14], net earnings (NET_ERN), per capita personal income (PC), and average earnings per job (AVG_EPJ).

The employment variables showed less correlation than would be expected but still enough to cause issues. County, state, and federal unemployment rates all had about a 0.5 correlation between each other. Because of this correlation, both the federal and state unemployment rates were removed and the county level was included. The employment rate showed a negative correlation to all unemployment variables but was very low (-0.03). This is believed to be because the employment rate includes workers who travel into the county daily for work, unlike the unemployment rate. The final variables from employment added to the model were both the county level unemployment (UNEM_CTY) and the county level employment rate (EMP_RT).

All of the six poverty variables had high rates of correlation between each other, the income variables, and the population variables. To lessen this effect only the total poverty rate (POV_P) was included and the population variables were changed. Originally population demographics were split into sixteen different variables accounting for race, sex, and Hispanic origin. All of these variables besides white and African American population were very small. In order to decrease the amount of race variables the sexes were compiled and Hispanic origin was turned into its own variable. This left five demographic variables in the model: White (W), African American (B), Asian and Pacific Islander (A), Native American and Alaskan native (I), and those of Hispanic origin (HISP). In order to decrease the correlation with population, these variables were changed from a count to a percent by dividing by total population. In order to add these variables to the model, one had to be removed. This is because the total of all percentages was equal to one and thus the model could not be run using inclusive variables. To adjust for this the race variable, W was excluded and it can be assumed that its effects are represented in the intercept. This variable

[14] Non-farm income and farm income were included not only as income variables but to account for the differences in regional economies. It can be assumed that the attitudes towards and precedence of firesetting would change in economies where farming is more common not only from a greater understanding of the practice of burning but also due to the amount of individuals present in the urban landscape (Which would change rates of being caught).

was chosen to be removed because past sociological studies conducted in the South (Doolittle, 2005, Auburn, 1975, Barker, 1994, ect.) have shown that woodsburners were most commonly white. This study will test these finding by determining the effects of other race variables compared to whites. Along with these race variables an all-inclusive variable for total population (POP) was included (Prestemon and Butry, 2005; Butry and Prestemon, 2005). This variable was included because it did not have a high correlation to the race variables due to their differences through space.

The weather data were collected and run in early models to determine which variables to include. Of the three El Niño anomalies (N3, N3.4, and N4), N3 was shown to have the greatest significance to wildfire ignitions and the lowest standard error so it was chosen to be included in the model. The variables for precipitation, temperature, and Palmer drought index were calculated by averaging the yearly rates. When these aggregates were used in the model, they were shown to have less significance than N3. Also, while creating a correlation matrix it was found that N3 had a high significance to all variables. From these results it was concluded that N3 alone was a sufficient weather variable to work as a proxy for all weather variables.

The two quantitative geospatial variables collected were determined to not be useful in the study. Highway location was planned to be used to determine the distance from a highway in which a fire was ignited. This distance has been found significant in recent studies on human caused wildfire (Romero-Calcerrada, 2007). However, this variable was removed because it showed very little significant effect on incendiary fire counts. Similarly, county area had a weak significance to ignition counts in early model runs and was excluded as it did not act as a proxy for other unknown variables.

In order to account for geospatial differences, it was decided to use the qualitative ecoregions variables. Because one of the main goals of the study was to determine the different effects of socioeconomic variables in space, these variables were used to create different models for each ecoregion. Separate models were also created for each state to account for political differences and differences in space[15]. Along with the regional models, a

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[15] Because of data size limitations models could not be created by state and ecoregion. (i.e. separate ecoregion models for each state)

pooled total model was created for all ignitions in the study area. This model form allowed the study to see regional variation on right hand variables, and how variables significance and sign varied (Romero-Calcerrada et al., 2008).

The ten models which were calculated were pooled (total), Georgia (GA), North Carolina (NC), South Carolina (SC), Blue Ridge (BLUE), Middle Atlantic Coastal plain (MAC), Piedmont (PED), Ridge and Valley (RAV), Southeastern Plains (SOP), and Southern Coastal Plain (SCP). All of these regional models used county level data. The final variables included in this model and their units are shown in Chart 1. The final regression equation can now be written as a function of independent variables where $Y_{t,c}$ is the fire count for year t and county c (Equation 15).

$$\log(Y_{t,c}) = \beta_0 + \beta_1 YEAR_{t,c} + \beta_2 POP_{t,c} + \beta_3 N3_{t,c} + \beta_4 A_{t,c} + \beta_5 B_{t,c} + \beta_6 I_{t,c} + \beta_7 HISP_{t,c} + \beta_8 POV\_P_{t,c} + \beta_9 UNEM\_CTY_{t,c} + \beta_{10} EMP\_RT_{t,c} + \beta_{11} NFI\_RT_{t,c} + \beta_{12} FI\_RT_{t,c} + \beta_{13} NET\_ERN_{t,c} + \beta_{14} PC_{t,c} + \beta_{15} AVG\_EPJ_{t,c} \tag{16}$$

Table 1 Variables Selected in Model and their Units

Variable	Explanation	Units
Year	Year	Years-1990
POP	Population	Ten Thousands
N3	El Niño anomaly	Difference from mean
A	Asian	Percent of population
B	African American	Percent of population
I	Native American	Percent of population
HISP	Hispanic	Percent of population
POV_P	Poverty	Percent
UNEM_CTY	County Unemployment	Percent
EMP_RT	Employment rate	Percent
NFI_RT	Non-Farm Income	Ten thousands/POP
FI_RT	Farm Income	Ten thousands/POP
NET_ERN	Net Earnings	Hundred thousands
PC	Per capita Income	Ten Thousands
AVG_EPJ	Average earnings per job	Ten thousands

Results

In order to determine the functional form of the models, both goodness of fit and problems with multicollinearity will be discussed. This is important because the model could show significant parameter estimated, but because of inherent flaws in the model, these estimates could be biased. After this the structural results of the model, parameter estimates, will be discussed for each variable class.

Goodness of Fit

Table 2 shows the calculated goodness of fit statistics for all of the models. The first statistic to consider in the estimated dispersion parameter is shown in Equation 11. For a negative binomial model to be appropriate, the dispersion parameter must be greater than one. As discussed earlier, as the dispersion parameter approaches zero, a Poisson model becomes more appropriate for the data. All of the ten models run had a dispersion parameter greater than zero. Most of the models had a dispersion parameter of about one, but the Ridge and Valley model and Southern Coastal plain model had lower values. This lower value suggests that the models distribution is closer to that of a Poisson but the variables show enough dispersion that a negative binomial model is warranted (Pahl, 1969).

Table 2 Goodness of fit Statistics

Goodness of Fit Statistics

	BLUE	MAC	PED	RAV	SOP	SCP	GA	NC	SC	TOTAL
Dispersion	**0.8548 (0.06)**	**1.2661 (0.07)**	**1.0244 (0.03)**	**0.2615 (0.03)**	**1.006 (0.03)**	**0.4492 (0.03)**	**0.9697 (0.02)**	**1.6958 (0.06)**	**1.0355 (0.04)**	**1.4326 (0.02)**
DF	484	778	2204	184	1884	384	3084	1978	904	5998
Deviance	566.4	911.4	2502	210.4	2188	433	3517	2243	1049	6904
Value/DF	**1.17**	**1.17**	**1.14**	**1.14**	**1.16**	**1.13**	**1.14**	**1.134**	**1.16**	**1.15**
P. Chi-sq	535	786.5	2364	217.5	1883	473.4	3643	2097	1029	7344
Value/DF	1.11	1.01	1.07	1.18	0.99	1.24	1.18	1.06	1.14	1.22
p-val	**0.946**	**0.591**	**0.991**	**0.954**	**0.501**	**0.999**	**1**	**0.969**	**0.998**	**1**

The second goodness of fit estimator to consider is the deviance value over degrees of freedom. This value shows the overall fit of the model as concerned with the estimated dispersion parameter. The deviance follows an appropriate chi-squared distribution with degree of freedom equal to n-p, where n is the number of observations and p is the number of predictor variables, and the expected value of a chi-squared random variable is equal to zero. Thus, if the model fits the data well, the ratio of the deviance to degrees of freedom should be about one. Larger ratios represent an over-dispersed response variable or model misspecification. Table 2 shows that all models had deviance ratios of around one with a range from 1.13 to 1.17. This shows that there is dispersion in each model and a negative binomial model is appropriate.

The third statistic of goodness of fit is the p value. This value is the probability that an observation from a chi-square distribution is equal to the actual observation. This is not a test of the model coefficients, but instead a test of the overall model. In other words, this test shows the probability that the model fits the actual data. A low p-value suggests a problem or misspecification of the model. In order to reject the model the p-value must be less than 0.1. Table 2 shows that all models have significantly high p-values. Only two of the models showed p-values less than 0.9. While these models had lower p-values, they are still much greater than the threshold of 0.1 and can be concluded significant (Hubbard, 2005). Overall, the models fit the data fairly well. Figure 11 shows the frequency distribution between the actual fire count data and the estimated counts for each model. The fit is not perfect and all of the models seemed to under predict for low counts, over predict at mid-range counts, and under predict at high counts Out of all three models, the ecoregion models seem to predict incendiary fire counts the best.

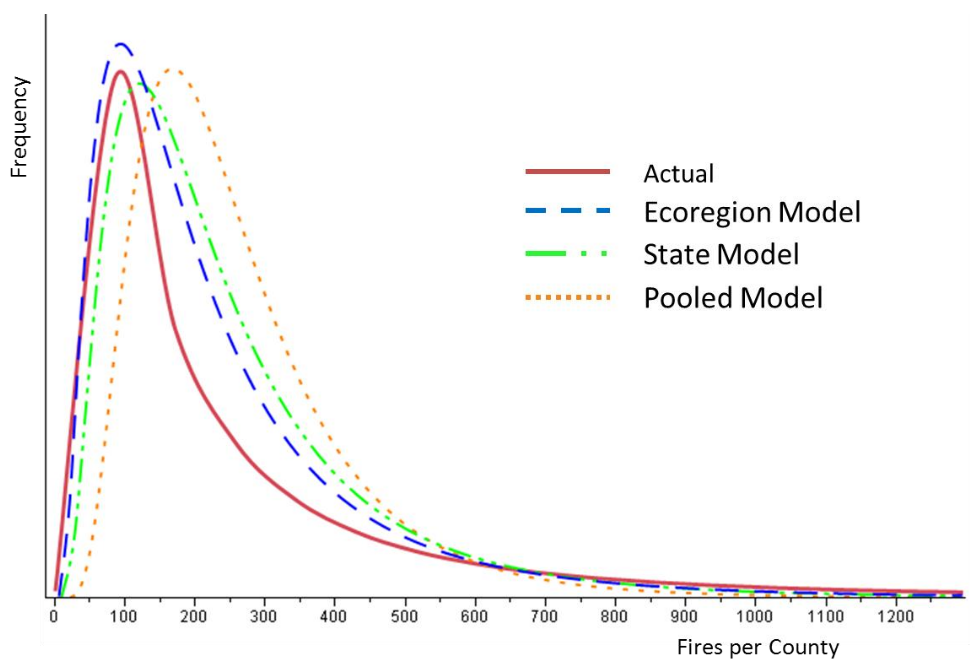

Figure 11 Frequency distribution of actual counts and Predicted Counts by model

These results can also be seen in Figure 12, which shows the predicted incendiary counts for each inclusive model (Total, State, and Ecoregion). The total model seems to poorly predict ignitions. This is similar to the state model, which shows that South Carolina is highly over predicted due to pockets of extraordinarily high incendiary fire counts in parts of the state. Ecoregion, on the other hand, tends to predict ignition counts fairly well amongst the whole study area and resembles the actual counts. This same pattern of comparrison can also be seen in Figures 20 (Appendix E), which shows the difference in incendiary predictions compared to actual ignitions for each model.

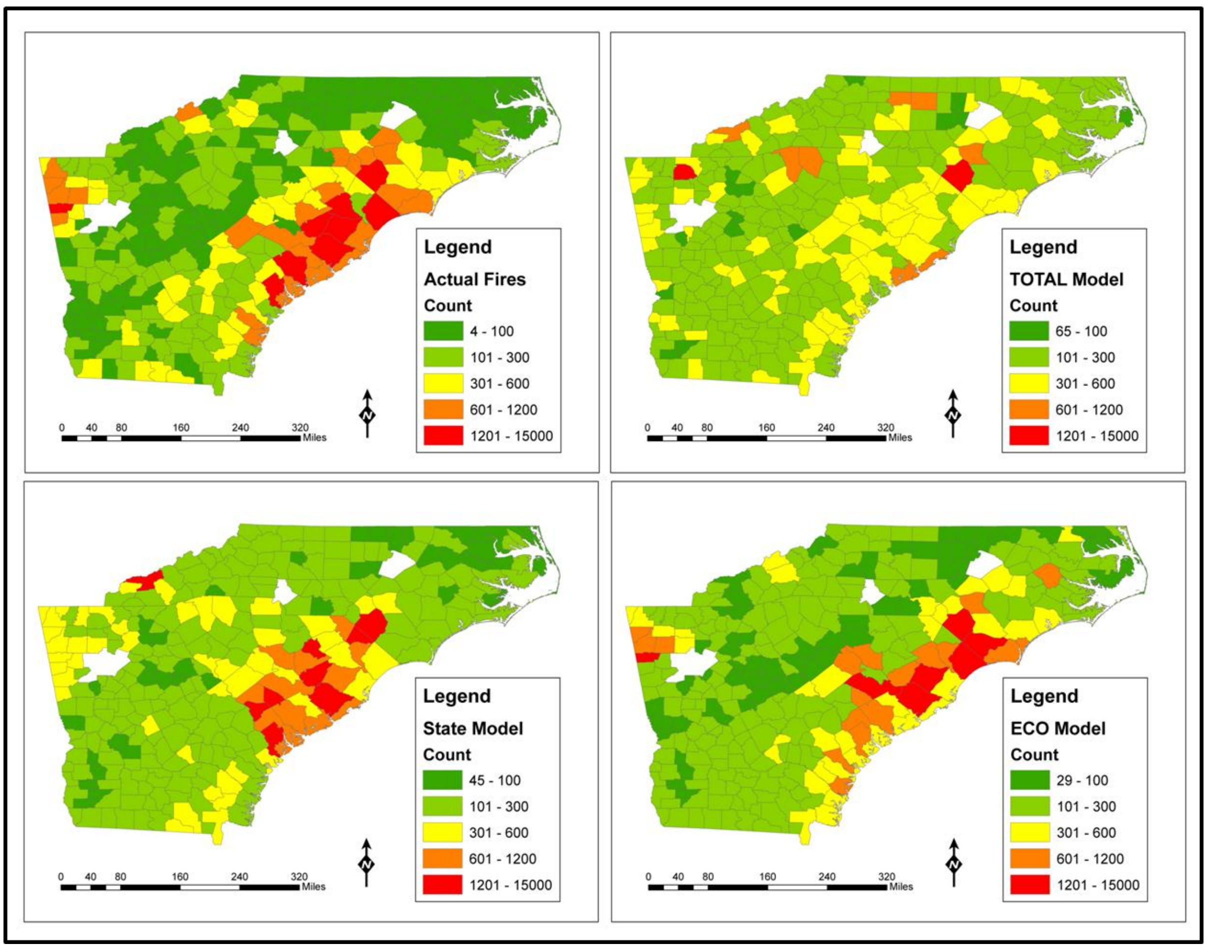

Figure 12 Actual wildfires per county (1990-2009) and Predicted Values for all Models

Multicollinearity

One problem is that a few models show high levels of multicollinearity (SC, SOP, and RAV). This multicollinearity can cause parameter estimates to vary drastically because of their correlation with other similar parameters. Appendix D shows the Pearson's correlation matrix for all models. While this multicollinearity does not invalidate a model's validity, it should be taken into account when interpreting individual parameter estimates. With an understanding of the goodness of fit statistics and clear signs of proper model selection the socioeconomic parameter estimates (Table 3 and 4) and their elasticity[16] (Table 5) can now be discussed.

[16] Elasticity was calculated by multiplying the sample mean by parameter estimates. Data summary for all models can be found in Appendix A.

Table 3 Parameter Estimates for Ecoregion Models

	BLUE	MAC	PED	RAV	SOP	SCP
Intercept	-3.8891*** (1.4987)	9.6173*** (1.1675)	7.3201*** (0.6268)	7.4469*** (1.7677)	6.4587*** (0.6562)	10.953*** (1.0706)
Year	0.0712*** (0.016)	-0.0747*** (0.0153)	-0.0432*** (0.0067)	-0.0524*** (0.0179)	-0.0155** (0.0072)	-0.0727*** (0.0108)
POP	0.1033*** (0.0169)	0.2314*** (0.0188)	0.0029 (0.0049)	0.0612 (0.049)	0.0921*** (0.0086)	0.002 (0.0074)
N3	-0.1804** (0.0794)	-0.0764 (0.0726)	-0.2848*** (0.0422)	-0.141* (0.0763)	-0.2143*** (0.041)	-0.1311** (0.0604)
A	-62.4831*** (22.1339)	-77.4021*** (12.8878)	-3.447 (3.3335)	-127.189*** (24.4581)	-25.4163*** (8.6923)	-2.7594 (11.0666)
B	11.2488*** (3.4509)	3.531*** (0.7027)	-2.6202*** (0.2324)	12.7965*** (1.3566)	-2.951*** (0.3131)	2.465*** (0.5852)
I	-2.3607** (1.1231)	63.857*** (9.2768)	-3.5735 (5.7136)	24.6803 (35.9055)	6.6067*** (0.8362)	8.8943 (16.3926)
HISP	-14.7168*** (2.8101)	12.5967*** (3.2532)	-0.1482 (0.968)	0.3694 (1.3263)	-2.0795* (1.0912)	2.041* (1.1142)
POV_P	0.1194*** (0.0289)	0.0056 (0.0188)	0.041*** (0.0113)	0.0278 (0.0355)	0.0149* (0.0082)	-0.0326** (0.0162)
UNEM_CTY	-0.1023*** (0.0225)	0.097*** (0.022)	-0.018 (0.0136)	-0.0189 (0.0285)	0.006 (0.012)	-0.0273 (0.0258)
EMP_RT	-6.5435*** (0.6737)	-5.3484*** (0.6274)	-1.2758*** (0.297)	-1.2205* (0.7269)	-1.0699*** (0.3061)	-1.9802*** (0.4657)
NFI_RT	-0.1567 (0.0976)	0.7414*** (0.1141)	0.3109*** (0.0618)	0.1462 (0.1428)	0.2324*** (0.0712)	0.5044*** (0.1157)
FI_RT	0.433*** (0.1336)	-1.2863*** (0.1063)	-0.4832*** (0.0635)	0.8411** (0.3676)	-0.2456*** (0.0381)	-0.3833*** (0.0879)
NET_ERN	0.1241*** (0.0144)	0.0524*** (0.0146)	0.0034 (0.0065)	-0.0519 (0.0561)	-0.013* (0.0076)	-0.0079 (0.0135)
PC	-0.9348*** (0.2662)	-0.7701*** (0.2506)	-0.5884*** (0.0937)	0.614 (0.5871)	-0.9133*** (0.1201)	-0.1663 (0.131)
AVG_EPJ	0.458** (0.1896)	0.0685 (0.1621)	0.2118*** (0.0596)	-0.0895 (0.2159)	0.2525*** (0.0688)	0.0335 (0.1013)
Dispersion	0.8548 (0.0677)	1.2661 (0.0713)	1.0244 (0.0386)	0.2615 (0.0312)	1.006 (0.0367)	0.4492 (0.0361)

Table 4 Parameter Estimates for Pooled and State Models

	TOTAL	GA	NC	SC
Intercept	7.9567*** (0.4004)	4.9431*** (0.5245)	5.107*** (0.7812)	17.1339*** (1.0089)
Year	-0.0539*** (0.0043)	-0.0189*** (0.0057)	-0.0357*** (0.0092)	-0.1678*** (0.0109)
POP	0.0694*** (0.0044)	0.0855*** (0.0074)	0.0301*** (0.0085)	0.0012 (0.0096)
N3	-0.2191*** (0.0272)	-0.2161*** (0.0326)	-0.1761*** (0.0508)	-0.2475*** (0.0595)
A	-16.2475*** (3.1993)	- 45.3758*** (4.2896)	5.1557 (5.611)	89.891*** (11.5199)
B	-0.8217*** (0.1552)	-2.8972*** (0.1921)	-2.6719*** (0.3369)	1.285*** (0.475)
I	4.1532*** (0.647)	13.8007 (9.2091)	7.5686*** (0.935)	15.0402** (6.7168)
HISP	2.3508*** (0.6405)	0.6019 (0.7407)	4.1767*** (1.4689)	-0.1387 (2.1373)
POV_P	0.0651*** (0.0062)	0.0648*** (0.0072)	0.0724*** (0.0143)	0.117*** (0.0171)
UNEM_CTY	-0.0119 (0.0079)	-0.0513*** (0.0104)	-0.0193 (0.0169)	-0.0624*** (0.0169)
EMP_RT	-2.4703*** (0.183)	-1.517*** (0.2191)	-1.3444*** (0.3703)	-2.3951*** (0.6094)
NFI_RT	0.3388*** (0.0397)	0.0539 (0.0416)	0.2557*** (0.0677)	0.5701*** (0.1047)
FI_RT	-0.4999*** (0.0283)	-0.4473*** (0.0329)	-0.137** (0.065)	-0.3022 (0.2115)
NET_ERN	0.001*** (0.0041)	0.0157*** (0.0054)	-0.016** (0.008)	-0.0487*** (0.0152)
PC	-0.5838*** (0.0605)	-0.7304*** (0.0694)	-0.47*** (0.1248)	0.6004*** (0.1898)
AVG_EPJ	0.3147*** (0.0431)	0.4181*** (0.0468)	0.4318*** (0.0982)	-0.1136 (0.1059)
Dispersion	1.4326 (0.0275)	0.9697 (0.028)	1.6958 (0.0603)	1.0355 (0.0482)

Table 5 Elasticity for all models and variables (red denoted significance <0.1)

	Total	Georgia	North Carolina	South Carolina	Blue Ridge	Middle Atlantic Coastal Plain	Piedmont	Ridge and Valley	Southeastern Plains	Southern Coastal Plains
						Elasticity				
Year	-5.37	-1.88	-3.56	-16.70	7.08	-7.46	-4.30	-5.21	-1.54	-7.23
POP	0.38	0.30	0.21	0.01	0.39	1.22	0.02	0.32	0.38	0.01
N3	-0.04	-0.03	-0.03	-0.04	-0.03	-0.01	-0.05	-0.02	-0.03	-0.02
A	-0.11	-0.29	0.04	0.57	-0.25	-0.48	-0.03	-0.73	-0.13	-0.02
B	-0.22	-0.79	-0.57	0.48	0.24	1.21	-0.60	0.80	-1.12	0.56
I	0.03	0.05	0.13	0.07	-0.05	0.39	-0.02	0.10	0.07	0.05
HISP	0.07	0.02	0.14	0.00	-0.33	0.26	0.00	0.02	-0.06	0.08
POV_P	1.14	1.20	1.13	2.11	1.76	0.10	0.59	0.38	0.33	-0.59
UNEM_CTY	-0.07	-0.30	-0.12	-0.46	-0.62	0.66	-0.10	-0.10	0.04	-0.15
EMP_RT	-1.13	-0.66	-0.66	-1.11	-3.29	-2.48	-0.58	-0.57	-0.48	-0.87
NFI_RT	0.43	0.06	0.39	0.69	-0.29	1.06	0.41	0.19	0.24	0.61
FI_RT	-0.25	-0.27	-0.07	-0.05	0.17	-0.58	-0.15	0.14	-0.20	-0.15
NET_ERN	0.02	0.27	-0.29	-0.84	2.08	0.90	0.07	-0.93	-0.21	-0.13
PC	-1.58	-1.91	-1.35	1.60	-2.55	-2.11	-1.68	1.62	-2.31	-0.43
AVG_EPJ	1.08	1.41	1.50	-0.41	1.41	0.23	0.74	-0.31	0.89	0.12

Parameter Estimates

The time trend (YEAR) was among the few variables in which every model showed a significant effect. This seems likely due to the changing patterns documented in Figures 5, 6, and 7. All models, except Blue Ridge, showed a negative time trend. The elasticity shows the expected percent change in wildfire arson over approximately one year (actually 0.995 years). This percent varies from a minimum of -16.7% to a maximum of 7.08%.

The N3 anomaly variable also followed a logical trend as shown in Figure 8. All models showed a negative relationship with only the MAC model being insignificant. This negative relationship shows how increase in factors such as precipitation and humidity resulting from a higher N3 decrease the rate of incendiary firesetting success.

The population variable showed a positive relationship with incendiary wildfires for all models. Its elasticity ranged from 0.01 to 1.22, showing a great deal of variation across the regions. Of the ten models, four had insignificant parameter estimates (SC, PED, RAV, and SCP). The race variables changed greatly between model regions. The Asian variable and African American variable showed mostly negative relationships for all regions while the Native American and Hispanic variable showed a mostly positive relationship. Because these are dummy variables, they represent the difference over the excluded variable White.

The variable for percent of population in poverty showed a positive relationship for all but one model region (SCP). The two employment variables (EMP_RT and UNEM_CTY) show contradicting results; both have a negative relationship with incendiary firesetting. Farm income rate (FI_RT) showed a negative relationship with incendiary fires while non-farm income rate (NFI_RT) showed a positive relationship. The net earnings variable (NET_ERN) showed a varied response to incendiary firesetting with half of the models showing a negative relationship and half showing a positive.

The PC variable showed a negative relationship with incendiary firesetting for the majority of the models. This means that as per capita income increases, individuals are less likely to start fires. The per capita income differs from net earnings because it is measured from tax returns of the resident population only. The final income variable, average earnings per job, showed mostly positive relationships among the regional models, which is opposite of what would be expected in the utility maximizing model.

Discussion

The discussion will include a description of how each of the variable categories compare to past studies of wildfire arson as well as to the expected utility function of woodsburners. As discussed earlier, incendiary fires have decreased over time. This can be seen not only graphically but also spatially. Figures 16, 17, and 18 (Appendix E) show how not only has the amount of incendiary wildfires decreased, but also the area in which fires are started has changed. Both Figures 15 and 16, shown in the same scale, show how the area with higher incendiary fire counts has shrunk in size over time. This decrease in size could be due to the fact that as there are fewer woodsburners, the travel distance needed to find land suitable for burning becomes smaller. Another possible reason for this could be the same as Prestemon and Butry (2005), reflecting on Doolittle and Lightsey (1979), suggested for Florida. Namely, that as legal prescribed burning has become more commonplace since the early nineties, part of the remaining incentives for normative firesetting have receded. This means that increases in prescribed fires might have decreased the amount of normative incendiary woodsburners.

Both Population and El Niño variables showed similar results to past studies (Mercer and Prestemon, 2005; Thomas et al., 2010). Increased population in a county resulted in a higher chance of a woodsburner being present and thus more fires ignited. The El Niño anomaly, on the other hand, showed that wildfires do decrease as sea temperatures increase due to greater than normal precipitation and lower than normal temperatures.

Race variables have not been included in any previous quantitative analysis of wildfire arson. While the exact estimates differ for each model, there is a trend of Asian and African Americans having a negative relation with wildfire arson ignitions and Native American and Hispanic populations having a positive relationship with wildfire arson ignition. This study cannot explain the reasons for such relationships but it is hypothesized that African American and Asian populations are higher in more urban areas with lower incendiary wildfire ignitions thus leading to the negative relationship. Hispanic populations also are expected to follow this trend, but the results do not show this expected relationship. The most interesting finding in the race variables was the strong positive relationship with Native American populations. From socioeconomic studies (Doolittle, 1975), it can be assumed that this relationship is due to a strong normative firesetting belief within these populations. However, one important factor to consider is if the relationship in this study has causality and not just correlation; this means that it might be some other factor in the county accounting for high incendiary wildfire counts and it is just coincidence that these counties also have a higher Native American population. Figure 12 shows a clear positive correlation between Native American population and Incendiary wildfire counts.

The reason for this positive relationship seems to be the Lumbee Tribe in the Sand Hills of North Carolina. The Lumbee have a high percentage of the population in Robeson county and Neighboring Hoke and Scotland County. These counties also have higher than average Incendiary wildfire counts (Also seen in Figure 15). This trend can also been seen in the elasticity for I in each model. The NC and MAC models, where the Lumbee tribe is located, have the highest elasticity for I. There is no research to suggest that the Lumbee Tribe has a strong normative firesetting culture but this study suggests that this might be possible, although further research is needed.

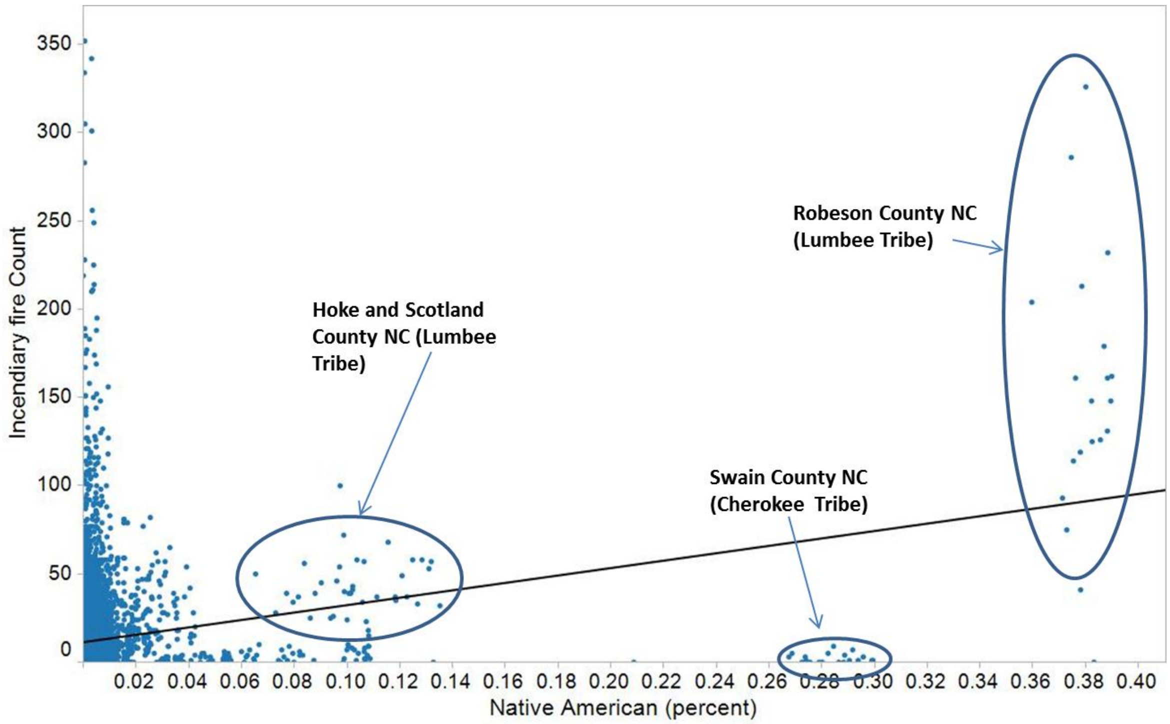

Figure 13 Scatterplot of Native American Population and Incendiary Counts

The poverty variable (POV_P) seemed to follow the same positive relationship found by Prestemon and Butry (2005) but was different than Mercer and Prestemon (2005). This difference might be attributed to the study area or scope, although it cannot be concluded from this study. This relationship follows the expected relationship from the utility model. Poverty, a sign of lower income, would result in less costs of starting wildfires. It can also be assumed that high rates of poverty are correlated with areas with lower education levels and thus an area which holds normative firesetting beliefs. Another possible reason for this relationship could be the possible correlation between poverty rate and law enforcement efforts. Thomas et al. (2010) found that the poverty rate was negatively correlated with number of law enforcement officers in Florida because higher poverty, and thus lower tax revenues, led to less officers being employed. Because of this correlation the poverty rate variable might be also showing the effects of law enforcement on wildfire arson ignitions. In other words, poverty rate increase is simultaneous to a decrease in law enforcement effort, leading to an increase in ignitions.

The income variables do tend to follow the expected utility maximizing function. The most significant income variable was per-capita personal income, which showed a negative relationship to incendiary wildfire ignitions unlike Prestemon and Butry's (2005) study. This negative relationship is similar to those hypothesized and shown by Becker (1968). These results are in contradiction to the average earning per job variable, which showed a positive relationship. This goes directly against the expected utility model. Because the expected utility model is a function of wages and employment, it would be expected that as wage rates increase, the amount of firesetting would decrease. However, this relationship was only shown to be true in the models for South Carolina and the Ridge and Valley ecoregion. One important factor to consider is that both PC and AVG_EPJ show inverse relationships (for every model with a negative PC parameter the AVG_EPJ parameter is positive). This might show that these two variables are introducing the same information to the model, or that they are correlated. The correlation matrices for each model (Appendix D) show a correlation between PC and AVG_EPJ ranging from 0.28 to 0.71. This correlation might explain the conflicting results because PC might be showing the majority of the income effect while AVG_EPJ is simply showing the small amount of different information not shown in the PC variable.

The NET_ERN variable showed a widely varying relationship across model estimates. This variable was a measure of overall total earnings per county and might not be a good indicator of individual income. This could be attributed to net earnings including not only local income, but also income received by large corporations or landowners who do not reside in the county. Because of this, one could assume that net earnings might be working as a proxy for retaliatory firesetting if the majority of the nonresident income was from out of state land owners. But because the study did not include a breakdown of net earnings by type, it is hard to make this assumption.

The final income variables are the farm and non-farm income rates. These rates show how local economies are structured. If farm income rate is larger, it shows that the local economy is based more on farming. The relationship showed by the model tends to follow rational beliefs on incendiary firesetting. It can be assumed that areas with a larger rate of farm income would have more individuals present in the rural landscape and thus illegal woodsburners would have a higher probability of being caught. Along with this, high farm rate areas would also have more individuals who know proper land management techniques and would be more likely to use legal prescribed burning on their land, which would lead to less of a need for individual woodsburners to ignite fires. Both of these rates followed this trend. Another possible explanation for these results could be the possible correlation between farm income/non-farm income and amount of timberland. A high farm income rate could mean that there is less forested land in the county and thus less land for wildfire arsonists to ignite.

As shown in the results section, the unemployment rate (UNEM_CTY) and employment rate (EMP_RT) showed the same negative relationship to fire counts. The expected utility model of firesetting would suggest that unemployment would have a positive relationship with firesetting while employment rate would have a negative relationship. In all models, the employment rate was statistically significant, showing that it might be a better representation of employment at the county level. If this is true, then the results do follow the expected utility model. One problem with this assumption is that it goes directly against the current literature. Mercer and Prestemon (2005), Prestemon and Butry (2005), and Thomas et al. (2010) all found that the unemployment rate was negatively related to incendiary wildfire counts. Further research is needed to determine which employment figure is a better measure of the true employment effect.

Conclusion

In conclusion, this study provides evidence that incendiary woodsburners follow the expected utility theory. All variables except for the unemployment rate, net earnings, and average earnings per job showed evidence of this theory. The study also showed that the effects of socioeconomic variables did change over the study region. This change was most commonly seen in the areas with high incendiary wildfire ignitions, such as the Mid Atlantic Coastal Plain and the Southern Coastal Plain which both had much larger elasticity for socioeconomic variables than did the areas with lower counts.

While this study does follow Becker’s crime model (1968), there is need for further research to determine the effects using a lagged dependent variables and lagged spatial variables. Prestemon and Butry (2005) and Butry and Prestemon (2005) showed very strong evidence that incendiary wildfires were not only a result of socioeconomic variables but also an effect of lagged counts and lagged counts in neighboring regions. These variables help account for some of the cultural beliefs of normative firesetting within a population. In order to do this, a study using a Poisson autoregressive model, like in Prestemon and Butry (2005), should be implemented using the same socioeconomic variables in this study to determine if the socioeconomic variables show the same effects as well as the lagged variable effects.

While these lagged variables will help to explain some of the cultural effects, there is also a need for a large scale sociological study within the South to determine cultural beliefs on firesetting. By using the maps of high density areas and following race variable effects shown by this study, a survey could be used to create quantitative geospatial data on normative wildfire behavior. A study of this type would then be able to be run a statistical model to obtain a more robust explanation of socioeconomic effects. This sociological study would also be advantageous to wildfire prevention agencies and law enforcement as it would help them target these high risk areas.

Another possible addition to the study could be the inclusion of more variables which other studies have shown to be significant. Some of these variables include Police per capita, arson arrest rate, amount of forest land, and prescribed fires. The inclusion of these variables would help to make the study's findings more robust.

Overall, this study not only followed the expected utility theory but it also gives evidence that is useful in wildfire prevention and law enforcement. From this study, it is clear that socioeconomic variables do play an important role in explaining woodsburners behavior and that specific areas with low employment numbers, low personal income, low farm income, high poverty rates, and a high percentage of Whites or Native Americans are more likely to harbor incendiary woodsburners. From these results, wildfire prevention specialists can better target high incendiary wildfire areas in an effort to decrease the loss of both timber and non-timber goods.

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Appendices

Appendix A

Table 6 Data Statistics for all Models

	GA	NC	SC	Total	BLUE	MAC	PED	RAV	SOP	SCP
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	99.50	99.66	99.50	99.55	99.50	99.91	99.50	99.50	99.50	99.50
Std Dev	5.77	5.85	5.77	5.79	5.77	5.96	5.77	5.78	5.77	5.77
Minimum	90	90	90	90	90	90	90	90	90	90
Maximum	109	109	109	109	109	109	109	109	109	109
POP										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	3.56	6.82	8.75	5.43	3.74	5.29	6.97	5.22	4.18	5.39
Std Dev	4.35	6.91	9.01	6.49	4.61	5.01	7.48	2.48	5.69	8.10
Minimum	0.00	0.38	0.89	0.00	0.69	0.38	0.18	1.33	0.22	0.00
Maximum	28.12	48.77	45.80	48.77	23.44	26.72	48.77	9.74	37.84	36.01
N3										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	0.16	0.17	0.16	0.16	0.16	0.17	0.16	0.16	0.16	0.16
Std Dev	0.59	0.59	0.59	0.59	0.59	0.58	0.59	0.59	0.59	0.59
Minimum	-0.8	-0.8	-0.8	-0.8	-0.8	-0.8	-0.8	-0.8	-0.8	-0.8
Maximum	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9
A										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	0.0064	0.0073	0.0063	0.0067	0.0040	0.0062	0.0088	0.0057	0.0050	0.0075
Std Dev	0.0080	0.0085	0.0060	0.0079	0.0041	0.0062	0.0101	0.0039	0.0058	0.0077
Minimum	0.0000	0.0000	0.0001	0.0000	0.0000	0.0002	0.0000	0.0005	0.0000	0.0000
Maximum	0.055	0.066	0.030	0.066	0.043	0.048	0.066	0.018	0.037	0.033
B										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	0.274	0.214	0.371	0.269	0.022	0.343	0.231	0.062	0.378	0.229
Std Dev	0.170	0.165	0.159	0.174	0.023	0.171	0.158	0.048	0.125	0.101
Minimum	0.000	0.001	0.070	0.000	0.000	0.028	0.000	0.003	0.104	0.000
Maximum	0.790	0.627	0.713	0.790	0.166	0.666	0.790	0.141	0.713	0.431
I										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	0.004	0.017	0.005	0.008	0.023	0.006	0.004	0.004	0.011	0.005
Std Dev	0.003	0.049	0.006	0.029	0.058	0.006	0.005	0.003	0.041	0.004
Minimum	0	0	0	0	3E-04	0	0	5E-04	0	0
Maximum	0.019	0.39	0.042	0.39	0.299	0.036	0.056	0.012	0.39	0.017
HISP										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	0.029	0.032	0.02	0.029	0.023	0.021	0.029	0.051	0.03	0.041
Std Dev	0.037	0.031	0.021	0.033	0.023	0.018	0.031	0.064	0.032	0.053
Minimum	0	0.001	0.002	0	0.002	0.001	0	0.003	0	0
Maximum	0.317	0.22	0.164	0.317	0.133	0.144	0.27	0.31	0.239	0.317

Table 6 Cont. Data Statistics for all Models

Variable	GA	NC	SC	Total	BLUE	MAC	PED	RAV	SOP	SCP
POV_P										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	18.55	15.56	18.06	17.48	14.72	18.41	14.27	13.79	21.83	18.17
Std Dev	6.147	4.498	5.7	5.746	3.06	5.317	4.458	2.427	5.237	4.448
Minimum	0	7.49	8.863	0	5.408	7.49	3.275	9.567	8.863	0
Maximum	40.5	31.5	41.38	41.38	24.92	35.58	35.84	22.42	41.38	28.59
UNEM_CTY										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	5.924	6.176	7.361	6.228	6.089	6.846	5.77	5.473	6.789	5.422
Std Dev	2.26	2.544	3.004	2.53	2.919	2.645	2.448	2.026	2.452	1.88
Minimum	1.4	1.2	1.7	1.2	1.5	2.4	1.2	2.5	1.7	2
Maximum	19.3	19.7	20.8	20.8	19.7	20.5	20	13	20.8	14.7
EMP_RT										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	0.433	0.493	0.464	0.458	0.502	0.463	0.454	0.468	0.452	0.44
Std Dev	0.172	0.146	0.119	0.159	0.277	0.137	0.143	0.144	0.138	0.174
Minimum	0	0.069	0.212	0	0.131	0.069	0.092	0.296	0.116	0
Maximum	5.866	2.963	1.036	5.866	5.866	1.456	2.963	0.835	2.271	1.315
NFI_RT										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	1.158	1.507	1.214	1.282	1.874	1.429	1.308	1.31	1.05	1.203
Std Dev	1.225	0.849	0.698	1.054	2.773	0.827	0.645	0.585	0.66	0.689
Minimum	0	0.121	0.282	0	0.374	0.121	0.209	0.384	0.08	0
Maximum	60.09	16.58	3.731	60.09	60.09	5.709	9.299	2.941	16.05	3.731
FI_RT										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	0.606	0.483	0.153	0.496	0.389	0.448	0.309	0.172	0.818	0.403
Std Dev	0.747	0.616	0.212	0.667	0.503	0.592	0.435	0.139	0.842	0.694
Minimum	-0.3	-0.248	-0.389	-0.389	-0.067	-0.248	-0.3	-0.028	-0.389	-0.027
Maximum	8.173	4.981	1.659	8.173	2.722	3.452	2.997	0.679	8.173	3.55
NET_ERN										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	17.29	18.31	17.15	17.61	16.74	17.09	19.28	17.98	16.21	16.92
Std Dev	8.558	7.208	4.23	7.612	17.66	5.383	6.49	2.791	5.415	4.566
Minimum	0	2.454	7.506	0	4.799	2.454	5.633	11.82	7.114	0
Maximum	369.4	213.6	49.81	369.4	369.4	107.7	213.6	24.5	152.3	60.7
PC										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	2.613	2.873	2.658	2.706	2.726	2.744	2.862	2.631	2.534	2.599
Std Dev	0.45	0.471	0.49	0.479	0.415	0.48	0.489	0.329	0.379	0.642
Minimum	0	1.683	1.641	0	1.683	1.786	1.684	1.968	1.641	0
Maximum	4.724	4.794	4.657	4.794	3.961	4.228	4.794	3.285	4.158	4.657
AVG_EPJ										
N	3100	1994	920	6014	500	794	2220	200	1900	400
Mean	3.364	3.472	3.601	3.436	3.068	3.319	3.484	3.488	3.508	3.496
Std Dev	0.624	0.589	0.49	0.6	0.41	0.468	0.601	0.434	0.611	0.812
Minimum	0	2.182	2.516	0	2.182	2.344	1.885	2.46	2.186	0
Maximum	8.827	6.775	5.135	8.827	4.078	5.847	6.775	4.484	8.827	6.684

Appendix B

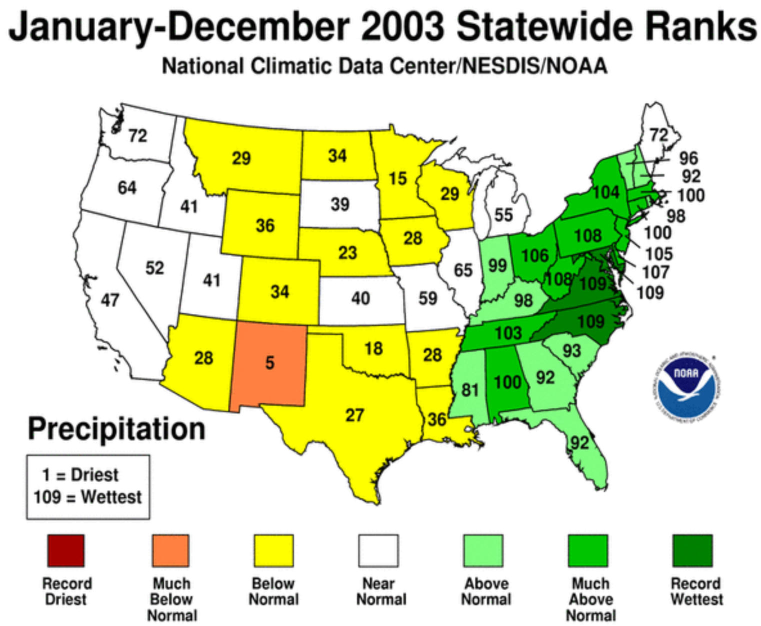

Figure 14 Rainfall Rankings for 2003

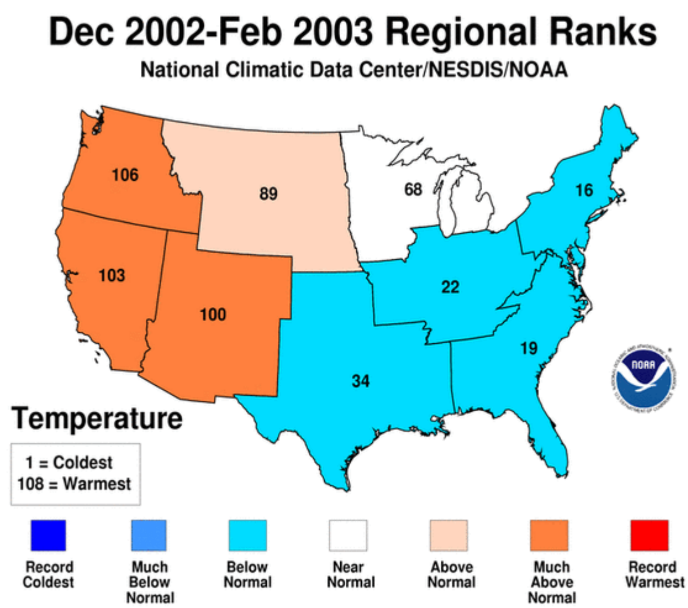

Figure 15 Temperature Rankings for 2003

Appendix C

Excerpt from Griffin (2010) explaining ecoregions in this study

BLUE RIDGE
Location: Adjacent to the Piedmont (8.3.4), the Blue Ridge extends from Southern Pennsylvania to northern Georgia.
Climate: The ecoregion has a severe mid-latitude humid continental climate in the north, and mild mid-latitude humid subtropical climate in the South. It is marked by hot summers and cold to mild winters. The mean annual temperature is approximately 7°C at high elevations and 14°C in the Southern low elevations. The frost-free period ranges from 130 to 210 days. The mean annual precipitation is 1420 mm, ranging from 1100 mm to 2500 mm on high peaks to the South.
Vegetation: Part of one of the richest temperate broadleaf forests in the world, with a high diversity of flora. Mostly Appalachian oak forests, but a variety of oak, hemlock, cove hardwoods, and pine communities within this forest type. Many forests once dominated by American chestnut, an ecologically and economically important tree that provided food and shelter to many animal species. The Chestnut blight, introduced to the U.S. around 1904, killed most all of the chestnut trees by the 1930's. In place of the chestnut, other trees, such as tulip poplar, chestnut oak, white oak, black locust, red maple, and pine species have become important canopy dominants. At higher elevations, northern hardwoods of beech, yellow birch, yellow buckeye, and maples are typical. At the highest elevations, Southeastern spruce-fir forests of Fraser fir, red spruce, yellow birch, and rhododendron are found.
Hydrology: High density of perennial high gradient, cool, clear streams with bedrock and boulder substrates. Lacks lakes, but a few large reservoirs.
Terrain: Varies from narrow ridges to hilly plateaus to more massive mountainous areas with high peaks reaching over 1800 m. Generally rugged terrain on primarily metamorphic bedrock (gneiss, schist, and quartzites). Minor areas of igneous and sedimentary geology also occur. Elevations range from 300 m to 1500 m, with Mount Mitchell, the highest point in the U.S. east of the Mississippi River, reaching 2037 m. Inceptisols and Ultisols are typical, with mesic soil temperatures and udic soil moisture regimes.
Wildlife: Black bear, white-tail deer, wild boar, bobcat, red squirrel, northern flying squirrel, cottontail rabbit, rock vole, wild turkey, raven, grouse, saw-whet owl, blackburnian warbler, brook trout, red-spotted newt, long-tailed salamander (one of the most diverse salamander populations in the world), many species of reptiles, thousands of species of invertebrates.
Land Use/Human Activities: Forest-related land uses occur along with some small areas of pasture and hay production, apple orchards, and Fraser fir Christmas tree farms. Recreation, tourism, and hunting are important. Some large areas of public lands including national forests and national parks. Larger settlements include Mountain City, Erwin, and Gatlinburg, Tennessee; Boone, Asheville, Franklin, and Brevard, North Carolina; and Blue Ridge, Jasper, and Canton, Georgia.

MIDDLE ATLANTIC COASTAL PLAIN
Location: Covers parts of the outer coastal plain from Southern New Jersey to the South Carolina/Georgia border.
Climate: The ecoregion has a mild mid-latitude humid subtropical climate, marked by hot, humid summers and mild winters. The mean annual temperature ranges from approximately 14°C in the north to 17°C in the South. The frost-free period ranges from 190 to 300 days. The mean annual precipitation is 1229 mm, ranging from 1020 mm to 1420 mm.
Vegetation: Forest cover in the region was once dominated by longleaf pine, with more oak-hickory-pine to the north. It is now mostly loblolly and some shortleaf pine, with patches of oak, gum, and cypress near major streams. On Southern barrier islands, some maritime forests of live oak, sand laurel oak, and loblolly pine. Cordgrass, saltgrass, and rushes in coastal marshes; beach grass and sea oats on dunes.
Hydrology: Low gradient streams and rivers, numerous swamps, marshes, and estuaries, a few large lakes. Carolina bays and pocosins occur in some areas.
Terrain: Low elevation flat plains, low terraces, dunes, barrier islands, and beaches are underlain by unconsolidated sediments. Poorly drained soils are common, and the region has a mix of coarse and finer textured soils. Typically lower, flatter, less dissected, and more poorly drained, than Ecoregion 8.3.5 to the west. Ultisols, Entisols, and Histosols are dominant, with mostly thermic soil temperatures (some mesic in the north) and aquic and udic soil moisture regimes.
Wildlife: Black bear, white-tailed deer, bobcat, gray fox, raccoon, cottontail rabbit, gray squirrel, wild turkey, bobwhite, mourning dove, cormorants, herons, northern cardinal, prothonotary warbler, box turtle, alligator in the South.
Land Use/Human Activities: Pine plantations for pulpwood and lumber are typical, with some areas of cropland especially in the central and northern parts of the region. Crops include wheat, corn, soybeans, potatoes, cotton, blueberries, and peanuts. Chicken, turkey, and hog production has a high density in some areas. Recreation and tourism along coastal strips. Larger cities from north to South includeWilmington, Dover, Salisbury, Norfolk, Virginia Beach, Elizabeth City, Greenville, New Bern, Jacksonville, Wilmington, and Myrtle Beach.

PIEDMONT
Location: Extends from Virginia in the north to Alabama in the South. It comprises a transitional area between the mostly mountainous ecological regions of the Appalachians to the northwest and the relatively flat coastal plain to the Southeast. Its eastern border is the fall line, where erosion-resistant rocks give way to the sands and clays of the coastal plain.
Climate: The ecoregion has a a mild, mid-latitude humid subtropical climate. It has hot, humid summers and mild winters, with little snow. The mean annual temperature is approximately 13°C in the north to 17°C in the South. The frost-free period ranges from 170 days to 250 days. The mean annual precipitation is 1229 mm, ranging from 1080-1650 mm, and is fairly evenly distributed throughout the year.
Vegetation: The historic oak-hickory-pine forest was dominated by white oak, Southern red oak, post oak, and hickory, with some shortleaf pine and loblolly pine.

Hydrology: Moderate to dense network of perennial streams and rivers, generally moderate to low gradient. Stream drainage in the Piedmont tends to be perpendicular to the structural trend of the rocks across which they flow. Few natural lakes but numerous large reservoirs.
Terrain: An erosional terrain of moderately dissected irregular plains with some hills, with a complex mosaic of Precambrian and Paleozoic metamorphic and igneous rocks. Most rocks of the Piedmont are covered by a thick mantle of saprolite, except along some major stream valley bluffs and on a few scattered granitic domes and flatrocks. Rare plants and animals are often found on the rock outcrops. The soils are mostly Ultisols and are generally finer-textured than those found in coastal plain regions with less sand and more clay.
Wildlife: Mammals include white-tailed deer, black bear, bobcat, gray fox, raccoon, gray squirrel, eastern chipmunk, pine vole. Birds include eastern wild turkey, northern cardinal, Carolina wren, wood thrush, tufted titmouse, prairie warbler, field sparrow. Herpetofauna includes eastern box turtle, common garter snake, copperhead, timber rattlesnake.
Land Use/Human Activities: Several major land cover transformations have occurred in the Piedmont over the past 200 years, from forest to farm, back to forest, and now in many areas, spreading urban- and suburbanization. Once largely cultivated with crops such as cotton, corn, tobacco and wheat, most of the Piedmont soils were moderately to severely eroded. Much of this region is now in planted pine or has reverted to successional pine and hardwood woodlands, with some pasture in the landcover mosaic. Larger cities include Lynchburg, Greensboro, Raleigh, Charlotte, Greenville, and Atlanta.

SOUTHEASTERN PLAINS
Location: .An inner coastal plain that stretches from Maryland in the north to Mississippi and Louisiana in the South.
Climate: The ecoregion has a mild, mid-latitude humid subtropical climate.It has hot, humid summers and mild winters. Mean annual temperatures range from 13°C in the north to 19°C in the South. The frost-free period ranges from 200 days in the north to 300 days in the South. The mean annual precipitation is 1358, and ranges from 1140 mm to 1520 mm. Precipitation is fairly evenly distributed throughout the year.
Vegetation: Natural vegetation was predominantly longleaf pine with smaller areas of oak-hickory-pine, and in the South some Southern mixed forest with beech, sweetgum, Southern magnolia, laurel and live oaks, and various pines. Floodplains include bottomland oaks, red maple, green ash, sweetgum, and American elm, and areas of bald cypress, pond cypress, and water tupelo.
Hydrology: Moderate to dense network of perennial streams and rivers, generally moderate to low gradient, often with sandy substrates. Few natural lakes but several large reservoirs.
Terrain: Dissected, rolling to smooth plains. The Cretaceous or Tertiary-age sands, silts, and clays of this region contrast geologically with the older metamorphic and igneous rocks of the Piedmont (8.3.4), and with the Paleozoic limestone, chert, and shale of the Interior Plateau (8.3.3). Elevations and relief are greater than in the Southern Coastal Plain (8.5.3) and Mississippi Alluvial Plain (8.5.2).
Wildlife: Mammals include white-tailed deer, black bear, bobcat, gray fox, raccoon, gray squirrel, swamp rabbit, eastern chipmunk, pine vole. Birds include eastern wild turkey, northern cardinal, Carolina wren, wood thrush, tufted titmouse, hooded warbler, summer tanager, herons, and egrets. Herpetofauna includes American alligator, eastern box turtle, common garter snake, copperhead, eastern diamondback rattlesnake.
Land Use/Human Activities: Mosaic of cropland, pasture, woodland, and forest land cover. Large areas of pine plantations and successional pine and hardwood woodlands. Agriculture includes corn, cotton, soybeans, peanuts, onions, sweet potatoes, melons, tobacco, poultry, and hogs. Cities include Richmond, Fayetteville, Columbia, Augusta, Columbus, Tallahassee, Montgomery, and Hattiesburg

RIDGE AND VALLEY
Location: A diverse ecoregion of long latitudinal stretch, sandwiched between generally higher, more rugged mountainous ecoregions 8.4.2, 8.4.4, and 8.4.9. It occurs in New York, Pennsylvania, Maryland, West Virginia, Virginia, Tennessee, Georgia, and Alabama.
Climate: The ecoregion has a humid continental climate, mild mid-latitude to the South, severe mid-latitude with cold winters to the north. Summers are hot and humid. The mean annual temperature varies from approximately 8°C in the north to 16°C in the South. The frost-free period ranges from 125 to 235 days. The mean annual precipitation is 1138 mm, and ranges from 900 mm to 1350 mm.
Vegetation: Generally, Appalachian oak forest in the north, and oak-hickory-pine forest to the South.
Hydrology: Much of the drainage is in a trellised pattern, with small streams draining the ridge slopes, joining at right angles with larger, lower-gradient stream courses that meander along the parallel valley floors. The ecoregion has a diversity of aquatic habitats and species of fish. Springs and caves are relatively numerous. Some large reservoirs in the South.
Terrain: A northeast-Southwest trending region, relatively low-lying, with ridges, rolling valleys, and low irregular hills. As a result of extreme folding and faulting events, the region’s roughly parallel ridges and valleys have a variety of widths, heights, and geologic materials, including limestone, dolomite, shale, siltstone, sandstone, chert, mudstone, and marble. Some ridges rise to 1500 m in elevtion. Ultisols and Inceptisols are typical, with mesic to thermic soil temperature regimes and udic soil moisture regimes.
Wildlife: White-tailed deer, black bear, bobcat, red fox, gray fox, raccoon, skunk, muskrat, mink, cottontail rabbit, eastern fox squirrel, bald eagle, wild turkey, bobwhite, red-eye vireo, cardinal, box turtle, timber rattlesnake, sculpins, minnows, darters.
Land Use/Human Activities: A mosaic of woodland, pasture, and cropland. Present-day forests cover about 50% of the region. Some areas of pine plantations. Hay, pasture, and grain for beef and dairy cattle are common crops, along with some areas of corn, soybeans, tobacco, and cotton in the South. Areas of rural residential, urban, and industrial. Larger cities include Scranton, Wilkes Barre, Reading, Harrisburg, and State College, Pennsylvania; Hagerstown and Cumberland, Maryland; Martinsburg, West Virginia; Winchester, Harrisonburg, Staunton, Roanoke, and Blacksburg, Virginia; Johnson City, Knoxville, Oak Ridge, and Chattanooga, Tennessee; Dalton and Rome, Georgia; and Gadsden, Anniston, and Birmingham, Alabama.

SOUTHERN COASTAL PLAIN
Location: Extends from South Carolina and Georgia through much of central Florida, and along the Gulf coast lowlands of the Florida Panhandle, Alabama, Mississippi, and eastern Louisiana.

Climate: The ecoregion has a mild mid-latitude humid subtropical climate, characterized by hot humid summers and warm to mild winters. The mean annual temperature is approximately 19° to 22°C. The frost-free period ranges from 280 to 360 days. The mean annual precipitation is 1338 mm, ranging from 1170 mm to 1650 mm.
Vegetation: Once covered mainly by longleaf pine flatwoods and savannas, this ecoregion also had a variety of other communities that supported slash pine, pond pine, pond cypress, beech, sweetgum, Southern magnolia, white oak, and laurel oak forest. Southern floodplain forests with bald cypress, pond cypress, water tupelo, bottomland oaks, sweetgum, green ash, water hickory.
Hydrology: Numerous low-gradient, perennial streams and large rivers, wetlands, and lakes.
Terrain: Mostly flat plains, it also includes barrier islands, coastal lagoons, marshes, and swampy lowlands along the Gulf and Atlantic coasts. In Florida, an area of more rolling discontinuous highlands contains numerous lakes. This ecoregion is lower in elevation with less relief and wetter soils than the Southeastern Plains (8.3.5) ecoregion to the north. Ultisols, Spodosols, and Entisols are common, with thermic and hyperthermic soil temperature regimes and aquic and some udic soil moisture regimes.
Wildlife: Black bear, white-tailed deer, bobcat, marsh rabbit, fox squirrel, manatee, egret, blue heron, red-cockaded woodpecker, indigo bunting, Florida scrub jay, box turtle, gopher tortoise, Southern dusky salamander, scrub lizard, cottonmouth, alligator.
Land Use/Human Activities: Pine plantations and forestry, pasture for beef cattle, citrus groves, tourism and recreation, fish and shellfish production. Some large areas of urban, suburban, and industrial uses.
Larger cities from north to South includeGeorgetown, Charleston, Savannah, Waycross, Brunswick, Jacksonville, Hammond, Slidell, Gulfport, Biloxi, Pascagoula, Mobile, Pensacola, Gainesville, Ocala, Orlando, Tampa, St. Petersburg, and Fort Myers.

Appendix D

Table 7 Correlation Matrices for all models (highlighted values <-0.5, and > 0.5)

STATE	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
GA	CORR	Year	1	0.1	-0.27	0.3	0.01	0.65	0.36	-0.06	0.06	-0.01	0.15	0.05	0	0.38	0.12
GA	CORR	POP	0.1	1	-0.03	0.7	-0.06	0.12	0.23	-0.35	-0.18	0.29	0.1	-0.35	0.22	0.49	0.49
GA	CORR	N3	-0.27	-0.03	1	-0.1	0	-0.22	-0.11	0.08	0.17	-0.02	-0.05	-0.02	-0.04	-0.1	-0.05
GA	CORR	A	0.29	0.71	-0.09	1	-0.1	0.31	0.33	-0.39	-0.18	0.29	0.08	-0.3	0.23	0.48	0.52
GA	CORR	B	0.01	-0.06	0	-0.1	1	-0.22	-0.2	0.68	0.39	-0.01	-0.16	0.18	-0.22	-0.3	0.1
GA	CORR	I	0.65	0.12	-0.22	0.3	-0.22	1	0.36	-0.25	-0.19	0.01	0.15	-0.08	0.09	0.32	0.15
GA	CORR	HISP	0.36	0.23	-0.11	0.3	-0.2	0.36	1	-0.06	-0.06	0.19	0.08	0.07	0.04	0.12	0.24
GA	CORR	POV_P	-0.06	-0.35	0.08	-0.4	0.68	-0.25	-0.06	1	0.51	-0.01	-0.15	0.38	-0.34	-0.6	-0.14
GA	CORR	UNEM_CTY	0.06	-0.18	0.17	-0.2	0.39	-0.19	-0.06	0.51	1	-0.02	-0.1	0.12	-0.21	-0.4	-0.02
GA	CORR	EMP_RT	-0.01	0.29	-0.02	0.3	-0.01	0.01	0.19	-0.01	-0.02	1	0.67	-0.11	0.63	0.19	0.42
GA	CORR	NFI_RT	0.15	0.1	-0.05	0.1	-0.16	0.15	0.08	-0.15	-0.1	0.67	1	-0.08	0.83	0.26	0
GA	CORR	FI_RT	0.05	-0.35	-0.02	-0.3	0.18	-0.08	0.07	0.38	0.12	-0.11	-0.08	1	-0.08	-0.2	0
GA	CORR	NET_ERN	0	0.22	-0.04	0.2	-0.22	0.09	0.04	-0.34	-0.21	0.63	0.83	-0.08	1	0.41	0.16
GA	CORR	PC	0.38	0.49	-0.14	0.5	-0.31	0.32	0.12	-0.6	-0.37	0.19	0.26	-0.15	0.41	1	0.28
GA	CORR	AVG_EPJ	0.12	0.49	-0.05	0.5	0.1	0.15	0.24	-0.14	-0.02	0.42	0	0	0.16	0.28	1

STATE	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
NC	CORR	Year	1	0.07	-0.25	0.3	-0.05	0.03	0.51	0.06	0.2	-0.02	0.4	-0.09	0.03	0.47	0.14
NC	CORR	POP	0.07	1	-0.03	0.6	-0.02	-0.03	0.29	-0.27	-0.19	0.37	0.15	-0.32	0.26	0.49	0.68
NC	CORR	N3	-0.25	-0.03	1	-0.1	0	-0.01	-0.16	0.02	0.14	-0.01	-0.13	0.02	-0.04	-0.1	-0.08
NC	CORR	A	0.28	0.59	-0.09	1	-0.05	-0.04	0.39	-0.21	-0.13	0.3	0.19	-0.29	0.24	0.51	0.58
NC	CORR	B	-0.05	-0.02	0	-0.1	1	-0.01	-0.03	0.62	0.17	-0.12	-0.34	0.3	-0.06	-0.2	0.24
NC	CORR	I	0.03	-0.03	-0.01	-0	-0.01	1	-0.01	0.31	0.27	-0.05	-0.1	-0.08	-0.12	-0.3	-0.07
NC	CORR	HISP	0.51	0.29	-0.16	0.4	-0.03	-0.01	1	-0.05	0	0.1	0.25	0.05	0.15	0.36	0.33
NC	CORR	POV_P	0.06	-0.27	0.02	-0.2	0.62	0.31	-0.05	1	0.51	-0.17	-0.26	0.37	-0.27	-0.5	-0.12
NC	CORR	UNEM_CTY	0.2	-0.19	0.14	-0.1	0.17	0.27	0	0.51	1	-0.08	-0.09	0.03	-0.23	-0.3	-0.14
NC	CORR	EMP_RT	-0.02	0.37	-0.01	0.3	-0.12	-0.05	0.1	-0.17	-0.08	1	0.56	-0.18	0.66	0.36	0.39
NC	CORR	NFI_RT	0.4	0.15	-0.13	0.2	-0.34	-0.1	0.25	-0.26	-0.09	0.56	1	-0.18	0.53	0.54	0.04
NC	CORR	FI_RT	-0.09	-0.32	0.02	-0.3	0.3	-0.08	0.05	0.37	0.03	-0.18	-0.18	1	-0.1	-0.2	-0.07
NC	CORR	NET_ERN	0.03	0.26	-0.04	0.2	-0.06	-0.12	0.15	-0.27	-0.23	0.66	0.53	-0.1	1	0.38	0.27
NC	CORR	PC	0.47	0.49	-0.13	0.5	-0.24	-0.25	0.36	-0.53	-0.31	0.36	0.54	-0.22	0.38	1	0.46
NC	CORR	AVG_EPJ	0.14	0.68	-0.08	0.6	0.24	-0.07	0.33	-0.12	-0.14	0.39	0.04	-0.07	0.27	0.46	1

STATE	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
SC	CORR	Year	1	0.08	-0.27	0.3	-0.02	0.34	0.53	-0.01	0.22	0.04	0.47	0.08	0.13	0.42	0.15
SC	CORR	POP	0.08	1	-0.02	0.8	-0.47	-0.01	0.22	-0.49	-0.41	0.7	0.51	-0.35	0.6	0.66	0.59
SC	CORR	N3	-0.27	-0.02	1	-0.1	0.01	-0.11	-0.15	0.07	0.09	-0.03	-0.16	-0.01	-0.09	-0.1	-0.08
SC	CORR	A	0.33	0.77	-0.1	1	-0.42	0.14	0.37	-0.45	-0.32	0.45	0.48	-0.34	0.54	0.61	0.49
SC	CORR	B	-0.02	-0.47	0.01	-0.4	1	0.04	-0.23	0.83	0.47	-0.3	-0.32	0.25	-0.54	-0.6	-0.32
SC	CORR	I	0.34	-0.01	-0.11	0.1	0.04	1	0.09	0.1	0.21	-0.12	0.08	0.15	-0.04	0.03	0.07
SC	CORR	HISP	0.53	0.22	-0.15	0.4	-0.23	0.09	1	-0.17	-0.14	0.17	0.34	0.18	0.33	0.5	0.2
SC	CORR	POV_P	-0.01	-0.49	0.07	-0.5	0.83	0.1	-0.17	1	0.61	-0.35	-0.35	0.29	-0.62	-0.6	-0.42
SC	CORR	UNEM_CTY	0.22	-0.41	0.09	-0.3	0.47	0.21	-0.14	0.61	1	-0.34	-0.23	0.2	-0.52	-0.4	-0.26
SC	CORR	EMP_RT	0.04	0.7	-0.03	0.5	-0.3	-0.12	0.17	-0.35	-0.34	1	0.66	-0.32	0.67	0.67	0.53
SC	CORR	NFI_RT	0.47	0.51	-0.16	0.5	-0.32	0.08	0.34	-0.35	-0.23	0.66	1	-0.16	0.62	0.77	0.32
SC	CORR	FI_RT	0.08	-0.35	-0.01	-0.3	0.25	0.15	0.18	0.29	0.2	-0.32	-0.16	1	-0.15	-0.2	-0.25
SC	CORR	NET_ERN	0.13	0.6	-0.09	0.5	-0.54	-0.04	0.33	-0.62	-0.52	0.67	0.62	-0.15	1	0.76	0.53
SC	CORR	PC	0.42	0.66	-0.14	0.6	-0.57	0.03	0.5	-0.63	-0.41	0.67	0.77	-0.2	0.76	1	0.6
SC	CORR	AVG_EPJ	0.15	0.59	-0.08	0.5	-0.32	0.07	0.2	-0.42	-0.26	0.53	0.32	-0.25	0.53	0.6	1

Table 7 Cont. Correlation Matrices for all models

Region		_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
Total	CORR	Year	1	0.08	-0.26	0.3	-0.02	0.07	0.42	-0.02	0.13	-0.01	0.24	0.01	0.02	0.4	0.13
Total	CORR	POP	0.08	1	-0.02	0.6	-0.1	0.02	0.2	-0.35	-0.18	0.38	0.18	-0.33	0.25	0.52	0.56
Total	CORR	N3	-0.26	-0.02	1	-0.1	0	-0.02	-0.13	0.06	0.14	-0.02	-0.08	-0.01	-0.04	-0.1	-0.06
Total	CORR	A	0.29	0.61	-0.09	1	-0.12	0.01	0.35	-0.34	-0.17	0.31	0.15	-0.28	0.25	0.5	0.53
Total	CORR	B	-0.02	-0.1	0	-0.1	1	-0.06	-0.18	0.68	0.35	-0.09	-0.24	0.16	-0.2	-0.4	0.11
Total	CORR	I	0.07	0.02	-0.02	0	-0.06	1	0.03	0.08	0.15	0.01	0	-0.05	-0.05	-0.1	-0.02
Total	CORR	HISP	0.42	0.2	-0.13	0.4	-0.18	0.03	1	-0.08	-0.07	0.16	0.15	0.08	0.09	0.24	0.25
Total	CORR	POV_P	-0.02	-0.35	0.06	-0.3	0.68	0.08	-0.08	1	0.49	-0.12	-0.23	0.35	-0.35	-0.6	-0.18
Total	CORR	UNEM_CTY	0.13	-0.18	0.14	-0.2	0.35	0.15	-0.07	0.49	1	-0.07	-0.1	0.04	-0.24	-0.3	-0.07
Total	CORR	EMP_RT	-0.01	0.38	-0.02	0.3	-0.09	0.01	0.16	-0.12	-0.07	1	0.65	-0.15	0.64	0.33	0.43
Total	CORR	NFI_RT	0.24	0.18	-0.08	0.2	-0.24	0	0.15	-0.23	-0.1	0.65	1	-0.11	0.74	0.4	0.05
Total	CORR	FI_RT	0.01	-0.33	-0.01	-0.3	0.16	-0.05	0.08	0.35	0.04	-0.15	-0.11	1	-0.09	-0.2	-0.06
Total	CORR	NET_ERN	0.02	0.25	-0.04	0.3	-0.2	-0.05	0.09	-0.35	-0.24	0.64	0.74	-0.09	1	0.43	0.22
Total	CORR	PC	0.4	0.52	-0.13	0.5	-0.35	-0.07	0.24	-0.6	-0.34	0.33	0.4	-0.17	0.43	1	0.38
Total	CORR	AVG_EPJ	0.13	0.56	-0.06	0.5	0.11	-0.02	0.25	-0.18	-0.07	0.43	0.05	-0.06	0.22	0.38	1
ECO	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
BLUE	CORR	Year	1	0.09	-0.27	0.4	-0.04	0.05	0.49	-0.02	-0.05	-0.03	0.05	-0.22	-0.06	0.52	0.11
BLUE	CORR	POP	0.09	1	-0.03	0.7	0.57	-0.13	0.3	-0.48	-0.28	0.02	0	-0.21	0.1	0.57	0.61
BLUE	CORR	N3	-0.27	-0.03	1	-0.1	-0.03	-0.02	-0.16	0.1	0.21	-0.02	-0.05	0.03	-0.02	-0.2	-0.09
BLUE	CORR	A	0.36	0.65	-0.12	1	0.56	-0.04	0.48	-0.34	-0.19	0.01	0.02	-0.27	0.08	0.52	0.52
BLUE	CORR	B	-0.04	0.57	-0.03	0.6	1	-0.06	0.17	-0.21	-0.16	0.23	0.14	-0.12	0.22	0.33	0.45
BLUE	CORR	I	0.05	-0.13	-0.02	-0	-0.06	1	-0.09	0.4	0.45	0.03	-0.06	-0.18	-0.06	-0.3	0.03
BLUE	CORR	HISP	0.49	0.3	-0.16	0.5	0.17	-0.09	1	-0.19	-0.1	-0.02	0.02	0.09	0.05	0.44	0.3
BLUE	CORR	POV_P	-0.02	-0.48	0.1	-0.3	-0.21	0.4	-0.19	1	0.61	0.09	0	0.06	-0.11	-0.6	-0.5
BLUE	CORR	UNEM_CTY	-0.05	-0.28	0.21	-0.2	-0.16	0.45	-0.1	0.61	1	-0.01	-0.05	-0.04	-0.08	-0.5	-0.29
BLUE	CORR	EMP_RT	-0.03	0.02	-0.02	0	0.23	0.03	-0.02	0.09	-0.01	1	0.93	0.11	0.93	0.06	0.13
BLUE	CORR	NFI_RT	0.05	0	-0.05	0	0.14	-0.06	0.02	0	-0.05	0.93	1	0.03	0.95	0.13	0.08
BLUE	CORR	FI_RT	-0.22	-0.21	0.03	-0.3	-0.12	-0.18	0.09	0.06	-0.04	0.11	0.03	1	0.05	-0	-0.02
BLUE	CORR	NET_ERN	-0.06	0.1	-0.02	0.1	0.22	-0.06	0.05	-0.11	-0.08	0.93	0.95	0.05	1	0.16	0.19
BLUE	CORR	PC	0.52	0.57	-0.2	0.5	0.33	-0.26	0.44	-0.63	-0.52	0.06	0.13	-0.02	0.16	1	0.61
BLUE	CORR	AVG_EPJ	0.11	0.61	-0.09	0.5	0.45	0.03	0.3	-0.5	-0.29	0.13	0.08	-0.02	0.19	0.61	1
ECO	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
MAC	CORR	Year	1	0.08	-0.22	0.3	-0.14	0.35	0.5	-0.17	0.11	0.16	0.45	0	0.18	0.64	0.2
MAC	CORR	POP	0.08	1	-0.03	0.7	-0.32	0.12	0.28	-0.3	-0.13	0.34	0.16	-0.43	0.23	0.33	0.59
MAC	CORR	N3	-0.22	-0.03	1	-0.1	-0.03	-0.11	-0.15	0.05	0.14	-0.02	-0.09	-0.01	-0.05	-0.1	-0.12
MAC	CORR	A	0.29	0.68	-0.08	1	-0.37	0.16	0.54	-0.4	-0.23	0.14	0.12	-0.31	0.3	0.41	0.53
MAC	CORR	B	-0.14	-0.32	-0.03	-0.4	1	-0.18	-0.23	0.83	0.36	-0.29	-0.56	0.22	-0.44	-0.7	-0.03
MAC	CORR	I	0.35	0.12	-0.11	0.2	-0.18	1	0.28	-0.09	-0.02	0.1	0.14	0.04	0.12	0.26	0.22
MAC	CORR	HISP	0.5	0.28	-0.15	0.5	-0.23	0.28	1	-0.13	-0.07	0.17	0.23	-0.07	0.2	0.36	0.39
MAC	CORR	POV_P	-0.17	-0.3	0.05	-0.4	0.83	-0.09	-0.13	1	0.52	-0.23	-0.46	0.29	-0.47	-0.7	-0.14
MAC	CORR	UNEM_CTY	0.11	-0.13	0.14	-0.2	0.36	-0.02	-0.07	0.52	1	0.04	-0.04	0.01	-0.3	-0.2	-0.16
MAC	CORR	EMP_RT	0.16	0.34	-0.02	0.1	-0.29	0.1	0.17	-0.23	0.04	1	0.64	-0.23	0.52	0.5	0.31
MAC	CORR	NFI_RT	0.45	0.16	-0.09	0.1	-0.56	0.14	0.23	-0.46	-0.04	0.64	1	-0.24	0.43	0.72	0
MAC	CORR	FI_RT	0	-0.43	-0.01	-0.3	0.22	0.04	-0.07	0.29	0.01	-0.23	-0.24	1	-0.15	-0.2	-0.03
MAC	CORR	NET_ERN	0.18	0.23	-0.05	0.3	-0.44	0.12	0.2	-0.47	-0.3	0.52	0.43	-0.15	1	0.52	0.24
MAC	CORR	PC	0.64	0.33	-0.11	0.4	-0.69	0.26	0.36	-0.66	-0.21	0.5	0.72	-0.17	0.52	1	0.3
MAC	CORR	AVG_EPJ	0.2	0.59	-0.12	0.5	-0.03	0.22	0.39	-0.14	-0.16	0.31	0	-0.03	0.24	0.3	1

Table 7 Cont. Correlation Matrices for all models

ECO	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
PED	CORR	Year	1	0.11	-0.27	0.3	-0.01	0.35	0.47	0.08	0.27	-0.05	0.41	-0.05	0.03	0.36	0.13
PED	CORR	POP	0.11	1	-0.03	0.6	-0.1	0.03	0.34	-0.28	-0.15	0.51	0.33	-0.32	0.27	0.47	0.67
PED	CORR	N3	-0.27	-0.03	1	-0.1	0	-0.12	-0.14	0.04	0.11	-0.02	-0.15	0	-0.06	-0.1	-0.06
PED	CORR	A	0.3	0.56	-0.09	1	-0.13	0.1	0.46	-0.27	-0.16	0.39	0.31	-0.21	0.31	0.53	0.54
PED	CORR	B	-0.01	-0.1	0	-0.1	1	0.07	-0.19	0.71	0.39	-0.07	-0.25	-0.17	-0.28	-0.4	-0.04
PED	CORR	I	0.35	0.03	-0.12	0.1	0.07	1	0.17	0.08	0.11	-0.03	0.19	0.04	0.1	0.08	0.05
PED	CORR	HISP	0.47	0.34	-0.14	0.5	-0.19	0.17	1	-0.16	-0.02	0.25	0.35	-0.03	0.17	0.4	0.37
PED	CORR	POV_P	0.08	-0.28	0.04	-0.3	0.71	0.08	-0.16	1	0.56	-0.07	-0.21	0.08	-0.43	-0.6	-0.2
PED	CORR	UNEM_CTY	0.27	-0.15	0.11	-0.2	0.39	0.11	-0.02	0.56	1	-0.15	-0.15	-0.08	-0.32	-0.4	-0.11
PED	CORR	EMP_RT	-0.05	0.51	-0.02	0.4	-0.07	-0.03	0.25	-0.07	-0.15	1	0.52	-0.1	0.52	0.35	0.55
PED	CORR	NFI_RT	0.41	0.33	-0.15	0.3	-0.25	0.19	0.35	-0.21	-0.15	0.52	1	-0.07	0.51	0.59	0.21
PED	CORR	FI_RT	-0.05	-0.32	0	-0.2	-0.17	0.04	-0.03	0.08	-0.08	-0.1	-0.07	1	-0.04	-0.1	-0.2
PED	CORR	NET_ERN	0.03	0.27	-0.06	0.3	-0.28	0.1	0.17	-0.43	-0.32	0.52	0.51	-0.04	1	0.54	0.24
PED	CORR	PC	0.36	0.47	-0.14	0.5	-0.4	0.08	0.4	-0.59	-0.37	0.35	0.59	-0.12	0.54	1	0.41
PED	CORR	AVG_EPJ	0.13	0.67	-0.06	0.5	-0.04	0.05	0.37	-0.2	-0.11	0.55	0.21	-0.2	0.24	0.41	1

ECO	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
RAV	CORR	Year	1	0.21	-0.27	0.6	0.04	0.76	0.45	0.22	0.02	0	0.63	-0.05	0.16	0.41	0.14
RAV	CORR	POP	0.21	1	-0.06	0.8	0.3	0.04	0.44	-0.11	-0.04	0.63	0.49	-0.19	0.65	0.82	0.75
RAV	CORR	N3	-0.27	-0.06	1	-0.2	-0.01	-0.26	-0.14	0.09	0.24	-0.03	-0.19	-0.01	-0.12	-0.2	-0.06
RAV	CORR	A	0.55	0.75	-0.15	1	0.12	0.4	0.59	-0.01	-0.04	0.56	0.72	-0.07	0.59	0.81	0.57
RAV	CORR	B	0.04	0.3	-0.01	0.1	1	-0.21	0	0.49	0.26	0.06	0.05	-0.26	-0.2	0.08	0.21
RAV	CORR	I	0.76	0.04	-0.26	0.4	-0.21	1	0.19	-0.02	-0.12	-0.12	0.52	-0.05	0.23	0.37	-0.07
RAV	CORR	HISP	0.45	0.44	-0.14	0.6	0	0.19	1	0.11	0.03	0.62	0.37	-0.02	0.31	0.49	0.63
RAV	CORR	POV_P	0.22	-0.11	0.09	-0	0.49	-0.02	0.11	1	0.59	-0.26	-0.22	-0.31	-0.63	-0.3	-0.18
RAV	CORR	UNEM_CTY	0.02	-0.04	0.24	-0	0.26	-0.12	0.03	0.59	1	-0.14	-0.18	-0.03	-0.39	-0.3	-0.07
RAV	CORR	EMP_RT	0	0.63	-0.03	0.6	0.06	-0.12	0.62	-0.26	-0.14	1	0.33	0.16	0.67	0.71	0.77
RAV	CORR	NFI_RT	0.63	0.49	-0.19	0.7	0.05	0.52	0.37	-0.22	-0.18	0.33	1	-0.01	0.61	0.7	0.34
RAV	CORR	FI_RT	-0.05	-0.19	-0.01	-0.1	-0.26	-0.05	-0.02	-0.31	-0.03	0.16	-0.01	1	0.17	0.02	0.13
RAV	CORR	NET_ERN	0.16	0.65	-0.12	0.6	-0.2	0.23	0.31	-0.63	-0.39	0.67	0.61	0.17	1	0.86	0.62
RAV	CORR	PC	0.41	0.82	-0.17	0.8	0.08	0.37	0.49	-0.3	-0.25	0.71	0.7	0.02	0.86	1	0.71
RAV	CORR	AVG_EPJ	0.14	0.75	-0.06	0.6	0.21	-0.07	0.63	-0.18	-0.07	0.77	0.34	0.13	0.62	0.71	1

ECO	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
SOP	CORR	Year	1	0.05	-0.27	0.3	0.01	0.05	0.43	-0.07	0.07	-0.04	0.31	0.08	0.01	0.42	0.14
SOP	CORR	POP	0.05	1	-0.01	0.7	-0.16	0.16	0.13	-0.45	-0.16	0.39	0.27	-0.33	0.32	0.55	0.44
SOP	CORR	N3	-0.27	-0.01	1	-0.1	0	-0.02	-0.13	0.1	0.15	-0.02	-0.11	-0.02	-0.05	-0.1	-0.05
SOP	CORR	A	0.31	0.68	-0.09	1	-0.2	0.08	0.34	-0.39	-0.11	0.5	0.2	-0.33	0.26	0.42	0.57
SOP	CORR	B	0.01	-0.16	0	-0.2	1	-0.1	-0.35	0.54	0.35	-0.14	-0.25	0.1	-0.25	-0.3	0.09
SOP	CORR	I	0.05	0.16	-0.02	0.1	-0.1	1	0.08	0.03	0.1	-0.04	-0.01	-0.1	-0.05	-0.1	0
SOP	CORR	HISP	0.43	0.13	-0.13	0.3	-0.35	0.08	1	-0.15	-0.1	0.21	0.32	0.11	0.1	0.23	0.15
SOP	CORR	POV_P	-0.07	-0.45	0.1	-0.4	0.54	0.03	-0.15	1	0.42	-0.25	-0.3	0.25	-0.4	-0.6	-0.34
SOP	CORR	UNEM_CTY	0.07	-0.16	0.15	-0.1	0.35	0.1	-0.1	0.42	1	-0.07	-0.17	-0.04	-0.23	-0.3	0.02
SOP	CORR	EMP_RT	-0.04	0.39	-0.02	0.5	-0.14	-0.04	0.21	-0.25	-0.07	1	0.46	-0.28	0.56	0.3	0.5
SOP	CORR	NFI_RT	0.31	0.27	-0.11	0.2	-0.25	-0.01	0.32	-0.3	-0.17	0.46	1	-0.11	0.7	0.51	0.05
SOP	CORR	FI_RT	0.08	-0.33	-0.02	-0.3	0.1	-0.1	0.11	0.25	-0.04	-0.28	-0.11	1	-0.05	-0	-0.05
SOP	CORR	NET_ERN	0.01	0.32	-0.05	0.3	-0.25	-0.05	0.1	-0.4	-0.23	0.56	0.7	-0.05	1	0.46	0.27
SOP	CORR	PC	0.42	0.55	-0.14	0.4	-0.27	-0.06	0.23	-0.59	-0.29	0.3	0.51	-0.02	0.46	1	0.4
SOP	CORR	AVG_EPJ	0.14	0.44	-0.05	0.6	0.09	0	0.15	-0.34	0.02	0.5	0.05	-0.05	0.27	0.4	1

Table 7 Cont. Correlation Matrices for all models

ECO	_TYPE_	_NAME_	Year	POP	N3	A	B	I	HISP	POV_P	UNEM_CTY	EMP_RT	NFI_RT	FI_RT	NET_ERN	PC	AVG_EPJ
SCP	CORR	Year	1	0.06	-0.27	0.3	-0.03	0.65	0.35	-0.12	0	0.1	0.42	-0.01	0.15	0.34	0.1
SCP	CORR	POP	0.06	1	-0.01	0.5	0.48	-0.07	-0.09	-0.27	-0.14	0.67	0.6	-0.3	0.53	0.67	0.49
SCP	CORR	N3	-0.27	-0.01	1	-0.1	0.01	-0.22	-0.11	0.12	0.19	-0.04	-0.13	-0.01	-0.08	-0.1	-0.02
SCP	CORR	A	0.32	0.54	-0.09	1	0.53	0.29	0.05	-0.44	-0.14	0.43	0.31	-0.41	0.5	0.49	0.68
SCP	CORR	B	-0.03	0.48	0.01	0.5	1	-0.1	-0.19	0.13	-0.02	0.5	0.14	-0.31	0.07	0.2	0.48
SCP	CORR	I	0.65	-0.07	-0.22	0.3	-0.1	1	0.51	-0.05	-0.21	-0.13	0.09	-0.01	0.05	0.03	-0.02
SCP	CORR	HISP	0.35	-0.09	-0.11	0.1	-0.19	0.51	1	0.18	-0.03	-0.04	0.02	0.51	-0.06	-0.1	-0.04
SCP	CORR	POV_P	-0.12	-0.27	0.12	-0.4	0.13	-0.05	0.18	1	0.36	-0.1	-0.34	0.43	-0.57	-0.5	-0.3
SCP	CORR	UNEM_CTY	0	-0.14	0.19	-0.1	-0.02	-0.21	-0.03	0.36	1	-0.05	-0.21	0.26	-0.33	-0.3	0.08
SCP	CORR	EMP_RT	0.1	0.67	-0.04	0.4	0.5	-0.13	-0.04	-0.1	-0.05	1	0.61	-0.18	0.53	0.62	0.65
SCP	CORR	NFI_RT	0.42	0.6	-0.13	0.3	0.14	0.09	0.02	-0.34	-0.21	0.61	1	-0.21	0.63	0.8	0.24
SCP	CORR	FI_RT	-0.01	-0.3	-0.01	-0.4	-0.31	-0.01	0.51	0.43	0.26	-0.18	-0.21	1	-0.27	-0.3	-0.12
SCP	CORR	NET_ERN	0.15	0.53	-0.08	0.5	0.07	0.05	-0.06	-0.57	-0.33	0.53	0.63	-0.27	1	0.74	0.44
SCP	CORR	PC	0.34	0.67	-0.11	0.5	0.2	0.03	-0.05	-0.54	-0.29	0.62	0.8	-0.3	0.74	1	0.47
SCP	CORR	AVG_EPJ	0.1	0.49	-0.02	0.7	0.48	-0.02	-0.04	-0.3	0.08	0.65	0.24	-0.12	0.44	0.47	1

Appendix E

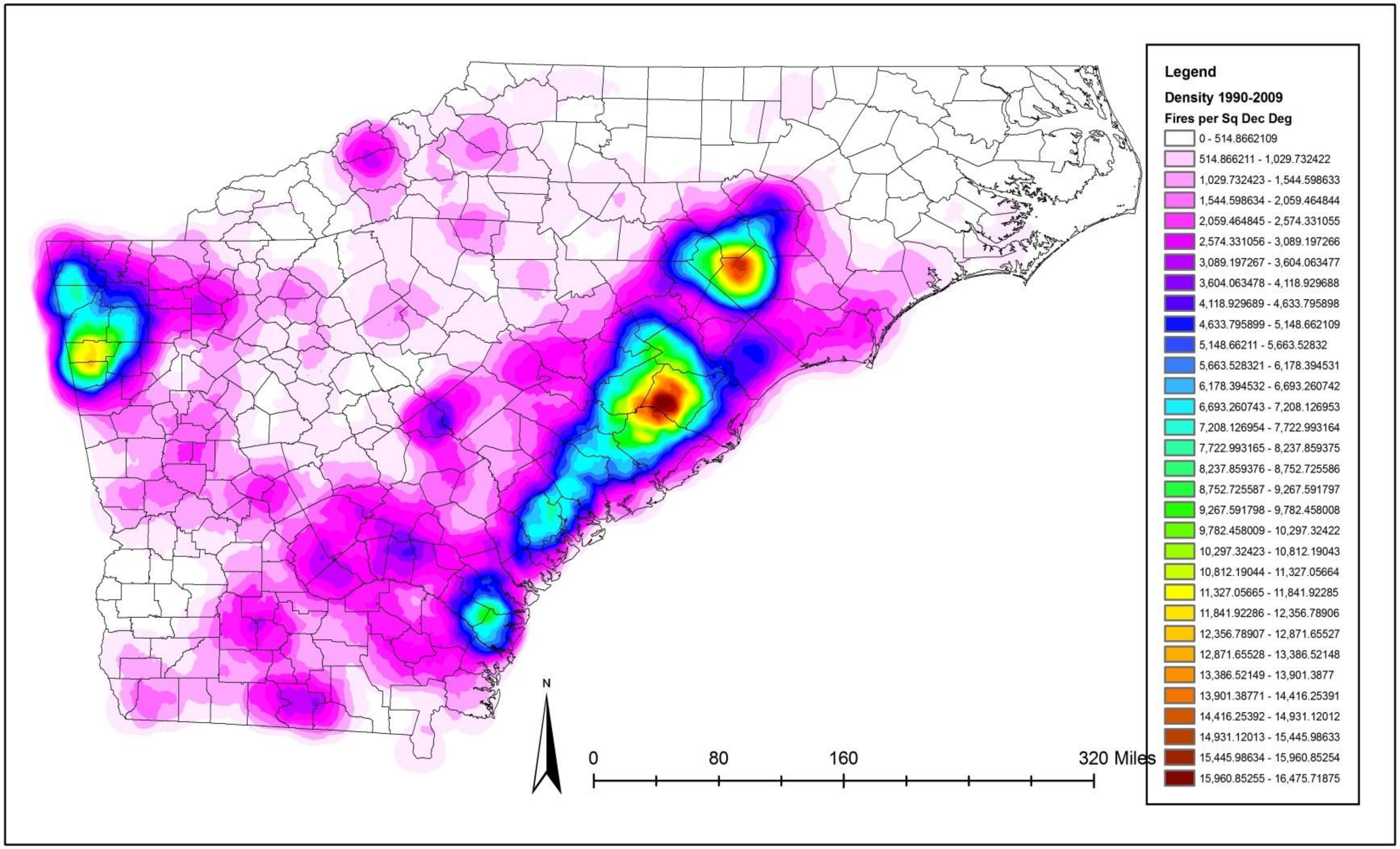

Figure 16 Total Fire Density between 1990-2009

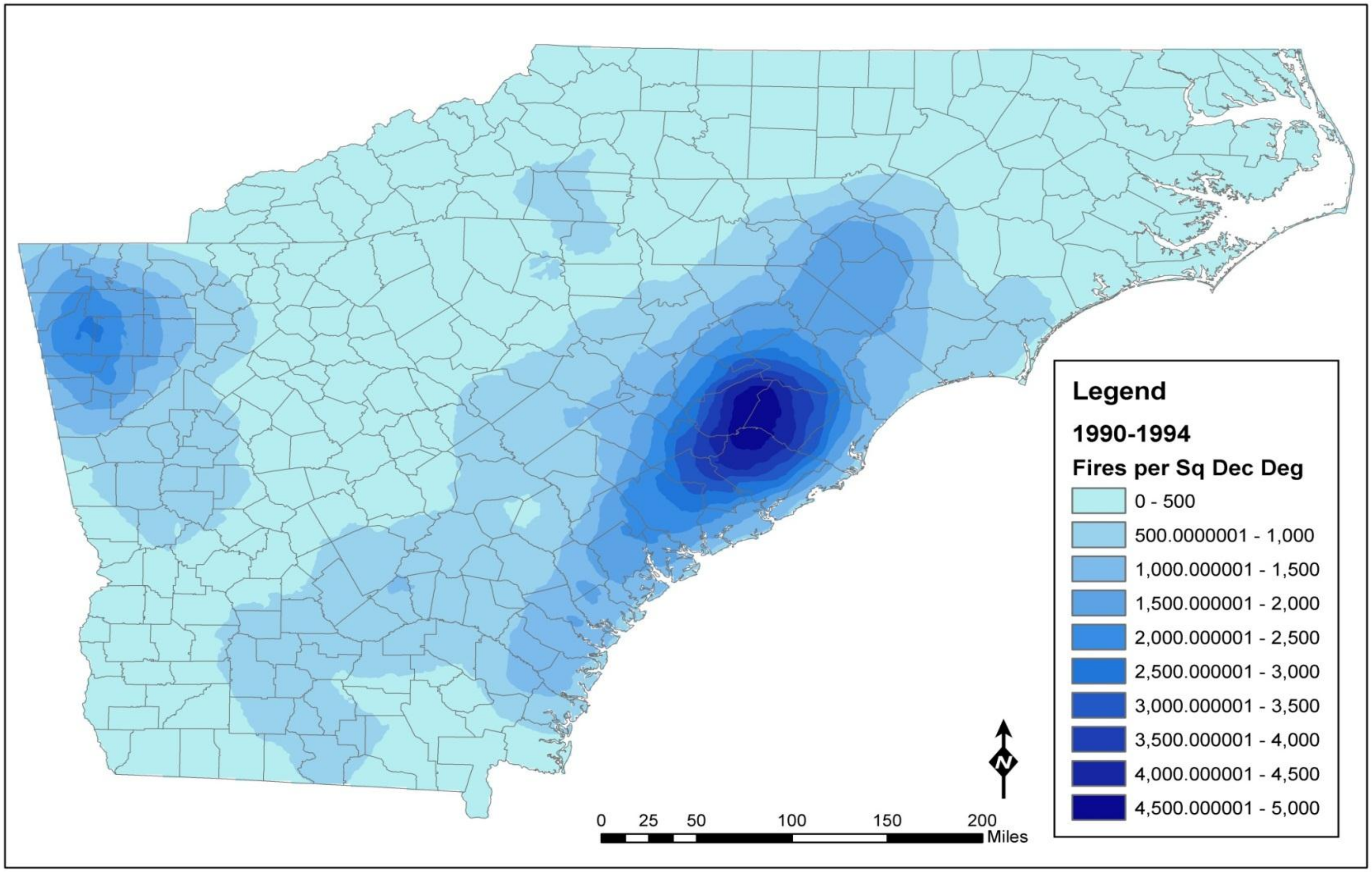

Figure 17 Incendiary Fire densities for years 1990-1994

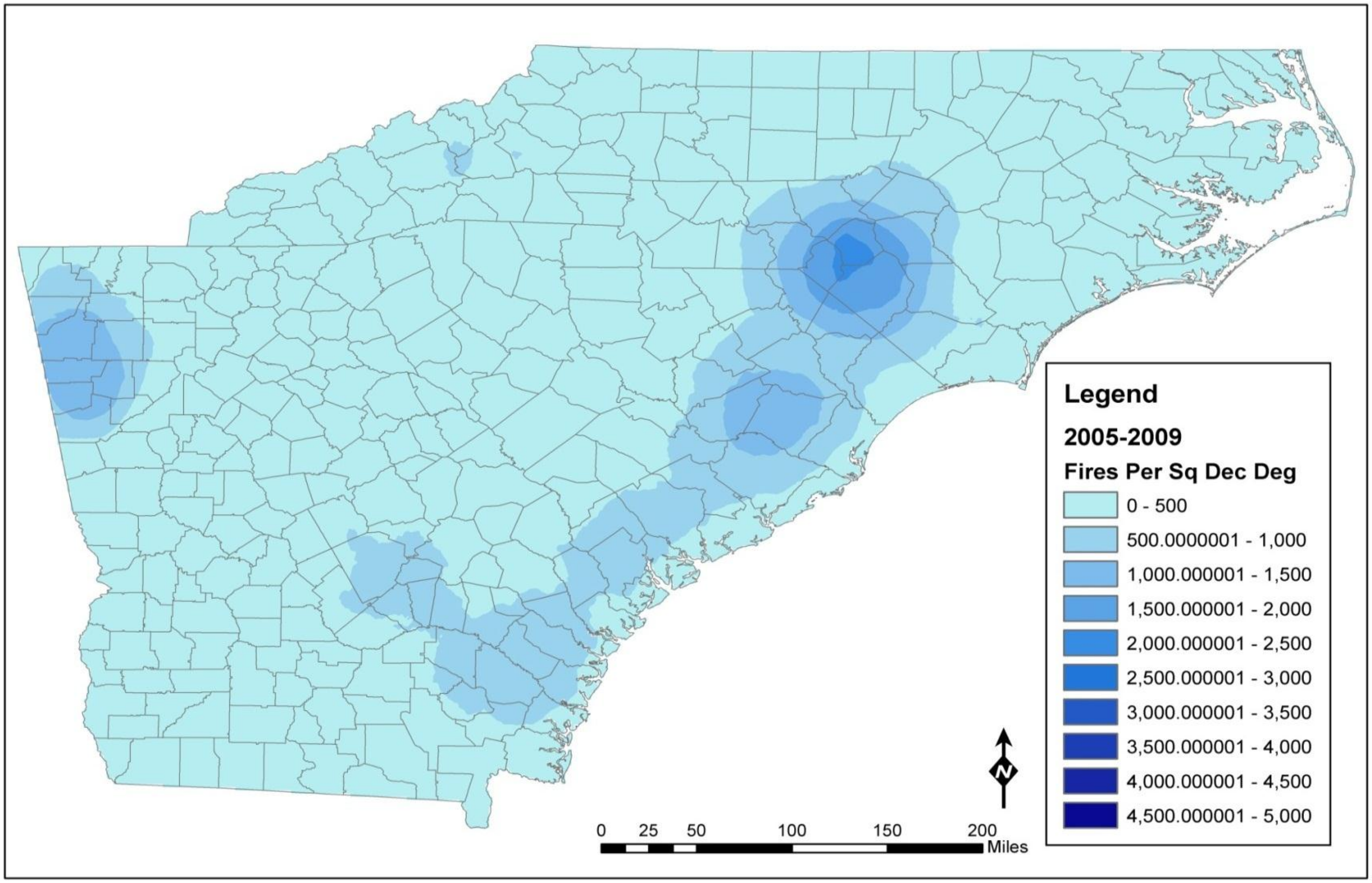

Figure 18 Incendiary Fire densities for years 2005-2009

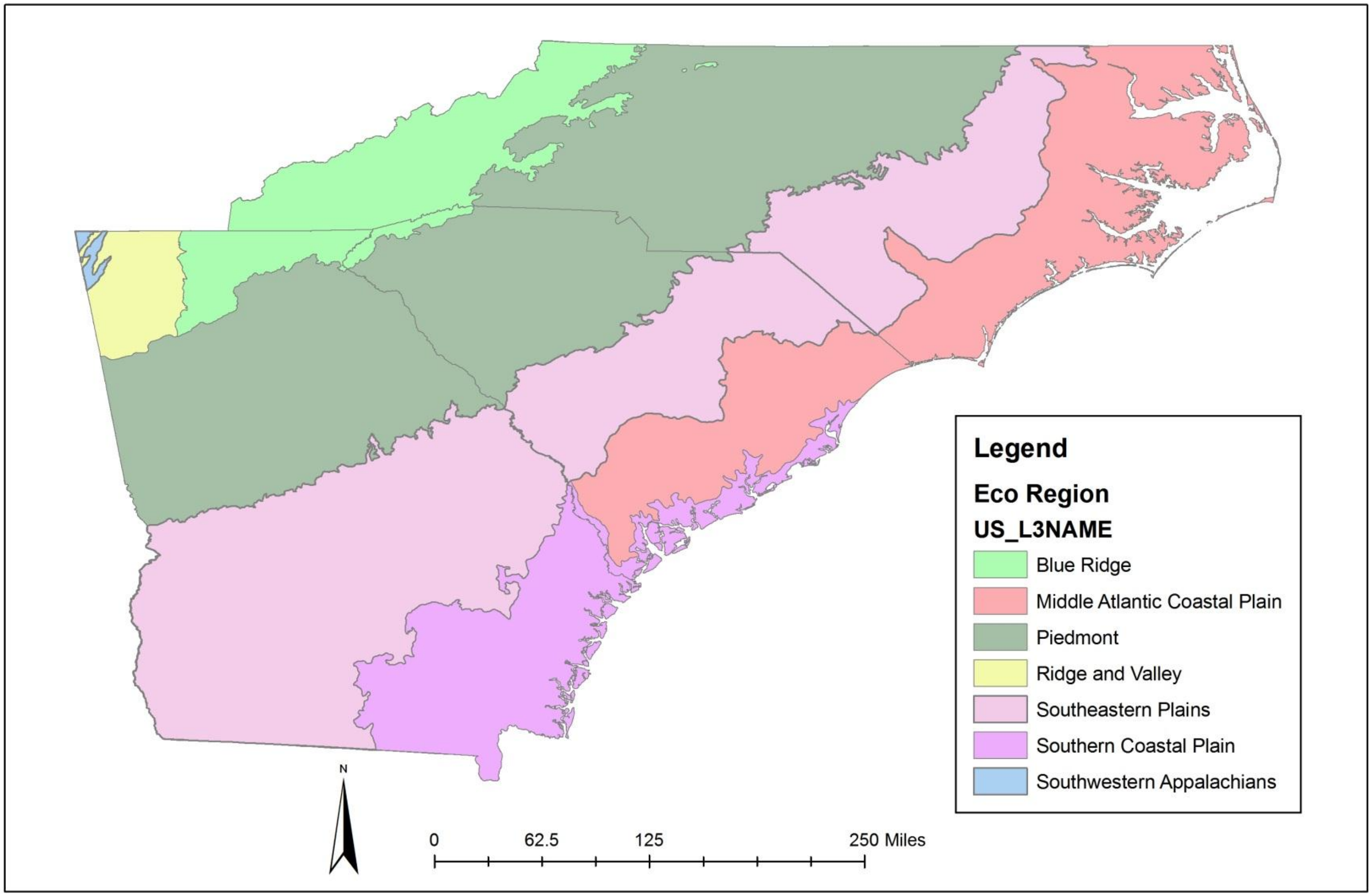

Figure 19 Ecoregion Boundaries in Study Area

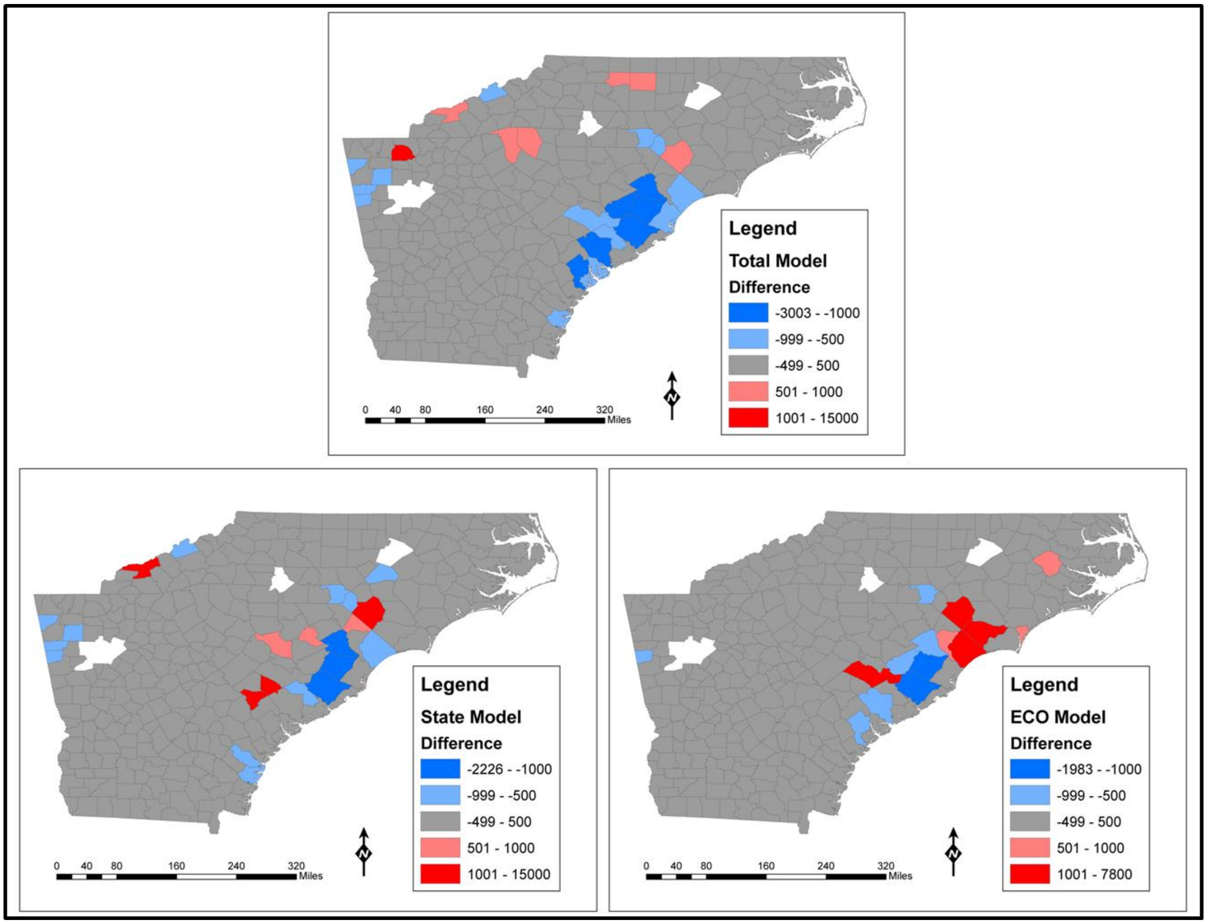

Figure 20 Difference between model predictions and actual fire counts from 1990-2009