Prescribed Fire in a Florida Landscape with Mixed Ownership: Spatial Interactions

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ABSTRACT

Across the U.S., wildfires have become increasingly destructive and costly over the past few decades, with impacts particularly severe in the State of Florida. Because of an increase in wildfire frequency, severity and the number of people living in fire-prone areas, the issue of wildfire risk management is of growing significance. One of the most important wildfire risk reduction tools is prescribed fire to reduce fuel loads, thereby reducing wildfire intensity and resulting damages. Because fire moves across a landscape and ownership boundaries, the spatial pattern of fuel load reduction may influence individual landowners' decisions about fire risk management on their own property. We develop and empirically test a spatial econometric model to study the interaction between Florida landowners in their wildfire risk management decisions.

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Introduction

Across the US, wildfires have become increasingly destructive and costly, with impacts particularly severe in the State of Florida. On average, Florida experiences approximately 5,000 wildfires a year, the second highest number of wildfires among all states in the US (Florida Division of Forestry, 2012). For example, from January 1, 2010 to November 4, 2010, Florida experienced 2,334 wildfires which burned 37,929 acres (NIFC, 2012). Large-scale wildfires are a major public concern because they can cripple local economies, destroy structures, and end lives (Prestemon et al., 2002).

Wildfires are especially destructive and frequent in Florida in part due to the regional climate and the presence of invasive species. Many wildfires in Florida are often sparked by lightning in April and May, when the region is in transition between the dry winter seasons to the wet summer. During the spring, naturally ignited wildfires can become large scale issues (Beckage et al., 2003). Foreign species such as the Melaleuca, a tree from Australia that was introduced to Florida in the 19th century and present in high concentrations in Southern Florida, burn much more intensely than native vegetation, making fire control more difficult (Diamond et al., 1991).

In addition to the factors that make Florida particularly susceptible to wildfire, from 1990 to 2000, Florida saw a dramatic expansion the number of people living in the wildland urban interface (WUI) – the area where humans and their development meet or intermix with wildland fuel (Federal Register, 2001). During this period, Florida experienced the greatest WUI expansion in the southeastern US; WUI land cover went from 14.9% to 19.2% and the housing density increased from 36,408/km^2in 1990 to 44,019/km^2in 2000 (Zhang et al., 2008). With more people living in fire-prone areas, the cost of protecting property and human lives from natural hazards, such as wildfire, increases.

One important wildfire risk reduction tool is prescribed fire to reduce fuel loads (Graham et al, 1999). Removing forest fuels from land within the WUI reduces wildfire intensity and severity in these populated, high-value areas. The State of Florida recommends the use of prescribed fire to landowners as a cost-effective method to reduce wildfire risk (Florida Division of Forestry, 2012). According the Florida Forest Service, areas that are treated with prescribed fire have fewer large-scale wildfires. During the 1985 fire season, on federal land in the south, only 17% of wildfires that burned more than 300 acres occurred in areas where prescribed burns were performed (Florida Forest Service, 2012).

Because fire moves across a landscape and ownership boundaries, the spatial pattern of fuel load reduction determines its effectiveness in reducing wildfire risk across the landscape. With more and more private landowners moving to the WUI, the level of fuel treatment on the landscape comes, increasingly, from the sum of the uncoordinated actions of all the landowners. Several studies suggest that private landowners perceive the benefits of fuel treatment as greatest when forest fuels are reduced on both their property and that of neighbors, which implies that fuel treatment on an individual parcel may induce fuel treatment on nearby parcels (Brenkert-Smith et al., 2006; Agee and Skinner, 2005). Agee and Skinner (2005) describe five cases where fuel treatments had been undertaken and later experienced wildfire finding that proper use of prescribed fire was highly effective in reducing wildfire losses. However, it is also plausible that fuel treatment on an individual parcel allows neighbors to free ride and may create a disincentive for neighbors to undertake fuel treatment.

Because nearby landowners cannot be excluded from the protection provided by fuel treatment on an individual parcel, fire risk management exhibits public good characteristics (Nicholson and Snyder, 2008; Yoder et al., 2004). In the context of the wildfire risk management problem, free riding occurs when there is an absence of contribution towards provisions of a public good by individuals who cannot be excluded from benefiting from the public good. If a landowner does not undertake fuel treatment because a neighbor has done so, the parcel owner is free riding on the neighboring landowner's protective action. Cooperation is another possible outcome of landowner interaction in the fuel management decision. Cooperative behavior occurs when one landowner's fuel treatment effort does not reduce the amount of fuel treatment undertaken by neighboring landowners. Cooperation implies an absence of free riding, but does not require explicit coordination among individual agents (Serrano, 2007). If a landowner undertakes fuel treatment when a nearby landowner also does so, , the landowner is exhibiting cooperative behavior.

To understand the risk of fire damage on a landscape, it is necessary to understand how landowners' risk-mitigating decisions interact. With this in mind, we develop and empirically test a spatial econometric model to study the interaction between Florida landowners in their wildfire risk management decisions. Our primary research objectives are to (1) determine if landowner interaction in the wildfire risk decision-making is characterized by cooperation or free riding, (2) determine if vegetation type is a significant determinant of prescribed fire decision and (3) gain insight into how ownership fragmentation influences wildfire risk reduction decision-making. We also explore the effects of recent wildfire activity, ownership type, and socioeconomic variables on landowners' fuel treatment decisions.

Insight into parcel and county-level attributes that are positively or negatively associated with fuel treatment will be of particular interest to policy makers. For example, if we find evidence that ownership fragmentation is negatively associated with fuel treatment, as suggested by Busby et al. (2012), policies that encourage risk mitigation might be targeted in these under-protected areas. With our results, policy makers will gain insight into where policy measures to encourage fuel treatment are most needed.

The remainder of the paper is structured as follows. In the Literature Review, we present a discussion of past research in the area of wildfire risk, focusing on papers featuring optimization models, spatially explicit econometric models and studies that use a similar data set. The Model section includes a description of the model and tests for spatial dependence. The dependent and independent variables are described in the Data section. The Results section includes results from spatial dependence tests and model estimation. In the Discussion section, we examine significant coefficient results, spatial interaction observed in the Florida setting, and policy applications. Finally, in the Conclusion section, important findings are highlighted and opportunities for future work are presented.

Literature Review

In this section, we briefly review the literature exploring fire risk management and spatial interactions among landowners. We begin with a description of non-economic fire literature examining landowner attitudes towards fuel treatments and their perceived impact on risk. These studies help frame our own study of landowner interaction in wildfire risk management decisions. Next we examine papers featuring optimization models of landowner's wildfire risk management decisions. Then we review papers that employ spatially explicit econometric models to examine wildfire mitigation externalities. Finally, we describe previous studies using a similar prescribed fire permit data featured in our study.

Qualitative studies

Several studies suggest that private landowners perceive the benefits of fuel treatment as greatest when forest fuels are reduced on both their property and that of neighbors, implying that fuel treatment on an individual parcel may induce more fuel treatment (Brenkert-Smith et al., 2006;). Brenkert-Smith et al. (2006) conduct interviews with homeowners living in Colorado WUI communities about the factors that contribute to their decisions to perform wildfire mitigation. They find that most community-wide discourse about wildfire focuses on the response to wildfire as opposed to prevention of wildfire, which leads to a disjointed wildfire mitigation effort among landowners. Informal discussions among landowners are important as Brenkert-Smith et al. (2006) find that these types of conversations lead to coordinated wildfire mitigation efforts. Our research will empirically test how the interactions of the Floridian landowners in our sample size are characterized.

Optimization models of fire risk management

Many studies utilize optimization models to analyze fire risk management to gain insight into hazardous fuel reduction treatments as a means to minimize wildfire risk (Pollet et al., 2002; Donovan and Rideout, 2003; Amacher et al., 2005; Mckee et al., 2004; Butry and Donovan, 2008; Mercer et al., 2007, Crowley et al., 2009). Pollet et al., 2002 compare the severity of wildfires that occur in areas that have been treated to reduce wildfire risk and those that had not been treated and find that areas that have received wildfire treatment unequivocally experience lower wildfire severity than untreated areas (Pollet et al., 2002). Amacher et al. (2005) use a landowner decision model to examine the amount and timing of fuel treatments, finding that when fuel management is performed, the optimal rotation age increases and optimal planting density decreases as fire risk increases. Butry and Donovan (2008) use a stochastic fire-spread model and examine the optimal levels of wildfire mitigation in a community with mixed ownership. They find that wildfire mitigation is most effective when concentrated in communities in the WUI and that wildfire risk mitigation can have a significant, positive spillover effect on the wildfire risk of neighboring houses.

Busby et al. (2012) use a spatially-explicit game theoretic framework to examine how the spatial configuration of forest ownership influences the risk-mitigating behavior of landowners. They find that spatial configuration of ownership parcels affects both the location and amount of fuel treatment on the landscape. They also observe less investment in fuel treatment on landscapes characterized by fragmented ownerships and find that the type of strategic interaction between landowners depends critically on the shape of the damage function. Busby et al.'s (2012) theoretical model predicts that greater ownership fragmentation will be associated with less fuel treatment, but does not provide empirical evidence of either free riding or cooperative behavior among landowners. Our research builds directly on this work and extends the analysis by empirically testing two of the main results described in Busby et al. (2012).

Spatially explicit econometric models

To address the spatial interaction inherent in the wildfire management problem, we develop an econometric model that incorporates spatial interactions across landowners. Other papers exploring similar topics have also used spatially explicit econometric models including Shafran (2008) and Prestemon et al. (2002). Shafran (2008) uses a spatially explicit econometric model to study the outcome of a parcel owner's defensible space decision given the defensible space decision of their neighbors. Like Shafran (2008), we use a spatial weights matrix to explicitly account for spatial externalities associated with fuel treatments across parcels in a setting with multiple landowners. Shafran (2008) finds that landowners behave strategically in their defensible space decisions, investing more in risk mitigation when nearby landowners make similar investments.

Prestemon et al. (2002) use a dynamic model of annual wildfire activity to evaluate effect of vegetation management, land use and climatic factors on wildfire in Florida. Four wildfire risk functions are constructed, the first considers all wildfires, regardless of ignition location, and the next three considered specific ignition sources: arson, lightening and human error. Prestemon et al. (2002) find that wildfire risk is negatively correlated with recent wildfire and fuel treatment.

Florida prescribed fire permit data

Mercer et al. (2007), Prestemon et al. (2002) and Mercer et al. (2005) use prescribed fire permit data from the Florida Division of Forestry. Mercer et al. (2007) estimate a wildfire risk model with a measure of wildfire output, intensity weighted risk and use a Monte Carlo simulation to estimate welfare changes from alternative prescribed policies, using Volusia County, Florida as a case study. They find that the amount of prescribed fire that minimizes the net economic losses from wildfire depends on the measure of damages from wildfire. Economic damages of fires depend on the scope and intensity of wildfire and ignoring these components will lead to less than optimal levels of prescribed fires for society. Mercer et al. (2005) estimate three classes of wildfire production functions for the state of Florida and find that socio-economic variables, including poverty and population, are significant factors positively correlated with the size and intensity of wildfires.

Model

In this section we describe our model that examines landowner behavior with regard to the prescribed fire decision. We begin by specifying a non-spatial econometric model and then test for spatial dependence. Methods for testing for spatial dependence include construction of a semi-variogram, a graphical representation of the variance among residuals between all pairs of sampled locations, and the calculation of five test statistics. Next, we specify a spatial econometric model to test for the presence of spatial dependence in the data. A spatial model allows us to test for interactions across space. In our case, we are examining if neighbors influence one another's fuel treatment decisions. If neighbors do influence one another, with the spatial model, we are able to classify the interaction among neighbors as cooperation or free riding. Non spatial models do not allow us to test or and identify this spatial interaction. Finally, we describe the maximum likelihood estimation technique used to estimate the spatial model.

Model of landowner behavior

Using prescribed fire and ownership data obtained from the Florida Division of Forestry, an econometric model that incorporates cross-sectional information of landowner prescribed fire decisions is estimated. The landowner behavior model is described by Equation 1, below. The dependent variable is continuous and describes the number of acres treated. Independent variables include county level median household income the year of the prescribed burn, absentee ownership, private ownership, county level number of acres burned by wildfire in the one year before prescribed burn was performed, ownership fragmentation within a 5 mile radius of parcel *i*, mean drought metric in the county of the prescribed burn on the day of prescribed burn, size in acres of parcel *i*, and vegetation type.

Figure 1: Equation 1: Model of landowner behavior

$$Acres_i = k + \beta_1 * income + \beta_2 * absentee_i + \beta_3 * private_i + \beta_4 * wildfire + \beta_5 * frag_i + \beta_6 * KBDI + \beta_7 * Pineland_i + \beta_8 * Urban_i + \beta_9 * Wet_i + \beta_{10} * Wooded_i + B_{11} * parcel\ size_i + \varepsilon_i$$

Where

$\boldsymbol{i}$
$= parcel\ index, 0, i; i\ if\ a\ prescribed\ burn\ was\ performed\ on\ the\ parcel\ and\ 0\ if\ otherwise$

$\boldsymbol{k} \quad = constant$
$\boldsymbol{Acres_i} = number\ of\ acres\ treated\ with\ prescribed\ fire\ on\ parcel\ i$
$\boldsymbol{income}$
$= county\ level\ median\ household\ income\ the\ year\ of\ the\ prescribed\ burn$
$\boldsymbol{absentee_i}$
$= 0{,}1; if parcel\ i\ is\ owned\ by\ an\ owner\ who\ is\ not\ living\ within\ the\ county\ and\ 0\ otherwise$
$\boldsymbol{private_i} = 0{,}1; 1\ if\ parcel\ i\ is\ owned\ by\ a\ private\ land\ owner\ and\ 0\ otherwise$
$\boldsymbol{wildfire}$
$= county\ level\ number\ of\ acres\ burned\ by\ wildfire\ one\ year\ before\ prescribed\ burn$
$\boldsymbol{frag_i} = ownership\ fragmentation\ within\ a\ 5\ mile\ radius\ of\ parcel\ i$
$\boldsymbol{KBDI} \quad = county\ level\ mean\ drought\ metric\ on\ day\ of\ prescribed\ burn$

$\boldsymbol{Urban_i}$
$= 0{,}1; 1\ if\ urban\ is\ predominant\ vegetation\ type\ on\ parcel\ i\ and\ 0\ otherwise$
$\boldsymbol{Wet_i}$
$= 0{,}1; 1\ if\ wet\ (freshwater\ marsh, shrub\ swamp, cypress\ swamp, mixed\ wetland, hardwood$
$swamp, mangrove\ swamp, open\ water)\ \ is\ the\ predominant\ vegetation\ type\ on\ parcel\ i\ and\ 0\ otherw$

$\boldsymbol{Wooded_i}$
$= 0{,}1; 1\ if\ wooded\ (mixed\ pine\ hardwood, hardwood\ hamock, bottomland\ hardwood, shrub\ brushlan$

$vegetation\ is\ predominant\ vegetation\ type\ on\ parcel\ i\ and\ 0\ otherwise$

$\boldsymbol{Pineland_i}$

$= 0{,}1; 1\ if\ pineland\ is\ predominant\ vegetation\ type\ on\ parcel\ i\ and\ 0\ otherwise$

$\boldsymbol{Parcel\ size_i} = size\ of\ parcel\ i, in\ acres$

Equation 1 is estimated individually for each of the four counties included in our analysis: Hamilton, Hendry, Jackson and Wakulla.

To begin, we estimate Equation 1 using OLS. However, coefficient estimates are not best linear unbiased if spatial dependence is detected. Further, if spatial dependence is present, the assumption that the error terms are uncorrelated is violated and the OLS model is inefficient. If a non-zero spatially lagged dependent variable is omitted, the assumption of independent observations and homoscedasticity is violated, resulting in a biased and inefficient estimator. Even though the OLS model is not BLUE in a spatially dependent data set, it is still a valuable component of spatial analysis. The residuals derived from the OLS regression without spatially explicit variables will allow us to test for spatial dependence by using the semi-variogram, Moran's I test and Lagrangian Multipler tests for spatial dependence in the error term and spatial dependence due to an omitted spatially lagged variable.

Testing for Spatial Dependence

To test for spatial dependence, we begin by constructing a semi-variogram which allows us to visualize the relationship between distance among observations and the difference between variance among residuals. Next, Moran's I test statistic is used to detect autocorrelation among residuals of observations over space, indicating the presence of spatial dependence. Then, LM Error and LM Lag tests are performed to classify the type of spatial dependence present. Finally, Robust LM Error and Robust LM Lag tests are performed to identify if controlling for one type of spatial dependence corrects the other type of spatial dependence if present in the data.

Semi-variogram

Semi-variograms are used to model the relationship between variance among pairs of observations at varying distances, to detect spatial autoregressivity among residuals. A semivariogram plots the difference between residuals from pairs of observations on the y-axis and the distance between each observation in the pair on the x-axis. Autoregressivity among residuals exists if the difference between variance among observations that are closer in physical distance is less than the variance among observations that are further apart. In general terms, if a landowner’s decision to perform a controlled burn is influenced by their neighbor’s decision to perform controlled burns, the first rule of geography – everything is related to everything else, but near things are more related than distant things (Tobler, 1970) –suggests that burns that are closer to one another are going to be more similar than the burns that are performed further away from one another. The variance among prescribed burns that are closer to one another will have a smaller difference in variance than the burns performed further away from one another.

Because distance is plotted on the x-axis of a semi-variogram, we can visualize the length of distance over which a spatially dependent relationship between the number of acres treated by parcel i and the number of acres treated by parcel j exists. We can limit the distance in which the spatial lag variable samples other prescribed burns, and limit the spatial analysis to just the area where this spatial dependence is present. This allows us to examine how neighbors influence one another across space and if the distance between individual parcels affects the magnitude of the influence.

The semi-variogram function is defined as:

Figure 2: Equation 2: Semi-variogram

$$y(s_i, s_j) = {}^{1}\!/_{2} \, \frac{\llbracket (Z(s_i) - Z(s_j)) \rrbracket^{2}}{2}$$

where $s_i$and $s_j$are prescribed burns, Z variance of each observation of prescribed burn $s_i$and s_j , and y is the distance between burns $s_i$and s_j. The distance between points is plotted on the horizontal axis and the difference between the residuals $s_i$and s_j is plotted on the vertical axis (ESRI, 2012).

Test statistics

Results from the estimation of Equation 1 are used to calculate five statistical tests designed to identify and characterize the presence of spatial dependence. The Moran's I test is used to test for the presence of spatial autocorrelation among the residuals from the estimation of the model using Equation 1. The test statistic reports the slope of the linear best fit line through the Moran scatterplot. The Moran scatterplot is centered on the mean of the scatter points and displays the value of the dependent variable, $Acres_i$, on the horizontal axis and the spatial lag, w, on the vertical axis. If positive spatial dependence is present, above average spatial lag values will result in above average dependent values and below average spatial lag values will result in below average dependent values. The opposite is true in the presence of negative spatial dependence. The magnitude of the coefficient is of less importance than the direction of the dependence (Anselin, 2000). Equation 3 (Paradis, 2012) describes the slope of the best fit line through the distribution of points on the Moran scatterplot, which can be interpreted as the spatial autocorrelation, or the correlation between the variable and the spatial lag (Anselin, 1988).

Figure 3: Equation 3: Moran's I test statistic/Slope through Moran's I scatterplot

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(Acres_i - \overline{Acres})(Acres_j - \overline{Acres})}{\sum_i (Acres_i - \overline{Acres})^2}$$

Where

$Acres_i = number\ of\ acres\ treated\ with\ prescription\ burn\ on\ parcel\ i$

$Acres_j$
$= number\ of\ acres\ treated\ with\ prescription\ burn\ on\ parcel\ j, neighbor\ to\ parcel\ i$

$\overline{Acres} = mean\ of\ all\ Acres_i$

$w_{ij} = spatial\ weight\ of\ all\ neighboring\ parcels\ j, on\ parcel\ i$

$n = number\ of\ observations$

$S_0 = sum\ of\ all\ w_{ij}$

If spatial dependence is detected with Moran's I test, four Lagrange Multiplier tests are used to identify the nature of the spatial dependence. Spatial lag dependence occurs when the dependent variable at location *i* is affected by an omitted spatially lagged independent variable and spatial error dependence occurs when the error term across different spatial units are correlated (Logan, 2005). Spatial lag dependence can be controlled by introducing a spatially lagged variable. The Robust LM Lag tests if spatial dependence associated with a missing lagged is present when error dependence is controlled. If the test statistic is insignificant, both types of spatial dependence are controlled when using a Spatial Lag model, which can be estimated using maximum likelihood technique (Logan, 2005).

The LM Error test detects if dependent variable y in place i is affected by the error term in place j. If this dependence is detected, a spatially lagged variable can be introduced in the error term to control for this omission (Logan, 2005). The Robust LM Error tests if error dependence is present when spatial lagged dependence is controlled. If the test statistic is insignificant, neither type of spatial dependence is present when using a Spatial Error model, which can be estimated using maximum likelihood technique (Logan, 2005).

A statistically significant LM Lag test statistic indicates $Acres_i$ is affected by a missing spatially lagged dependent variable and a statistically significant LM Error test statistic indicates $Acres_i$ is affected by the error term in $Acres_j$. A statistically significant Robust LM Lag indicates that spatial error and spatial lag dependence are not present when the Spatial Lag model is used and a statistically significant Robust LM Error indicates that error and spatial lag dependence is not present when the Spatial Error model is used. If all of the spatial tests discussed above are insignificant, spatial dependence is not present, the model is correctly specified by Equation 1, and OLS is the appropriate method of estimation (Anslin, 2005).

Spatial model of landowner behavior

As described in the previous section, spatial dependence can exist in two forms: spatial lag dependence and spatial error dependence. If spatial lag dependence is detected, a spatial lag model is used account for this dependence. If spatial error dependence is detected, a spatial error model is used to account for this dependence. In this section, we describe both the spatial lag and spatial error models. Both model specifications introduce a spatially lagged component to test for spatial interaction among pairs of observations over a range of distances. A spatial model allows us to determine if landowner interaction in the wildfire risk decision-making is characterized by cooperation or free riding.

Spatial Lag Model

If spatial lag dependence is detected, it can be corrected for by specifying a **spatial lag model**, or mixed regressive-spatial autoregressive model (Anselin, 1988). For the model of the fuel treatment decision, the spatial lag model is specified as:

Figure 4: Equation 4: Spatial Lag Model

$$Acres_i = k + \beta_1 * income + \beta_2 * absentee_i + \beta_3 * private_i + \beta_4 * wildfire + \beta_5 * frag_i + \beta_6 * KBDI + \beta_7 * Pineland_i + \beta_8 * Urban_i + \beta_9 * Wet_i + \beta_{10} * Wooded_i + \beta_{11} * parcel\ size_i + \rho \sum_{j \neq i} w_{ij} a_j + \varepsilon$$

Where

$Acres_i = number\ of\ acres\ treated\ on\ parcel\ i$

$\rho = effect\ of\ prescribed\ burn\ on\ neighboring\ parcels\ j\ within\ a\ the\ spatial\ lag\ cutoff$

$distance\ of\ \ parcel\ i$

$w_{ij=}spatial\ weight\ assigned\ to\ \ parcel$

$j = number\ of\ acres\ treated\ on\ parcel\ j$

$\varepsilon = error\ term$

Equation 4 is identical to Equation 1 except Equation 4 is estimated using maximum likelihood estimation technique, as opposed to OLS estimation technique used in Equation 1, and the coefficient, ρ. Spatial weight, $w_{ij,}$ represent the spatial relationships among observations. We generate an inverse distance spatial weight matrix, where the weights are larger for nearby neighbors and as the parcels get further away, the weight gets closer to zero. The weight assigned to neighbors ranges between 1 and 0 (ESRI, 2012). Later in the analysis, we will discuss the four distance bands placed on the spatial weights, w_{ij}. When larger distance bands are placed on spatial weights, w_{ij}, a larger community is included in the spatial analysis. For example, the largest distance band we use is 19,000 meters. The spatial weight, $w_{ij,}$ that is generated with the 19,000 meter radius will assign a weight from 1 to 0 to all observations that are within 19,000 meters of the observation on parcel i. When the distance bands become shorter, a smaller community is assigned spatial weights, w_{ij}. All observations outside of the distance band are assigned a weight of 0 (Jeanty, 2010). We can use distance bands of variable lengths to determine at what distance cross-ownership externalities are present.

The coefficient, ρ, estimates the degree of spatial dependence within data and reflects the average influence of a landowners' prescribed fire choice on nearby landowners prescribed burn choice. A negative coefficient on ρ indicates that the individual landowners tend to free ride on fuel treatment undertaken by nearby landowners. A positive coefficient on ρ indicates that landowners are more likely to perform a prescribed burn if nearby landowners do so.

Spatial Error Model

The spatial error model is defined as in Viton (2010):

Figure 5: Equation 5: Spatial Error Model

$$Acres_i = k + \beta_1 * income + \beta_2 * absentee_i + \beta_3 * private_i + \beta_4 * wildfire + \beta_5 * frag_i + \beta_6 * KBDI + \beta_7 * Pineland_i + \beta_8 * Urban_i + \beta_9 * Wet_i + \beta_{10} * Wooded_i + \beta_{11} * parcel\ size_i + \varepsilon$$

$$\varepsilon = \gamma w_{ij}\varepsilon + \mu$$

Where

$\gamma = magnitude\ of\ spatial\ dependence$

$w_{ij=} spatial\ weight\ assigned\ to\ parcel\ \ j$

$\mu = vector\ of\ error\ terms$

The Spatial Error Model may be the correct model specification if the Spatial Error dependence is detected, the LM Error statistic is statistically significant, and in cases where Spatial Lag dependence is also detected and the LM Robust Error statistic is statistically significant. Further in the spatial error model, the vector of error terms is defined as:

Figure 6: Equation 6: Vector of Error Terms

$$\mu = \gamma M\mu + n$$

Where

$\mu = vector\ of\ error\ terms$

$n = independent\ error\ terms$

$\gamma = magnitude\ of\ spatial\ dependence$
$M = weight\ matrix, which\ may\ or\ may\ not\ equal\ W$

Evidence within the literature presents a case to only use the spatial lag model, and to avoid estimating the spatial error model. First, Shafran (2008) describes that using the spatial error model to identify the spatial lag, ρ, and spatial error parameter, γ, in this more general model is not possible if $W = M$. Next, Anselin (2002) explains that the spatial error model is the equivalent of estimating a standard regression of spatially filtered variables, where all spatial interaction among observations are removed from the observations and the spatial interaction among observations is not represented in the regression analysis. The spatial autoregressive parameter cannot be generated from an auxiliary regression. The estimation must be performed jointly with that of other model parameters. Because of this, the spatial error model is not a solution to the estimating a spatially dependent data set, but, according to Anselin (2002), a "convenient interpretation." Furthermore, when spatial error dependence is present, the coefficient estimates are only inefficient, not biased. And when spatial lag dependence is present, coefficient estimates are inefficient and bias. Given these pieces of evidence, we only estimate the spatial lag model without spatial error dependence, assuming that $\gamma = 0$, therefore $\mu = n$.

Estimation technique

When spatial dependence is present, unbiased regression estimates are generated using alternative estimation techniques such as maximum likelihood, as in Shafran (2008). Because dependent variable, $Acres_i$, is determined by the dependent variables at all locations, the spatially lagged variable is endogenous, and necessitates a specialized estimation technique such as maximum likelihood estimation (Anselin, 2002).The method of maximum likelihood is broadly applicable and provides standard errors, statistical tests and other useful results. A likelihood function is similar to a probability function, but where the value of the parameter is fixed in a probability function the value of the data is fixed in the likelihood function. The basic properties of maximum likelihood estimators are as follows: (1) maximum likelihood estimators are consistent, (2) maximum likelihood estimators are asymptotically unbiased, (3) maximum likelihood estimators are asymptotically normally distributed and (4) maximum likelihood estimator of the parameter is a function of a sufficient statistic, a statistic that exhausts all of the information in the sample about the parameter of interest (Bakker, 2012).

Data

In this section, we describe the data applied to the econometric model. First, we describe the dependent variable, the number of acres treated on parcel *i*. Next we describe the independent variables' source and method of construction, where applicable.

Dependent Variable

The dependent variable in our study is the number of acres treated with prescribed fire on parcel *i*. The data was obtained from the Florida Division of Forestry's prescribed fire permit records for the period September 2010 to December 2012. Mercer et al (2005) and Mercer et al (2007) assume that all permit requests were completed as described in the permit database and we continue that assumption in our work. Only prescribed burns with a classified purpose of Hazard Removal[1] are included in the present study, as we are interested in permitted fires ignited for wildfire risk reduction. Shafran (2008) uses a similar dependent variable, homeowners' defensible space decision, which also indicates the level of wildfire mitigation effort performed by landowners.

Independent variables

Independent variables include: county-level median household income in year y, absentee parcel ownership, private parcel ownership, number of acres burned by wildfire in the county one year before prescribed burn, ownership fragmentation, the ratio of total parcel border length to total parcel area, within a 5 mile radius of parcel i, mean drought metric in county on day of prescribed burn, size of parcel *i* in acres, and vegetation type. In addition to the number of acres burned, prescribed fire permit data includes the type of burn performed, as well as site-specific information, including the address of the parcel where the prescribed burn was performed, the name of property owner requesting permit, and the landowner's legal mailing address.

[1] Other purposes for requesting a fire permit include site preparation, disease control, wildlife management, range management and biological community restoration and maintenance (Florida Forest Service, 2012)

The absentee variable was constructed using the legal address of the permit applicant. Landowners with a legal address in the same county where the prescribed fire was performed are defined as local. Landowners with a legal address outside of the county where the prescribed fire was performed are defined as absentee. The absentee variable is 1 if the owner of parcel i lives outside of the county and 0 otherwise. The name and address of the permit applicant were used to classify the ownership type of each parcel i as "public" or "private". Public owners included local, state or federal government agencies and private landowners included individual property owners, non-governmental businesses and private estates. The private variable is 1 if parcel i is owned by a private land owner and 0 otherwise.

Median household income was obtained from US Census data (2010) for the years 2008-2010. We expect that if a landowner lives in a county with relatively high average income per capita, community members may have better access to information about the risks associated with wildfires in their region and how to protect themselves with prescribed fire. Lower-income communities may lack the resources to access information about risk or may simply lack the resources to undertake fuel treatment activities and, therefore, be less likely to undertake risk mitigating activities. Mercer et al. (2005) included poverty as an independent variable and found it to be positively correlated with annual wildfire area in Florida for the period 1995 to 2001.

Spatial data describing vegetation type for the state was provided by the Florida Fish and Wildlife Conservation Commission. There are nine possible vegetation types, listed in Table 1. By including vegetation type, we will determine if and how vegetation present on an individual parcel affects the landowners' decision to undertake fuel treatment. We expect that landowners with certain vegetation types are more likely to conduct a prescribed fire. For example, we expect that landowners with parcels characterized as "pinelands" are at higher risk of wildfire damage and are more likely to undertake fuel treatment than landowners with parcels characterized as "urban." For all vegetation variable, the variable equals 1 if the predominant vegetation type on parcel i is that vegetation type and 0 otherwise.

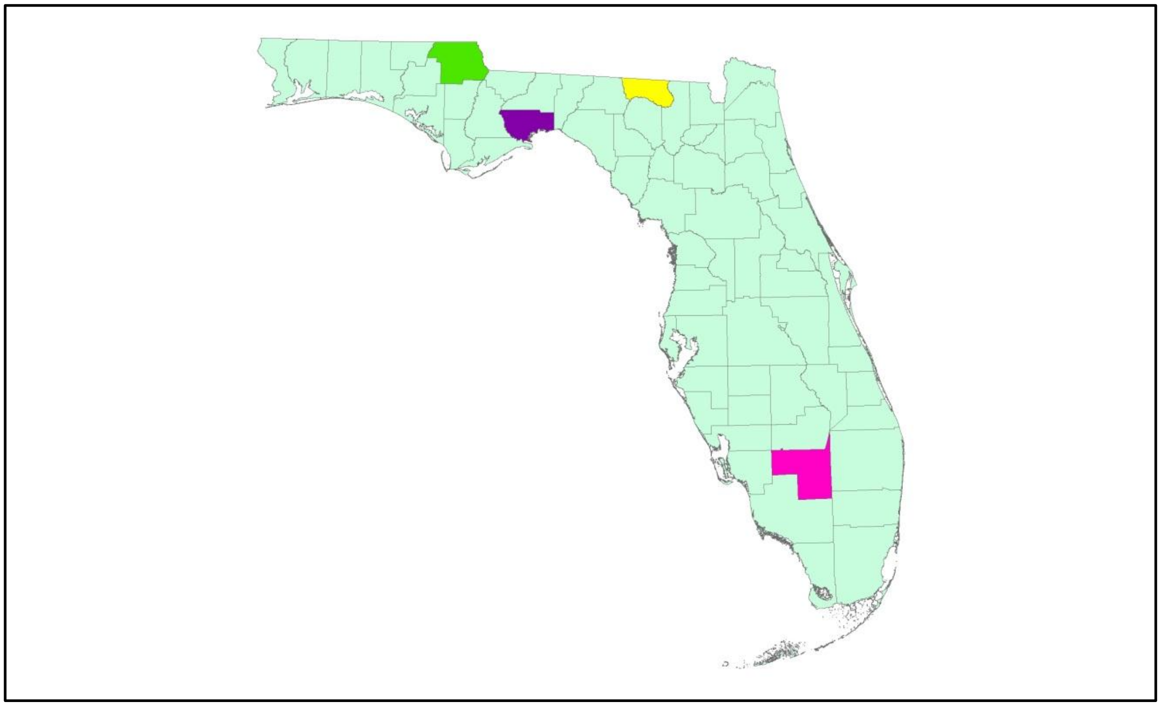
County-level wildfire data for the period 2007 to 2009 was obtained from the Florida Division of Forestry. We include the average number of acres burned by county the year before a prescribed fire was performed as an independent variable. If the number of acres burned by wildfire is low, this may mean that the county is less vulnerable to wildfire and the benefit from prescribed fire is low. Or if the number of acres burned by wildfire is high, it is possible such large wildfire have occurred in recent history that the land does not have vegetation to reduce, as it was destroyed by recent wildfires. It is also possible, as shown by Shafran (2008), that if an area has an abnormally high risk of wildfire, parcel owners may be discouraged, and presume that any amount of wildfire mitigation they perform would not reduce their risk of wildfire damage. Therefore it is not obvious whether the number of acres burned by wildfire will positively or negatively associated with an individual landowner's fuel treatment decision.

Parcel-level GIS data describing ownership parcels Florida Department of Revenue and was used to calculate the fragmentation metric. To generate the fragmentation metric, the total length of all parcel boundaries was divided by the total area of all parcels within a five mile radius of each parcel. The higher the fragmentation metric, the more individual owners are within the immediate vicinity. Higher levels of fragmentation may make it more difficult for landowners to coordinate fuel treatment. Busby et al. (2012) observe less fuel treatment in areas with highly fragmented ownership. Size of parcel *i* in acres was also provided from this data set

KBDI (Keetch-Bryam drought index) data was provided by Florida Forest Service for the period 2008-2010 with daily observations for each county in the State reported. The KBDI is a scale for quantifying the dryness of soil. The higher the index, the more favorable the conditions are to encourage the spread of wildfire (Florida Forest Service, 2012). The average KBDI index for the day each burn was performed is included as a dependent variable to control for the soil conditions at the time of the prescribed fire. Shafran (2008) finds that if the risk of wildfire in an area reaches a certain threshold, the parcel owner no longer believes that the wildfire mitigation that they could perform would protect their community from the risk of wildfire.

We estimate Equation 1 for four individual non-contiguous counties: Hamilton, Hendry, Jackson and Wakulla Counties (Map 1). These four counties were chosen because they exhibit varying levels of wildfire risk, wildfire histories, size of parcel where prescribed burns were performed and average number of acres treated with prescribed burn (Table 1). They are in different areas of the state so we can observe if spatial dependence varies by region. Although it is possible that cross-county spatial interactions are present, that is beyond the scope of the present study and we focus only on within county spatial interactions, estimating Equation 1 for each county individually. By selecting counties from different regions within the state we are, however, able to determine if spatial dependence exists in some regions and not others.

Figure 7: Map 1: Florida Counties in study



(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Where:

Yellow = Hamilton County

Pink = Hendry County

Green = Jackson County

Purple = Wakulla County

Table 1: Summary statistics describing independent and dependent variables

	Hamilton	***Hendry***	***Jackson***	***Wakulla***

# of observations	118	91	441	285
Acres treated				
mean	91.398	270.604	43.603	379.509
min	1	1	1	1
max	1000	5000	300	4000
std. dev.	115.405	594.235	48.028	706.218
Parcel size (acres)				
mean	240.43	429.76	136.59	349.97
min	2	0.3	0.22	0.4
max	685	739.15	630.69	1492
std. dev.	209.75	234.35	144.88	336.98
Fragmentation metric (perimeter/area)				
mean	0.005	0.005	0.006	0.006
min	0.002	0.001	0.003	0.001
max	0.012	0.032	0.022	0.019
std. dev.	0.002	0.007	0.002	0.004
Median household income (2010 US dollars)				
mean	$31,371.97	$36,908.99	$36,684.82	$50,272.49
min	$31,038.00	$35,858.00	$35,968.00	$49,215.00
max	$32,444.00	$38,771.00	$37,707.00	$54,420.00
std. dev.	$414.65	$1,058.89	$701.12	$1,219.01
KBDI				
mean	300.246	434.626	212.388	267.695
min	17	21	15	11
max	550	708	595	582
std. dev.	214.772	232.178	150.049	155.266
Privately owned parcels	97	54	421	163
Publically owned parcels	21	37	20	122
Absentee owners	59	51	135	23
Local owners	59	40	306	262
Average area burned by wildfire (acres)				
2007	2.445	89.808	3.052	1.632
2008	7.365	32.174	3.588	7.608
2009	7.253	39.936	1.978	6.658

Vegetation types				
Sand hill	4	0	8	2
Pinelands	62	4	248	123
Bare soil/Clear cut	3	0	2	38
Pasture	11	5	0	4
Row/Field crops	1	2	132	0
Extractive	1	6	0	11
Urban	2	3	2	1
Wet vegetation	2	60	21	32
Wooded vegetation	32	11	28	74

Results

Results from the spatial diagnostic tests and regressions are reported in this section. First, semi-variograms are presented to visualize the relationship of distance between observations and magnitude of difference among residuals. Next, results from Equation 1 estimated using OLS are reported for all four counties individually. Then, using the residuals from the estimation of Equation 1, we present results from the five spatial dependence tests: Moran's I, LM Lag, LM Robust Lag, LM Error and LM Robust Error. Finally, we present results from the estimation of Equation 4, the spatial lag model for each county where spatial dependence is found to be present.

Semi-variograms

To identify if the residuals are spatial autoregressive, semi-variograms are presented for each county. The lag distance, in units of 100 meters, among pairwise observations of the dependent variable is on the x-axis and difference among residuals of pairwise observations is on the y-axis.

Figure 8: Semi-variogram A: Hamilton County

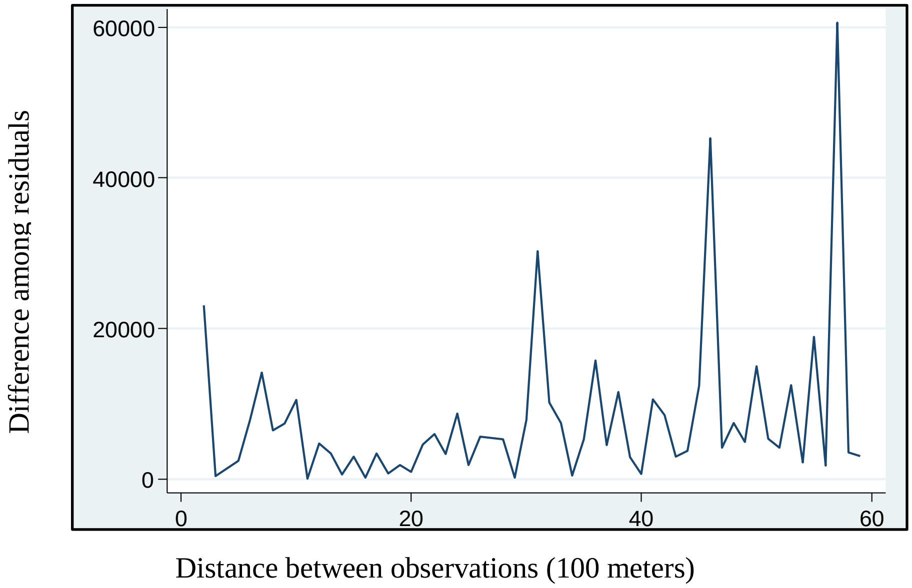


Figure 9: Semi-variogram B: Hendry County

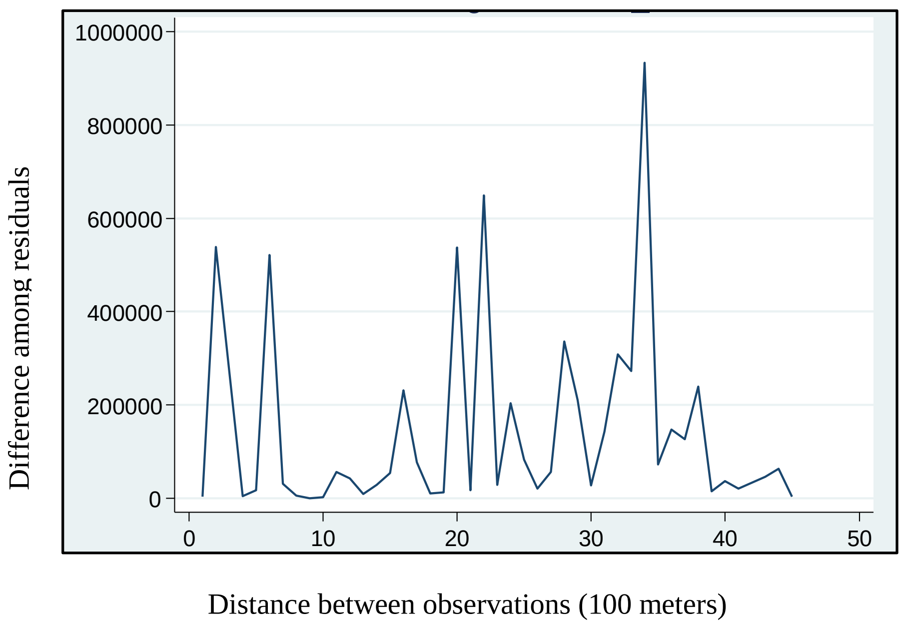


Figure 10: Semi-variogram C: Jackson County

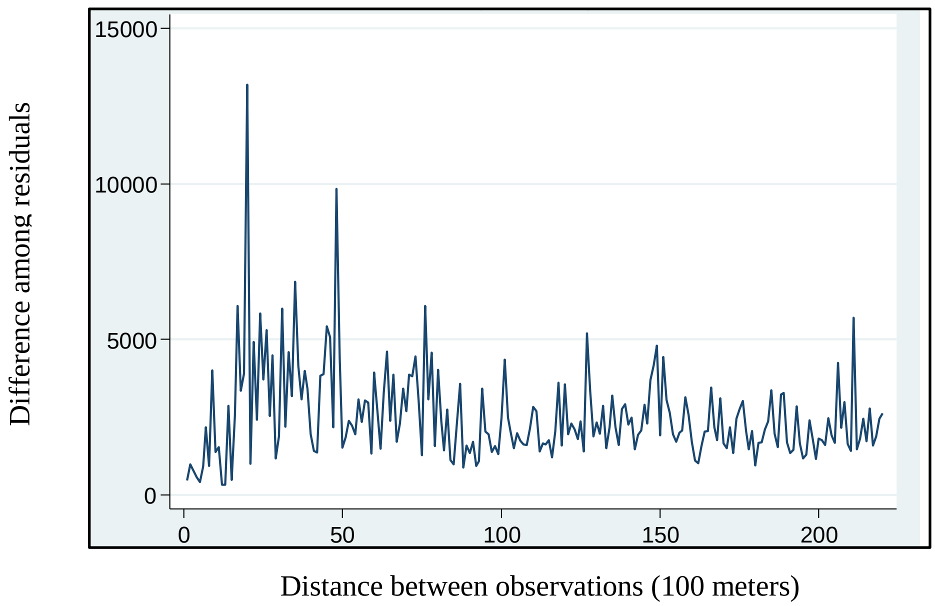
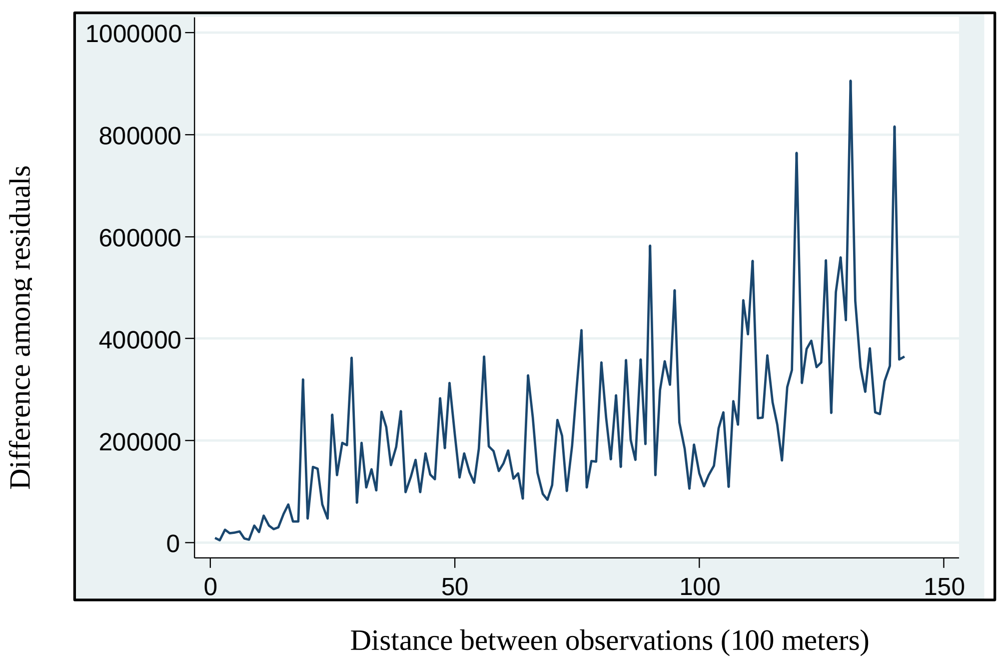


Figure 11: Semi-variogram D: Wakulla County



Figures 1 and 2 indicate that spatial dependence is not present in Hamilton or Hendry County. That is, there is no observable pattern between variance and distance between observations. However, Figures 3 and 4 indicate that spatial dependence is present in Jackson and Wakulla Counties as both exhibit a positive relationship between distance between prescribed burns and difference in variance. In Jackson County, the semi-variogram has a positive trend to approximately 2,500 meters, and then tapers off and rest of the trend is flat and unchanging. In Wakulla County, the semi-variogram has a positive trend over the whole semi-variogram, for 150,000 meters. The findings of the semi-variograms are confirmed by the results of the five spatial dependence tests reported next.

Model of Landowner Behavior and Spatial Test Results

To test for spatial dependence in the model we estimate Equation 1 and calculate the five test statistics described in the Model section. Table 2 includes the regression results from the estimation of Equation 1 for Hamilton, Hendry, Jackson and Wakulla Counties. The standard error is reported below each coefficient in parenthesis. Below all of the coefficient results is the R^2 value, the number of observations in each data set and the results of all five spatial dependence tests: Moran's I test, LM Error, LM Robust Error, LM Lag and LM Robust Lag tests.

Table 2: Equation 1 regression results, OLS estimation

	Hamilton	***Hendry***	***Jackson***	***Wakulla***
Income	.142** (.056)	.128 (0.483)	-0.023* (0.012)	.046 (.086)
Absentee	38.134 (0.159)	-9.697 (436.018)	1.293 (5.099)	177.565 (148.398)
Private	-59.428* (34.200)	-129.205 (411.318)	28.509** (13.038)	-89.716 (92.658)
KBDI	.251**	-.358	-.021	.049

	(0.011)	(.429)	(.018)	(.305)
Fragmentation metric	3650.124 (6522.324)	-4941.641 (13743.430)	-2908.245 *** (1104.391)	-76424.340 *** (9493.718)
Parcel Size	.174** (.080)	.476 (.342)	.048 *** (.018)	-.069 (.128)
Wildfire Area	51.218** (20.413)	-2.220 (8.804)	-18.236 * (11.002)	64.278 (91.429)
Pine	-58.846* (32.507)	-130.987 (410.910)	7.344 (5.042)	72.539 (106.816)
Urban	-71.598 (84.437)	60.305 (400.782)	41.632 (33.643)	-121.587 (645.994)
Wet	-94.212 (87.495)	107.125 (245.494)	19.334 (12.573)	161.429 (149.993)
Wooded	-28.848 (36.394)	-150.551 (370.896)	19.113 * (10.111)	69.344 (117.659)
constant	-4795.527** (1896.351)	-4352.890 (6468.098)	910.266** (471.871)	-2675.949 (4947.353)
r^2	0.17	0.18	0.07	0.22
# of obs	118	91	441	285
Moran's I	0.710 (0.475)	0.790 (0.432)	2.350** (0.019)	7.760*** (0.000)
LM Error	0.000	0.010	3.910*	49.95***

	(0.985)	(0.940)	(0.048)	(0.000)
Robust LM Error	0.140 (0.704)	0.000 (0.9492)	0.410 (0.522)	5.420* (0.020)
LM Lag	0.020 (0.892)	0.000 (0.954)	4.800** (0.029)	46.030*** (0.000)
Robust LM Lag	0.16 (0.687)	0.000 (0.966)	1.300 (0.255)	1.490 (0.223)

coefficient

(P-values in parenthesis)

****significant at 1% level*

*** significant at 5% level*

** significant at 10% level*

The significant results of the Moran's I test statistic for Jackson and Wakulla counties indicate that spatial dependence is present in these two counties. The significant LM test statistics indicate that both spatial error and spatial lag dependency exist. The significance of the robust LM error test tells us that when a spatially lagged variable is introduced into the regression, the spatial error dependence is present in Wakulla County. Although the significant robust LM error test statistic for Wakulla County indicates that the lag dependence and error dependence occur simultaneously, as stated before, we will focus our analysis using only the spatial lag model to control the spatial lag dependence as the spatial error model does not correct the estimation problem that occurs when spatial dependence is present (Anselin, 2002).

Income and acres burned by wildfire are positive and significant in Hamilton County and negative and significant in Jackson County. Private ownership is negative and significant in Hamilton County and positive and significant in Jackson County. KBDI is positive and significant in Hamilton County. Fragmentation metric is negative and significant in both Jackson and Wakulla Counties. Size of parcel is positive and significant in Hamilton and Jackson

Counties. Pinelands vegetation is negative and significant in Hamilton County. Wooded vegetation is positive and significant in Jackson County.

Spatial Lag Model

To control for the spatial dependence in Jackson and Wakulla counties, we estimate the spatial lag model (Equation 4). The spatial lag model features a spatially explicit dependent variable is estimated for Jackson and Wakulla Counties individually. The spatial lag model is estimated using the maximum likelihood estimation technique.

The spatial lag distance used to specify the spatial weight variable in the spatial lag model, w_{ij}, is defined in our analysis using four different distances in our analysis to enable us to test for spatial dependence within different sizes of communities. So that $w_{ij} \in (0,1]$ for all parcels where fuel treatment occurred within a specified distance of parcel i. The spatial weight is set equal to zero ($w_{ij} = 0$) for all other parcels *i* beyond the specified distance.

Guided by the outcome of the semi-variograms reported above, it is clear that the spatial relationship between landowners' fuel treatment decisions is stronger among nearby neighbors than distant neighbors. As in Shafran (2008), we specify multiple distance bands as a robustness check. Distance bands are specified as follows: W1, 19,000 meters; W2, 5,750 meters; W3, 4,250 meters; and W4, 3,150 meters. As the distance band shortens, fewer permits are assigned a positive weight ($w_{ij} > 0$).

There are slight differences in the data for the estimation of Equation 4 for each lag distance. This is because each parcel *i* must have at least one other treated parcel located within the distance band otherwise the observation must be dropped from the data set Because of this, there are fewer total observations in each county as the distance band shortens. The total number of observations for each lag distance is included in Tables 3 and 4.

Table 3: Equation 4 - Spatial Lag Model regression results, Maximum Likelihood Estimation), Jackson County

	W1	***W2***	***W3***	***W4***
Income	-.023** (.012)	-.024** (.012)	-.023* (.013)	-.023* (.013)
Absentee	.942 (4.955)	.979 (5.045)	.165 (5.227)	-.342 (5.384)
Private	24.437* (12.905)	25.709** (12.921)	16.207 (15.457)	16.949 (15.674)
KBDI	-.0186 (.017)	-.187 (.018)	-.019 (.018)	-.021 (.019)
Fragmentation metric	-2687.352** (1086.088)	-2892.193** (1107.252)	-3066.682*** (1184.736)	-3244.579*** (1215.250)
Parcel Size	.03** (.018)	.039** (.018)	.039** (.019)	.039** (.019)
Wildfire Area	-19.232* (10.742)	-19.356* (10.849)	-18.382* (11.591)	-18.776 (11.762)
Pine	7.165 (4.937)	6.879 (4.976)	6.539 (5.258)	7.600 (5.444)
Urban	38.731 (32.963)	39.158 (33.086)	38.357 (33.651)	38.818 (34.141)
Wet	18.616 (12.313)	18.332 (12.362)	12.731 (13.439)	13.139 (13.663)
Wooded	18.113* (9.909)	22.316** (10.312)	21.688** (10.627)	22.243** (10.811)
constant	942.173**	946.712**	926.382*	927.782*

	(462.193)	(464.060)	(498.141)	(505.324)
rho	.183** (.086)	.134* (.074)	.133* (.071)	.102 (.068)
Wald test of rho =0	Chi2(1) = 4.586**	3.242*	3.568*	2.228
Log likelihood	-2316.067	-2291.041	-2197.979	-2134.645
# of obs	441	436	417	404

Table 4: Equation 4 - Spatial Lag Model regression results, Maximum Likelihood Estimation, Wakulla County

	W1	***W2***	***W3***	***W4***
Income	.054 (.078)	.035 (.085)	0.021 (.081)	0.0154 (0.084)
Absentee	229.667* (134.382)	202.556 (139.490)	206.375 (139.015)	174.146 (144.026)
Private	-78.191 (75.644)	-86.711 (87.202)	-108.177 (87.327)	-96.659 (89.456)
KBDI	.028 (96.492)	.024 (.286)	0.030 (0.285)	0.116 (0.294)
Fragmentation	-49241.040***	-60701.62***	-61142.490***	-62689.760***

Metric	(9656.048)	(9699.213)	(9610.605)	(9782.287)
Parcel Size	.00006** (.000)	-.045 (.120)	-0.082 (0.120)	-0.067 (0.122)
Wildfire Area	59.867 (82.717)	48.365 (88.746)	36.381 (85.833)	35.889 (87.892)
Pine	60.156 (96.492)	56.527 (100.469)	64.433 (100.189)	41.935 (102.581)
Urban	89.768 (586.584)	-67.288 (606.709)	-80.415 (604.459)	-124.291 (612.860)
Wet	113.439 (136.281)	163.056 (140.874)	162.765 (140.426)	175.251 (142.967)
Wooded	111.172 (107.053)	66.319 (110.511)	46.694 (110.328)	39.912 (113.386)
Constant	-2797.758 (4521.196)	-1468.143 (4911.564)	-596.825 (4690.531)	-352.471 (4827.328)
Rho	.687*** (.105)	.284*** (.066)	.275*** (.062)	.191*** (.056)
Wald test of rho =0	42.509***	18.388***	19.971***	11.778***

Log likelihood	-2220.851	-2222.214	-2205.662	-2145.3392
# of obs	285	284	282	274

Rho, ρ, is positive and significant for all specifications of the Spatial Lag model using Wakulla County data and for the three Spatial Lag model estimations of the Jackson County data that feature weight matrices W1, W2 and W3. Private ownership is positive and significant in Jackson County. The fragmentation metric is negative and significant in both Jackson and Wakulla Counties. Income per capita is negative and significant for all specifications of the Jackson County regression. Area burned by wildfire is negative and significant in Jackson County but only in regressions with weight matrices W1, W2 and W3. Wooded vegetation is positive and significant for all model specifications using Jackson County data. Absentee ownership is positive and significant in Wakulla County in the regression with weight matrix W1.

Discussion

In this section, we begin by discussing the significant results of the of Equations 1 and 4 all four counties. Next we analyze the results of the spatial dependence tests. We find that Jackson and Wakulla Counties exhibit spatial dependence and we offer a few hypotheses as to why Hamilton and Hendry Counties do not. Finally, we discuss the possible policy applications of the results.

Estimated Coefficients

Table 2 reports the OLS estimation results of Equation 1 for all counties. These results are biased and inconsistent for Jackson and Wakulla Counties as they exhibit spatial dependence, as described in the Model section, but the statistically significant confident results of Equation 1 using Hamilton County data support some important findings supported by past literature. In Hamilton County, private ownership (supported by Shafran 2008) and size of parcel (Shafran, 2008) are all positive and significant and KBDI (Shafran, 2008) and ownership fragmentation (Busby et al., 2012) are negative and significant.

Table 3 reports the maximum likelihood estimation results of Equation 4, using Jackson County data. Table 4 reports the maximum likelihood estimation results of Equation 4, using Wakulla County data. The following are results from Equation 4.

Absentee ownership is positive and significant for Wakulla County. Private ownership is positive and significant for Wakulla County. Median income is negative and significant in Jackson County. It is possible in Jackson County, there are abnormal characteristics about higher income areas that do not exist in other counties that discourage wildfire treatment that is not captured by the regression.

Fragmentation metric is negative and significant in Jackson and Wakulla Counties. This result is supported by Busby et al. (2012), stating that when ownership becomes more diverse, the community is less likely to receive the optimal prescribed level of fire prevention.

Size of parcel is positive and significant in Jackson and Wakulla Counties, indicating that as parcel owners have more property to protect, and subsequently, more property to be damaged by wildfire. There is an increasing return to scale for every additional acre protected by controlled burn for a landowner’s investment. This was the result of the same variable in Shafran’s 2008 analysis.

Area burned by wildfire the year prior to prescribed treatment is negative and significant in Jackson County. This coefficient is consistently negative and significant though out all spatially explicit regressions for Jackson County. This may indicate different reactions to wildfires among communities. The negative coefficient may suggest that some parcel owners are wary to perform controlled burns, as they may get out of control. The positive coefficient may indicate the community is more educated on how to safely perform controlled burns and their benefits.

Of the vegetation types, wooded vegetation is positive and significant in Jackson County. This could indicate that parcels that have wooded vegetation as their predominant vegetation land cover is owned by individuals who know the dangers of wildfire in their area and how to protect themselves. It is possible that this type of land cover is maintained more frequently than other vegetation types due to the high level of fuels produced by wooded vegetation compared to other land cover types.

Spatial lag model

In Wakulla County, ρ, the estimate of the degree of spatial dependence within data, is positive and significant for all four spatial weight matrices specified for the spatial lag model. In Jackson County, ρ is positive and significant for three of the four spatial weight matrices (W1, W2 and W3) specified for the spatial lag model. This indicates that in both counties there are significant spatial interactions among landowners with fuel treatment on an individual parcel positively associated with fuel treatment on nearby parcels. The externalities generated by fuel treatment on an individual parcel increase the likelihood of fuel treatment on other parcels within both Wakulla and Jackson Counties. For all estimations of Equation 4 for Wakulla County and most estimations for Jackson County, the Wald test rejected the null hypothesis that rho equals zero. Only in Jackson County and given the spatial weight matrix W4 did the Wald test fail to reject the null, indicating that ρ is not statistically different from zero and, hence, no spatial interaction was detected.

Spatial interaction in Jackson and Wakulla Counties

There are a few possible explanations for the spatial interaction observed in Jackson and Wakulla Counties. First, there were more prescribed fires performed during the September 2008-December 2010 time period in Jackson and Wakulla Counties 448 and 285 permits respectively, than in Hamilton and Hendry Counties. The sample size for Hamilton, with 118 permits, and Hendry, with 91 permits, Counties may have simply been too small to detect the statistical significance of the spatial interactions.

Second, Wakulla and Jackson Counties have the highest percentage of homeownership, as opposed to renters, out of the four counties. Homeownership rate in Wakulla was 83.6% and in Jackson 77.2% from the years 2006-2010 (US Census Bureau, 2012). Homeowners have greater incentive to protect their property, may have a stronger sense of regional pride, be more active in the community's safety efforts or more aware of the fire risk. Because the owner of the rental properties may not see the property on a daily basis, fuel treatment may occur less often than on non-rental properties.

Third, Wakulla and Jackson have the greatest number of high school and college graduates of people 25 years or older. Wakulla had a high school graduation rate of 84.5% and college graduation rate of 17.3% and Jackson had a high school graduation of rate of 77.4% and a college graduation rate of 12.8% of citizens over the age of 25 in between the years 2006-2010 (US Census Bureau, 2012). Counties with highly educated citizens may be more aware of fire risks in their communities and how to protect their property than counties with less educated citizens.

Fourth, the largest number of prescribed fires performed in moderately fragmented areas characteristic of Wakulla and Jackson Counties. Individuals living in moderately fragmented communities, with average parcel size of approximately 45 acres, may have more opportunities to discuss the treatment they have performed on their land, sharing information, and encouraging one another to protect themselves and their communities. We observe clustering of prescribed burns in the northeast corner of Jackson County in the Lovedale and Bascom communities. In Wakulla County, the communities of Wakulla and Wakulla Springs, in the northeast part of the county, and communities south on the Peninsula have the most fuel treatment.

Table 5: County statistics

Demographics	**Hamilton**	**Hendry**	**Jackson**	**Wakulla**
Homeownership	74%	69.20%	77.20%	83.60%
High school graduation (persons 25+)	73.90%	62%	77.40%	84.50%

College graduation (persons 25+)	7.80%	8.20%	12.80%	17.30%
Permits in higher fragmented areas	Hamilton	Hendry	Jackson	Wakulla
.01-.015	3	1	10	24
.015-.02	0	1	2	9
.02-.025	0	1	1	0
.025-.03	0	1	0	0
.03-.035	0	1	0	0

Policy applications

The results from our study will be of particular interest to policy makers. Currently, there are no policies in Florida that require private parcel owners to perform fuel treatment of any kind on their property (Saddler, 2012). The only regulation that pertains to prescribed fire in Florida is the 1990 Prescribed Burning Act. This legislation passed by the State of Florida is nationally recognized to be landmark in its protection of landowners who carry out prescribed burns from civil liability with the goal to increase the number of acres treated with prescribed fire in Florida (Brenner and Wade, 2003).

Prescribed burning was first made legal in Florida in 1943, and permits were only issued to forest managers of national forests on a case by case basis. In 1977, Florida passed the Hawkins Bill, which allowed prescribed burns on privately owned lands. This bill was deemed necessary as the WUI began to expand and Florida’s forests, and fuel reduction efforts, began to become increasingly fragmented. From 1943 to the late 1970’s, Florida led the country in acreage treated with prescribed burns. However, in the 1980’s, the number acres prescribed burnedsharply declined, for many reasons, including concerns from private landowners aboutprescribed fire smoke damage liability. In the 1990 case of Midyett v. Madison, a private landowner hired a contractor to perform a controlled burn on the land owner's property and both the land owner and contractor were held responsible for a smoke-related automobile fatality. The case was brought to the Florida Supreme Court and the court ruled that "setting a fire was clearly a dangerous agency because it possesses an inherently dangerous propensity" and that "it is equally self-evident that smoke blowing across a heavily traveled traffic corridor also possesses a dangerous propensity." This case is one reason why the land management community felt it necessary to put legal measures in place to protect the skilled application of fire to reduce the risk of wildfire (Brenner and Wade, 2003).

In 1990, the Florida land management community wrote a piece of regulation that explained the need for prescribed fire to reduce the risk of wildfire and maintain a healthy ecosystem. This piece of legislation outlines the acceptable prescribed burn practices, protected prescribed burners from civil liability as long as the burner was not deemed to be "generally negligent," as was defined in the 1990 case of Midyett v. Madison, and stated that prescribed burns that were in accordance with the legislation could not be terminated due to nuisance complaints. By protecting the rights of individuals performing prescribed burning, the law authorized and promoted the use of prescribed burning for many purposes, including wildfire mitigation. This act was revised in 1999 and the term "general negligence" was replaced with "gross negligence," which is significant, because the prescribed burner is protected under law as long as the fire is performed within the "accepted forestry practices." This protection of prescribed burners has incentivized more private homeowners to perform prescribed burns on their property (Brenner and Wade, 2003).

Florida leads the country in protecting and incentivizing its citizens to perform prescribed burns with the 1990's Prescribed Fire Act (Saddler, 2012). However, in addition to the legal protection of the 1990's Prescribed Fire Act, policy makers might also consider additional methods in which to incentivize parcel owners to perform prescribed burns on their property, especially those who live in areas where there is possible underinvestment in fuel treatment. Our research gives policy makers information about where additional incentive programs for fuel treatment on private land would be most successful. Because we observe spatial externalities in the prescribed fire decision, there is the possibility for underinvestment in fuel management. Policy intervention that provides landowners additional incentives or requirements to undertake fuel management may improve outcomes on the landscape. This could be accomplished providing landowners with financial incentives to undertake fuel treatment on private property or by requiring fuel treatment on private property.

Because landowners in highly fragmented landscapes are less likely to undertake fuel treatment, underinvestment in fire risk management in these areas is most likely. To improve outcomes in these areas, policy makers may consider providing incentives, such as tax deductions or subsidies, to parcel owners to undertake fuel treatment or spearhead efforts to bring these communities together to address wildfire risk management or creating regulations requiring parcel owners with a specified level of fuels to perform fuel treatment to reduce their fuel loads. Similar initiatives might be undertaken in in areas with lower average income, where underinvestment in fuel treatment is also likely. By targeting fragmented landscapes with low average income, policy makers can help to ensure that values in these areas are adequately protected.

Given the spatial interaction observed in Jackson and Wakulla Counties, landowners may be encouraged to undertake fuel treatment following fuel treatment on public land. Fuel treatment on public land would simultaneously protect values on public land and lead to more fuel treatment on private land. Large, public parcels that are adjacent to private parcels may be more influential to private land owners as they are more visible to private landowners and may inspire the private parcel owners to free ride or cooperate more than smaller, less visible.

Conclusions

In this final section, we summarize our major findings, specifically addressing the three research objectives, and describe opportunities for future work. Our first research objective was to gain insight into how ownership fragmentation influences wildfire risk reduction decision-making. We find that ownership fragmentation is negatively associated with prescribed burning. We find that as ownership becomes more fragmented, underinvestment in fuel treatment in more likely. This outcome is supported by Busby et al. (2012).

Our second research objective was to determine if vegetation type is a significant determinant of prescribed fire decision. We found that wooded vegetation type is positively associated with prescribed burning. This could indicate that parcels that have wooded vegetation as their predominant vegetation land cover is owned by individuals who know the dangers of wildfire in their area and how to protect themselves. It is possible that this type of land cover is maintained more frequently than other vegetation types due to the high level of fuels produced by wooded vegetation compared to other land cover types.

Our third research objective was to determine if landowner interaction is characterized by cooperation or free riding. Based on the positive spatial interactions present in Wakulla and Jackson Counties, we find that landowners cooperate with one another in their fuel management decisions. Fuel treatment on an individual parcel increases the likelihood of fuel treatment on nearby parcels leaving the community and local values better protected against wildfire damage.

There are a number of additional research questions that can be answered using the data set generated for the present study. An interesting research question could be what are the determinants of the decision to carry out a prescribed fire? The present study did not address the temporal element of the fuel management decision, but this is an important question particularly with regard to the longevity of prescribed burns. How long does fuel treatment on an individual parcel positively influence nearby landowners to undertake fuel treatment? Another interesting research question that might be answered using the current data set is how wildfire suppression effort influences the fuel treatment decision? Landowners may view fire suppression as either a substitute for or a complement to fuel treatment on their individual parcel. Finally, due to time constraints, we focused on only four counties within the state of Florida, however, the study could be expanded to include all counties within the state.

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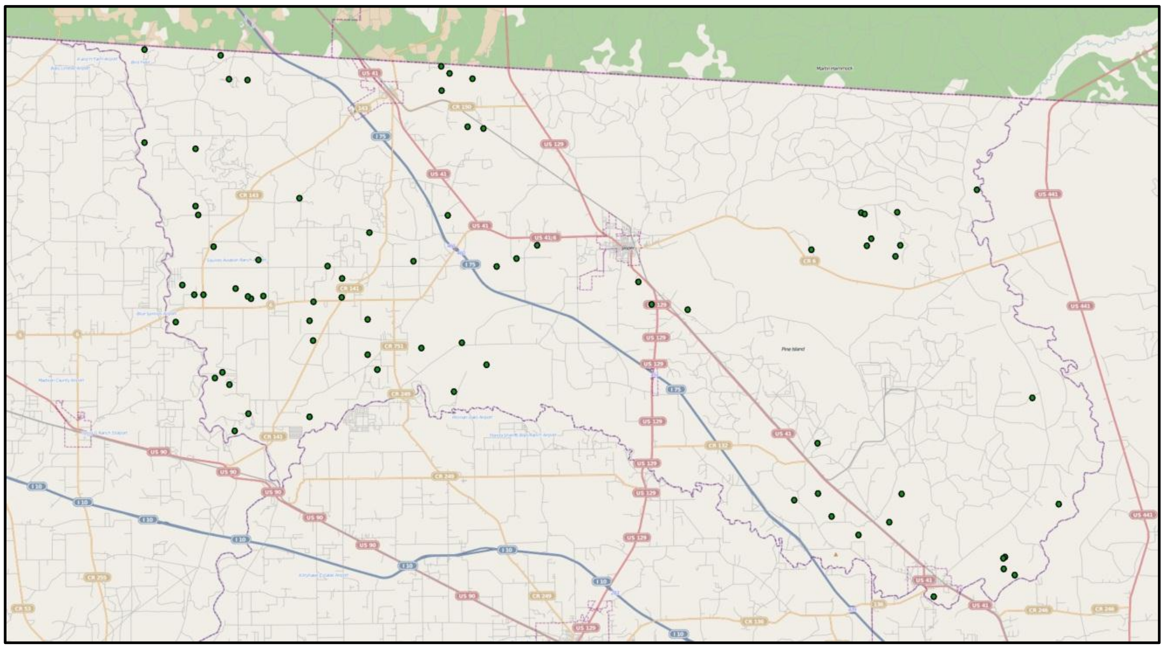
Appendix A: Maps

Maps 2: Locations of prescribed burns, September 2008-December 2010

Where:

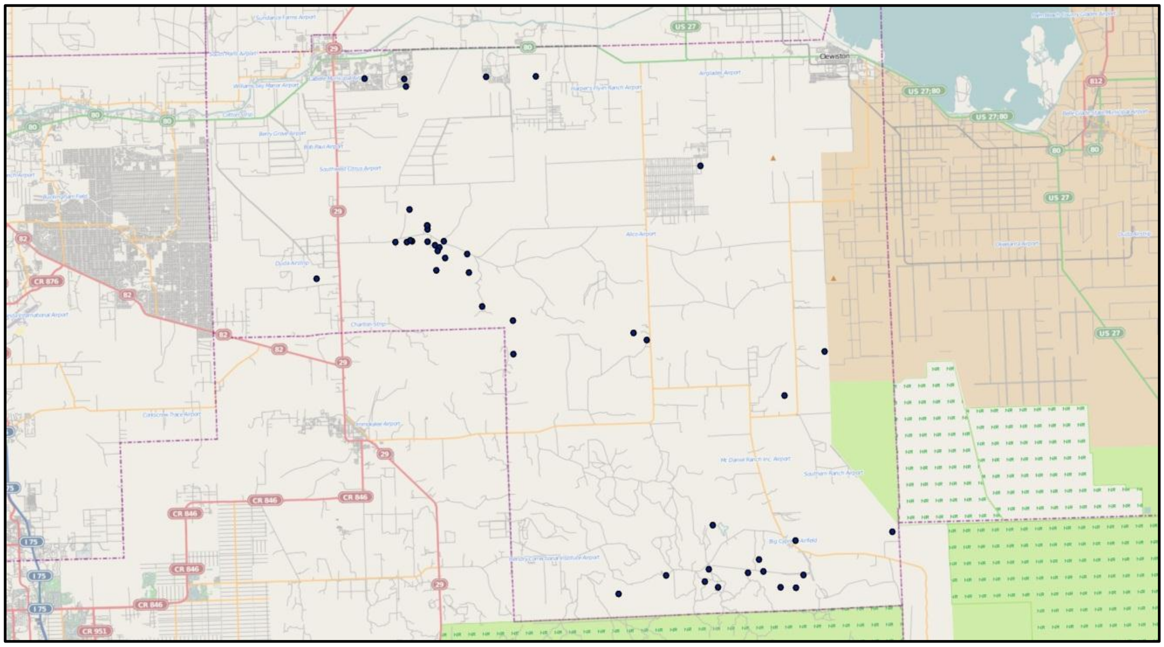
Dot = location of prescribed burn

Figure 12: Map 2 A: Hamilton County- location of prescribed burns, September 2008-December 2010



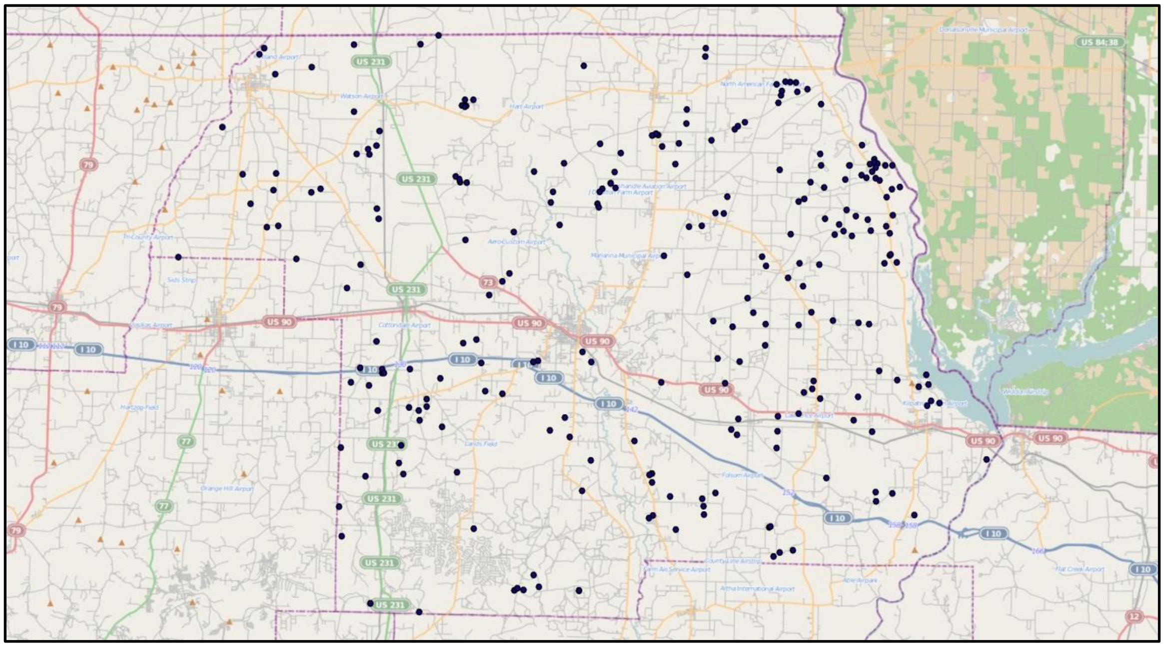
(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 13: Map 2 B: Hendry County- location of prescribed burns, September 2008-December 2010



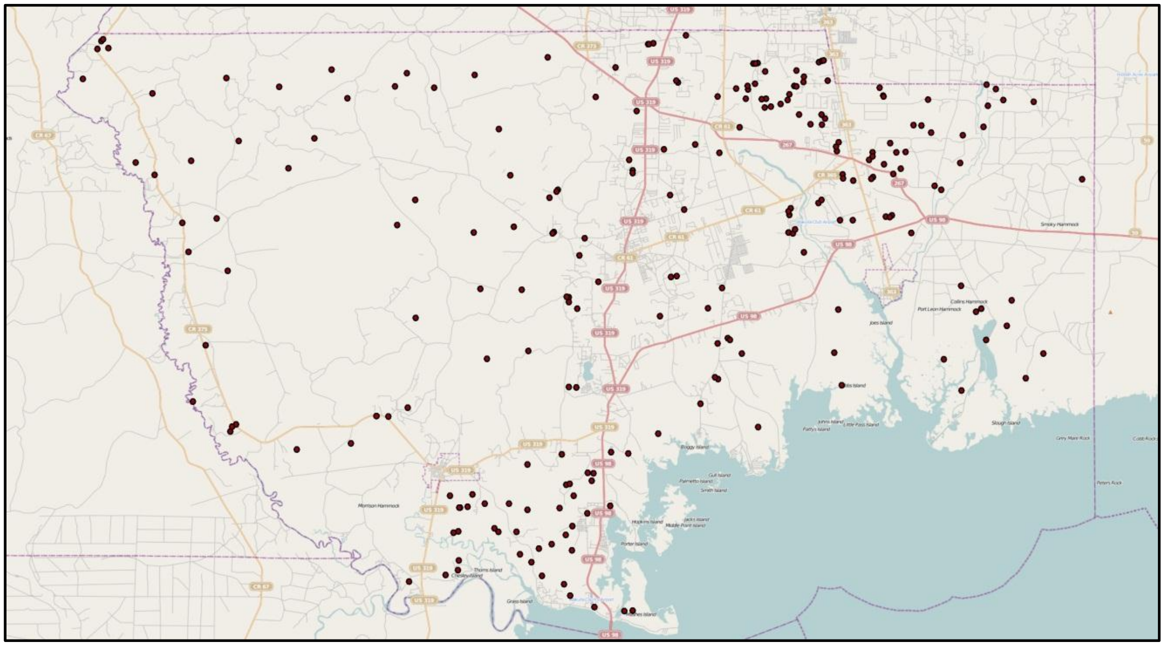
(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 14: Map 2 C: Jackson County- location of prescribed burns, September 2008-December 2010



(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 15: Map 2 D: Wakulla County- location of prescribed burns, September 2008-December 2010



(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

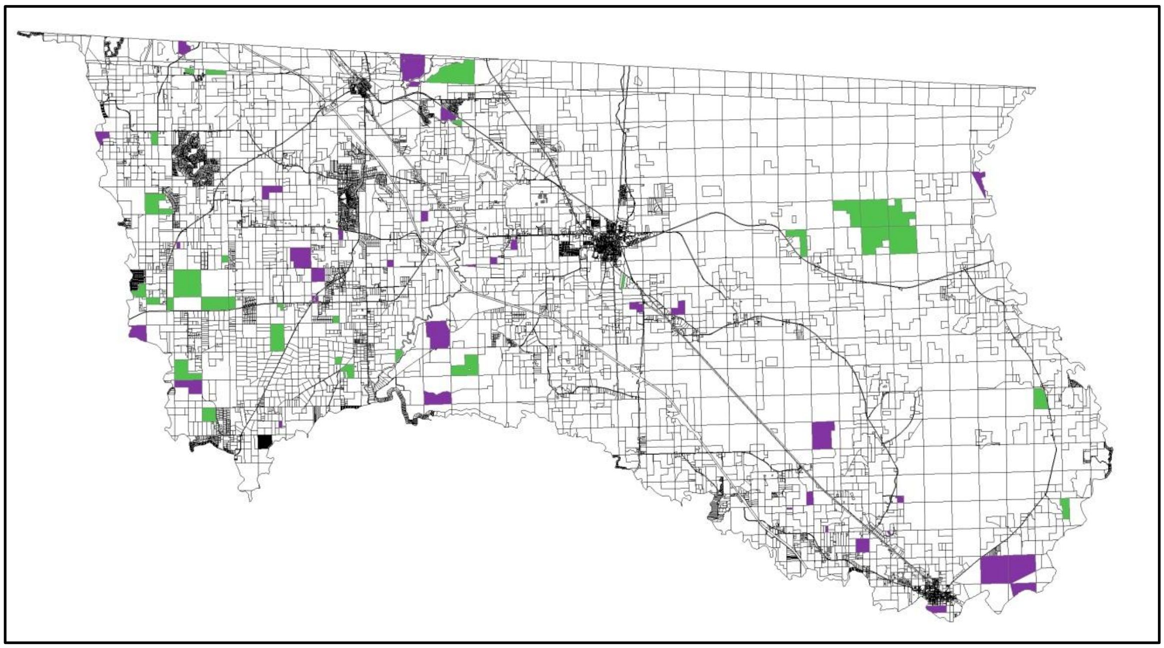
Maps 3: Local/absentee ownership of parcels

Where:

Purple = local ownership

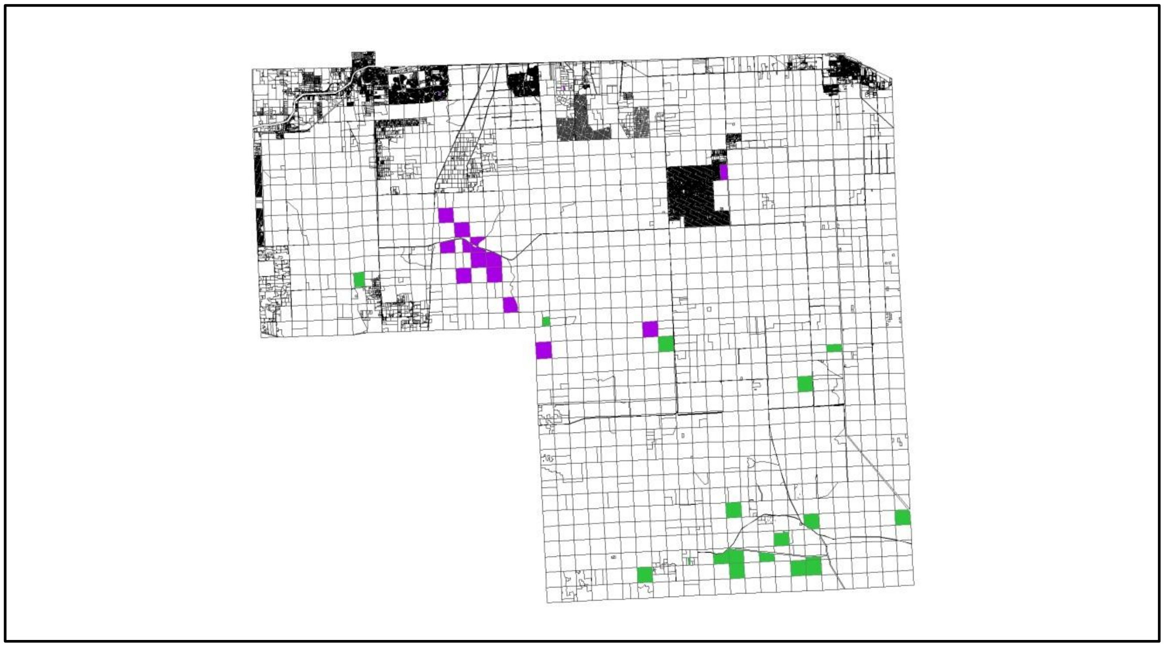
Green = absentee ownership

Figure 16: Map 3 A: Hamilton County- absentee/local ownership, parcel level



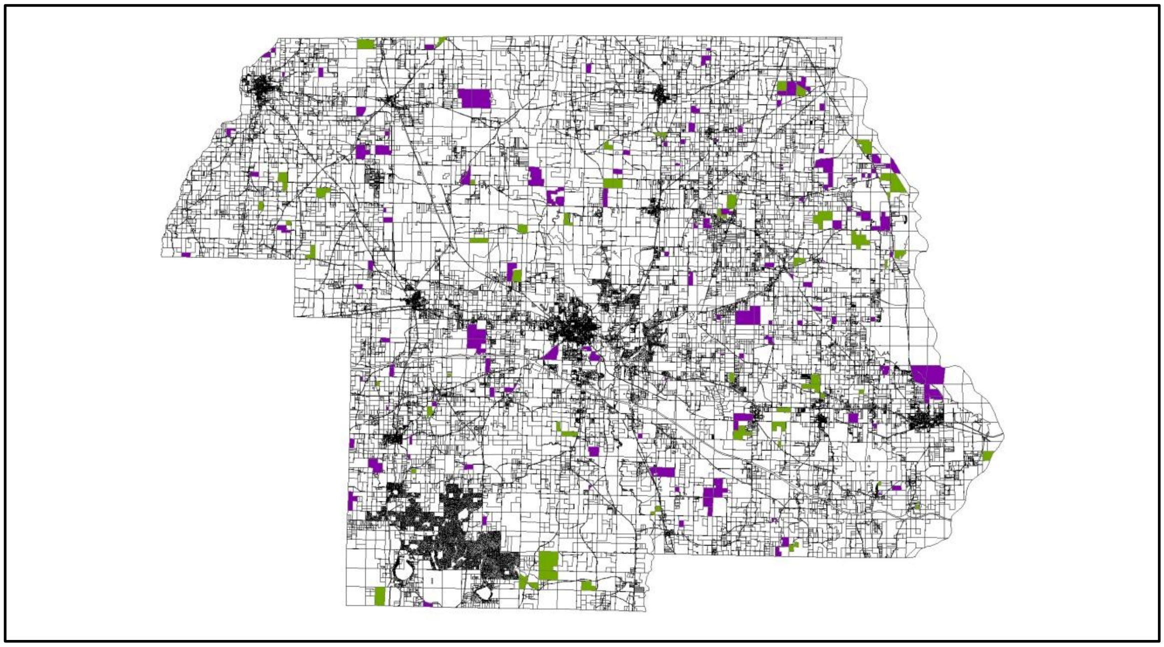
(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 17: Map 3 B: Hendry County- absentee/local ownership, parcel level



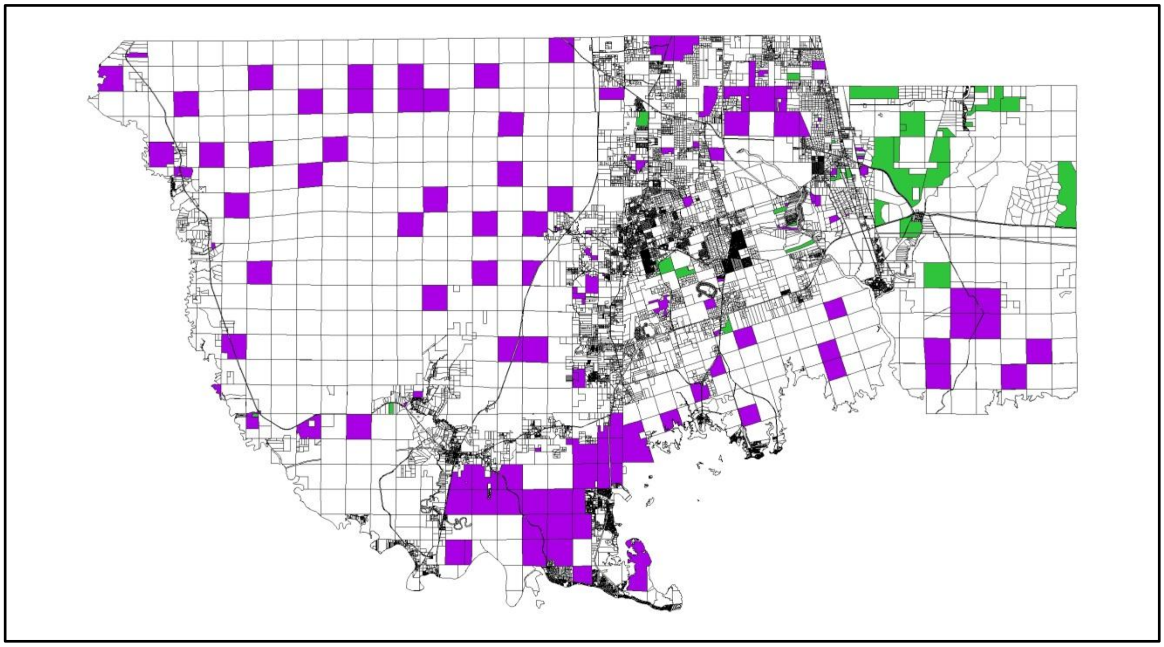
(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 18: Map 3 C: Jackson County- absentee/local ownership, parcel level



(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 19: Map 3 D: Wakulla County- absentee/local ownership, parcel level



(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

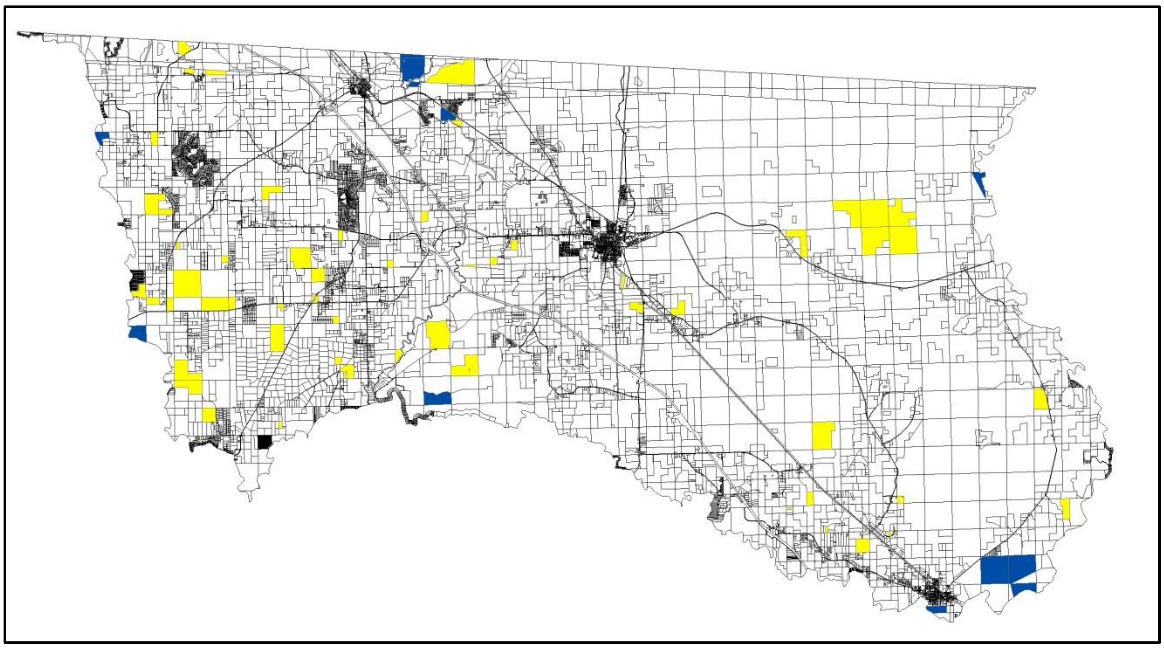
Maps 4: Public/private ownership of parcels

Where:

Blue = Public ownership

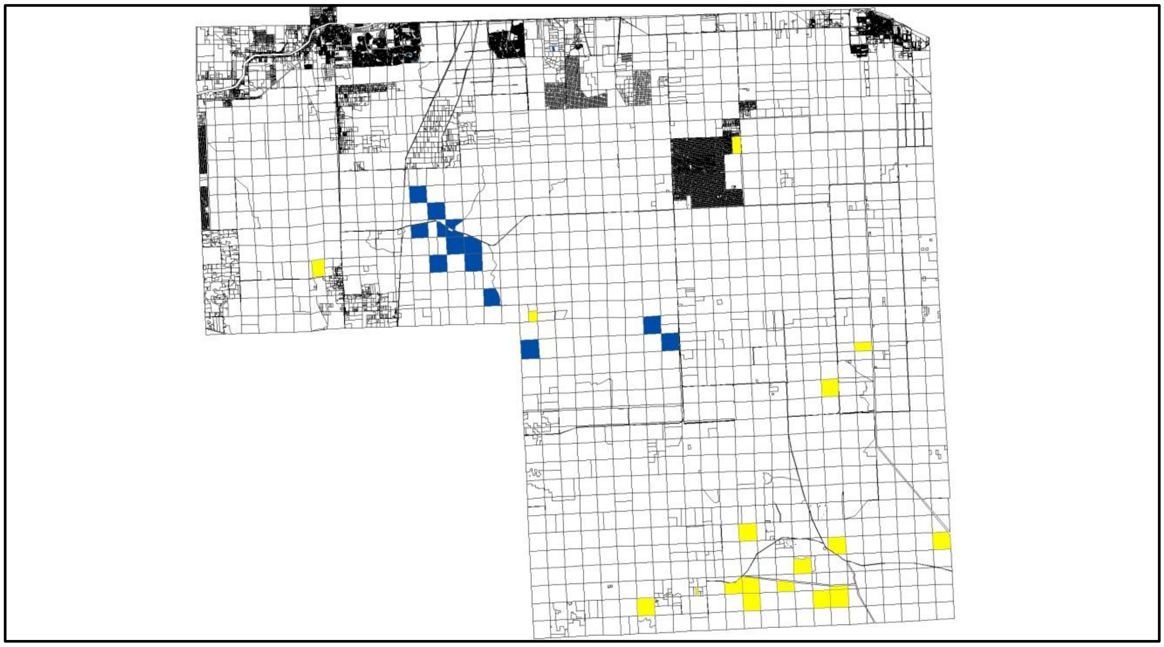
Yellow = Private ownership

Figure 20: Map 4 A: Hamilton County- public/private ownership, parcel level



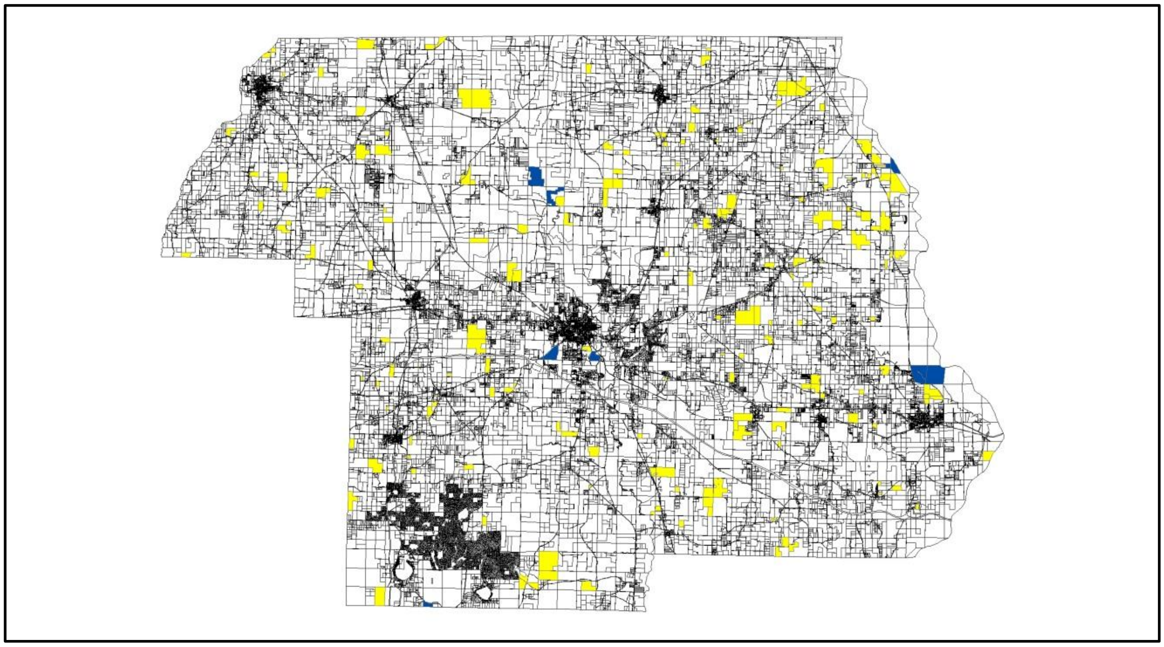
(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 21: Map 4 B: Hendry County- public/private ownership, parcel level



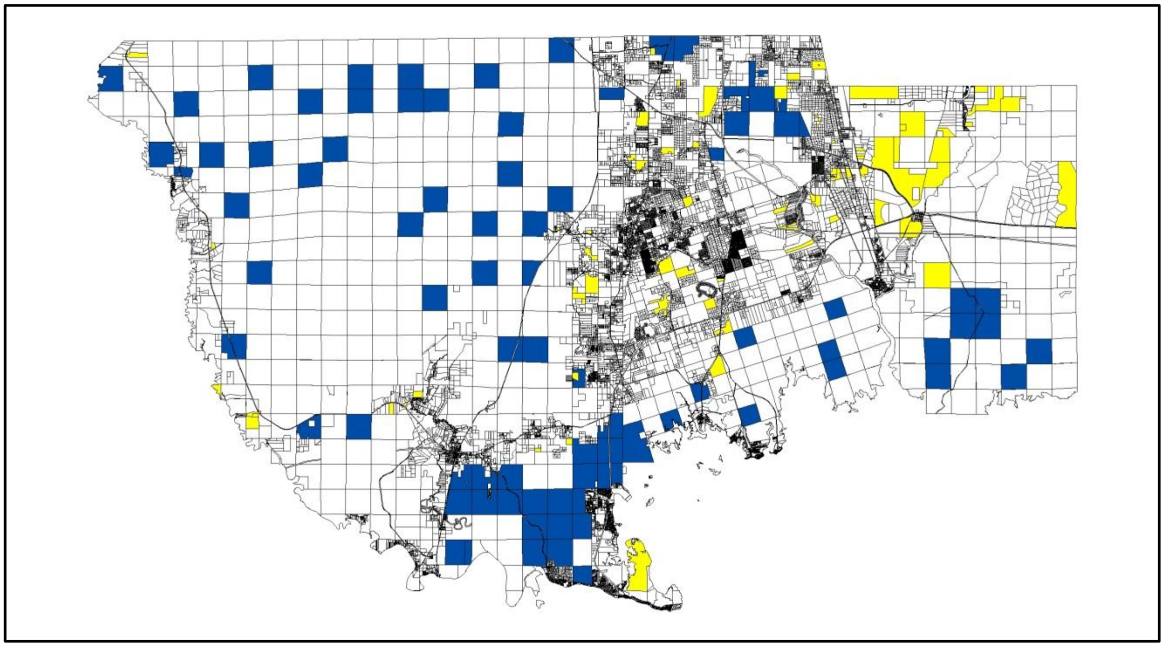
(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 22: Map 4 C: Jackson County- public/private ownership, parcel level



(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Figure 23: Map 4 D: Wakulla County- public/private ownership, parcel level



(Map generated using GIS data from Florida Division of Forestry and Florida Department of Revenue)

Maps 5: Predominant vegetation type of parcels

Where:

Light brown = Sandhill

Dark brown = Wooded Vegetation

Dark green = Pine

Blue = Wet Vegetation

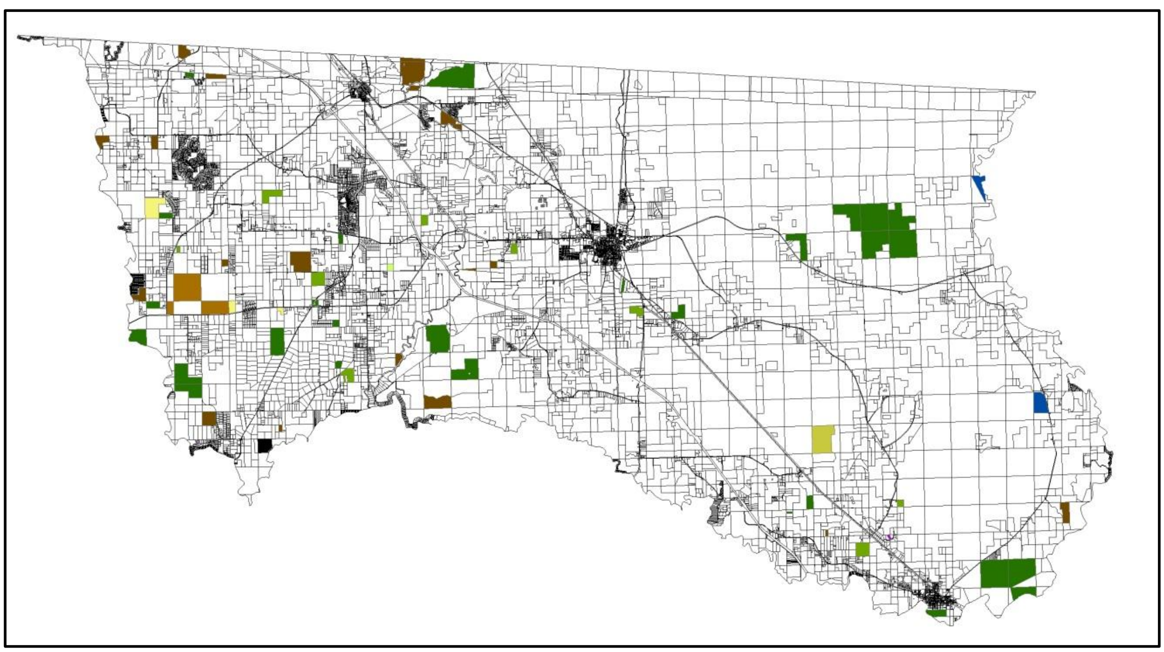
Yellow = Bare Soil

Moss green = Pasture

Pale lime green = Row field

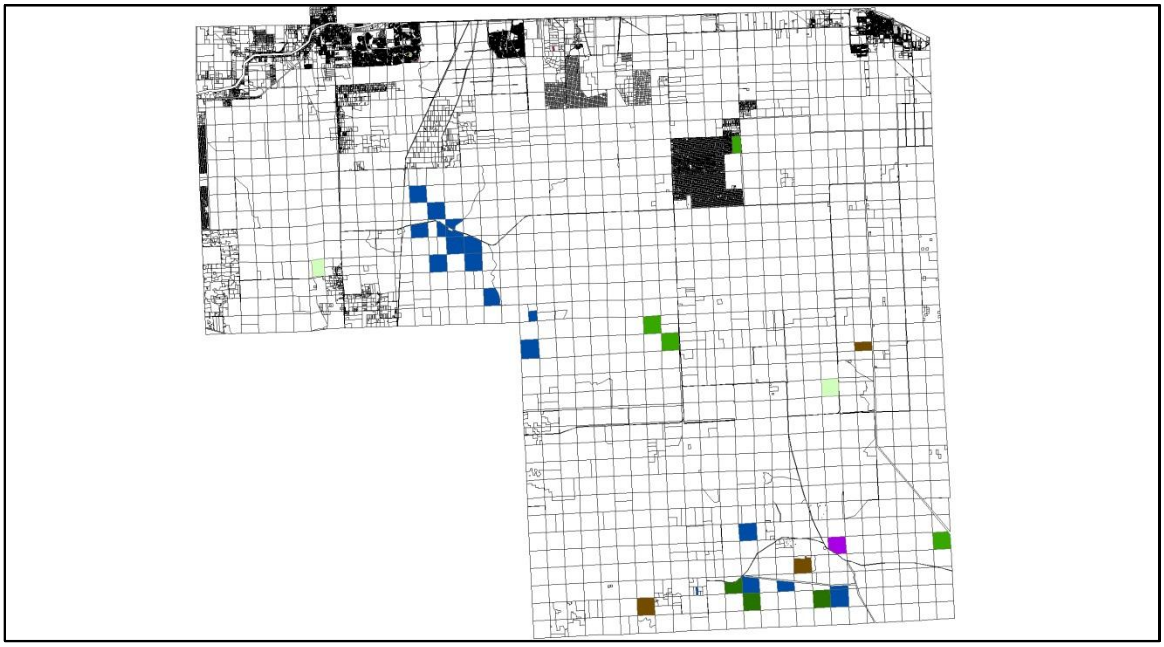
Sand = Extractive

Figure 24: Map 5 A: Hamilton County-predominant vegetation type, parcel level



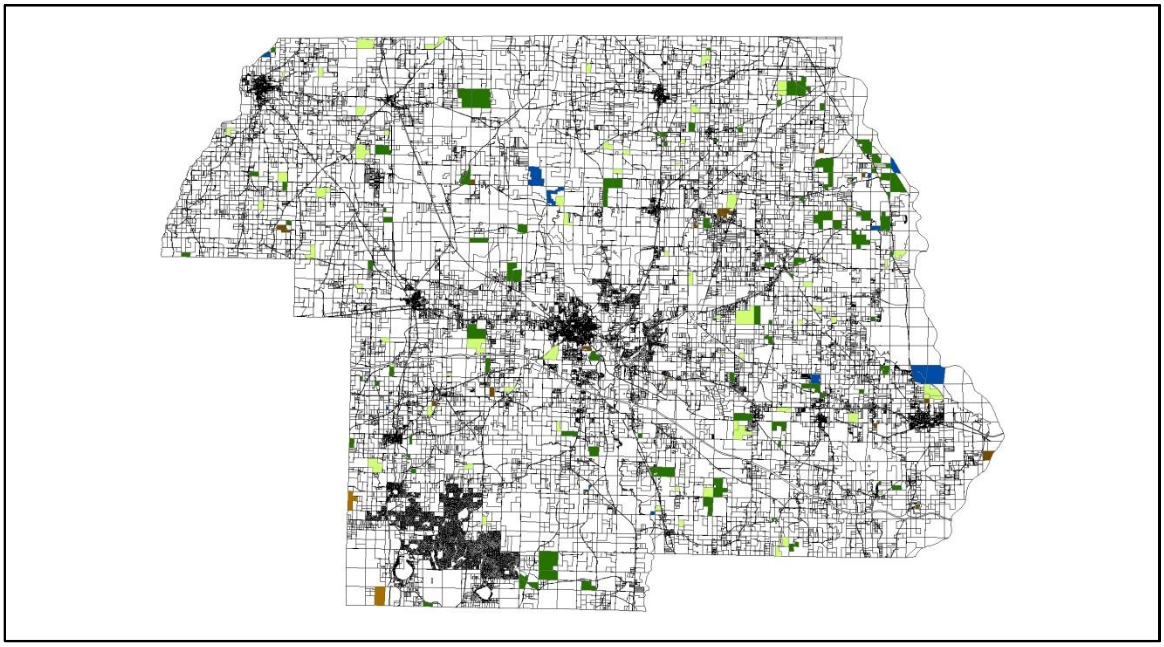
(Map generated using GIS data provided by Florida Division of Forestry and Florida Fish and Wildlife Conservation Commission)

Figure 25: Map 5 B: Hendry County-predominant vegetation type, parcel level



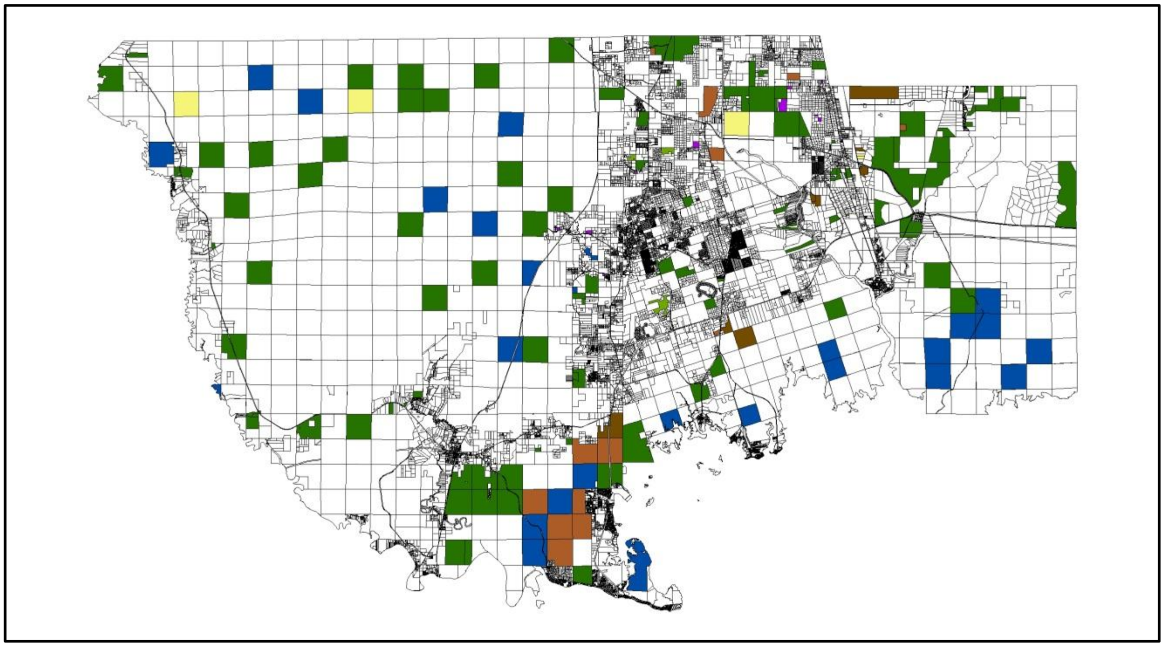
(Map generated using GIS data provided by Florida Division of Forestry and Florida Fish and Wildlife Conservation Commission)

Figure 26: Map 5 C: Jackson County-predominant vegetation type, parcel level



(Map generated using GIS data provided by Florida Division of Forestry and Florida Fish and Wildlife Conservation Commission)

Figure 27: Map 5 D: Wakulla County-predominant vegetation type, parcel level



(Map generated using GIS data provided by Florida Division of Forestry and Florida Fish and Wildlife Conservation Commission)

Appendix B: Tables

Table 6: OLS Results, Jackson County, W2, W3, and W4

	W2	W3	W4
Income	-.023* (.012)	-.023* (.013)	-.023* (.013)
Absentee	1.326 (5.139)	.609 (5.331)	.033 (5.481)
Private	28.729** (13.061)	20.276 (15.627)	20.170 (15.824)

KBDI	-.201 (.018)	-.021 (.019)	-.022 (.019)
Fragmentation Me.ric	- 3138.917*** (1120.141)	-3240.023*** (1205.970)	-3358.933*** (1236.185)
Parcel Size	.048*** (.048)	.049*** (.018)	.046*** (.019)
Wildfire Area	-18.791* (11.056)	-18.553 (11.832)	-18.463 (11.986)
Pine	7.164 (5.071)	7.051 (5.363)	7.974 (5.543)
Urban	41.739 (33.699)	41.490 (34.328)	41.528 (34.749)
Wet	18.989 (12.597)	14.154 (13.699)	14.389 (13.899)
Wooded	23.225** (10.499)	23.191** (10.819)	23.468** (10.987)
constant	930.053** (473.005)	913.654* (508.549)	916.857* (514.999)
r^2	.068	0.063	.064
# of obs	436	417	404
Moran's I	1.95**	1.81*	1.26
LM Error	2.57	2.24	0.94
Robust LM	0.93	2.36	1.31

Error			
LM Lag	3.51*	3.41*	1.50
Robust LM Lag	1.87	3.53*	1.87

Table 7: OLS Results, Wakulla County, W2, W3, and W4

	W2	**W3**	**W4**
Income	0.045 (.090)	0.041 (0.087)	0.029 (0.088)
Absentee	175.789 (148.338)	176.159 (148.309)	145.811 (151.057)
Private	-96.102 (29.797)	-103.933 (93.269)	-90.415 (93.959)
KBDI	0.049 (0.304)	0.051 (0.305)	0.101 (0.309)
Fragmentation Metric	-76976.23*** (9501.566)	-77077.920*** (9532.507)	-74291.240*** (9643.644)
Parcel Size	-0.070 (0.128)	-0.0856 (0.128)	-0.067 (0.128)
Wildfire Area		60.528 (91.497)	50.654 (92.225)
Pine	76.611	83.529	46.951

	(106.832)	(106.916)	(107.756)
Urban	-122.136 (645.698)	-123.464 (645.549)	-154.605 (643.772)
Wet	158.062 (149.955)	157.399 (149.985)	157.261 (157.261)
Wooded	66.204 (117.639)	56.958 (117.818)	42.786 (119.115)
constant	-1917.886 (5227.161)	-1648.567 (5003.716)	-1006.620 (5067.387)
r^2	.222	0.223	0.212
# of obs	284	282	274
Moran's I	5.20***	5.30***	4.67***
LM Error	23.74***	25.23***	19.75***
Robust LM Error	0.92	1.36	0.61
LM Lag	30.73***	31.22***	19.17***
Robust LM Lag	7.91***	7.35***	0.03

Table 8: Jackson summary statistics, data sets used to estimate Spatial Lag Models using W2, W3, and W4

	W2	**W3**	**W4**
# of observations	436	417	404
Acres treated (acres)			

mean	43.892	44.341	44.483
min	1	1	1
max	300	300	300
std. dev.	48.173	48.844	49.429
Parcel size (acres)			
mean	137.253	131.625	130.937
min	0.525	0.525	0.525
max	630.685	630.685	630.685
std. dev.	145.469	140.741	142.012
Fragmentation metric (perimeter/area)			
mean	0.006	0.006	109.364
min	0.003	0.003	0
max	0.022	0.022	14105
std. dev.	0.002	0.002	992.768
Median household income (US dollars)			
mean	$36,683.53	$36,672.16	$36,667.43
min	$35,968.00	$35,968.00	$35,968.00
max	$37,707.00	$37,707.00	$37,707.00
std. dev.	$701.28	$700.98	$701.36
KBDI			
mean	211.911	213.837	215.171
min	15	15	15
max	595	595	595
std. dev.	150.307	149.568	149.285
Privately owned parcels	416	402	389
Publically owned parcels	20	15	15
Absentee owners	134	128	123
Local owners	302	289	281
Average area burned by wildfire (acres)			
2007	3.052	3.052	3.052
2008	3.588	3.588	3.588
2009	1.978	1.978	1.978
Vegetation types			
Pinelands	246	241	233
Urban	2	2	2
Wet vegetation	21	21	21

Wooded vegetation	26	26	26

Table 9: Wakulla summary statistics, data sets used to estimate Spatial Lag Model using W2, W3, and W4

	W2	**W3**	**W4**
# of observations	284	282	274
Acres treated (acres)			
mean	380.757	378.777	356.555
min	1	1	1
max	4000	4000	4000
std. dev.	707.146	707.206	699.384
Parcel size (acres)			
mean	349.285	348.988	352.192
min	0	0.4	0.4
max	1492	1492	1492
std. dev.	337.382	338.02	339.517
Fragmentation metric (perimeter/area)			
mean	0.006	0.006	0.006
min	0.001	0.001	0.001
max	0.018	0.019	0.019
std. dev.	0.004	0.004	0.004
Median household income (US dollars)			
mean	$50,276.21	$50,283.74	$50,279.22
min	$49,215	$49,215	$49,215
max	$54,420	$54,420	$54,420
std. dev.	$1,219.54	$1,220.56	$1,227.32
KBDI			
mean	267.405	267.238	266.996
min	11	11	11
max	582	582	582
std. dev.	155.462	155.99	155.341
Privately owned parcels	163	163	157
Publically owned parcels	121	119	117

Absentee owners	23	23	22
Local owners	261	259	252
Average area burned by wildfire (acres)			
2007	1.632	1.632	1.632
2008	7.608	7.608	7.608
2009	6.658	6.658	6.658
Vegetation types			
Pinelands	122	121	116
Urban	1	1	1
Wet vegetation	32	32	32
Wooded vegetation	74	73	71

Appendix C: STATA Code

Figure 28: Code 1: STATA code used to estimate Spatial Lag Model

```
clear
insheet using filename.csv
destring, replace
set more off
*Create an inverse distance spatial weights matrix
spwmatrix gecon xcoord ycoord, cart wname(w_county) rowstand wtype(inv) eignvar(eigv_rent)
mataf alpha(1), dband(0 19000)
*Create an inverse distance squared spatial weights matrix
spwmatrix gecon xcoord ycoord, cart wname(w_county2) rowstand wtype(inv)
eignvar(eigv_county2) mataf alpha(2), dband(0 19000)
reg acres absentee private kbdi frag acrea wf pine urban wet wood
predict county_hat
generate resid_county=acres-county_hat
*semivariogram of OLS residuals
variog2 resid_county xcoord ycoord, width(100)
*Lag model using the inverse distance squared spatial weights matrix
spmlreg acres absentee private kbdi frag acrea wf pine urban we. wood, weights(w_county2)
wfrom(Mata) eignvar(eigv_county2) model(lag)
*LM test for an error process in the lag model residuals
anke.est, wname(w_county) wfrom(Mata) model(sar)
```