Spatial interactions in wildfire risk management decisions

Gwen Busby, GreenWood Resources, Email: gwen.busby@gwrglobal.com

Richelle Geiger, Washington State Legislature, Email: geiger.richelle@gmail.com

Evan Mercer, Southern Research Station, USDA Forest Service, Email: emercer@fs.fed.us

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

1. Introduction

In recent years, wildfires have become increasingly destructive and costly. With a growing population living in the wildland urban interface—the area where forests and human development meet and intermix—the level risk-mitigation on the landscape comes, increasingly, from the sum of the uncoordinated actions of individual landowners. Fuel treatments allow landowners to pay to reduce forest fuels and, in turn, the severity of wildfire damage. Because wildfire spreads across the landscape and ownership boundaries, risk is determined by the spatial pattern of these fuel treatments. To understand the risk of wildfire damage on a landscape, therefore, we must first understand how landowners' risk-mitigating decisions interact. We address the spatial dimension inherent in the wildfire risk management problem with an econometric model that incorporates spatial interactions across landowners. Using fuel treatment data from Florida, USA, we empirically test our spatial econometric model to determine whether landowner interaction is characterized by cooperation or free riding and how ownership fragmentation influences decisions.

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 WUI. During this period, Florida experienced the greatest WUI expansion in the southeastern US with WUI land cover expanding from 14.9% to 19.2% and housing density increasing from 36,408/km^2 to 44,019/km^2 (Zhang et al., 2008).

One important wildfire risk-reduction tool is prescribed fire to reduce the quantity of forest fuels, such as grasses, leaf litter, and dead branches (Graham et al, 1999). Reducing the amount of forest fuels in the WUI reduces wildfire intensity and severity in these populated areas. The State of Florida promotes the use of prescribed fire as a cost-effective method to reduce wildfire risk (Florida Division of Forestry, 2012). In particular, during the 1985 fire season, on federal land in the US South, only 17% of wildfires that burned more than 300 acres occurred in areas where prescribed burns were performed (Florida Forest Service, 2012).

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; Agee and Skinner, 2005). In these settings, neighbors cooperate by undertaking similar risk-mitigating actions. However, it is also plausible that fuel treatment on an individual parcel allows nearby landowners to free-ride and creates a disincentive for others to undertake fuel treatment, as they may perceive they will benefit from their neighbor's fuel treatment. Our research empirically tests for the presence of spatial interaction across landowners and whether it is characterized by cooperation or free-riding.

Many studies have utilized optimization models to analyze fire risk management to gain insight into hazardous fuel reduction treatments as a means to minimize wildfire risk (Omi et al., 2002, Donovan and Rideout, 2003, Amacher et al., 2005, Berrens et al., 2004, Butry et al., 2007, Butry et al., 2002). Amacher et al. (2005) examine landowner behavior to include amount of and timing of fuel treatments. Butry et al. (2002) use a dynamic time-series cross-sectional optimization model to evaluate the statistical correlation between forest wildfire and vegetation management, human land use, and climatic factors. These studies of wildfire risk management and landowner behavior do not, however, incorporate spatial interaction across landowners.

To address the spatial dimension inherent in the wildfire management problem, we develop an econometric model that incorporates spatial interactions across landowners. 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 wildfire risk mitigation when nearby landowners make similar investments. Taking another modeling approach, 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 affects both the location and amount of risk-mitigating activities on the landscape and observe less investment in risk-mitigation 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 prescribed fire treatment, but does not provide empirical evidence of either free riding or cooperative behavior among landowners. Our research builds on Busby et al. (2012), extending the analysis by empirically testing two of the main results. Using prescribed fire treatment data from Florida for the period 2003 to 2010, we test the effect of ownership fragmentation on fuel treatment decisions and provide empirical evidence to characterize the nature of the strategic interaction between landowners over time.

We model landowner interaction using a spatially explicit econometric model. We specify a spatial lag model to test for interactions among nearby landowners, controlling for ownership, environmental, and economic variables. Model results will be of particular interest to public land managers and policy makers. Public land managers will gain insight into the impact prescribed fire on public land has on private landowners' risk management decisions. Policy makers will gain insight into how to design effective policy measures to manage wildfire risk; the optimal location of fuel treatment on public land; where incentive programs for fuel treatment on private land would be most successful; and when fuel treatment requirements on private land might be optimal.

The remainder of the paper is structured as follows. In Section 2, we describe the data and the econometric model. The empirical results are outlined in Section 3. Finally, a discussion of results and concluding remarks are provided in section 4.

2. Data and Econometric Model

To test for spatial interaction in landowners' wildfire risk management decisions, we specify a spatial lag model (Anselin, 1988) describing the prescribed fire decision as a function of physical, environmental, economic, and ownership variables as well as the prescribed fire decisions of nearby landowners. Empirical results will indicate whether individual landowners undertake more prescribed fire when nearby landowners undertake more. Following Shafran (2008) and others (e.g., Case et al., 1993 and Murdoch et al., 1993), we use maximum likelihood estimation to address the simultaneity of prescribed fire choices.

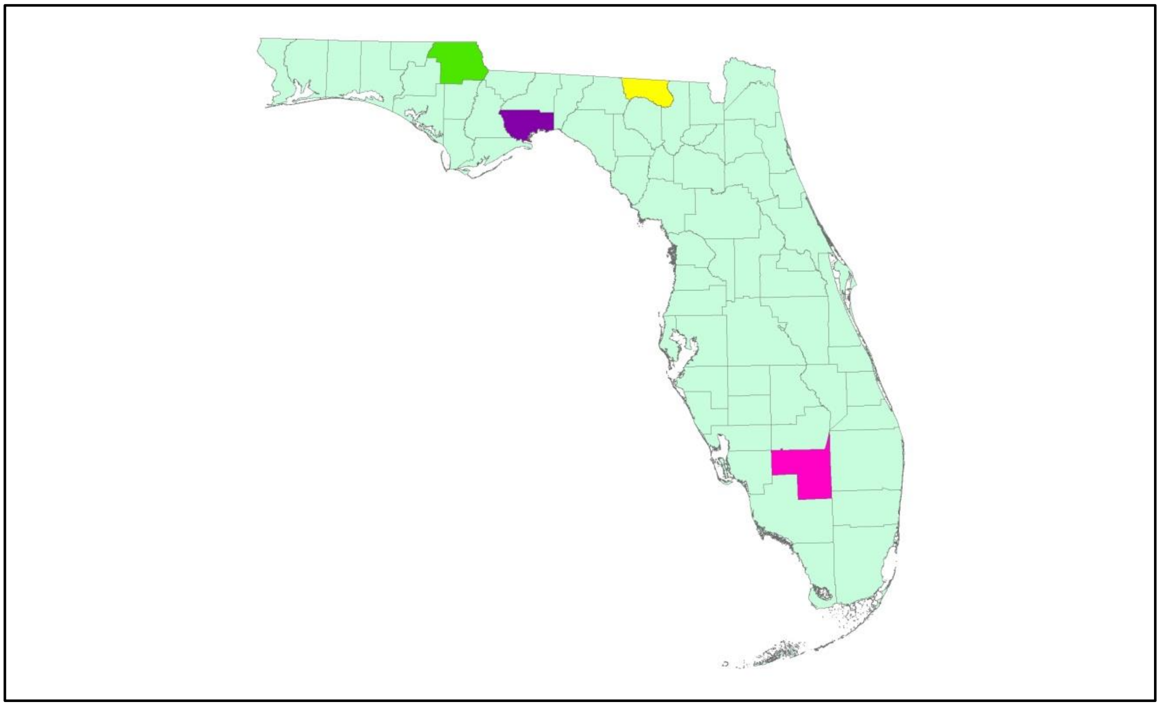
2.1 Data

The dependent variable is the number of acres treated with prescribed fire on parcel *i* and in county *k*. Prescribed fire treatment data were obtained from the Florida Division of Forestry's fire permit records for the period September 2010 to December 2012. Like Mercer et al. (2005) and Mercer et al. (2007), we assume that all permit requests were completed as indicated on the permit. Because we are interested in wildfire risk management decisions, we include only prescribed fire permits with a stated purpose of "Hazard Removal."[1] We focus the present study on prescribed fire outcomes in four Florida counties: Hamilton, Hendry, Jackson, and Wakulla (Figure 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).

Independent variables include: county-level median household income, absentee owner, private ownership, number of acres burned by wildfire in the county one year before the prescribed fire outcome, ownership fragmentation, mean drought metric in county *k* on day of prescribed burn, size of parcel *i* in acres, and vegetation type. We estimate ownership fragmentation as the ratio of ownership boundary length to total area within a 5 mile radius of parcel *i*.

Figure 1: Hamilton, Hendry, Jackson and Wakulla Counties, Florida, USA

[1] Other purposes for requesting a prescribed fire permit include site-preparation, disease control, wildlife management, range management, and biological community restoration and maintenance.



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, by parcel				
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, by County (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 type				
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

2.2 Econometric model

The models of landowner behavior are specified in Equations [1] and [2] and describe the relationship between the prescribed fire outcomes on parcel *i* in county *k* and the chosen independent variables. We first estimate Equation [1] to calculate spatial dependence test statistics in order to justify the use of the spatial lag model, shown by Equation [2]. Unlike Equation [1], the spatial lag model includes a weighted sum of nearby landowners' prescribed fire outcomes. The parameter rho captures the effect of nearby prescribed fire treatments on the parcel *i*'s prescribed fire outcome. A positive coefficient would indicate prescribed fire on an individual parcel makes fuel treatment on nearby parcels more likely, suggesting nearby landowners cooperate in their risk mitigation decisions. And a negative coefficient on rho indicates that the individual landowners tend to free-ride on risk mitigation undertaken by nearby landowners.

$$Acres_{ik} = c + \beta_1 * income_k + \beta_2 * absentee_{ik} + \beta_3 * private_{ik} + \beta_4 * wildfire_k + \beta_5 * frag_{ik} + \beta_6 * KBDI_k + \beta_7 * Pineland_{ik} + \beta_8 * Urban_{ik} + \beta_9 * Wet_{ik} + \beta_{10} * Wooded_{ik} + B_{11} * parcel\ size_{ik} + \varepsilon_{ik} \quad [1]$$

$$Acres_{ik} = c + \beta_1 * income_k + \beta_2 * absentee_{ik} + \beta_3 * private_{ik} + \beta_4 * wildfire_k + \beta_5 * frag_{ik} + \beta_6 * KBDI_k + \beta_7 * Pineland_{ik} + \beta_8 * Urban_{ik} + \beta_9 * Wet_{ik} + \beta_{10} * Wooded_{ik} + \beta_{11} * parcel\ size_{ik} + \rho \sum_{j \neq i} w_{ij} a_j + \varepsilon_{ik} \quad [2]$$

Where

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

$c = constant$

$Acres_{ij} = number\ of\ acres\ treated\ with\ prescribed\ fire\ on\ parcel\ i\ in\ county\ j$

$income_j = county - level\ median\ household\ income\ the\ year\ of\ the\ prescribed\ burn$

$absentee_{ij} = 0,1; if parcel\ i's\ owner\ is\ not\ living\ in\ the\ county, 0\ otherwise$

$private_{ij} = 0,1; 1\ if\ parcel\ i\ is\ privately\ owned, 0\ otherwise$

$wildfire_j$

$= county\ level\ number\ of\ acres\ burned\ by\ wildfire\ one\ year\ before\ prescribed\ burn$

$frag_{ij} = ownership\ fragmentation\ within\ a\ 5\ mile\ radius\ of\ parcel\ i$

$KBDI_j = county\ level\ mean\ drought\ metric\ on\ day\ of\ prescribed\ burn$

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

Wet_{ij}

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

$Wooded_{ij}$

$= 0,1; 1\ if\ wooded\ (mixed\ pine\ hardwood, hardwood\ hamock, bottomland\ hardwood, shrub\ brushland, citrus\ )$

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

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

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

$\rho = effect\ of\ prescribed\ fire\ on\ neighboring\ parcels\ j\ within\ a\ fixed\ distance\ from\ parcel\ i$

$w_{ij} = weight\ of\ prescribed\ fire\ outcome\ by\ landowner\ j\ on\ parcel\ i$

$a_j = landowner\ j's\ prescribed\ fire\ outcome$

$j = number\ of\ acres\ treated\ with\ prescribed\ fire\ on\ parcel\ j$

The choice of the weights matrix is of particular importance because it determines the estimated coefficient for rho. Fire behavior modeling studies find that the fuel condition on adjacent parcels have a greater impact on wildfire damage on an individual parcel than distant parcels. With this in mind, we generate an inverse distance spatial weight matrix, where the weights are larger for nearby parcels and as the parcels get further away, weights approach zero. Spatial weights range from 0 to 1 and the weights matrix has zeros on the diagonal with rows summing to one.

As part of our sensitivity analysis, we specify four distinct spatial weights matrices: W1, W2, W3, and W4. Each weights matrix assigns positive weights to prescribed fire within a fixed radius from an individual parcel *i*. Prescribed fires outside the fixed radius are assigned a weight of zero. We define the four spatial weights matrices W1 to W4 setting radiuses equal to 19,000 meters (11.8 miles), 5,750 meters (3.6 miles), 4,250 meters (2.6 miles), and 3,150 meters (2.0 miles), respectively. When the spatial weights matrix is specified using a shorter radiuses, fewer parcels *j* are assigned a positive weight ($w_{ij} > 0$). By varying the radius length, we are able to determine distance cross-ownership externalities are present.

3. Results

Results of the OLS regression of the prescribed fire decision on economic, environmental, and ownership variables in Hamilton, Hendry, Jackson, and Wakulla Counties are shown in Table 2. The significant Moran's I test statistics for Jackson and Wakulla Counties indicate that spatial dependence is present. We do not find evidence of spatial dependence in Hamilton and Hendry Counties. Following Anselin et al. (1996), we also report results of the Lagrange Multiplier (LM) tests. Significant LM test statistics for both Jackson and Wakulla Counties indicate that both spatial error and spatial lag dependency exist. 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).

Table 2: OLS estimates

	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** (0.011)	-.358 (.429)	-.021 (.018)	.049 (.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)
R2	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 (0.985)	0.010 (0.940)	3.910* (0.048)	49.95*** (0.000)
LM Lag	0.020 (0.892)	0.000 (0.954)	4.800** (0.029)	46.030*** (0.000)

P-values in parenthesis

****significant at 1% level*

*** significant at 5% level*

** significant at 10% level*

Tables 3 and 4 show the results of the maximum likelihood estimation for Wakulla and Jackson Counties and for each of the four previously defined spatial weights matrices. Table 4 shows that rho is positive and significant for all specifications of the spatial lag model estimated for Wakulla County. When the spatial lag model is estimated for Jackson County, Table 3 shows that for all but the most narrowly defined spatial weights matrix, rho is positive and significant. These results provide evidence to support the view that landowners cooperate in their prescribed fire decisions.

Also shown in Tables 3 and 4, the fragmentation metric is negative and significant in both Jackson and Wakulla Counties for all four weights matrices. This indicates that more fragmented landscapes, with many small parcels, are less likely to undertake a prescribed fire on their parcel. This result supports the finding in Busby et al. (2012) that there is less investment in wildfire risk mitigation on landscapes where ownership is more fragmented.

Surprisingly, we find that income is negative and significant for all specifications of the spatial lag model estimated for Jackson County. This result implies that prescribed fire is more likely in years with income per capita in the County is lower. Given that the sample includes only two years of data this result may be an artifact of the limited variation of the income variable. Also for Jackson County, wooded vegetation is positive and significant for all model specifications and area burned by wildfire is negative and significant for spatial weight matrices W1, W2 and W3. Absentee ownership is positive and significant in the spatial lag model estimated for Wakulla County and for the spatial weights matrix W1.

Table 3: Maximum likelihood estimates for the spatial lag model, 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** (462.193)	946.712** (464.060)	926.382* (498.141)	927.782* (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

P-values in parenthesis

****significant at 1% level*

*** significant at 5% level*

** significant at 10% level*

Table 4: Maximum likelihood estimates for the spatial lag model, 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 Metric	-49241.040*** (9656.048)	-60701.62*** (9699.213)	-61142.490*** (9610.605)	-62689.760*** (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	66.319	46.694	39.912

	(107.053)	(110.511)	(110.328)	(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

P-values in parenthesis

****significant at 1% level*

*** significant at 5% level*

** significant at 10% level*

4. Discussion and Concluding Remarks

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.

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. Notably, this piece of legislation 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, but at the time permits were only issued to forest managers of national forests and 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 where prescribed fire was used sharply declined. The decline was partly due to concerns from private landowners about prescribed fire smoke damage and 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 underinvestment in wildfire risk mitigation is most likely. Policy intervention that provides landowners additional incentives or requirements to undertake fuel management may improve outcomes on the landscape. This could be accomplished by providing landowners with financial incentives to undertake fuel treatment on private property or by requiring fuel treatment on private property.

Given the spatial interaction observed in Jackson and Wakulla Counties, prescribed fire on public land would encourage wildfire risk-mitigation on nearby private land. Fuel treatment on public land would simultaneously protect values on public land and lead to more efficient levels of wildfire protection on private land. We would expect that highly-visible or well-publicized risk-mitigating activity on public land would maximize the response from private landowners.

Results from the present study contribute to the body of economic literature informing the development of wildfire policy. Positive spatial interaction among landowners, provides evidence of cooperation in prescribed fire decisions in two Florida Counties. Fuel treatment on an individual parcel increases the likelihood of fuel treatment on nearby parcels, resulting in a more efficient level of wildfire protection. In addition, we find that ownership fragmentation is negatively associated with prescribed burning. We find that as the ownership pattern becomes more fragmented, underinvestment in fuel treatment is more likely. These findings may inform the ongoing dialogue over wildfire management in Florida and other fire-prone regions.