CHAPTER 5

THE PRODUCTION OF LARGE AND SMALL WILDFIRES

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1. INTRODUCTION

Natural large (catastrophic) disturbances are important because of their potential long-lasting impact on their surroundings, but underlying differences between frequent small and less common large disturbances are not well understood (Turner and Dale 1997, Romme et al. 1998, Turner and Dale 1998, chapter 4 of this book). Smaller disturbances may be better understood given their relative abundance, which lends itself more readily for study, but it is, perhaps, more useful to understand the forces driving damaging, catastrophic events. Wildland fires represent a perfect example. Nationwide, over 130,000 wildfires burn more than 4 million acres annually (1960-2002), these fires costing Federal agencies in excess of $768 million a year (1994-2002) in suppression alone (National Interagency Fire Center, http://www.nifc.gov/stats/index.html). Average wildfire size was 31 acres, with a suppression cost of $4800 per fire. The average wildfire does not appear a catastrophic threat, however this ignores the spatial distribution of these fires in relation to values at risk (an averaged size fire in a heavily populated area poses a different risk than a similarly size fire far removed from people and items of value). Catastrophic fire events, while relatively infrequent, do occur with some regularity—the 2000 Cerro Grande fire in New Mexico devastated 47,650 acres, two fire complexes in California in fall of 1999 each burned for three months and consumed a total of 227,647 acres, and during the 1998 Florida summer wildfire season, two fire complexes accounted for 205,786 acres or 9 percent of all wildfire acres, nationwide, in that year (National Interagency Fire Center, http://www.nifc.gov/stats/index.html).

Do the largest fires account for a disproportional amount of the area burned and damage? Is it possible that the largest 1 percent of fires account for 99 percent of the area, as Strauss et al. (1989) explored? For the state of Florida, the largest 1 percent accounted for 67 percent of total area burned with an average fire size of 2,641 acres versus 13 acres for the smallest 99 percent (1981-2001). Understanding the differences between small and large wildfires, including the exogenous factors influencing each, may provide decision-makers with better tools to mitigate future large-scale fire events. It is not necessarily true that large

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disturbances will respond to the same controls that smaller disturbances do (Romme et al. 1998), thus wildfires should be modeled in a way that is flexible to potential differences.

Our objectives in this paper are to examine the wildfires that occurred in the St. Johns River Water Management District (SJRWMD) in Florida between 1996 and 2001. We explore four main questions: (1) Do small and large wildfires behave differently? (2) What are the implications for wildland management decisions? (3) Does spatial information enhance wildfire modeling? (4) Does spatio-temporal scale matter? We are interested in differences exhibited by large and small wildfire regimes—differences in fire damages (area), causes (arson, lightning, and accidents), ignition sources (dominant fuel source), climatic and weather influences, land use and wildland management (fuels management) strategies, landscape characteristics, and spatio-temporal factors (including fire and fuels management on neighboring areas) and their relevance for future mitigation. We use a scale fine enough to allow spatio-temporal effects to be observed, yet at the same time, a scale broad enough to be policy relevant to decision-makers interested in minimizing the damaging effects of wildfire.

We model large infrequent wildland fires separately, those in excess of 1,000 acres, to ascertain whether these potentially catastrophically large fires are fundamentally different, and hence whether they respond differently to various mitigation approaches, than their smaller counterparts. We conclude that there are differences between the two fire regimes and examine factors correlated with the probability that a small wildfire will become large.

2. FIRE MODELING REVIEW

Previous empirical findings show wildfire behavior (whether meaning frequency, occurrence, size, or severity) to be related to four general sets of factors: wildfire specific characteristics, climate and weather, wildland/wildfire management and mitigation, and landscape attributes (including both landuse/landcover and socioeconomic characteristics). We review some of the results below, but first note the rarity of studies that include a full suite of factors from each set (chapter 3).

2.1 Wildfire Characteristics

Wildfire characteristics include factors to explain the *when*, *where*, and *why* of the fire occurrence. This includes factors such as the time of ignition (e.g., year, month, day, hour, or season), some set of locational factors (e.g., latitude and longitude or county), and fire cause (e.g., lightning, arson, or accidental). For instance, year and day variables, perhaps capturing seasonal and daily fluctuations, were found to be related to wildfire (Prestemon et al. 2002, Preisler et al. 2004). Location is important, whether meaning latitude and/or longitude (Donoghue and Main 1985, Preisler et al. 2004) or the geopolitical unit in which the fire ignition occurred (Garcia et al. 1995), which may signal the possibility that wildfires are spatially autocorrelated (Chou et al. 1993). Ignition cause also matters. Prestemon et al. (2002) found evidence that wildfires of different causes (lightning, arson, and accidents) were correlated with different exogenous factors.

2.2 Climate and Weather

Climate has been shown to influence wildfire size and severity in Florida (Barnett and Brenner 1992, Harrison and Meindl 2001, Prestemon et al. 2002, Beckage et al. 2003). The La Niña phase (colder than normal deviations in Pacific sea surface temperatures) of the El Niño Southern Oscillation (ENSO) has been associated with warmer, drier weather, but with more lightning strikes and more wildfire than the El Niño phase (Beckage et al. 2003).

The Keetch-Byram Drought Index (KBDI) provides a measure of organic fuels flammability and is calculated using maximum temperature and precipitation of the previous seven days (Keetch and Byram 1968). The KBDI provides an indicator (predictor) of fire danger (Butry et al. 2002, Goodrick 2002, Janis et al. 2002). Others have found that precipitation (Donoghue and Main 1985), temperature (Chou et al. 1993, Preisler et al. 2004) and humidity (Preisler et al. 2004) are each related to wildfire, with precipitation and humidity being negatively related and temperature positively. Preisler et al. (2004) included KBDI along with temperature into their models and found only temperature to be significant.

2.3 Management

Two dominant ways wildfire management may influence wildfire behavior are through fuels management (i.e., prescribed burning) and suppression. The relationship between prescribed fire and wildfire (either probability of ignition, fire size, or fire severity) has been shown to be negative at very fine scales (Brose and Wade 2002, Outcalt and Wade 2004) and even at very coarse scales (Davis and Cooper 1963, Gill et al. 1987, Prestemon et al. 2002). While prescribed fire has been found to be useful in reducing wildfire it does present users with several challenges, namely conducting prescribed fire on ideal weather days, as to prevent escapes and to limit its negative impacts (e.g., air quality) on local residents (Haines et al. 2001).

Much of the previous fire suppression literature has focused on understanding initial attack and fireline production (Fried and Fried 1996, Hirsch et al. 1998, Hirsch et al. 2004) or using simulations or other techniques to understand initial attack and containment (Donovan and Rideout 2003, Fried and Fried 1996). We know of no empirical research that quantifies the effectiveness of suppression, however defined, on wildfire behavior, at any scale, but especially at a relatively fine scale.

2.4 Landscape (Fuel & Socioeconomic) Characteristics

Landscape characteristics such as measures of landscape composition (e.g., fuel load, forest types, landcover, and landuse) and socioeconomic factors (e.g., population) are related to wildfire. Fuels buildup (Garcia et al. 1995), fuels moisture and susceptibility to burning (Preisler et al. 2004) have been found to be related to wildfire, where fuels buildup and susceptibility to burning were positively related to wildfire and fuel moisture negatively related. The fire spread index (a measure of fire spread potential) and the burn index (a function of potential fire spread and energy release) (Preisler et al. 2004), have both been found to be positively associated with fire probability (Garcia et al. 1995, Preisler et al. 2004).

Softwood and mixed (hardwood and softwood) forest were found to be positively correlated with wildfire occurrence (Zhai et al. 2003), with amount of forest cover (closed forests) to be negatively associated with high severity fires (Odion et al. 2004).

Previous wildfire has been shown to provide a protective effect on future wildfire (Chou et al. 1993, Prestemon et al. 2002), although nearby wildfire has been found to be positively correlated with fire probability (Chou et al. 1993).

Socioeconomic factors, such as population (Donoghue and Main 1985), distance to city (Zhai et al. 2003), and land ownership (Zhai et al. 2003) were found to be related to wildfire.

3. DATA SOURCES AND DESCRIPTION

This analysis focuses on the St. Johns River Water Management District (SJRWMD) located in northeast Florida, which includes portions of 18 counties (fig. 5.1). The SJRWMD was chosen primarily due to its abundance of wildfire, both large and small, within the wildland-urban interface (WUI) and availability of data. Wildfire presence within the WUI creates potentially large values at risk.

Wildfire data used in this analysis are divided into the four general categories outlined above (wildfire characteristics, climate and weather, wildland/wildfire management and mitigation, and landscape attributes).

3.1 Wildfire Characteristics

Data on individual wildfire occurrences were obtained from the Florida Division of Forestry (FDOF). FDOF's wildfire data contains detailed information of fires found on private and state-owned lands including, but not limited to, the date and time of ignition, location (Public Land Survey township, range, and cadastral section), size (acres), and cause (arson, campfires, cigarettes, children, debris burning, equipment, lightning, miscellaneous, railroad, and unknown) from 1981-2001. Fires on federal lands are excluded.

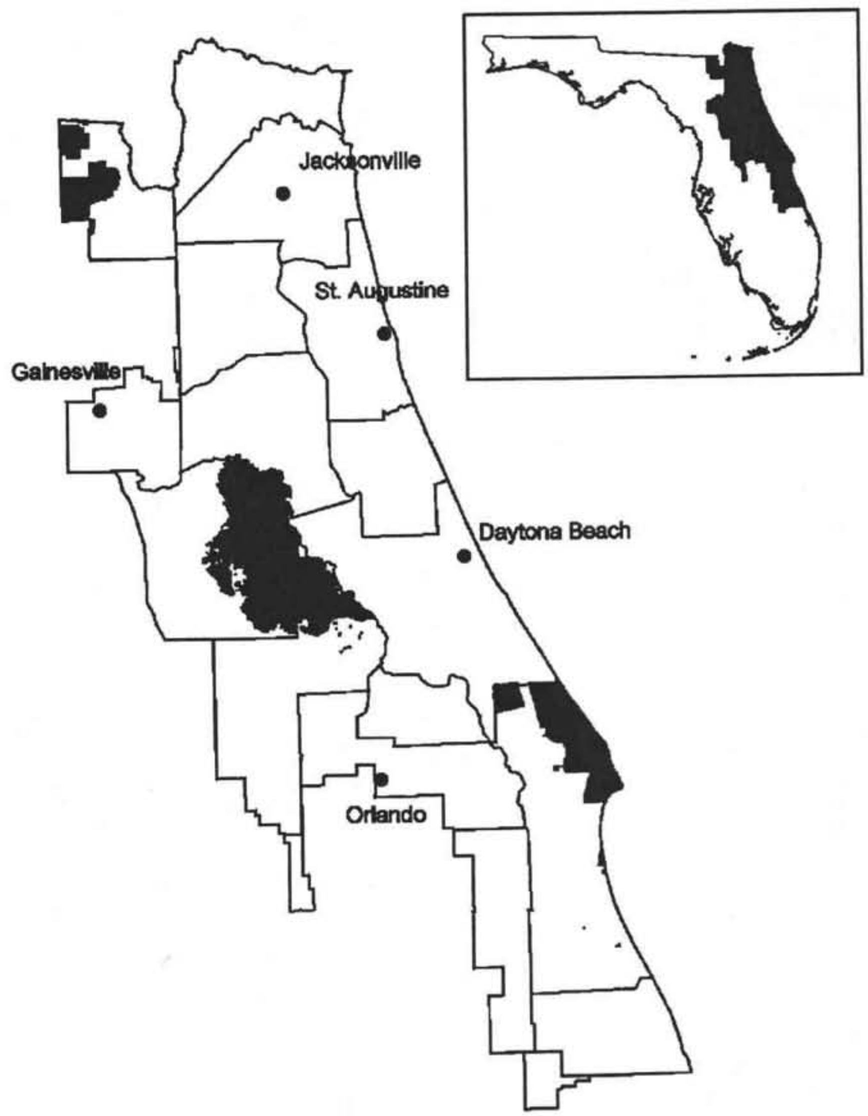

Figure 5.1. The St. Johns Water Management District, Florida. The black shading represents federal lands excluded from the analysis.

3.2 Climate/Weather

The ENSO measure used in this analysis is the Niño3 sea-surface temperature (SST) anomaly, which was obtained from the National Oceanic and Atmospheric Administration (National Oceanic and Atmospheric Administration, ftp://ftp.ncep.noaa.gov/pub/cpc/wd52dg/data/indices/sstoi.indices). The Niño

3 SST anomaly is measured as the positive (El Niño) or negative (La Niña) deviation from a moving average, in Celcius, of the Pacific sea surface temperature (at a specific location). KBDI was calculated for two weather stations in the SJRWMD region using daily data collected by the National Climate Data Center and provided by EarthInfo (2002). Each wildfire record was matched with a daily KBDI value based on its proximity to one of the two weather stations. The two weather stations reside in Volusia County (Deland) and in Duval County (Jacksonville).

The FDOF wildfire database also provides information on the humidity, wind speed, and dominant wind direction (calm, variable, east, north, west, south, northeast, northwest, southeast, and southwest) associated with each individual fire.

3.3 Management/Mitigation

The FDOF provided a second dataset that details all prescribed fire activities within the state (in order to conduct a prescribed burn in Florida, a permit must be obtained from the FDOF). Permit data includes information on the location (located by the township, range, and cadastral section), reason/type (hazard reduction, prior to seeding, site preparation, disease control, wildlife, ecological, or other), and total size (in acres). The dataset includes permits issued between 1989 and 2001.

The FDOF wildfire database also provides information on whether a fire is a "limited action wildfire" (whether a wildfire was allowed to burn). In addition, we use each wildfire start time and fire crew arrival time, from the FDOF database, to create a measure of initial attack/suppression (response time).

3.4 Public Land Survey Township/Range/Cadastral Section (Landscape) Characteristics

Section-level road and census data (population, income, and education) were created from U.S. Census Bureau TIGER/Line GIS data. Fire department location (Florida Department of Emergency Management, http://www.dca.state.fl.us/fdem/) was used to calculate the distance between each section and the closest fire department (straight line distance was used).

National Land Cover Data, based on the Multi-Resolution Land Characteristics (MRLC) Consortium's land cover map (30-meter resolution grid) was used to determine landcover composition within and surrounding each section. Five landcover classes were assembled—grass (grassland/herbaceous), upland forest (deciduous, evergreen, and mixed forest), urban (low intensity residential, high intensity residential, and commercial/industrial/transportation), water (open water), and wetland (woody wetland).

The FDOF database also provided an indicator for the fire district where each wildfire began (fig. 5.1 also depicts fire district boundaries), ignition fuel type (grass, hardwoods, muck, palmetto-gallberry, pine, swamp, and other), and information on fuels moisture (buildup index) and the potential that conditions may have on fire spread (fire spread index).

3.4.1 Descriptive statistics

Table 5.1 provides descriptive statistics of wildfire attributes, climate and weather, management and mitigation, and landscape/section characteristics, as defined above, for large and small wildfires. This table provides statistics based on wildfires occurring in 1996-2001, the period of analysis.

We examine 7,302 wildfires that occurred between 1996 and 2001 in the SJRWMD. These wildfires ranged in size from 0.1 acres to 61,500 acres. Of these 7,302 ignitions, only 53 were greater than 1,000 acres and the majority of large fires (32) occurred during the summer of 1998. Although large wildfires accounted for a mere 0.7 percent of all ignitions, they were a whopping 74 percent of the area burned!

The leading cause of large wildfires was lightning (55 percent), followed by accidents (unintentional human-caused fire—campfires, cigarettes, children, debris burning, equipment, miscellaneous, railroad, and unknown; 28 percent) and arson (17 percent). The leading cause of small wildfires was accidents (43 percent), followed by lightning (32 percent), then arson (25 percent). Roughly, the same percentage of large and small fire ignitions occurred in palmetto-gallberry fuel types (53 percent and 51 percent, respectively) and in pine (15 percent and 12 percent, respectively). A greater percentage of small fires occurred in grasslands (19 percent versus 9 percent) and hardwoods (5 percent versus 0 percent) than large fires. Of the remaining fuel type (swamp/muck/other), a larger percentage of large fires (23 percent) occurred there than small (13 percent).

Comparing large fires to small fires, we find several statistical differences (at the 5 percent level) between the estimated means of several of their attributes. Large wildfires appear to correspond with dry, hot days (larger mean KDBI values) with lower humidity, larger negative Niño3 SST anomaly values (negative values correspond with the La Niña phase), in areas with a greater accumulations of flammable fuels (fuels buildup), a greater propensity to spread (fire spread index), and in areas with fewer roads and fewer, but wealthier, people. It appears that large and small wildfires occurred in areas with similar landscapes, the exception being urban areas and areas under water. Larger fires occurred in areas with less urbanization and more water. Statistically, smaller fires were associated with hazard reducing prescribed burning during the previous year, burning three years lagged, and in neighboring areas during the current year.

3.4.2 Exploratory spatial data analysis

Next, we examine and compare the spatial distribution of the large and small wildfires. In particular, we were interested whether or not large or small fires demonstrate spatial clustering—do fires, either large or small, reside proximately to other fires? Alternatively, do large/small fires seem to occur in the

Table 5.1. Select descriptive statistics—for each variable the mean is shown with the exception of the categorical variables (mode) and the 0/1 variables (frequency).

Variable	Units	Wildfire			
		Large		Small	
		Statistic	*SE*	*Statistic*	*SE*
Area Burned	Acres	6240.1	1522.52	16.1	0.80
Fire Characteristics (X^F)					
1998	Count	32		1399	
Fire Cause					
Arson	Count	9		1834	
Accident	Count	15		3119	
Lightning	Count	29		2296	
Climate/Weather (X^C)					
Niño3 SST Anomaly	Celsius	-0.14	0.02	-0.03	0.01
KBDI	Index, 0-800	558.2	20.07	424.1	2.04
Humidity	Percent	44.5	1.13	48.8	0.16
Wind Speed	MPH	10.0	0.74	9.0	0.06
Management/Mitigation (XM)					
Response Time	Hours	7.7	2.16	3.5	0.11
Let Burn	Count	7		219	
Prescribed Burn (Hazard Reduction)					
Own Section—Current Year	Acres	8.6	6.06	3.9	0.59
Own Section—Lag 1 Year	Acres	0	0.00	3.6	0.52
Own Section—Lag 2 Year	Acres	8.5	5.00	5.6	0.96
Own Section—Lag 3 Year	Acres	1.5	1.03	4.7	1.11
Neighbor Sections—Current Year	Acres	8.9	4.66	18.8	1.40
Neighbor Sections—Lag 1 Year	Acres	68.5	31.07	34.6	2.04
Neighbor Sections—Lag 2 Year	Acres	122.9	74.20	34.8	2.53
Neighbor Sections—Lag 3 Year	Acres	46.3	20.26	39.5	2.73
Section Characteristics (X^S)					
Population Density	People/KM²	15.4	2.58	93.5	2.52
Income	Dollars	31199.5	1238.28	28053.4	104.99
College	Percent	39.2	2.35	35.2	0.18
Roads	Kilometers	4.0	0.76	7.4	0.09
Distance to Fire Dept.	Kilometers	13.5	1.20	14.7	0.14
Buildup	Index, 0-250	68.1	5.67	47.0	0.40
Spread Index	Index, 0-100	27.5	2.24	20.4	0.16
Fuel Type					
Palmetto-Gallberry	Count	28		3682	
Grass	Count	5		1382	
Pine	Count	8		888	
Hardwood (Leafy)	Count	0		353	
Swamp/Muck/Other	Count	12		944	

(continued)

Table 5.1. Select descriptive statistics—for each variable the mean is shown with the exception of the categorical variables (mode) and the 0/1 variables (frequency). *(continued)*

Variable	Units	Wildfire			
		Large		Small	
		Statistic	*SE*	*Statistic*	*SE*
Own Section Landcover					
Grass	Percent	8.4	1.56	8.1	0.12
Upland Forest	Percent	37.0	4.10	35.9	0.29
Urban	Percent	3.7	1.30	15.4	0.26
Water	Percent	1.6	0.48	1.3	0.04
Wetland	Percent	22.8	2.53	17.3	0.18
Neighboring Sections Landcover					
Grass	Percent	8.6	1.09	8.1	0.10
Upland Forest	Percent	37.7	3.33	34.6	0.23
Urban	Percent	3.9	0.85	14.4	0.21
Water	Percent	1.7	0.38	1.6	0.03
Wetland	0-100 %	22.4	1.67	18.6	
	N	53		7249	

same area, year after year? Genton et al. (2006) analyzed the spatio-temporal distribution of the wildfire ignitions (using the same FDOF wildfire data), as a spatial-point process, and found that the degree of spatial clustering varied by year and by cause. They did not examine, however, differences in the spatial structure between small and large wildfires, meaning they did not examine how the spatial clustering was different between small and large fires. Figure 5.2 depicts each fire's location by cause (accident, arson, and lightning) and size for 53 large wildfires that occurred between 1996 and 2001. The majority of large fires were clustered along the coastline, where lightning fires appear to dominate. There were fewer large fires, regardless of cause, farther inland.

The spatial distribution of small wildfires is presented in figure 5.3, which depicts the location and cause of more than 7,000 small wildfires in our analysis. Small lightning fires were clustered along the coastline, similar to their larger counterparts, whereas accidental fires appeared mostly in the interior of the SJRWMD. Although not explicit in the figure, arson ignitions appeared to follow major roadways (especially the I-95, I-10, and I-4 corridors). Unlike large wildfires, small fires were fairly well distributed across the SJRWMD landscape, with a couple of notable exceptions. Areas without wildfires include the St. Johns River, which runs from the Jacksonville area southward to Lake George and that borders another notable void in the figure, the Ocala National Forest (federal data not included in the FDOF dataset), found in the middle of the SJRWMD area. Also, note the Intracoastal Waterway edging the coastline.

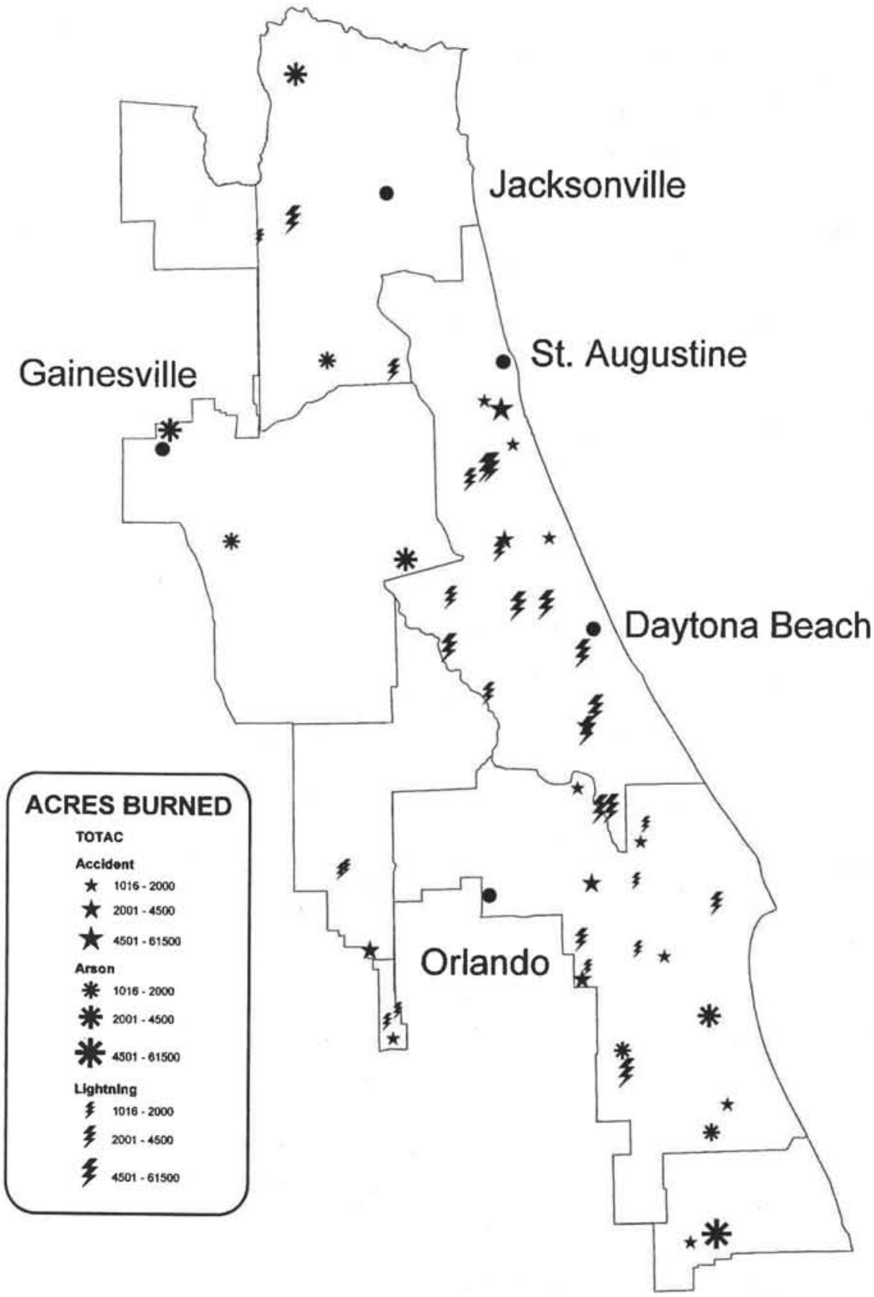

Figure 5.2. Spatial distribution of large wildfires (those fires greater than 1,000 acres) by cause by size from 1996-2001.

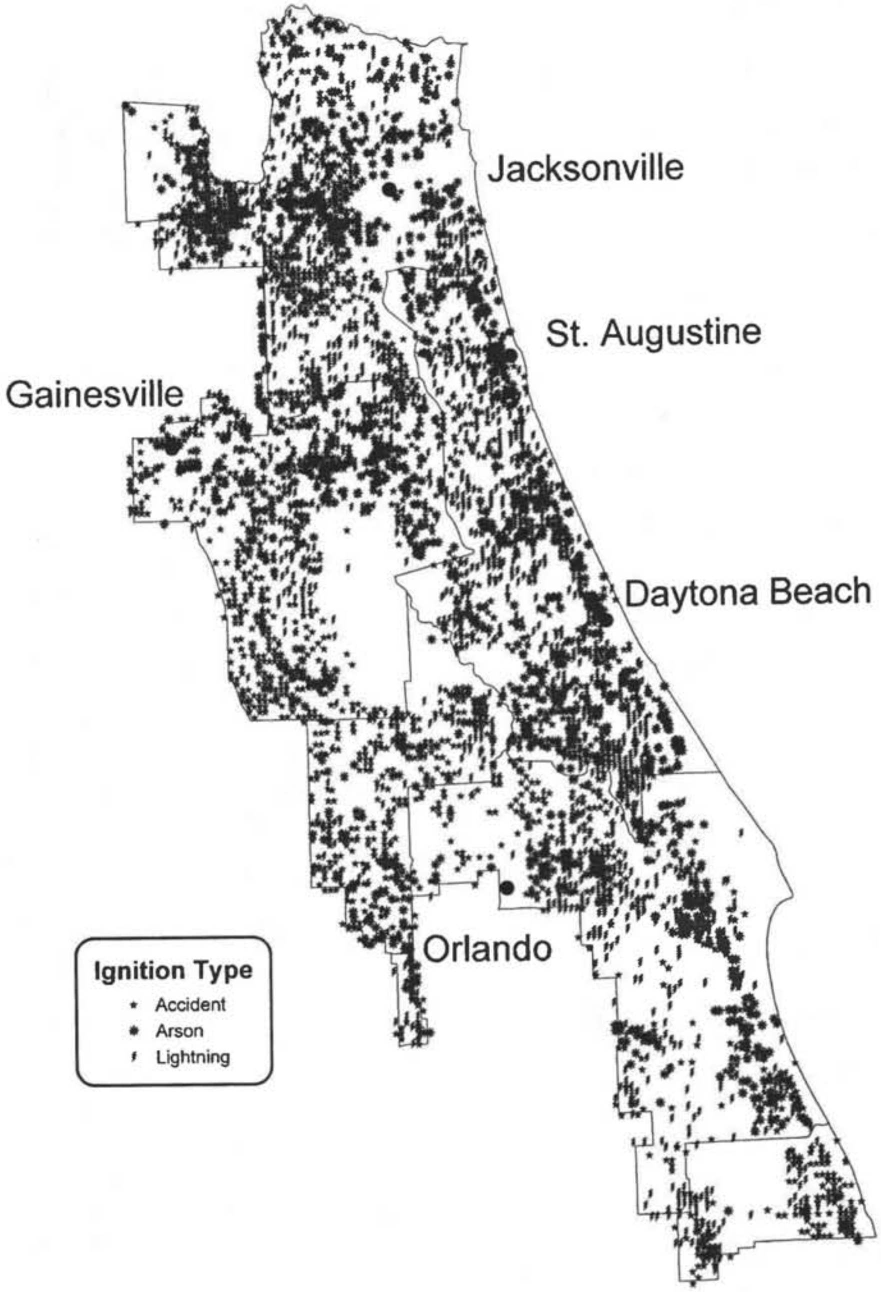

Figure 5.3. Spatial distribution of small wildfires (those less than or equal to 1,000 acres) by cause from 1996-2001.

4. MODELS

Three empirical models are estimated—two estimating the wildfire final size and one estimating the probability that a small wildfire (a wildfire less than or equal to a thousand acres) will become large (a wildfire greater than a thousand acres). Two wildfire size models are used to assess statistical differences between small fires and larger, more catastrophic fires. If there are differences, this implies that large, catastrophic wildfires are not simply big, small fires. Rather, differences might imply that large wildfires respond to different factors (and mitigation strategies) than smaller fires.

4.1 Wildfire Size Models

Wildfire size is modeled as a semi-log function specified as:

$$w = \alpha + X^F\beta^F + X^C\beta^C + X^M\beta^M + X^S\beta^S + Z\gamma + \varepsilon \tag{5.1}$$

where w is a (Nx1) vector of the natural log of wildfire size, α is a constant term, X^F is a (Nxk_1) matrix of k_1 wildfire characteristics, β^F is a (k_1x1) vector of parameters for the wildfire characteristics, X^C is a (Nxk_2) matrix of k_2 climate and weather variables, β^C is a (k_2x1) vector of parameters for the climate and weather variables, X^M is a (Nxk_3) matrix of management variables, β^M is a (k_3x1) vector of parameters for the management variables, X^S is a (Nxk_4) matrix of section attributes, β^S is a (k_4x1) vector of parameters for the section attributes, Z is a (Nxk_5) matrix of variables specifying amount of previous wildfire in the same section or a neighboring section, γ is a (K_5x1) vector of parameters for the previous wildfire, and ε is a (Nx1) i.i.d. error vector. There are k parameters to be estimated ($k = k_1 + k_2 + k_3 + k_4 + k_5 + 1$).

The complete menu of exogenous variables includes:

Fire Characteristics (X^F): start time (morning, afternoon, evening, overnight), start year, and cause (arson, accident, and lightning).

Climate/Weather (X^C): Niño3 SST anomaly (La Niña and El Niño phase), KBDI, humidity, wind speed, wind direction, KBDI interactions (with kilometers of road, wind speed, buildup, La Niña, El Niño, response time, amount of upland forest, wetland forest, water, grass, and urban in the section, and all prescribed burning variables), and wind speed-buildup interaction. Second-order effects allowed for wind speed.

Management/Mitigation (X^M): Response time, limited action fires (let burn), prescribed fire in section and neighboring sections including lags, response time interactions with all prescribed burning variables. Second-order effects allowed for response time.

Section Characteristics (X^S): Population density, income, percent of population who have attended college, amount of road, distance to nearest fire department, percent of landscape and neighboring landscape in grass, upland forest, urban, water, and wetland forest, ignition fuel type (palmetto-gallberry, grass, pine, hardwood, swamp/muck/other), latitude, longitude, buildup, spread index, fire district, amount of previous wildfire in section and neighboring sections including lags, whether the section resided within a GIS "hole"[1], GIS "hole" and 1998 year interaction, GIS "hole" and wetland forest interaction, and GIS "hole" and water interaction. Second-order effects allowed for amount of road, distance to fire department, latitude, longitude, population density, income, and percent of population who have attended college.

The Niño3 SST anomaly variable is separated into two variables, La Niña and El Niño. The La Niña variable equals the Niño3 SST anomaly when it is negative (zero otherwise). Conversely, the El Niño variable equals the Niño3 SST anomaly when it is positive (zero otherwise). This allows us to examine the relationship between these two phases with wildfire size separately. We include the location of the fire (the latitude and longitude of the Public Land Survey section centroid), thereby allowing for spatial variation in wildfire size across the landscape not controlled by the other variables included in the model, as well as year dummy variables (1996 is included in the intercept) and start time (morning, afternoon, evening dummy variables; overnight is included in the intercept). In addition, we use the natural log of population density and income.

Because previous values of wildfire and prescribed burning appear to influence the wildfire size (Prestemon et al. 2002), we include total wildfire acres burned for the previous 12 years (we also include previous wildfire occurring in the same year as the current wildfire, but before the ignition date). For Florida, prescribed burn treatments are thought effective for around three years (Brose and Wade 2002, Outcalt and Wade 2004). Because prescribed burning is performed for several reasons and not all pertain to wildfire reduction, we include two different measures: hazard reduction and other (all non-hazard reducing prescribed burning)

[1] Originally, a Public Land Survey section (PLSS) GIS was obtained from FDOF and spatially matched with wildfire records to various explanatory variables. However, upon further inspection of the GIS it was revealed that there were several wildfires that did not have a match on the GIS (there was not a PLSS id with the same id). While only a relatively small number of wildfires could not be matched, these wildfires accounted for 37 percent of all wildfire acres burned. A new GIS was assembled (North Carolina State University Center for Earth Observation 2002) that is able to locate 98 percent of the ignitions and acres burned. In modeling wildfire size, we include as an explanatory variable a dummy variable that identifies those wildfires that did not have a match in the original GIS. The majority of these wildfires resided in section that are surrounded by or adjacent to water, thus we believe that perhaps these sections may be periodically inundated with water. In Mercer et al. (2000) it was found that many of the large wildfires of 1998 occurred in cypress swamps, areas normally surrounded by water (potentially limiting fire spread), however in 1998, severe drought conditions removed many of the normal wet areas. Thus, we hypothesize fires beginning in one of these "holes" (missing in the original GIS) will become large due to lack of constraints.

prescribed burning. We use two measures of hazard reducing prescribed burning—hazard reducing prescribed burning acres in the current year of the fire (but before ignition) and hazard reducing prescribed burning acres from the previous three years—that are calculated for the same section as the wildfire and for the neighboring section. One measure of other prescribed burning is used—all non-hazard reducing prescribed burning acres from the previous three years including the current year—for the section of the wildfire and the neighboring areas.

The model is made spatially explicit by incorporating latitude, longitude, and neighborhood-level information, including previous wildfire and previous prescribed burning by type in the neighboring cadastral sections. Neighboring sections are defined as those with a centroid distance no more than 2.8 kilometers from the section of reference. Each cadastral section is approximately one square mile with the layout of sections in a fairly regular lattice, so a neighborhood was defined as the eight surrounding sections (contiguous neighbors). Because the lattice is not exactly regular, sections are defined to be neighbors whose centers are no more than 2.8 kilometers apart (roughly 1.7 miles) to ensure that all contiguous neighbors are included.

The wildfire data includes records spanning back to 1981, the prescribed burning data does not exhibit complete (statewide) reporting until 1993 (only a few counties reported prescribed fire permits from 1989 through 1992), so because we include three years of lagged prescribed burning in the model, the analysis includes only those wildfires that occurred between 1996-2001. Two different wildfire size models are estimated based on equation (5.1)—one for small (≤1000 acres) wildfires and another for large (>1000 acres) wildfires.

4.2 Large Wildfire Probability Model

We estimate the probability that a fire will become a large wildfire once an ignition has occurred (conditional large fire probability) using logistic regression. The model is

$$\Pr[Y_i = 1] = \frac{e^{X_i\beta}}{1+e^{X_i\beta}}, \tag{5.2}$$

where $Y_i = 1$ if the fire is large, $Y_i = 0$ if the fire remains small, $X_i = [1, X_i^F, X_i^C, X_i^M, X_i^S, Z_i]$, $\beta = [\alpha, \beta^{Ft}, \beta^{Ct}, \beta^{Mt}, \beta^{St}, \gamma^t]^t$, and i indexes wildfire (the unit of observation). The variables contained in X_i have been previously described.

The small wildfire size model and conditional large wildfire probability model are estimated using backward hierarchical selection, in which terms are dropped from the model if their significance level fails to reach 0.10. Potentially 100 explanatory variables can be included in the models, so the selection significance was set at 0.10 rather than a more customary 0.15 to keep the models parsimonious. The estimation starts by dropping the variable with the largest p-value. The model is re-run until all variables left achieve the 0.10 p-value level, the exception being those terms involved in a higher-order or interaction term. If the interaction term $A \times B$ is significant, then terms A and B must be included in the model regardless of their individual significances. Given the small number of observations in the large wildfire size model, backward selection cannot be used, so instead forward selection is used.

5. RESULTS

5.1 Wildfire Size Models

5.1.1 Small wildfire size model

We find statistically significant links between wildfire size and several exogenous variables (table 5.2). For continuous explanatory variables a positive coefficient indicates that the larger the exogenous variable, the larger the expected wildfire size; for qualitative factors a positive coefficient indicates that the category is associated with a larger wildfire size than a specified reference category. The following variables had significant positive coefficients (10 percent level): fire spread index, limited-action fires (those fires allowed to burn), palmetto-gallberry, grass, and pine fuel types (as opposed to swamp/muck), arson ignitions (as opposed to lightning ignitions), afternoon ignitions (as opposed to overnight ignitions), amount of wildfire in the neighboring sections lagged 1-12 years, and the amount of same section non-hazard-reducing prescribed burning lagged up to 3 years.

We would expect the fire spread index, limited-action fires, and fuel types (as opposed to swamp/muck) to be positively related to wildfire size. We had no prior expectation as to the sign of arson, amount of previous wildfire earlier (reduces fuel, yet proxies a higher probability of ignition), and non-hazard-reducing prescribed burning. Should arson fires be bigger than or smaller than lightning fires? It seems possible that lightning fires are more likely to occur in forested areas far removed from populated regions, thus they have the potential to grow before they are detected. However, lightning strikes are not targeted like arson ignitions are—the arsonist chooses the ignition point (chapter 7, Wildland Arson Management). It seems reasonable that an intentional fire setter would choose areas with a high probability of a successful ignition and for the ignition to become a larger fire. Analysis of the FDOF dataset reveals that the average size of arson fires is smaller than lightning fires; however, the partial effect of arson ignition is larger than that of lightning ignition if we adjust to common values of all other exogenous variables.

The area burned by previous wildfires (1-12 years previous) in the same section perhaps proxies for relative probability of ignition in that section that year. Non-hazard reducing prescribed burning is also correlated with increased wildfire size. While one might surmise that any prescribed burning might reduce the probability of ignition (because fuels material is removed), we find the opposite result.

La Niña, humidity, fire district 10, 14, and 16 (as opposed to district 6), years 1999-2001 (as opposed to 1996), amount of current year hazard reducing prescribed burning in the section, percent of water and wetland in the section,

Table 5.2. Small and large wildfire area model estimates. *Calm wind is the base case for the small wildfire model; however, there are no occurrences of calm winds and large wildfires, so variable wind becomes the base case for the large wildfire model.

	Small Wildfires			Large Wildfires		
Variable	Coefficient	S.E.	P-Value	Coefficient	S.E.	P-Value
Intercept (α)	-1.6879	13.8388	0.9029	0.9994	3.2785	0.7622
Fire Characteristics (β^F)						
Ignition Year (base=1996)						
1997	-0.0086	0.0926	0.9264			
1998	-0.1151	0.0869	0.1850	0.4986	0.2144	0.0256
1999	-0.3028	0.0881	0.0006			
2000	-0.5222	0.0807	<0.0001			
2001	-0.4821	0.0897	<0.0001			
Ignition Time of Day (base=night)						
Morning	0.0924	0.1317	0.4830			
Afternoon	0.2688	0.1193	0.0243			
Evening	-0.1156	0.1250	0.3551			
Fire Cause (base=lightning)						
Arson	0.1955	0.0665	0.0033	-0.6600	0.2487	0.0116
Accident	-0.0758	0.0624	0.2243	-0.5859	0.2183	0.0108
Latitude	-0.0383	0.0168	0.0222			
$(\text{Latitude})^2$	2.9E-5	1.4E-5	0.0394			
Longitude	0.0538	0.0409	0.1883			
$(\text{Longitude})^2$	-4.0E-5	3.2E-5	0.1600			
Climate/Weather (β^C)						
KBDI	-0.0026	0.0005	<0.0001			
KBDI*Roads	2.3E-4	1.2E-4	0.0458			
KBDI*Wind Speed	4.3E-4	1.5E-4	0.0036			
KBDI*Upland Forest	1.8E-5	6.3E-6	0.0044			
KBDI*Grass	2.9E-5	1.2E-5	0.0196			

(continued)

Table 5.2. Small and large wildfire area model estimates. *Calm wind is the base case for the small wildfire model; however, there are no occurrences of calm winds and large wildfires, so variable wind becomes the base case for the large wildfire model. ***(continued)***

	Small Wildfires			Large Wildfires		
Variable	Coefficient	S.E.	P-Value	Coefficient	S.E.	P-Value
KBDI*Urban	1.4E-5	7.5E-6	0.0585			
KBDI*LN(Neigh. Haz. PB Lags 1-3)	-7.0E-5	3.8E-5	0.0706			
La Niña	-0.2942	0.0975	0.0026			
Humidity	-0.0069	0.0018	<0.0001			
LN(Wind Speed)	-0.0949	0.0710	0.1817			
Management/Mitigation (β^M)						
LN(Response Time)	0.5845	0.0383	<0.0001			
(LN(Response Time))^2	-0.1050	0.0130	<0.0001			
Let Burn	0.7875	0.1277	<0.0001			
Own Section PB						
LN(Hazard Lag 0)	-0.0504	0.0216	0.0200			
LN(Other Lags 0-3)	0.0221	0.0130	0.0902			
Neighboring Sections PB						
LN(Hazard Lags 1-3)	0.0181	0.0177	0.3066			
Section Characteristics (β^S)						
LN(Population Density)	-0.1495	0.0445	0.0008	0.1834	0.0755	0.0201
(LN(Population Density))^2	0.0175	0.0069	0.0108			
LN(Income)				0.5421	0.3202	0.0989
Roads	-0.3003	0.0555	<0.0001			
GIS 'Hole'				-0.0779	0.5066	0.8786
GIS 'Hole'*Own Water				0.3407	0.0948	0.0009
Spread Index	0.0088	0.0022	<0.0001	0.0269	0.0069	0.0004
Previous Wildfire						
Own Wildfire Lag 0						
LN(Own Wildfire Lag 0)	0.0297	0.0132	0.0251	0.0847	0.0331	0.0147

(continued)

Table 5.2. Small and large wildfire area model estimates. *Calm wind is the base case for the small wildfire model; however, there are no occurrences of calm winds and large wildfires, so variable wind becomes the base case for the large wildfire model. ***(continued)***

	Small Wildfires			Large Wildfires		
Variable	Coefficient	S.E.	P-Value	Coefficient	S.E.	P-Value
Fire District (base=District 6)						
District 7	-0.1514	0.1850	0.4129			
District 8	0.2283	0.2224	0.3048			
District 10	-0.4080	0.2425	0.0925			
District 11	-0.2918	0.2792	0.2959			
District 12	0.0184	0.2940	0.9502	-0.6088	0.2213	0.0091
District 14	-0.8253	0.4173	0.0480			
District 16	-1.0766	0.4090	0.0085			
Fuel Type (base=swamp/muck)						
Palmetto-Gallberry	0.7339	0.7060	<0.0001	0.0783	0.2300	0.7356
Grass	0.4927	0.0796	<0.0001	-0.7734	0.3868	0.0530
Pine	0.9362	0.0868	<0.0001	-0.5475	0.3351	0.1107
Hardwood (Leafy)	0.1137	0.1182	0.3363			
Own Section Landcover						
Grass	-0.0120	0.0061	0.0492			
Upland Forest	-0.0105	0.0032	0.0012			
Urban	-0.0177	0.0036	<0.0001			
Water	-0.0152	0.0069	0.0277	0.0255	0.0316	0.4249
Wetland	-0.0037	0.0019	0.0582	0.0236	0.0054	<0.0001
Neighboring Sections Landcover						
Grass	-0.0126	0.0046	0.0063			
Upland Forest	-0.0057	0.0023	0.0137			
F Value	15.26		0.0003	6.81		<0.0001
R^2	0.16			0.73		
Number of Observations	7249			53		

and percent of grass and upland forest in the neighboring sections are all significantly negatively (10 percent level) related to wildfire area. We would expect humidity, La Niña, hazard reducing prescribed burning, and percent water in the section to be negatively related to fire size. As mentioned earlier, La Niña has been found to be positively correlated with fire in previous studies (Prestemon et al. 2002), which is what we find here. Hazard-reducing prescribed burning is targeted to areas for the express reason to reduce wildfire probability. The more a section is composed of water, the less burnable material is present. We have no prior expectations for the effects of fire districts or years on wildfire size.

A number of variables exhibit non-linear relationships with natural log of wildfire area. Response time, latitude, longitude, and population density all exhibit second-order effects. Increases in response time correspond with increases in wildfire size, up to 16 hours, where then it corresponds with decreases. Approximately 93 percent of all small fires are responded to within 16 hours. Increases in population density correspond with decreases in wildfire size, up to 71 people per square kilometer, where then it corresponds with increases in fire size. About three-quarters of all small wildfires occur in areas with population density less than 71. Population has at least two (opposite) influences on wildfires, one as an ignition source (arson and accidental ignitions), and two, as a source of fire detection. Also related to the second, with larger population we would expect greater fire fighting resources and capability. Wildfire size decreases going north, all else being equal, up to latitude 4 kilometers north of St. Augustine, beyond which it increases. Wildfire size increases going east, all else being equal, up to a longitude 13 kilometers west of Daytona Beach, beyond which it decreases.

Several statistically significant interactions exist between KBDI and other variables: roads, wind speed, percent of the section that is upland forest, grassland, and urban and hazard reducing prescribed burning acres from the previous three years in neighboring sections. Evaluating these variables at their means, we find that increases in KBDI reduce the expected size of wildfire. We expected KBDI to exhibit a positive relationship with wildfire size, which it does not at the means of the other interaction terms. However, a positive relationship does exist between KBDI and wildfire size for different combinations of the interaction terms. For example, if wind speed is set somewhere above its mean (with everything else held at its mean), then wildfire size increases with KBDI. For wind speeds at or above 14 mph, KBDI and wildfire size are positively related.

With KBDI set at its observed mean, wildfire size increases as wind speed and percent of the section in grass increases, whereas increased amounts of road, either upland forest or urban area in a section, and amount of neighboring hazard-reducing prescribed burning from the previous three years are negatively related with wildfire size. Figure 5.4 shows how the marginal effect of the natural log of prescribed burning on wildfire size changes for different levels of KBDI. Under medium-to-high drought conditions (KBDI>259), previous prescribed fire in the neighbors is correlated with smaller wildfire size, and the magnitude of this relationship increases as the drought index increases.

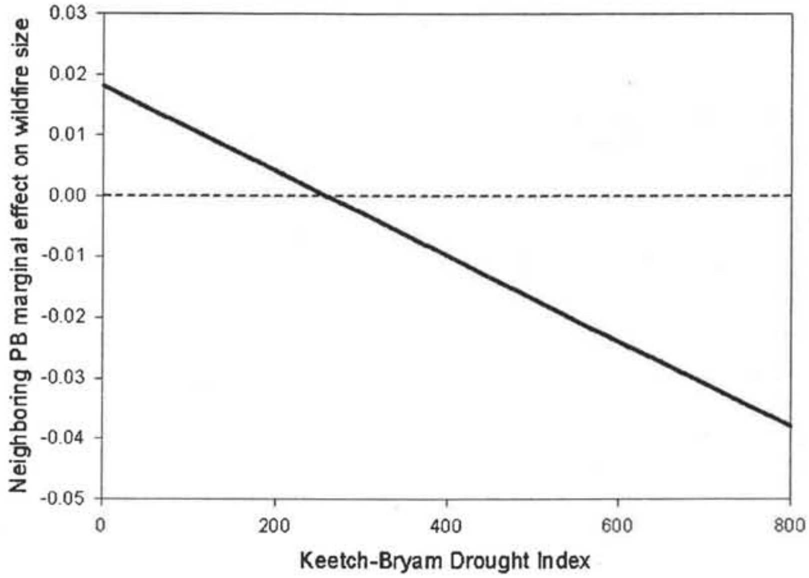

Figure 5.4. Marginal effect of small wildfire acre from an acre change in neighboring section prescribed burning, lagged 1-3 years, conditioned on KBDI.

Although we have found many significant predictor variables, a large proportion of the total variance in wildfire size remains unexplained. The model accounts for only 16 percent of wildfire size variation (table 5.2). We examine the residuals for the presence of spatial dependence using both regular and robust semivariograms of the residuals, for all years combined and then by year. When all years are included in one semivariogram, spatial dependency appears to exist. Pairs of neighbors that are, on average, no farther than 10 kilometers apart (lag distances are in meters) appear to be correlated. When the residuals are examined by year, it appears that all years, except 1999-2001, exhibit a white noise process, or no spatial dependence.

5.1.2 Large wildfire area model

We estimate the model of equation (5.1), but restrict the data to only large wildfires (those greater than 1,000 acres). The model explains 73 percent of the variation in large wildfire size and is highly significant (table 5.2). We find that population, spread index, 1998, percent of section in wetland forest, and amount of previous wildfire (1-12 years prior) have a significantly positive (to the 10 percent level) correlation with the size of large wildfire.

The fire spread index is a measure of potential fire spread, thus it makes sense that it should be positively correlated with larger fires. The 1998 wildfire season was quite notable for many large fires occurring during a six-week period in June and July, with 32 of the 53 large fires in our analysis beginning in 1998.

Grassland, fire district 12, and arson and accidental ignitions are found to have a significantly negative (to the 10 percent level) effect on the size of large wildfires. In addition, there are no instances of large wildfires beginning in hardwoods or occurring with calm winds. Grassland, fire district 12, and arson and accidental ignitions entered the model all as dummy variables. For grassland, the base case is swamp/muck/other fuel types. The base case for fire district 12 is all other fire districts in the SJRWMD, and the base case for arson and accidental ignitions is lightning ignitions.

There is an interaction between GIS "hole" and amount of water in the section that is statistically significant. Mercer et al. (2000) contends that 1998 was such a catastrophic year because areas that are usually under some standing water were arid due to the hot and dry conditions, thus increasing the potential wildfire connectivity and intensity across the landscape. Hence, the GIS "hole" would no longer be wet, and would no longer act as a natural firebreak. This coupled with the high fuel loads in these areas imply that GIS "holes" should be positively related to fire size.

A semivariogram analysis, like that discussed in the previous section, showed no spatial correlation among the residuals after fitting the regression model. All years were combined for the semivariogram analysis because there were only 53 large wildfires in all years combined.

5.1.3 Conditional large wildfire probability model

We use a backwards hierarchical logistic model (again, using a significance level of 0.10) to estimate the probability that a small wildfire will become large. The model explains 32 percent (pseudo R^2 from SAS Proc Logistic) of the variation of large versus small fire and is highly significant (table 5.3).

We find that the La Niña, natural log of income, fuels buildup, limited action fires, wind speed, percent of neighboring section in upland forest, and 1998 are significantly (10 percent level) positively related to the probability of a wildfire becoming large. We expect that increases in La Niña (linked to fire weather), fuels buildup, limited action fires (fires are allowed to burn), wind speed (quicker boundary spread), and 1998 increase the likelihood of a large wildfire. We have no prior expectations for income or upland forest in neighboring sections.

El Niño, latitude, and percent of urban areas in neighboring sections are statistically significantly (10 percent level) negatively associated with large wildfire probability. We also find an interaction between KBDI and percent of upland forest in the section, where KBDI exhibits a positive relationship with the probability of a large wildfire for percent of upland forest values in excess of 24 percent (note: the mean is 36 percent). Thus, areas with at least 1/4th of the land cover in upland forest experience higher probabilities of large, catastrophic fire probability, given an ignition, when KBDI rises. About half of all sections in the SJRWMD are covered by at least 24 percent upland forest. We also find an interaction between fire crew response time and current year hazard mitigating

Table 5.3. Conditional large wildfire probability model estimates. *Standardized coefficients are calculated in SAS as $\hat{\beta}_i/(s/s_i)$ where $\hat{\beta}_i$ is the estimated coefficient of the i[th] explanatory variable, s_i is the i[th] explanatory variable's sample standard deviation, and s is $\pi/\sqrt{3}$ when computing the standardized coefficient for a logistic regression. They are not computed for the intercept orfor the interaction terms.

Variable	Coefficient	S.E.	P-Value	Odds Ratio	Standardized Coefficients*
Intercept	-12.1708	5.4839	0.0265		
Fire Characteristics					
1998	1.4617	0.3824	0.0001	4.3130	0.3199
Latitude	-0.0086	0.0025	0.0006	0.9910	-0.4066
Climate/Weather					
KBDI	-0.0032	0.0015	0.0298		
KBDI*Upland Forest	1.36E-4	4.6E-5	0.0031		
La Niña	5.7364	1.5054	0.0001	309.9360	0.9071
El Niño	-6.7036	2.9025	0.0209	0.0010	-2.7508
Wind Speed	0.0644	0.0181	0.0004	1.0660	0.1748
Management/Mitigation					
LN(Response Time)	0.3870	0.2532	0.1264		0.2288
LN(Response Time) *LN(Own Haz. PB)	0.2165	0.1124	0.0540		
LN(Response Time) *LN(Neigh. Haz. PB)	-0.1686	0.0680	0.0132		
Let Burn	1.9797	0.4784	<0.0001	7.2400	0.1890
Own Sections PB					
LN(Hazard Reduction Lag 0)	-0.1227	0.2700	0.6495		-0.0681
Neighboring Section PB					
LN(Hazard Reduction Lag 0)	0.0437	0.0763	0.5668		0.0512
Section Characteristics					
LN(Income)	1.2835	0.5026	0.0107	3.6090	0.7859
Buildup	0.0092	0.0035	0.0092	1.0090	0.1716
Own Section Landcover					
Upland Forest	-0.0958	0.0307	0.0018		-1.2892
Neighboring Sections Landcover					
Upland Forest	0.0316	0.0148	0.0331	1.0320	0.3493
Urban	-0.0746	0.0225	0.0009	0.9280	-0.7427
Likelihood Ratio (Chi-Square)	194.0171				
Pseudo R-Square	0.3183				

prescribed burning (in the same section and neighboring sections). Holding the two prescribed burning variables at their means, we find that the probability of fire becoming large increases with firecrew response time (fig. 5.5). If the response time is short, prescribed burning is negatively correlated with probability of a large fire, but if the response time is longer than about an hour and 20 minutes, prescribed burning in the section of ignition has no effect (fig. 5.6). On the other hand, if the response time is long then the probability of a large fire is negatively correlated with the amount of prescribed burning in sections adjoining the section of ignition (fig. 5.7).

We also report the odds ratio and the standardized coefficients (beta weights). The standardized coefficients imply that a one-standard deviation change in an exogenous variable is associated with a one-standard deviation change in the log-odds of the response variable multiplied by the standardized coefficient. The odds ratio describes the effect of a one-unit change in the odds of a large fire. For instance, if La Niña decreases by one-unit, then the expected odds of a large wildfire, given an ignition, increases by 310. Note that while the change in odds from a one-unit change in La Niña is large, the range of La Niña in the data is 0 to -1.61 with the mean being -0.29.

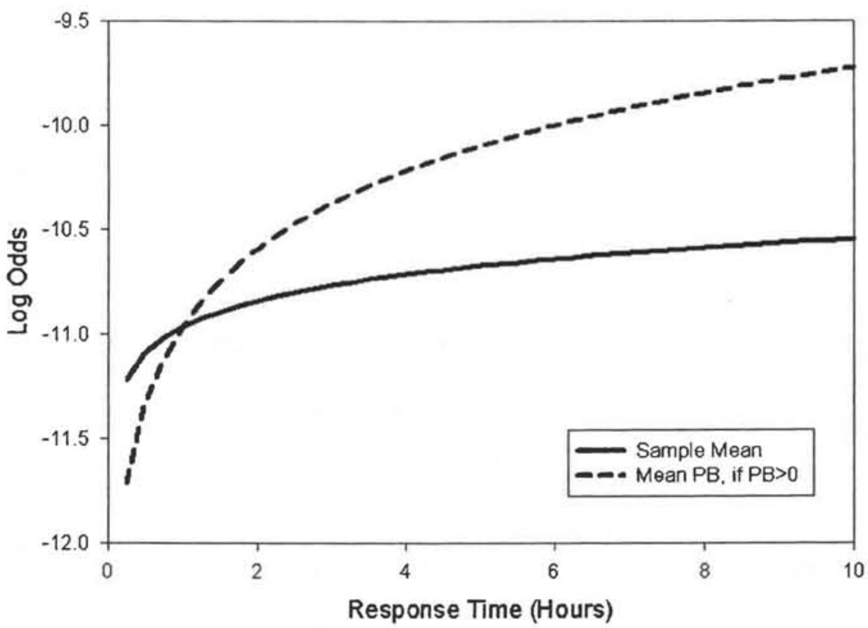

Figure 5.5. Response time versus log odds of catastrophic wildfire (from conditional large wildfire probability model) with (1) all explanatory variables set to their means, then (2) all explanatory variables set to their means except their own and neighboring section hazard mitigating prescribed burning, which is set to their means when there has been a prescribed burn (i.e., conditioned on PB>0).

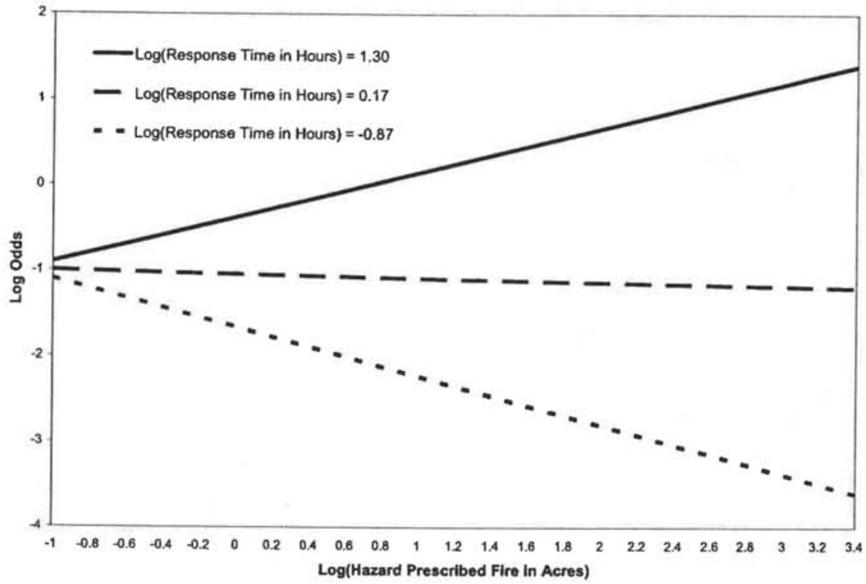

Figure 5.6. Predicted log odds of a large fire versus hazard reducing prescribed fire, varying firecrew response time.

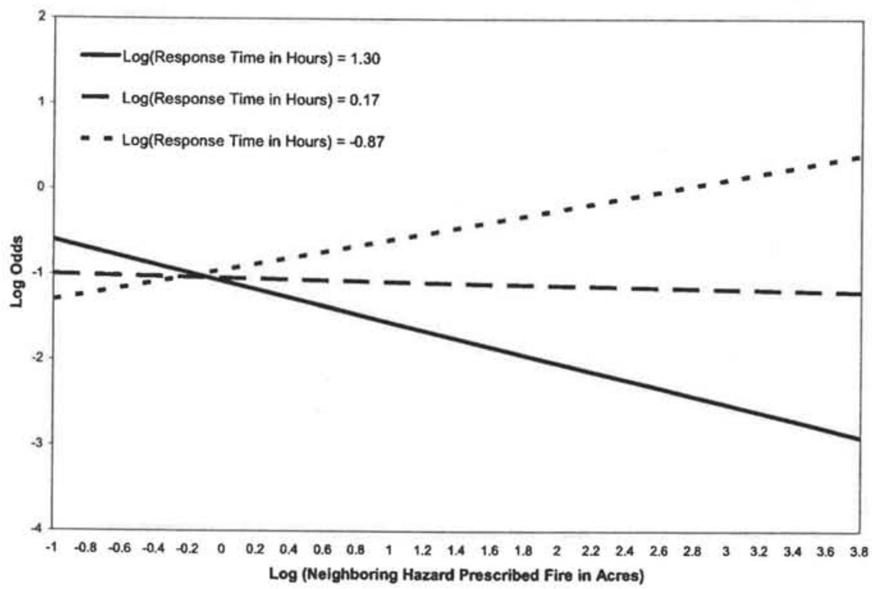

Figure 5.7. Predicted log odds of a large fire versus hazard reducing prescribed fire in the neighborhood, varying firecrew response time.

6. DISCUSSION

6.1 Does Spatial Information Enhance Modeling?

Incorporating spatial information into the wildfire models adds significant information and increases the amount of explained variation in wildfire size. For instance, removing some of the spatial variables (latitude, longitude, fire district, and neighborhood measures) reduces the amount of the explained variation of small wildfire size by 21 percent; removing the spatial variables (GIS "hole" and its interaction term) reduces the explained variation of large wildfire size by 11 percent.

6.2 What Does Fine Scale Modeling Add?

We use wildfire occurrence as the unit of observation, rather than an aggregated measure of wildfire (e.g., annual county or state level), which allows a finer exploration of the relationships between wildfire and others variables than at a coarser aggregated level. At a fine spatio-temporal scale, we find evidence that a wide range of factors matter, including fire specific characteristics, climate and weather conditions, management decisions, and landscape composition. We find strong empirical support for hazard reducing prescribed burning as mitigating wildfire size that occurs in the same section as the wildfire, at least when fires stay small, whereas at broader scales the evidence was shown to be weak (Prestemon et al. 2002).

6.3 Do Small and Large Wildfire Differ?

Our models suggest that small and large wildfires are truly different processes, related to a different set of factors. Interestingly, the two models have very few significant variables in common. If we regress small wildfire size on the set of exogenous factors found significant in the large model, they explain less than 1 percent of the variation in small wildfire size. It does not appear that large wildfires are simply small wildfires, only bigger, but something fundamentally different. This suggests that techniques used to mitigate small wildfires may not be appropriate for large wildfires.

6.4 What are Possible Management Implications?

Wildland management (as defined in this analysis) appears to have the greatest effect on reducing the likelihood that fires will become large (1,000 acres or more), and for those fires that stay small, management has the effect of mitigating final fire size (in acres). When fire crews cannot respond fast enough, perhaps when there are multiple fires, prescribed fire in surrounding areas limit ultimate fire size, thus retarding the probability that a fire will become large. In addition, prescribed fire was found to mitigate the effects of drought conditions on the probability of large fires. Keeping fires manageable is important, and unfortunately, we find no evidence that large wildfires respond to wildland management (again, as defined in this analysis). Instead, large fires appear sensitive only to weather and landscape conditions.

Ultimately, society may care less about fire size than fire-related damages. If acres burned by wildfire are closely related to wildfire-caused damages, then the above analysis provides insight into damage minimization and the role for fire management. However, if acres burned by wildfire are only loosely related to wildfire-caused damages, then the above analysis may underestimate the true effect wildfire management has on wildfire-caused damage.

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