Economic Effects of Catastrophic Wildfires:

Assessing the Effectiveness of Fuel Reduction Programs for Reducing the Economic Impacts of Catastrophic Forest Fire Events

By:

D. Evan Mercer, John M. Pye,

Jeffrey P. Prestemon, David T. Butry,

and Thomas P. Holmes[1]

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[1] SRS4851, Southern Research Station, 3041 E. Cornwallis Road, Research Triangle Park, NC 27709

http://www.rtp.srs.fs.fed.us/econ/

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Chapter 1: An Economic Analysis of Florida Wildfires

D. Evan Mercer, John M. Pye, Jeffrey P. Prestemon,

Thomas P. Holmes, and David T. Butry

Introduction

In reaction to the catastrophic wildfires during the summer of 1998, the worst wildfire season in Florida in recent memory**,** a variety of policy and programmatic changes have been proposed for reducing the probability of future catastrophic wildfires in Florida. Most of the proposals involve various intensities and means for implementing fuel reduction programs. For example, the Governor's Wildfire Response and Mitigation Review Committee recommends that pubic land management agencies implement aggressive and comprehensive prescribed burning programs on public lands and provide incentives for private landowners to develop pro-active fuel management strategies. One bill being drafted for the Florida Legislature in 1999 would give the Division of Forestry authority to prescribe burn any area of land (including private property) that the division reasonably determines to be in danger of wildfire. Although fuel reduction treatments may provide benefits in terms of reducing the probability of catastrophic wildfire, the treatments (particularly if initiated on a large scale) may also generate potentially large external costs in Florida, e.g. impacts of smoke on tourism, human health, and quality of life.

Our objective in this project is to use the recent history of wildfire in Florida to evaluate the efficacy of fuel reduction treatment policies and programs for reducing the economic impacts of catastrophic forest fires. To achieve this objective, we apply spatial and econometric analysis to the 1998 fire season in northeastern Florida and to a multi-decade analysis of fire patterns across the State. In this report, we present results of the following three analyses:

1. quantification of landowner and societal damages from the 1998 fire season in northeastern Florida (Chapter 2),

2. identification of stand and neighborhood factors associated with forests burned in 1998, including prescribed burning history (Chapter 3), and

3. statewide analysis of landscape to regional scale factors associated with total wildfire area and size distribution, including the frequency of prescribed burning permits (Chapter 4).

Together these analyses help to identify the magnitude of public concern over wildfires, isolate which policies might be effective in mitigating damages from future severe fire years, and aid forecasting of where and when such events might recur.

A better understanding of how human and natural factors influence wildfires in Florida may produce large economic payoffs. An accurate assessment of the overall net benefits of human efforts to influence the extent and character of wildfires requires a thorough understanding of the effectiveness of fuel reduction treatments. Accurate economic assessments, however, require an understanding of how vegetation management (including burning), wildfire suppression, characteristics of the landscape, and weather patterns interact to determine the level of catastrophic losses due to wildfire. Figure 1 is a graphical display of how wildfire area is determined each year and its effects.

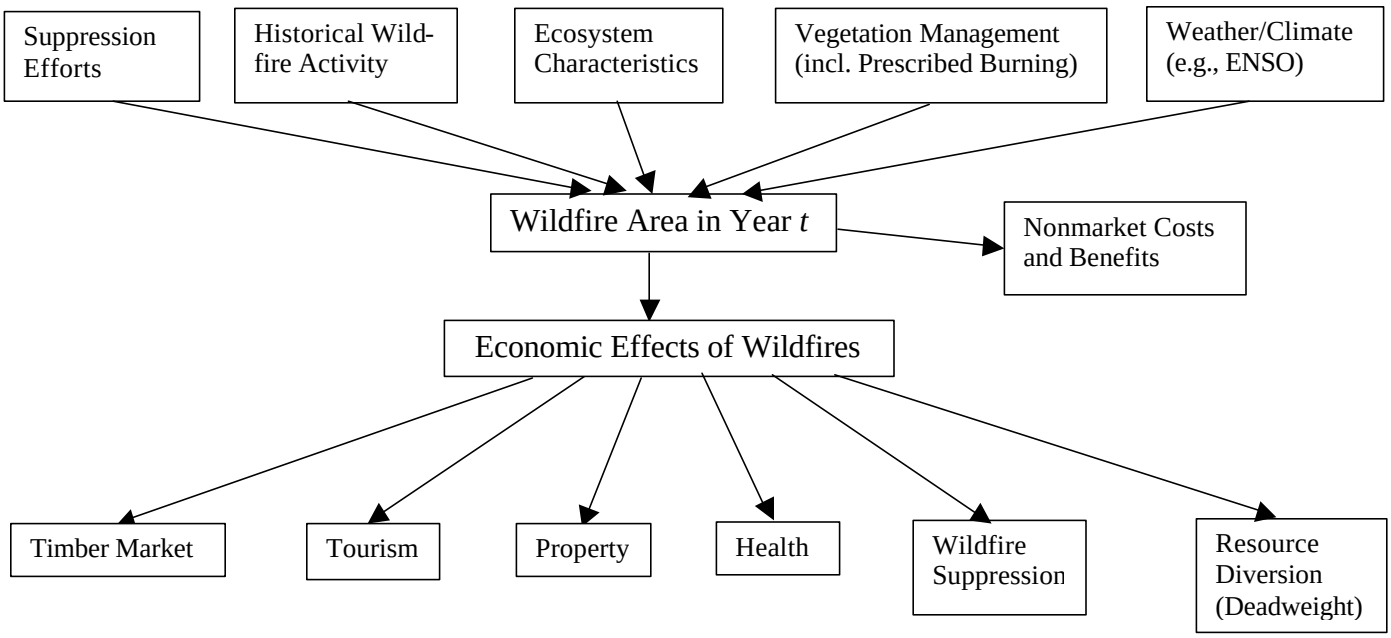

Figure 1.1 The determinants and economic costs of the area of wildfire in Florida.

Attempts have been made to understand how El Niño-Southern Oscillation (ENSO) patterns influence the area of annual wildfires in Florida (Brenner, Barnett). Others (e.g., Hesseln et al. 1998, Malamud et al. 1998, Keeley et al. 1999, Cochrane et al. 1999, Li et al. 1999) have examined size and frequency distributions of wildfires to improve wildfire forecasts and understanding of the role of prescribed burning. While data availability limited the scope of these analyses, several questions were left unanswered. First, Florida wildfire forecasting models using ENSO measures did not incorporate information on prescribed burning activities. Second, with the exception of Gardner et al.'s (1999) survey, empirical and theoretical analyses have not addressed how wildfire distributions are affected by human activities, including landscape fragmentation, active suppression, and vegetation management techniques such as prescribed burning. Finally, no attempts were made to identify the temporal dynamics of wildfire size-frequency distributions, a requisite for accurate forecasting models.

The research presented in this report, examines how human activities influence wildfire size, frequency, and temporal dynamics. We begin in Chapter 2 by examining some of

the costs of wildfires in Florida focusing on the 1998 fires, which illustrate the extent and nature of wildfires in extreme years. Then in Chapter 3, we use available data on the size and location of the 1998 fires and the landscapes in which they occurred to examine wildfire behavior under extreme conditions. Finally in Chapter 4, we evaluate a range of climatic and ecological conditions and the degree and extent of human activities in Florida over a longer time span (1983-1998) to place the 1998 fires into a larger context. This longer temporal analysis seeks to clarify how human activities can affect wildfire levels in extreme years, as compared to other years, and to put a value on those activities.

The Economics of Human Intervention

Net benefits of fire-related human activities can be evaluated from the perspectives of the landowners carrying them out and the larger public. Prescribed burning, for example, produces both private and public benefits and costs. Individual timber producers prescribe burn to enhance timber stand growth, improve physical access to stands for intermediate treatments, and to reduce risks of wildfire and pest-related losses. Other forestland owners may prescribe burn to increase forage production for grazing animals, improve habitat for game and non-game wildlife, and reduce their risks of catastrophic property loss. Geographic neighbors may also benefit from the activity if prescribed burning reduces the risk of wildfire in nearby stands. Similarly, the general public may benefit from prescribed burning if it reduces property losses, wildfire suppression costs, and negative health effects of catastrophic wildfires. From the perspective of timber markets, smaller annual catastrophic losses of timber may translate into increased production, higher land values, and, hence, increased consumer and producer surplus. Reducing the size and extent of catastrophic wildfires may also produce increased esthetic benefits enjoyed by the general public. Costs of prescribed burning include the direct expense to the landowner carrying out the burn; the losses associated with occasional escaped prescribed fires into surrounding lands; the negative health effects of increased air pollution; the temporary reduction (but perhaps long-run enhancement) in esthetic value of the landscape; and the general equilibrium costs to the rest of the economy in marshalling the economic resources required to carry out the activity.

The prevalence of prescribed burning in Florida implies that the net benefits of prescribed burning are positive for individual landowners carrying out the activity, which can be evaluated formally using an economic model of private net benefits. Timber producers prescribe burn for several reasons, including:

- to improve timber growth rates and reduce timber crop tree mortality in established stands by killing competing vegetation,
- to reduce tree mortality by depressing local populations of alternate hosts of diseases,
- to improve physical access to the stand for intermediate and final stand treatments, and
- to reduce the risk of catastrophic loss from wildfire.

The first two can be grouped into a category called “net growth enhancement,” the third “management or harvest cost reduction”, and the fourth “risk reduction.”

We model the decision to prescribe burn consistent with a Faustmann (1849) type model, as developed by Martell (1980). These models ignore non-market costs and benefits of forest management and the external (public) costs and benefits generated by management activities of the landowner. In this sense, the model maximizes the wealth of the landowner and not the welfare of the landowner or the larger public. We modify the Martell model by introducing parameters that describe the effectiveness of prescribed fires in reducing wildfire risk and in increasing growth. We also introduce a term that describes the salvage rate for stands affected by wildfire. We assume, consistent with Martell, that a stand affected by wildfire is killed, requiring a forestland owner to salvage and replant the stand in the year immediately following the wildfire. The model applies to even-age forests, which is consistent with most timber management in Florida.

The model maximizes the soil expectation value, V, over time (the optimal rotation age) and input quantities, subject to prices. Inputs include, in our most simplified version, prescribed burning and replanting costs. The results from the maximization problem identify the optimal combination of inputs, including time (the optimal rotation length, T^*) and prescribed burning (L^*), and optimal output quantity (q^*). The unit price of capital, a non-choice variable implicit in the analysis, is set at the alternative rate of return, r (the annual rate of return from comparably risk-adjusted non-land investments). Risk of wildfire is denoted $\Delta_i(L)$ and the salvage rate is set by s ($0 \leq s \leq 1$), which is the product of the volume salvage rate and the proportional price reduction. The maximization problem can be stated formally as:

(1)

$$\max_{T,L} V = \{[1 - \sum_{t=1}^{T} r_t(L)][Pq(T,L) + V]a^T\} + \{[\sum_{t=1}^{T} r_t(L)(sPq(T,L) + V)a^t]\} - wL - C$$

where $a = e^{-r}$.

Equation (1) is a discrete time, dynamic optimization problem that is solved by searching across the possible combinations of nonnegative T and L that obtain a maximum value of V. In concise economic terms, the optimum of V is found where the marginal increase in land value equals the cost of the last unit of prescribed burning input, i.e. where marginal timber revenue equals marginal prescribed burning cost. The value of that marginal unit is determined by the marginal effectiveness of prescribed fire in both increasing growth rate and lowering risk. As long as the cost of the first unit of prescribed fire input is less than the value it imparts to the land, then some nonzero level of prescribed burning will be optimal.

Cubbage and Redmond (1985) imply that lower expected mortality from catastrophic losses produces higher land values. Lowered risk effectively extends the length of optimal timber rotations in a way similar to reducing the discount rate used in economic optimization calculations (Weitzman 1994). Lowered risk should produce more prescribed burning than would occur if prescribed burning affected only timber growth and not risk. Fredericksen et al. (1991) show that southern pine growth responses to competing hardwood vegetation suppression are significant and positive, implying that vegetation management such as prescribed burning may increase expected timber

quantities. Little is known, however, about the value of prescribed burning in reducing catastrophic risk.

A brief review of Florida's recent wildfire history reveals that wildfire has been a significant problem in some locations and at some times. Between 1983-1998, Florida experienced an average of approximately 100,000 acres of wildfire annually. Relative to the 11.8 million acres of forest, the average annual risk of forest fuel type wildfires was approximately 0.86 percent, or one in 117. Over the 30-year time span of a typical slash pine rotation, the expected risk of wildfire occurring is 26 percent. Statewide, the average annual rate of prescribed silvicultural burning permits issued between 1993-1998[2] (assuming 100% completion rates), was 374,000 acres, which implies an average annual prescribed burning rate of 3.16 percent, or one out of every 32 acres. Spatial variation of these rates are substantial. For example, annual wildfire risk varied at the county level from 0.02 percent to 6.9 percent, while prescribed burning rates varied from 0.2 percent to 30.8 percent. Statewide, wildfire burned a scant 0.2 percent of forests in 1983 and 4.0 percent in 1998, while silvicultural burning permits covered 2.9 percent of forests in 1993 and 3.6 percent in 1996. This kind of spatial and temporal variability in wildfire and prescribed burning should enable detailed statistical analyses that control for factors that vary over space and time (climatic, ecological, and human factors) to estimate the overall effectiveness of prescribed burning in reducing wildfire risk.

Equation (1) suggests a way to calculate the optimal level of prescribed burning for a risk-neutral, timber producer. Since non-market and external effects are not included in equation (1) the optimal level for society at large may differ. Clearly, though, equation (1) shows that calculating the ultimate benefits of prescribed burning requires knowledge of how prescribed burning directly affects the risk of catastrophic loss. Chapters 3 and 4 attempt to quantify this effect using three different approaches: evaluating how stand conditions and wildfire history affected the risk of wildfire during 1998 (Chapter 3), and determining how prescribed burning in a region affects a region's risk of catastrophic wildfire in that region (Chapter 4).

At the landscape-level, fire management agencies are faced with making decisions regarding expenditures for pre-suppression and suppression activities. Economic analysis of efficient fuel management and fire suppression effort at a programmatic level generally utilizes the least-cost-plus-net-value-change model initially proposed by Sparhawk in 1925. In this model, an increase in pre-suppression cost (P) is associated with a decrease in suppression cost (S) and a decrease in net resource damage (eg., see Gorte and Gorte 1979; Bellinger, Kaiser and Harrison 1983; Rideout and Omi 1990). Net resource damage is the difference between resource value lost (D(P,S) which is shown in the bottom row of Figure 1.1) and any potential benefits from fire (B(P,S), which is shown as Nonmarket Benefits in Figure 1.1). The optimal program is the program that minimizes the sum of pre-suppression and suppression costs plus net value change. Assigning a wage for presuppression (w^p) and suppression (w^s) related labor inputs, the minimum cost plus net value change model can be written as:

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[2] Although data for wildfires were available from 1983, the State of Florida was only able to provide data for prescribed burning permits since 1993.

(2) $\text{Min } (C + NVC) = w^p P + w^s S + D(A_F(P,S)) - B(A_F(P,S)$

where $A_F(P,S)$ is the number of forest acres burned by wildfire.

Economic efficiency analysis cannot proceed, however, unless the fire production function $A_F(P,S)$ relating fuel management inputs and fire "outputs" are known. In addition to presuppression and suppression costs, fire production inputs include potentially complex conditioning factors shown in the top row of Figure 1.1 such as number of ignitions (I), land use characteristics (L), weather patterns (W), vegetation management history (V) and ecosystem characteristics (E). That is, the traditional economic efficiency model needs to consider potentially complex fire production functions conditioned on environmental and ecological inputs exhibiting spatial and temporal dynamics:

(3) $A_{F,t} = f(P_t, S_t| I_t, W_t, A_{,F,t-k}, V_{t-k}, E_t)$.

Unfortunately, detailed "fire production functions" that link inputs and outputs are not known for most ecosystems, including Florida's forests. Consequently, this report focuses attention on identification and quantification of temporal and spatial factors influencing fire production functions in Florida (Chapters 3 and 4).

Chapter 2: The Economic Effects of the 1998 Florida Wildfires

David T. Butry, D. Evan Mercer, Jeffrey P. Prestemon,

Thomas P. Holmes, and John M. Pye

Introduction

In Northeast Florida approximately 500,000 acres were burned by wildfires during the summer months of 1998. The fires engulfed federal, state, local, and privately held land, mostly in the St. John's River Water Management District (SJRWMD), which include the counties of Alachua, Baker, Brevard, Clay, Duval, Flagler, Indian River, Lake, Marion, Nassau, Okeechobee, Orange, Osceola, Polk, Putnam, St. John, Seminole, and Volusia (Figure 2.1). See Table 2.11 (at the end of Chapter 2) for a list of the acreage burned in all affected Florida counties.

The goal of this chapter is to estimate the economic costs of these wildfires. We refined the preliminary cost estimates by Price Waterhouse Coopers (PWC) for the suppression effort, property losses, losses in tourism and retail sales, and extend their estimates by assessing the timber market effects and pollution costs related to health. For this analysis whole counties are used rather than ignoring portions of counties that do not fall within the SJRWMD boundary. Table 2.1 provides a summary of the costs.

Figure 2. 1 Florida counties with shading indicating the St. John's River Water Management District.

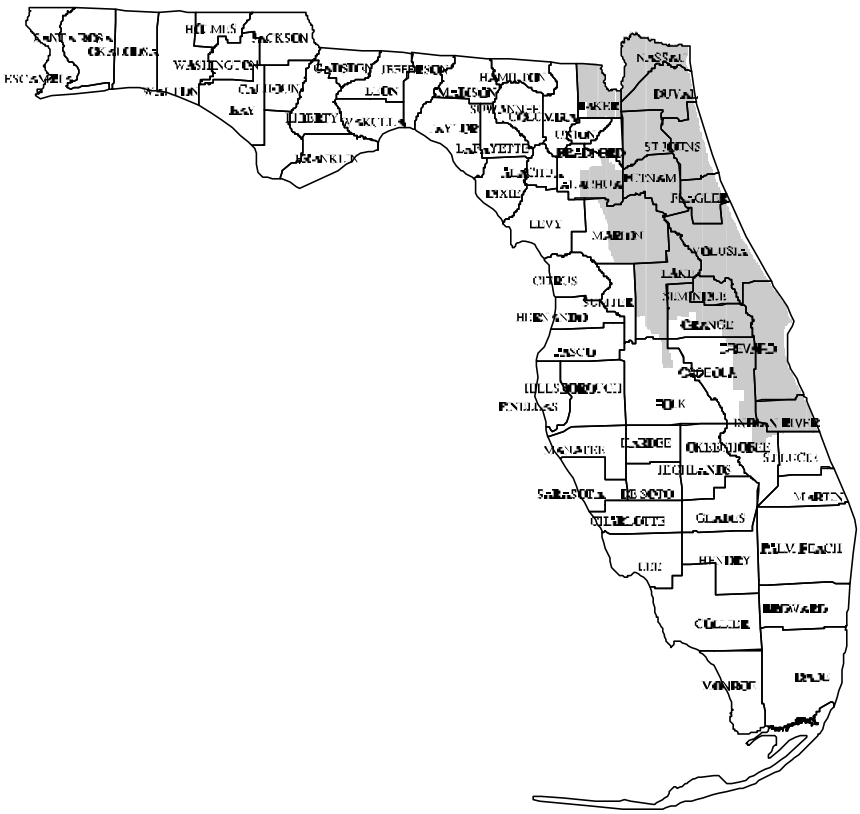

Table 2.1 Economic costs ($ million) of the wildfires in the SJRWMD

Wildfire Costs	
Timber	354 - 605
Suppression Effort	
Federal	>100
Disaster Relief	
Federal	15 -18.75
State&Local	5 - 6.25
Property Losses	10 - 12
Tourism	138*
Public Health	n/a
Total Estimated Costs**	**622 - 880(+)**

*Losses occuring during June, July, and August

**Gross sales and state sales tax receipts increased during the fire months (June & July) totaling roughly $1.7 billion while falling $553 million in August.

Timber Market Effects

Natural catastrophes such as wildfires may have short- and long-run effects on timber markets. Short-run effects include the absolute loss of timber that is killed and unsalvaged. But because at least some killed timber is salvaged, timber markets are confronted with a glut of salvage material that drives prices downward temporarily. Research by Holmes (1991) and Prestemon and Holmes (2000) has documented the short-run price drops caused by gluts of salvage material entering timber markets, and these drops persist for several months. Long-run effects on timber markets are caused by the loss of a large portion of immature standing inventory, a loss that tends to drive prices upward and that provides a windfall for owners of undamaged timber. Prestemon and Holmes (2000) found that the elimination of greater than 10% of the inventory in a region can drive up prices in the long-run. Because Hurricane Hugo damaged up to 20 percent of standing inventory in coastal South Carolina, prices increased by more than 10% for both sawtimber and pulpwood standing timber.

The analyses done by Holmes (1991) and Prestemon and Holmes (2000) relied on statistical techniques that could identify the magnitude of the catastrophe on timber market prices. Their techniques required long periods of price data corresponding to several years of price observations prior to the catastrophe and several years of price observations after the catastrophe. Because the 1998 wildfires are a very recent phenomenon, then, determination of the market effects of the 1998 wildfires must depend on established relationships between timber supply and demand and on estimates of the quantities of timber salvaged, timber killed and unsalvaged in the region of the 1998 Florida wildfires.

The goal of this section, therefore, is to use established structural supply and demand techniques and methods outlined in the literature to arrive at estimates of price and welfare effects of the 1998 wildfires in northern Florida. To do this, we use estimated

supply and demand elasticities as reported by Newman (1987) and established welfare economics approaches to calculating changes in consumer and producer surplus for the timber sector. Our approach is partial equilibrium, ignoring any feedback effects that may occur between the timber sector and other sectors. It utilizes production data obtained from the United States Forest Service for northern Florida (Brown 1996) to calibrate the supply and demand equations derived from Newman (1987), and timber salvage and loss data obtained from large industrial producers and the state of Florida; salvage amounts for nonindustrial private forestland owners were set to zero, and losses for that group were estimated using GIS techniques and average standing volume data obtained from the state of Florida and forest industry.

Approach

Figure 2.2 is a graphical representation of the northern Florida timber market, showing the shift in supply and the glut of salvage of either sawtimber or pulpwood stumpage offered to the market. Before the 1998 wildfires, equilibrium was at point a, the intersection of the supply curve based on the original available inventory, $S(I_0)$, and demand, D, establishing a price P_0 and a quantity Q_0. During the first period after the fires, the time of timber salvage, a glut of damaged material, V, entered the pulpwood and sawtimber markets. This material was combined with the undamaged timber (Q_U) offered from the new supply curve, $S(I_1)$. This new supply of timber was based on a smaller inventory (I_1) and intersected the demand curve at point b, establishing a short-run price of P_T and quantity Q_T. The salvage volume, V, gradually shifted toward the price axis as the salvage material was exhausted. In our analysis, we assumed that 5/8th's of the salvaged volume was recovered in the first period after the fires (the third quarter of 1998), 3/8th's in the fourth quarter of 1998, and 1/8th in the first quarter of 1999. After the salvage was exhausted, the new equilibrium, based on the new supply curve, was found at point c, a price of P_1 and a volume per quarter of Q_1.

Before proceeding with a description of the results of the pine timber market welfare analysis, it is useful to review the extent of timber damages caused by the 1998 wildfires in northern Florida. Data in Table 2.22 (located at the end of this chapter) describe the level of pine and hardwood inventory, average annual timber removals by sawtimber and pulpwood, and losses and salvage amounts deriving from the 1998 wildfires in northern Florida. The table shows that approximately 16% of pine sawtimber and 10% of hardwood sawtimber inventory in northern Florida was killed by the 1998 wildfires. For pulpwood, 19% and 16% of pine and hardwood inventories were lost, respectively. Of the sawtimber and pulpwood inventories lost in 1998, approximately 24% and 23% of pine and hardwood were salvaged (applying to both sawtimber and pulpwood). These salvage quantities amounted to half to more than twice the average annual removals for the region, implying that both pine and hardwood timber markets faced gluts of salvage materials for several months after the fires ended.

Based on the methods outlined above, then, both pine and hardwood markets were likely to have experienced both a short-run price drop, due to the salvage glut, and a long-run price rise, due to the reduction in timber inventories. Although the following welfare analysis is focused on the pine sector, then, we would expect similar short-run and long-run behavior of prices and similar kinds of welfare changes for hardwood sector in Florida. Our lack of reliable hardwood price data and applicable econometric estimates of

price and inventory elasticities for that part of the timber sector prevents us from making those estimates, however.

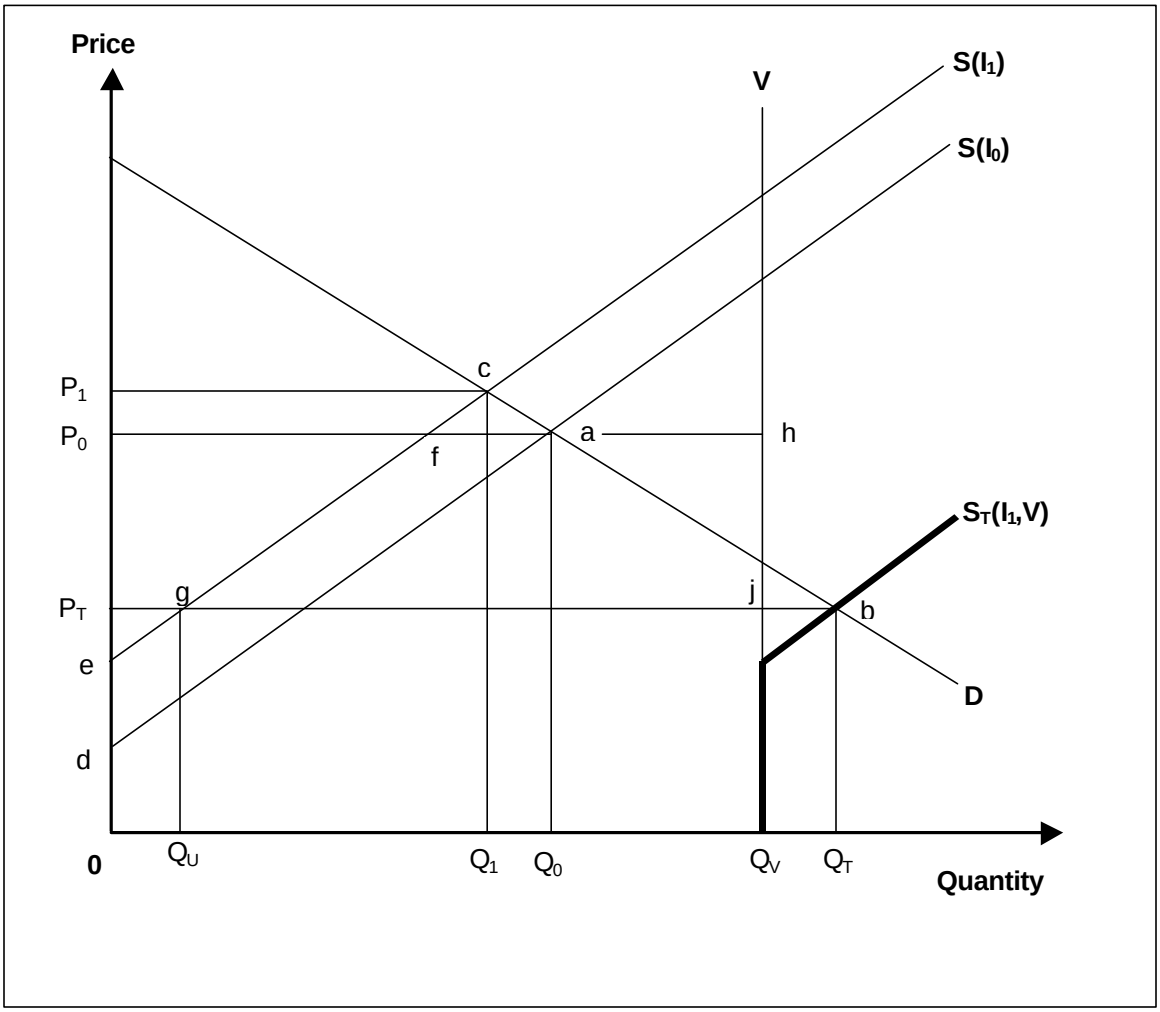

Figure 2.2 Supply and demand short-run equilibrium for salvage and timber from undamaged stands. The equilibrium immediately preceding the 1998 wildfires corresponded with a price P_0 and a quantity Q_0 (point a) based on a supply curve, $S(I_0)$, that was a function of inventory volume of I_0. Immediately after the fires, the underlying undamaged supply curve was $S(I_1)$, based on a new (smaller) inventory of I_1. The equilibrium was at P_T and Q_T (point b). The volume of salvage, V, and the volume of undamaged timber, Q_U, comprised the supply quantity. The salvage volume, V, gradually shifted back over time, until it disappeared, leaving a new, long-run equilibrium of supply and demand at price P_1 and quantity Q_1 (point c). Short-run welfare changes each period were as follows: surplus change for timber consumers = P_0abP_T; surplus change for owners of undamaged timber = $-P_1cgP_T$. In the long-run, welfare changes each period were: surplus change for timber consumers = $-P_1caP_0$; surplus change for owners of undamaged timber = P_1cfP_0. Each quarter, owners of salvaged damaged timber suffered welfare changes, as well, amounting to P_0hjP_T.

Welfare effects of the 1998 fires were calculated based on the short-run losses and gains experienced by producers and consumers during the salvage period and the long-run losses and gains experienced by timber consumers and producers of undamaged timber. Long-run losses and gains were calculated based on a 3% real discount rate. Welfare effects were calculated only for pine timber; hardwood timber sector welfare changes, arguably smaller because of lower timber prices, were probably economically significant. Slopes and intercepts of supply and demand curves were based on elasticity estimates reported by Newman (1987). Because there is some uncertainty regarding the actual elasticity figures for northern Florida, we performed a sensitivity analysis, multiplying supply and demand elasticities times 0.5 and 1.5.

Results

The 1998 wildfires had overall negative effects on the northern Florida market for pine timber. Estimates of the losses (Table 2.2), based on sensitivity analyses on assumed elasticities and a 3% real discount rate, range from $354 million to $605 million. We emphasize that these losses ignore the hardwood timber market. Effects on that portion of the northern Florida economy are probably smaller but likely are greater than $100 million. Table 2.2 shows, as well, that the 1998 wildfires had important redistributional effects. First, owners of salvaged material experienced a value loss that amounted to $36 to $69 million. Second, owners of unsalvaged fire-killed timber lost $319 million. Third, owners of undamaged pine timber lost in the short-run, due to lower prices, but will more than make up for that in the long run because of higher prices (Table 2.3), with long-term total gains of between $34 million and $186 million. Consumers of pine sawtimber and pulpwood, while gaining during the salvage period due to the influx of fire-killed material, will have long-run losses, due to higher prices paid, that outweigh the early gains; their ultimate losses will be from $21 million to $403 million, depending on the elasticities used to calculate them.

Table 2.2 Losses and gains in value and consumer and producer surplus caused by Florida's 1998 wildfires in the Saint John's Water Management District ($ million 1999), assuming a real discount rate of 3%.

	Point Estimates of Price Elasticities			Point Estimates of Inventory Elasticities	
	Inventory Elasticity			Price Elasticity	
	x 0.5	x 1.0	x 1.5	x 0.5	x 1.5
Change in Producer Surplus for Owners of Undamaged Stands	34	84	136	186	53
Change in Value of Salvaged Material	-48	-48	-47	-69	-36
Absolute Losses of Unsalvaged Material	-319	-319	-319	-319	-319
Consumer Surplus Changes During Salvage Period	-21	-135	-225	-403	-74
Total Change in Consumer and Producer Surplus	-354	-418	-454	-605	-375

Notes: Inventory and price elasticities were from Newman (1987). Negative numbers denote welfare losses and positive numbers denote welfare gains. Numbers in bold are midpoint estimates, based on the actual elasticities estimated by Newman (1987).

Price deviations, in dollars and in percentage terms, for each quarter are shown in Table 2.3. This table is based on the elasticity estimates of Newman (1987), so it is understood that there is some error around the price and percentage changes reported. In the first quarter, pine sawtimber prices had a negative departure from what they would have been had the 1998 fires not occurred. This departure was $156. In subsequent quarters, the departure became positive, to $15/mbf, or 5%, above what it would have been without the wildfires. Pulpwood prices dropped by $14/cord in the initial stages of salvage, but they recovered quickly, within six months, to rest at $20 above what they would have been had the 1998 wildfires not occurred.

Table 2.3 Price effects of the 1998 wildfires on northern Florida pine sawtimber and pine pulpwood stumpage, based on Newman's (1987) elasticity estimates.

Period	Pine Sawtimber		Pine Pulpwood	
	$/mbf	Percent	$/cord	Percent
1998, Quarter 3	-156.32	-56	-13.92	-31
1998, Quarter 4	-106.39	-38	-4.86	-11
1999, Quarter 1	-26.12	-9	17.48	39
1999, Quarter 2 and later	15.1	5	20.42	45

Note: Percent changes are percent departures from expected prices for the period, based on a sawtimber price of $280/mbf and a pulpwood price of $44.9/cord.

Suppression Costs[3]

FEMA approved two funding sources for fire suppression and related logistics for Florida's effort in 1998. The first source was the Fire Suppression Assistance Program (FEMA-2201-FSA-FL), which covered the bulk of fire fighting related costs. This program covered the following costs:

- Field camps and meals in lieu of per diem
- Use of publicly-owned equipment
- Use of Federally-owned equipment
- Tools, materials, and supplies expended or lost (less insurance proceeds)
- Replacement value of equipment lost (less insurance proceeds)
- Personal comfort and safety items for firefighter health and safety
- Mobilization and demobilization costs
- State costs for suppressing fires on Federal lands

3 This section draws exclusively from statements made June 21, 1999 by Lacy E. Suiter, Executive Associate Director Response and Recovery, and John B. Copenhaver, Regional Director, Region IV, FEMA to US House of Representative Committee on Resources, Subcommittee on Forests and Forest Health and Committee on Transportation and Infrastructure, Subcommittee on Oversight, Investigations and Emergency Management. See http://www.fema.gov/library/lib10c.htm.

- Fire suppression assistance grant administration costs

As of June 1999, FEMA approved more than $50 million for the Fire Suppression Assistance Program, however they expect final costs to exceed $100 million. The Federal government is reimbursing 100% of these costs. Much of these costs went to reimburse

- 2,265 USDA Forest Service personnel for strike teams, aviation, bulldozer, engine, hand crews and overhead teams
- Leasing of 18 fixed-winged aircraft, 20 helicopters, 97 bulldozers, 210 fire engines (including brush trucks, city and wildfire engines from out of state, and water tankers)
- Gear for 3,700 firefighters
- Airlift of 65 engines from the West Coast
- Airlift of South Dakota EMAC fire team

President Clinton declared a major disaster within the region, which "covers emergency measures for State and local governments that were not eligible under the Fire Suppression Assistance Program." The major disaster designation (DR-1223-FL) provided a second source of funds for:

- Emergency operations centers
- Evacuations
- Debris removal
- Direct federal Assistance
- Reimbursement of local government and volunteer firefighting departments
- Staging of Federal and State resources
- Use of police for barricading and traffic control

DR-1223-FL also provided funding for individual and family grants, temporary housing, disaster unemployment assistance, inspections, and crisis counseling.

FEMA has approved approximately $10 million for DR-1223-FL, but it is expected that final costs will reach $20-25 million. The Federal government will fund 75% of the final cost with the State and local governments contributing the remaining 25%, or about $5-$6.25 million.

Property Losses

Property losses include losses to homes, business, and automobiles. An estimated 340 homes, 33 businesses, and several cars and boats were damaged by the wildfires totaling between 10-12 million dollars [4]. These estimates include losses to insured property only, and it is probably conservative as there stands to be uninsured property losses. A

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[2] 10 to 12 million dollars as quoted from Sam Miller from the Florida Insurance Council by Jim Saunders, Florida Times-Union, September 8, 1998, per www.jacksonville.com/tu-online/stories/090998/met_2A1wildf.html on 7/30/99.

breakdown of total property loss was not available, but it appears that homes comprise the majority of it.

Retail Sales and Tourism

Gross Sales

We assessed the impacts of the fires on gross sales within the 18 counties lying at least partially within the SJRWMD. Gross sales data for the period 1988-1998 was obtained from the Florida Department of Revenue and included sales that are and are not subject to state sales tax. Only the months of June, July, and August were analyzed, with August included to account for any lagged effects the fires may have had on the economy.

Decreased tourism and sales due to forced evacuations, road closures, and negative publicity were expected to reduce actual gross sales. The change in sales and tourism is estimated by comparing "predicted" levels (without fire) with observed levels. The predicted sales level was determined by multiplying 1997 levels by one plus the mean percent change occurring over the previous10-year period. Calculations were performed separately for each month. To determine whether the change in gross sales from 1997 to 1998 was statistically significant, the percent change was compared to the 95% confidence interval for the average percent change occurring in the previous ten years[5].

We found no statistically significant change in gross sales for the SJRWMD between June of 1997 and June of 1998[6] (+$696 million). However, there was a statistically significant *increase* in July (+$966 million) and a statistically significant *decrease* in August (-$560 million). For the three months, sales were actually $1,102 million higher than one would have expected without the fires. Thus we observed an increase in sales in June and an even larger increase in July, which corresponds to the height of the fire fighting effort, then a significant decrease in sales in the wake of the fire event. It appears then that the fires forced increases in present consumption at the expense of future purchases. The decrease in sales may have lingered well past August making these cost estimates conservative.

Table 2.4 shows the sales impact by county. Only 6 counties experienced decreased sales for all three months, while 11counties actually showed increased sales. St. John's, Brevard, and Alachua were the biggest losers with sales decreases of $11-$158 million. See Tables 2.12, 2.13, and 2.14 for gross sales by month following Chapter 2.

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[5] The 95% confidence interval was calculated for each 10-year mean. If the percent change from 1997-8 fell outside of the confidence interval it was determined to be statistically significant.

[6] Osceola County not included in June's calculation.

Table 2.4. Wildfire impact on gross sales for counties of the SJRWMD

County	Projected Summer Gross Sales	Actual Summer Gross Sales	Difference
Alachua	1,022,083,892	1,010,319,252	(11,764,640)
Baker	57,079,279	52,984,515	(4,094,764)
Brevard	2,436,765,366	2,374,170,569	(62,594,797)
Clay	528,063,184	550,965,145	22,901,961
Duval	6,241,254,843	6,320,121,872	78,867,029
Flagler	161,191,639	156,868,511	(4,323,128)
Indian River	516,796,935	550,041,757	33,244,822
Lake	774,494,398	837,429,109	62,934,711
Marion	1,262,275,111	1,381,135,733	118,860,622
Nassau	311,948,316	340,641,535	28,693,219
Okeechobee	119,375,893	122,308,488	2,932,595
Orange	10,425,812,445	11,042,673,365	616,860,920
Osceola	1,380,159,757	1,456,472,285	76,312,528
Polk	2,992,845,358	3,277,193,336	284,347,978
Putnam	410,775,486	406,915,525	(3,859,961)
St. Johns	689,318,112	530,998,310	(158,319,802)
Seminole	2,346,834,646	2,343,981,524	(2,853,122)
Volusia	2,022,443,161	2,046,337,022	23,893,861
Total	**33,699,517,822**	**34,801,557,853**	**1,102,040,031**

Using a similar methodology and data form the Florida Department of Revenue we estimated the impact on state sales receipts. Table 2.5 provides the estimates by county. The results are similar to the gross sales analysis. See Tables 2.15, 2.16, and 2.17 for state sales tax receipts by month following Chapter 2.

Table 2.5. Wildfire impact on state sale tax receipts for counties of the SJRWMD

County	Projected Summer Sales Tax	Actual Summer Sales Tax	Difference
Alachua	35,908,803	35,503,673	(405,130)
Baker	1,652,210	1,505,878	(146,332)
Brevard	69,227,106	73,443,806	4,216,700
Clay	17,899,621	19,090,526	1,190,905
Duval	163,476,844	173,326,901	9,850,057
Flagler	4,470,592	4,270,548	(200,044)
Indian River	18,207,535	19,094,839	887,304
Lake	24,453,144	26,771,600	2,318,456
Marion	37,124,386	40,146,091	3,021,705
Nassau	8,528,884	9,177,661	648,777
Okeechobee	3,789,255	4,194,131	404,876
Orange	327,194,215	335,010,957	7,816,742
Osceola	37,208,729	36,203,108	(1,005,621)
Polk	73,547,243	79,393,574	5,846,331
Putnam	7,391,931	7,728,470	336,539
St. Johns	19,504,253	20,675,176	1,170,923
Seminole	69,901,279	74,548,263	4,646,984
Volusia	65,177,437	67,200,339	2,022,902
Total	**984,663,465**	**1,027,285,541**	**42,622,076**

Hotel Revenue

Hotel revenues were calculated using the Florida Department of Revenue's transient rental tax receipts, where revenues equaled the transient rental tax (hotel tax) divided by the corresponding county transient rental tax rate[7]. A net lost of $60,998,681 in hotel revenues for the 16 counties was estimated, although only August's total losses were statistically significant. At $77[8] a night the net loss in revenues implies a net loss of 792,191 hotel nights. If it is assumed that an average tourist spends $97.50[9] per day (non-lodging related spending) then the loss of hotel nights corresponds to a $77,238,590 net loss in tourist spending during the June, July, and August of 1998.

Table 2.6. Wildfire impact on tourism for counties of the SJRWMD

County	Change in Summer Hotel Revenue	Change in Summer Tourist Spending	Total
Alachua	(403,181)	(510,522)	(913,703)
Baker	n/a	n/a	n/a
Brevard	(4,599,448)	(5,823,976)	(10,423,424)
Clay	(35,744)	(45,260)	(81,004)
Duval	1,033,772	1,308,997	2,342,769
Flagler	(442,148)	(559,862)	(1,002,010)
Indian River	(302,288)	(382,768)	(685,056)
Lake	(330,676)	(418,713)	(749,389)
Marion	n/a	n/a	n/a
Nassau	(299,347)	(379,044)	(678,391)
Okeechobee	28,883	36,573	65,456
Orange	(48,835,556)	(61,837,230)	(110,672,786)
Osceola	9,169,125	11,610,256	20,779,382
Polk	(666,846)	(844,384)	(1,511,230)
Putnam	129,424	163,881	293,305
St. Johns	(7,823,967)	(9,906,972)	(17,730,939)
Seminole	1,169,430	1,480,771	2,650,201
Volusia	(8,790,112)	(11,130,336)	(19,920,448)
Total	**(60,998,680)**	**(77,238,589)**	**(138,237,269)**

Table 2.6 shows the total sales and tourism impacts during June, July, and August 1998. In sum, tourism in the SJRWMD fell quite heavily, while overall spending rose for two of the three months examined. See Tables 2.18, 2.19, and 2.20 for tourist revenues by month following Chapter 2.

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[7] Baker and Marion were not included in this section since they do not collect transient rental taxes.

[8] The average cost of a hotel night has been estimated at $77 a night. See PricewaterhouseCoopers, *Economic Assessment of 1998 Florida Fires*, Final Report, U.S. Department of Commerce Economic Development Administration, Washington, DC, September 4, 1998, Contract # ED0024268000024-12.

[9] $97.50 was used as the average per day spending per tourist family. It has been estimated that resident Florida family spends $95 a day and a non-resident family $100 per day. See PricewaterhouseCoopers, *Economic Assessment of 1998 Florida Fires*, Final Report, U.S. Department of Commerce Economic Development Administration, Washington, DC, September 4, 1998, Contract # ED0024268000024-12.

Tourism and overall sales fared the worst during August, weeks after the last wildfire, prompting the question whether the steep drop was due to the wildfires or some other event(s). Therefore, a regression model was estimated to examine statistical links between wildfire in a county and tourism spending. See Table 2.7. Changes in hotel revenue were modeled as a function of wildfire size, year, and economic productivity (US GDP). Initial results failed to establish a statistical relationship between wildfire size and percent change in hotel revenue (used as a proxy for tourism). The regressions exhibited a statistically significant negative relationship between tourist spending and the year 1998, meaning that 1998 was unique compared to the ten previous years. From the standpoint of tourism, 1998 was different for several reasons. First, the hot, dry conditions found that summer may have served to reduce the attraction of Florida. Second, nationwide media coverage that detailed the extent and side effects of the 1998 wildfires—mandatory evacuations, smoke, and road closures—may have served to discourage travel to the state.

Health Costs and Pollution

Pollution Estimates[10]

Wildfires produce smoke that contains air pollutants such as particulates, volatile organics (hydrocarbons), carbon monoxide (CO), and nitrogen oxides (NOx). The United States Environmental Protection Agency estimates amount of total emissions caused by fire with the following equation:

$$E_i = F_i A = P_i L A$$

where

- E_i is the total emission of pollutant "i"
- F_i is the emission factor (mass of pollutant per unit area of forest burned)
- A is the land area burned
- P_i is the yield of the pollutant "i" (mass of pollutant per unit mass of forest fuel burned)
- L is the fuel loading consumed (mass of forest fuel per unit land area burned)

Using this equation, we estimated wildfire emissions for the four pollutants listed above. The estimated average fuel loading is 9 tons per acre for the southern United States, and we assumed that this loading applied to northern Florida's forests. It should be noted that the estimated average fuel load (L) is based on "combustible material that will be consumed in a wildfire under specific weather conditions" or "available fuel." The yield of pollutant "i" (P_i), were determined to be 17 lb/ton, 140 lb/ton, 24 lb/ton, and 4 lb/ton

[10] This section draws exclusively from *Development of Emission Factors For Estimating Atmospheric Emissions From Forest Fires*, EPA-450/3-73-009, U.S. Environmental Protection Agency, Research Triangle Park, NC, October, 1973, unless otherwise noted.

for total particulates, carbon monoxide, total hydrocarbons, and nitrogen oxides, respectively. Emissions were calculated for the 1998 summer wildfires by county.

Brevard, Flagler, Osceola, and Volusia counties account for over 85% of the wildfire related pollution (see Table 2.8 and for a breakdown for all counties see Table 2.21 following Chapter 2). Although, these four counties border 9 of the remaining 13 counties, and depending on meteorological conditions, their emission could impact the health and well being of those outside the fire regions.

Table 2.8. Wildfire emissions by county for the SJRWMD

			Emissions (tons)		
County	***Acres Burned****	***Particulates***	***Carbon Monoxide***	***Volatile Organics*****	***Nitrogen Oxides***
Alachua	7,700	589	4,851	832	139
Baker	112	9	71	12	2
Brevard	75,444	5,771	47,530	8,148	1,358
Clay	7,161	548	4,511	773	129
Duval	6,386	489	4,023	690	115
Flagler	87,639	6,704	55,213	9,465	1,578
Lake	1,095	84	690	118	20
Marion	3,434	263	2,163	371	62
Nassau	2,915	223	1,836	315	52
Okeechobee	747	57	471	81	13
Osceola	20,307	1,553	12,793	2,193	366
Polk	1,443	110	909	156	26
Putnam	8,336	638	5,252	900	150
Seminole	2,148	164	1,353	232	39
St.Johns	12,667	969	7,980	1,368	228
Volusia	146,475	11,205	92,279	15,819	2,637
Total	384,009	29,377	241,926	41,473	6,912

*PricewaterhouseCoopers, Economic Assessment of 1998 Florida Fires,
Final Report, U.S. Department of Commerce Economic Development Administration,
Washington, DC, September 4, 1998, Contract # ED0024268000024-12.
**Expressed as methane

Health Implications

A primary concern deriving from the figures shown in Table 2.8 is whether the extreme levels of wildfire in northern Florida can be linked to actual public health conditions. We examined admissions records for hospital located in counties in the zone of greatest wildfire activity. We identified several anomalies in admission rates that are suggestive of the effects of the wildfires. The Volusia County Health Department and the Florida Department of Health studied the frequency of hospital visits for asthma, bronchitis, and other respiratory conditions during the period of June 1, 1998 through July 6, 1998[11]. Seven hospitals in Volusia County and one in Flagler were surveyed and the data

[11] Sorenson, Fuss, Mulla, Bigler, Wiersma, Hopkins. Surveillance of Morbidity During Wildfires—Central Florida 1998, Morbidity and Mortality Weekly Report, Volume 48, Number 4, Page 78, February 5, 1999. See http://www.cdc.gov/epo/mmwr/preview/mmwrhtml/00056377.htm.

compared to admissions and emergency room visits for June/July 1997. Emergency department visits increased for asthma (91%) and bronchitis with acute exacerbation (132%). However, the numbers of actual *admissions* were small and the frequency of some conditions decreased (see Table 2.9). Whether these changes were statistically significant or related to the wildfires was not examined.

Table 2.9. Comparsion of hospital visits/admissions for certain respiratory conditions during June1-July6 of 1997 and 1998*

Diagnosis	***Emergency Department Visits***			***Hospital Admissions***		
(ICD-9-CM codes)	1997	1998	% Change	1997	1998	% Change
Asthma (493-493.91)	77	147	91	13	19	46
Acute bronchitis (466.0-466.19)	134	107	(20)	5	4	(20)
Bronchitis with acute exacerbation (491.21)	28	65	132	56	56	-
Painful Respiration (786.52)	74	54	(27)	7	3	(57)
Shortness of breath/Wheezing (786.09)	68	90	32	1	1	-

*As reported by Sorenson, Fuss, Mulla, Bigler, Wiersma, and Hopkins. *Surveillance of Morbidity During Wildfires—Central* Florida 1998, Morbidity and Mortality Weekly Report, Volume 48, Number 4, Page 78, February 5, 1999.

In an attempt to link wildfire activity statistically to health effects, we estimated an equation that related the change in respiratory-related ambulatory care costs from each quarter in 1997 to the same quarter of 1998 on the similarly-defined change in wildfire area.[12] Ambulatory patient data for the entire state were provided by the Florida Agency for Health Care Administration for 1997 and 1998. Changes in second and third quarter wildfire size as related to ambulatory care for the years 1997 and 1998 were weak (p=.1918 and p=.2962, respectively). The second quarter exhibited a negative relationship and the third appeared to be positively related (see Table 2.10).

Table 2.10. The log percent change in 1997-1998 respiratory-related ambulatory care costs, as a function of wildfire area

Second Quarter		Third Quarter	
Intercept	0.0077	Intercept	-0.1782
	(0.061)		(0.046)
ln(Wildfire area (t)/Wildfire area (t-1))	-0.0637	ln(Wildfire area (t)/Wildfire area (t-1))	0.0241
	(0.043)		(0.023)
Sample Size	8	Sample Size	29
Adjusted R-squared	0.14	Adjusted R-squared	0.00

An area of future research is to conduct these analyses at the zip code rather than the county level, yielding a tighter physical relationship between wildfire proximity and patient residence. A complication may be that respiratory ailments are also affected by other factors driven by meteorological events, like ENSO, or other things such as pollen and fungal spores. Disentangling the specific effects of fire-created pollutants using empirical analyses may be challenging, but respiratory problems represent a tangible cost that can exceed thousands of dollars per patient for treatment and traditionally target

[12] January-March, April-June, July-September, October-December.

sensitive populations, such as children and the elderly. The effects of both wildfires and prescribed burns on public health are thus important factors in the public debate over policy response to the 1998 fires.

Discussion

The timber market effects measured by a detailed economic analysis were conservative, in that they ignored both the hardwood timber market and the general equilibrium effects that changes in the timber market have on the larger economy. Nonetheless, our estimates show that the 1998 wildfires had welfare effects that totaled $350 to $600 million for the pine timber market. To this total should be added effects on the hardwood market that probably amount to more than $100 million.

The losses calculated here were based on assumed price and inventory elasticities that may be very different from elasticities applicable to Florida in 1998. In that sense, price and welfare effects calculations could be refined with a more detailed analysis of the Florida timber sector. Specifically, it should be possible to relate wildfire extent to timber prices over time using historical price and historical wildfire data for northern Florida. Establishment of the true statistical relationship between wildfire in Florida and timber prices in Florida would permit a more accurate assessment of the price effects of the 1998 wildfires. Additionally, future analyses could examine more closely the welfare effects of wildfire on hardwood timber markets, identifying how hardwood prices are sensitive to wildfire extent in Florida and how wildfires affect the economic welfare of that part of the timber sector. These additional analyses could then be incorporated into a more detailed investigation into the economic effects of wildfire on public welfare and the economic relationships between wildfire, prescribed burning, and timber production in Florida and the southeastern United States.

As the $350 million to $600 million in timber losses were conservative, so too is the remaining $20 million to $280 million in losses. FEMA believes the $100 million in fire suppression and related support to be a minimum. Wildfire related property losses of $10 to $12 million doesn't include uninsured property losses, and doesn't account for resident's time and effort cleaning up and repairing such losses. Tourism losses may have lingered on well past August and may have become more severe as clean-up continued and media attention continued to buzz. Losses in August are almost as large as those experienced in June and July combined. Although the economy as a whole did well, as measured by the large increases in gross sales, distributional inequalities surely occurred. It is easy to imagine this as stores, hotels, gas stations, and other businesses in Volusia County were forced to close as areas were evacuated, whereas areas receiving those displaced flourished. Health costs are perhaps the most conservative, as no cost was estimated, but it should be understood that a real cost existed. Future analysis might quantify the relationship between wildfires, and prescribed burning for that matter, and the effect on human health. The 1998 wildfires were unique as almost 500,000 acres burned portions of Central Florida in a matter of six weeks, this opposed to the average 100,000 acres that burn statewide a year. The wildfire's price tag of $600 million to $800 million rivals that of tropical storms and small hurricanes.

Table 2.11. Estimates of acres burned during the 1998 wildfires by county*

County	Acres Burned	County	Acres Burned
Alachua	7,700	Lee	402
Baker	112	Levy	80
Bay	774	Madison	41
Bradford	2,244	Marion	3,434
Brevard	75,444	Martin	1,657
Charlotte	1,069	Nassau	2,915
Clay	7,161	Okaloosa	3,842
Collier	321	Okeechobee	747
Columbia	20,841	Osceola	20,307
Dixie	250	Pasco	3,455
Duval	6,386	Polk	1,443
Flagler	87,639	Putnam	8,336
Franklin	64	Santa Rosa	855
Gilchrist	43	Seminole	2,148
Glades	27	St.Johns	12,667
Gulf	1,069	Sumter	164
Hamilton	134	Taylor	32,291
Hernando	40	Union	14,859
Highlands	3,206	Volusia	146,475
Hillsborough	53	Wakula	26,314
Lafayette	80	Other Counties	1,081
Lake	1,095	Total	499,265

*PricewaterhouseCoopers, Economic Assessment of 1998 Florida Fires, Final Report, U.S. Department of Commerce Economic Development Administration, Washington, DC, September 4, 1998, Contract # ED0024268000024-12.

Table 2.12. June 1998 wildfire impact on gross sales for counties of the SJRWMD

County	Projected 6/98 Gross Sales	Actual 6/98 Gross Sales	Difference	
Alachua	336,489,002	318,349,665	(18,139,337)	
Baker	20,031,510	15,553,244	(4,478,266)	**
Brevard	818,415,133	785,972,027	(32,443,106)	
Clay	182,588,408	177,751,543	(4,836,865)	
Duval	1,958,446,681	2,026,618,661	68,171,980	
Flagler	55,036,857	51,148,123	(3,888,734)	
Indian River	179,142,383	181,544,797	2,402,414	
Lake	264,483,332	278,927,603	14,444,271	
Marion	388,437,328	463,423,312	74,985,984	**
Nassau	114,626,902	112,109,005	(2,517,897)	
Okeechobee	37,415,143	39,664,836	2,249,693	**
Orange	3,363,212,741	4,039,706,620	676,493,879	**
Osceola	447,541,932	542,940,654	95,398,722	**
Polk	1,036,038,966	945,916,352	(90,122,614)	**
Putnam	131,071,451	124,259,006	(6,812,445)	
St. Johns	184,765,606	171,139,061	(13,626,545)	
Seminole	786,737,916	755,421,085	(31,316,831)	
Volusia	698,002,375	668,135,193	(29,867,182)	
Total	**11,002,483,665**	**11,698,580,787**	**696,097,122**	

**Indicates statistical significance (p<.05)

Table 2.13. July 1998 wildfire impact on gross sales for counties of the SJRWMD

County	Projected 7/98 Gross Sales	Actual 7/98 Gross Sales	Difference	
Alachua	345,812,412	368,610,015	22,797,603	**
Baker	22,273,995	21,345,469	(928,526)	
Brevard	807,898,365	806,682,332	(1,216,033)	
Clay	168,332,736	201,868,948	33,536,212	**
Duval	2,123,248,551	2,301,269,676	178,021,125	**
Flagler	57,201,272	66,158,918	8,957,646	
Indian River	176,112,160	200,561,714	24,449,554	**
Lake	264,697,834	304,954,001	40,256,167	**
Marion	463,796,984	504,653,634	40,856,650	**
Nassau	100,553,427	121,149,251	20,595,824	**
Okeechobee	44,284,542	45,631,534	1,346,992	
Orange	3,505,176,558	3,732,272,524	227,095,966	
Osceola	459,296,570	481,266,078	21,969,508	
Polk	1,044,776,478	1,295,004,616	250,228,138	**
Putnam	135,709,417	147,845,917	12,136,500	
St. Johns	178,835,570	193,997,189	15,161,619	**
Seminole	844,654,161	838,032,276	(6,621,885)	
Volusia	667,533,251	744,508,521	76,975,270	**
Total	**11,410,194,282**	**12,375,812,613**	**965,618,331**	****

**Indicates statistical significance (p<.05)

Table 2.14. August 1998 wildfire impact on gross sales for counties of the SJRWMD

County	***Projected 8/98 Gross Sales***	***Actual 8/98 Gross Sales***	***Difference***	
Alachua	339,782,477	323,359,572	(16,422,905)	**
Baker	14,773,773	16,085,802	1,312,029	**
Brevard	810,451,868	781,516,210	(28,935,658)	
Clay	177,142,040	171,344,654	(5,797,386)	
Duval	2,159,559,612	1,992,233,535	(167,326,077)	**
Flagler	48,953,510	39,561,470	(9,392,040)	**
Indian River	161,542,393	167,935,246	6,392,853	
Lake	245,313,233	253,547,505	8,234,272	
Marion	410,040,800	413,058,787	3,017,987	
Nassau	96,767,987	107,383,279	10,615,292	**
Okeechobee	37,676,208	37,012,118	(664,090)	
Orange	3,557,423,146	3,270,694,221	(286,728,925)	**
Osceola	473,321,255	432,265,553	(41,055,702)	
Polk	912,029,914	1,036,272,368	124,242,454	**
Putnam	143,994,618	134,810,602	(9,184,016)	
St. Johns	325,716,936	165,862,060	(159,854,876)	**
Seminole	715,442,568	750,528,163	35,085,595	
Volusia	656,907,535	633,693,308	(23,214,227)	
Total	**11,286,839,875**	**10,727,164,453**	**(559,675,422)**	****

**Indicates statistical significance (p<.05)

Table 2.15. June 1998 wildfire impact on state sales tax for counties of the SJRWMD

County	***Projected 6/98 Sales Tax***	***Actual 6/98 Sales Tax***	***Difference***
Alachua	11,753,223	11,750,413	(2,810)
Baker	533,480	557,737	24,257
Brevard	23,715,054	23,873,212	158,158
Clay	6,150,000	6,379,156	229,156
Duval	53,845,064	56,256,644	2,411,580
Flagler	1,594,035	1,473,383	(120,652)
Indian River	6,469,163	6,434,689	(34,474)
Lake	8,442,491	8,969,207	526,716
Marion	12,781,808	13,427,362	645,554
Nassau	2,822,151	3,032,672	210,521
Okeechobee	1,344,465	1,414,220	69,755
Orange	111,383,762	111,017,459	(366,303)
Osceola	11,770,636	11,552,735	(217,901)
Polk	25,836,030	26,035,693	199,663
Putnam	2,571,474	2,522,669	(48,805)
St. Johns	6,377,148	6,935,154	558,006
Seminole	23,517,396	24,626,207	1,108,811
Volusia	21,482,157	22,884,851	1,402,694
Total	**332,389,537**	**339,143,463**	**6,753,926**

Table 2.16. July 1998 wildfire impact on state sales tax for counties of the SJRWMD

County	*Projected 7/98 Sales Tax*	*Actual 7/98 Sales Tax*	*Difference*	
Alachua	11,381,193	11,843,142	461,949	
Baker	642,124	423,253	(218,871)	**
Brevard	22,501,474	25,931,564	3,430,090	**
Clay	5,851,147	6,593,494	742,347	**
Duval	53,662,427	58,891,987	5,229,560	**
Flagler	1,355,089	1,509,631	154,542	**
Indian River	6,000,256	6,620,998	620,742	**
Lake	7,821,066	9,355,190	1,534,124	**
Marion	12,049,068	13,716,144	1,667,076	**
Nassau	2,795,142	3,118,678	323,536	**
Okeechobee	1,196,686	1,418,227	221,541	**
Orange	108,198,152	115,175,483	6,977,331	**
Osceola	12,438,550	12,296,295	(142,255)	
Polk	23,879,042	27,101,275	3,222,233	**
Putnam	2,267,506	2,718,475	450,969	**
St. Johns	6,454,069	7,011,201	557,132	**
Seminole	23,226,028	25,708,017	2,481,989	**
Volusia	21,505,145	23,073,990	1,568,845	**
Total	**323,224,163**	**352,507,044**	**29,282,881**	****

**Indicates statistical significance (p<.05)

Table 2.17. August 1998 wildfire impact on state sales tax for counties of the SJRWMD

County	*Projected 8/98 Sales Tax*	*Actual 8/98 Sales Tax*	*Difference*	
Alachua	12,774,387	11,910,118	(864,269)	**
Baker	476,606	524,888	48,282	**
Brevard	23,010,578	23,639,030	628,452	
Clay	5,898,474	6,117,876	219,402	
Duval	55,969,353	58,178,270	2,208,917	
Flagler	1,521,467	1,287,534	(233,933)	**
Indian River	5,738,116	6,039,152	301,036	
Lake	8,189,587	8,447,203	257,616	
Marion	12,293,510	13,002,585	709,075	**
Nassau	2,911,590	3,026,311	114,721	
Okeechobee	1,248,104	1,361,684	113,580	**
Orange	107,612,302	108,818,015	1,205,713	
Osceola	12,999,542	12,354,078	(645,464)	
Polk	23,832,171	26,256,606	2,424,435	
Putnam	2,552,951	2,487,326	(65,625)	
St. Johns	6,673,036	6,728,821	55,785	
Seminole	23,157,855	24,214,039	1,056,184	**
Volusia	22,190,135	21,241,498	(948,637)	**
Total	**329,049,766**	**335,635,034**	**6,585,268**	

**Indicates statistical significance (p<.05)

Table 2.18. June 1998 wildfire impact on tourism for counties of the SJRWMD

County	Projected 6/98 Hotel Revenue	Actual 6/98 Hotel Revenue	Change in 6/98 Hotel Revenue	Change in 6/98 Tourist Spending	Total
Alachua	3,494,805	3,181,500	(313,305)	(396,717)	(710,022)
Baker	n/a	n/a	n/a	n/a	n/a
Brevard	9,097,868	9,097,775	(93)	(118)	(211)
Clay	548,461	488,633	(59,827)	(75,755)	(135,582)
Duval	13,447,290	14,473,383	1,026,094	1,299,275	2,325,368
Flagler	1,040,072	719,200	(320,872)	(406,299)	(727,171) **
Indian River	1,946,977	2,016,367	69,390	87,864	157,254
Lake	1,959,957	1,633,350	(326,607)	(413,561)	(740,169) **
Marion	n/a	n/a	n/a	n/a	n/a
Nassau	6,139,182	6,335,950	196,768	249,154	445,922
Okeechobee	206,269	224,267	17,998	22,790	40,788
Orange	167,595,365	155,763,340	(11,832,025)	(14,982,110)	(26,814,135)
Osceola	46,740,560	48,723,150	1,982,590	2,510,422	4,493,012
Polk	5,995,821	5,681,550	(314,271)	(397,941)	(712,212)
Putnam	377,929	395,000	17,071	21,616	38,688
St. Johns	9,983,316	9,926,333	(56,983)	(72,154)	(129,137)
Seminole	3,831,353	4,333,433	502,080	635,751	1,137,832
Volusia	14,355,148	13,996,820	(358,328)	(453,726)	(812,054)
Total	**286,760,372**	**276,990,052**	**(9,770,321)**	**(12,371,510)**	**(22,141,830)**

**Indicates statistical significance (p<.05)

Table 2.19. July 1998 wildfire impact on tourism for counties of the SJRWMD

County	Projected 7/98 Hotel Revenue	Actual 7/98 Hotel Revenue	Change in 7/98 Hotel Revenue	Change in 7/98 Tourist Spending	Total
Alachua	3,114,267	2,900,733	(213,534)	(270,384)	(483,918)
Baker	n/a	n/a	n/a	n/a	n/a
Brevard	11,377,620	9,110,075	(2,267,545)	(2,871,242)	(5,138,786) **
Clay	480,541	508,833	28,292	35,825	64,117
Duval	14,354,333	13,557,817	(796,516)	(1,008,576)	(1,805,092)
Flagler	467,639	610,650	143,011	181,086	324,097 **
Indian River	2,184,314	2,131,767	(52,548)	(66,538)	(119,085)
Lake	993,181	796,350	(196,831)	(249,234)	(446,065) **
Marion	n/a	n/a	n/a	n/a	n/a
Nassau	6,099,444	6,029,100	(70,344)	(89,072)	(159,415)
Okeechobee	200,896	225,367	24,471	30,985	55,456
Orange	187,215,042	166,387,980	(20,827,062)	(26,371,930)	(47,198,992)
Osceola	47,963,588	52,944,500	4,980,912	6,306,999	11,287,911 **
Polk	5,789,172	5,180,750	(608,422)	(770,404)	(1,378,826)
Putnam	320,511	375,550	55,039	69,693	124,732
St. Johns	12,304,911	9,984,300	(2,320,611)	(2,938,436)	(5,259,047) **
Seminole	4,212,091	4,387,967	175,876	222,700	398,576
Volusia	16,304,882	16,023,660	(281,222)	(356,093)	(637,316)
Total	**313,382,432**	**291,155,398**	**(22,227,034)**	**(28,144,620)**	**(50,371,654)**

**Indicates statistical significance (p<.05)

Table 2.20. August 1998 wildfire impact on tourism for counties of the SJRWMD

County	***Projected 8/98 Hotel Revenue***	***Actual 8/98 Hotel Revenue***	***Change in 8/98 Hotel Revenue***	***Change in 8/98 Tourist Spending***	***Total***	
Alachua	2,842,676	2,966,333	123,657	156,579	280,237	
Baker	n/a	n/a	n/a	n/a	n/a	
Brevard	9,982,560	7,650,750	(2,331,810)	(2,952,617)	(5,284,427)	**
Clay	523,309	519,100	(4,209)	(5,330)	(9,539)	
Duval	13,141,189	13,945,383	804,194	1,018,298	1,822,493	
Flagler	688,487	424,200	(264,287)	(334,649)	(598,936)	**
Indian River	2,250,597	1,931,467	(319,130)	(404,094)	(723,224)	
Lake	1,235,138	1,427,900	192,762	244,082	436,844	
Marion	n/a	n/a	n/a	n/a	n/a	
Nassau	5,604,422	5,178,650	(425,772)	(539,126)	(964,898)	
Okeechobee	228,119	214,533	(13,585)	(17,202)	(30,787)	
Orange	166,494,529	150,318,060	(16,176,469)	(20,483,191)	(36,659,659)	
Osceola	42,885,601	45,091,225	2,205,624	2,792,835	4,998,459	
Polk	7,397,354	7,653,200	255,846	323,961	579,808	
Putnam	345,487	402,800	57,313	72,572	129,885	
St. Johns	13,473,907	8,027,533	(5,446,373)	(6,896,382)	(12,342,755)	**
Seminole	4,371,227	4,862,700	491,473	622,320	1,113,793	**
Volusia	24,843,822	16,693,260	(8,150,562)	(10,320,516)	(18,471,078)	**
Total	**296,308,421**	**267,307,095**	**(29,001,326)**	**(36,722,458)**	**(65,723,784)**	****

**Indicates statistical significance (p<.05)

Table 2.21. Wildfire emissions by county

		Emissions (tons)			
County	***Acres Burned****	***Particulates***	***Carbon Monoxide***	***Volatile Organics*****	***Nitrogen Oxides***
Alachua	7,700	589	4,851	832	139
Baker	112	9	71	12	2
Bay	774	59	488	84	14
Bradford	2,244	172	1,414	242	40
Brevard	75,444	5,771	47,530	8,148	1,358
Charlotte	1,069	82	673	115	19
Clay	7,161	548	4,511	773	129
Collier	321	25	202	35	6
Columbia	20,841	1,594	13,130	2,251	375
Dixie	250	19	158	27	5
Duval	6,386	489	4,023	690	115
Flagler	87,639	6,704	55,213	9,465	1,578
Franklin	64	5	40	7	1
Gilchrist	43	3	27	5	1
Glades	27	2	17	3	0
Gulf	1,069	82	673	115	19
Hamilton	134	10	84	14	2
Hernando	40	3	25	4	1
Highlands	3,206	245	2,020	346	58
Hillsborough	53	4	33	6	1
Lafayette	80	6	50	9	1
Lake	1,095	84	690	118	20
Lee	402	31	253	43	7
Levy	80	6	50	9	1
Madison	41	3	26	4	1
Marion	3,434	263	2,163	371	62
Martin	1,657	127	1,044	179	30
Nassau	2,915	223	1,836	315	52
Okaloosa	3,842	294	2,420	415	69
Okeechobee	747	57	471	81	13
Osceola	20,307	1,553	12,793	2,193	366
Pasco	3,455	264	2,177	373	62
Polk	1,443	110	909	156	26
Putnam	8,336	638	5,252	900	150
Santa Rosa	855	65	539	92	15
Seminole	2,148	164	1,353	232	39
St.Johns	12,667	969	7,980	1,368	228
Sumter	164	13	103	18	3
Taylor	32,291	2,470	20,343	3,487	581
Union	14,859	1,137	9,361	1,605	267
Volusia	146,475	11,205	92,279	15,819	2,637
Wakula	26,314	2,013	16,578	2,842	474
Other Counties	1,081	83	681	117	19
Total	499,265	38,194	314,537	53,921	8,987

*PricewaterhouseCoopers, Economic Assessment of 1998 Florida Fires,
Final Report, U.S. Department of Commerce Economic Development Administration,
Washington, DC, September 4, 1998, Contract # ED0024268000024-12

**Expressed as methane

Table 2.22 Inventory, removals, losses, and salvage of pine and hardwood timber in northern Florida.

	Pine	Hardwood
Inventory Sawtimber in 1995, MMBF	8,755.2	7,733.5
Lost Sawtimber Inventory in 1998, MMBF	1,225.7	755.1
Average Removals, Sawtimber, MMBF/Year	624.8	80.6
Salvaged Sawtimber, 1998-1999, MMBF	288.9	174.4
Inventory Pulpwood in 1995, MM Cubic Feet	1,394.1	987.3
Lost Pulpwood Inventory in 1998, MM Cubic Feet	259.7	161.5
Average Removals, Pulpwood, MM Cubic Feet/Year	117.4	14.3
Salvaged Pulpwood, 1998-1999, MM Cubic Feet	61.2	38.2

Notes: Inventory and removals volumes were obtained from the United States Forest Service Forest Inventory and Analysis survey of Florida in 1995 and based on a subset of Florida's counties. Data obtained from FIA were county-level pine and hardwood inventory and removals volumes. Counties included in the subset were based on Timber Mart-South (Norris Foundation 1977-1999) region 1, northern Florida, which formed the basis for the price and welfare modeling in this chapter.

Chapter 3: 1998 Wildfire Risk Factors at Forest Inventory Plots

John M. Pye, Jeffrey P. Prestemon, and David T. Butry

Introduction

The unusually severe wildfires experienced in 1998 in northeastern Florida were due most directly to a drought of a severity not previously recorded there, a drought associated with a particularly strong transition from El Niño to La Niña weather patterns. While weather was clearly the proximal cause of this disaster, questions have been raised about the role that forest management may have played in contributing to its severity. The importance of forest fires in this season raises the question whether increased prescribed burning might have ameliorated its damage, or whether other policies are available which if adopted might reduce damages when severe droughts return to the area.

The primary objective of this chapter is to examine empirically how the observed fire patterns under the conditions present in an extreme ENSO period relate to physiographic, vegetative, and human-related factors. Identification of statistical relationships between fire occurrence and these variables can improve our ability to model wildfire risk in forests of the Southern United States. An improved understanding of these relationships may also provide land managers, homeowners, and policy makers with some of the tools necessary to minimize economic losses from catastrophic wildfire by better targeting fuel management or other mitigation strategies to where they'll do the most good. While the next chapter extends this work to analyze wildfire risks at broader spatial and temporal scales, this analysis provides a detailed description of how site conditions influence the ignition and spread of catastrophic fires under extreme weather conditions.

Methods

Partly in recognition of the role of fire in lowering the risk of wildfires, many forested regions are subjected to frequent prescribed burning. Little is known, however, about the effectiveness of this and other fire prevention strategies under conditions of extreme wildfire risk. The ENSO pattern observed in Florida in 1997-1998 created such extreme conditions: first, by enhancing vegetation growth during an abnormally wet El Niño period in late 1997 and early 1998, and, second, by producing an intense drought from March through July 1998 during the transition to La Niña conditions. It is possible that efforts to control the ignition and spread of wildfire effective under normal weather patterns are largely ineffective under extreme conditions, the very situation in which the payoffs to management of fuel buildup would be highest. The effectiveness of fuel management, including prescribed burning, is what we attempt to address in this chapter.

To model the effects of landscape and human factors on wildfire occurrence in Florida, we relate the occurrence of a wildfire at particular locations in the St. John's Water Management District (SJRWMD) to previous and contemporaneous conditions in and around those locations. The locations used were permanent inventory plots maintained by the United States Forest Service's Forest Inventory and Analysis program in Asheville, NC. Their locations in the SJRWMD are shown in Figure 3.1. These plots were visited in 1985-86 and reported in the 1987 FIA survey, and visited again in 1993-1994 and reported in the 1995 FIA survey. Observations of plot conditions for 1993-1994, along with observations on activities occurring in the plot between the 1987 and 1995 surveys, were therefore available for modeling. Plot-specific information collected by the FIA ground crews was augmented with data from other sources and assigned to FIA plots using GIS intersection and neighborhood operations. FIA plot locations were only provided to the nearest one hundred seconds for privacy reasons, introducing an error of approximately 1.3 km E-W and 1.5 km N-S into each plot's location. This limited resolution was an important constraint on the formulation and accuracy of all GIS-based linkages.

Whether or not a plot was burned in the 1998 fire season was determined by overlaying a coverage of plot locations with a coverage of that season's wildfires obtained from Barbra Sapp of the St. Johns River Water Management District (1999). This wildfire coverage, shown in Figure 3.2, drew on maps from both the SJRWMD and the State Division of Forestry and was based on spatial information from diverse sources including satellite and ground-based information. The wildfire coverage only described fires during the June to early July wildfire season of 1998.

The occurrence of fire on these plots at any time during the fire season was then related to factors expected to have influenced the probability of fire. These factors included information on ignition sources, vegetation, broad ecological classification, and previous fire activity. Fire weather was not explicitly included as a predictive variable under the assumption that during this period of ubiquitously severe fire weather any important variability in drought stress would be accounted for by topographic or ecoregional differences. We did test for the significance of lightning as an ignition source.

Plot data: Measures of vegetation obtained from FIA records included forest type (pine, baldcypress, bottomland hardwood, etc.), physiographic class of the plot (hydric, mesic, xeric), a count of the number of trees of various sizes in the stand (1-2", 2-5", and 5"+ dbh), and two indices of the cover of non-tree vegetation on the plot in strata 0-3 feet and 3-8 feet above the forest floor. An index of forest fragmentation, was also obtained from the 1995 FIA survey: the amount of forest-nonforest edge at a set distance from the FIA plot center.

Indicators of whether the FIA plot had experienced a prescribed burn or had been subject to a wildfire between the 1987 and 1995 FIA surveys was taken from the 1995 FIA survey.

Figure 3. 1 FIA plot locations within the St. John's River Water Management District. See Figure 2.1 for its location in the state.

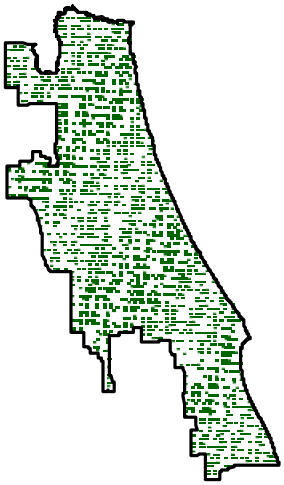


Figure 3. 2 Wildfires in the 1998 wildfire season in the SJRWMD.

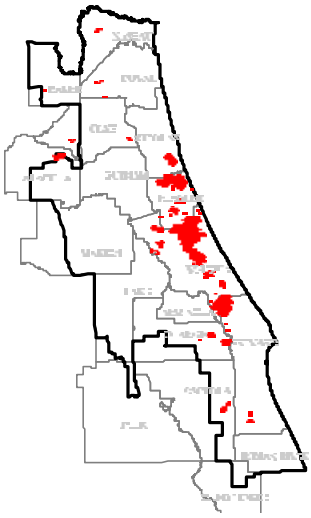


Figure 3. 3 Lightning ground strike activity in northeastern Florida during the 1998 wildfire season.

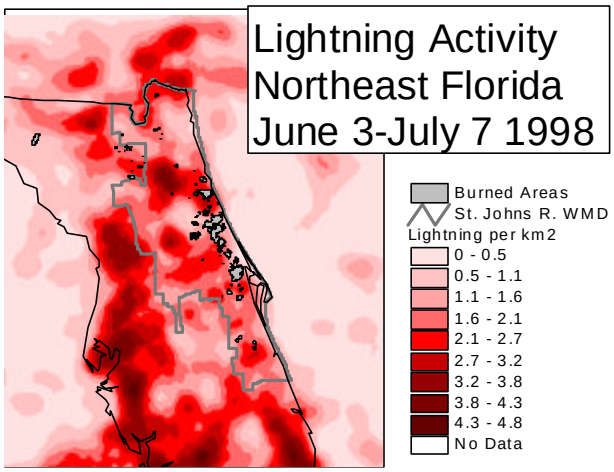
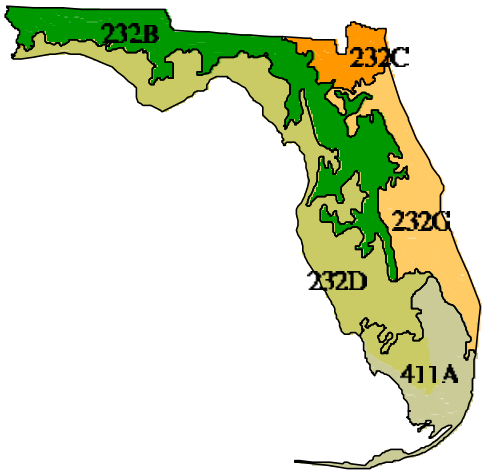


Figure 3. 4 Ecoregion provinces from Keyes et. al. 1995.



Neighborhood burning: Neighborhood prescribed burning information was obtained from the Florida Division of Forestry's individual records of silvicultural prescribed burning permits. The measure used in the analysis was the ratio of the sum of the area of the permits issued to the area of forest in the section in which the FIA plot was located.

Lightning: The primary ignition source during the 1998 fires was reported to be lightning so we obtained information on this factor from Stephen Root of Weatherbank, Inc. (Figure 3.3). Locations of every cloud to ground lightning strike in northeastern Florida from June 3rd through July 7th GMT were converted to a GIS point coverage and the number of strikes summed within three distances of each FIA plot: one quarter, one half and three quarter miles.

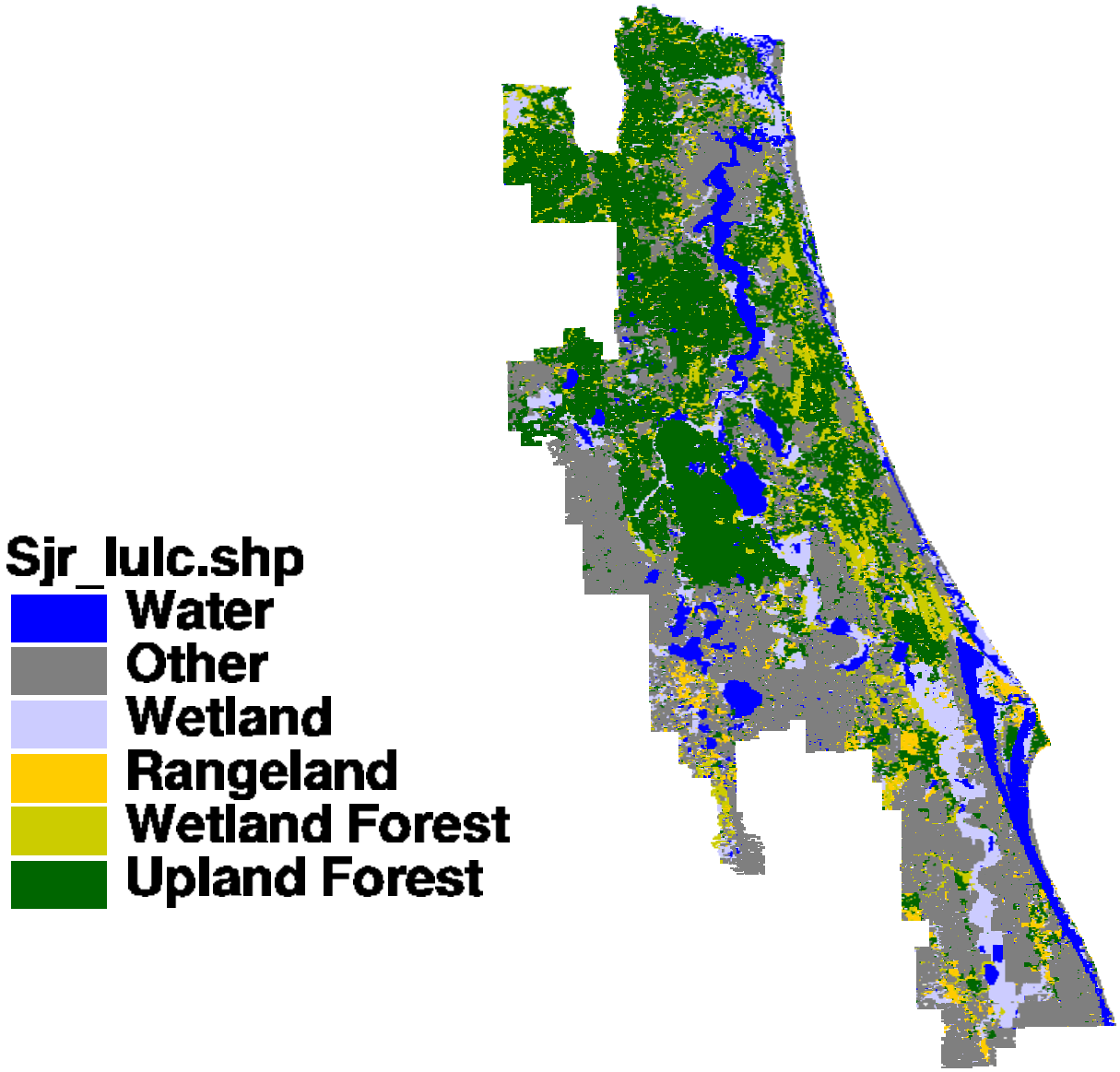
Ecoregion: Data on the ecological characteristics of the zone in which the plot was found were obtained from a GIS coverage of Bailey's Ecological Zones (Keys et al. 1995) and shown in Figure 3.4. Each FIA plot was assigned to one of three ecoprovinces found in the SJRWMD: 232B, 232C, and 232G (Figure 3.1).

Forest neighborhood: The amount of forests in the neighborhood of a plot might influence the likelihood that fires might burn from other areas into the plot itself. The amount of forest in the vicinity of each plot was estimated using two draft land-use/land-cover coverages from Barbra Sapp of the SJRWMD. Most of the area was covered by a source dated 1995, the four counties lying partially within the SJRWMD were dated 1998. The two coverages were combined and reclassed from 163 classes into 6 (Figure 3.5) and then rasterized to 100m cells and separated into binary coverages of upland forest and wetland forest. Upland forest used the entire broad category of upland pine, which includes subcategories of pine flatwoods, longleaf and sand pine, xeric oak and upland hardwood forest, Australian pine, tree plantations, and forest regeneration. Wetland forests were drawn from the following subcategories: wetland hardwood forests, mixed wetlands hardwoods, wetland coniferous forest, cypress, forested depressious [sic] pine, and wetland forested mixed. The amount of upland or wetland forest was calculated within a neighborhood 1.3 km wide and 1.5 km high and assigned to the overlaying FIA plot.

Model: The occurrence of a wildfire in the SJRWMD in 1998 was modeled as a binary choice, W^*=1 if a wildfire occurred on the FIA plot, 0 otherwise. This choice is indexed by a latent variable, W_{1998}, a function of hypothesized explanatory variables, such that $E[W^* \mid x] = \boldsymbol{b}'x$ where the vector $\boldsymbol{x}$ contains the explanatory variables and the vector **â** contains the parameters associated with each variable. The empirical representation of this model was a binary logit (Greene 1998, p. 664-665):

$$(2) \qquad \Pr[W_{1998} = 1] = \frac{\exp(\boldsymbol{b}'x)}{1 + \exp(\boldsymbol{b}'x)} = \Lambda(\boldsymbol{b}'x)$$

Figure 3. 5 Land use/land cover of the St. John's River Water Management District showing upland and wetland forests. Croplands and urban uses are classed as “Other."



where 7 is the logistic cumulative distribution function and $x = (T, P, C, U, L, Z, F, B, W_H, G, V, Y)$ contains the following:

T, a vector of dummies indexing FIA forest types;

P, a vector of two physiographic class dummies (hydric, xeric);

C, a vector of counts of the three diameter classes mentioned above;

U, a vector of the two non-tree vegetation amounts;

L, the number lightning strikes;

Z, a vector of two of three ecoprovince (232B, 232C) dummies, where the effects of 232G is contained within the constant;

F, a vector of the neighborhood upland and wetland forest proportions;

B, a dummy variable indicating whether the FIA plot experienced a prescribed burn between the 1987 and 1995 surveys;

W_H, a dummy indicating whether the FIA plot experienced a wildfire between the 1987 and 1995 surveys;

G, the number of times that a circle encompassing 50-acres centered around the FIA plot passes in and out of forest;

V, the product of the number of 1.0 to 1.9” dbh trees per acre times the number of 5.0” dbh (and larger) trees per acre on the plot, which measures the effects of having an overstory on fire probability; and

Y, a weighted sum of the area of prescribed burning permits in the section of the FIA plot issued in 1998, 1997, and 1996, calculated as $Y=4(\text{area}_{1998}) + 2(\text{area}_{1997}) + \text{area}_{1996}$.

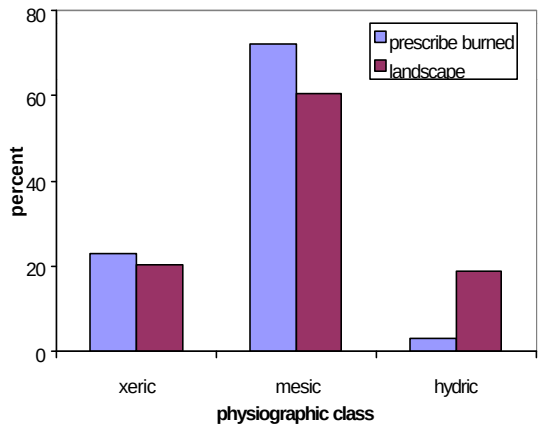
Results

Approximately 46%, or 1,346, of the 2,898 FIA plots in the SJRWMD were classified in 1995 by the FIA survey as being forested. Others were classified as nonforest and were excluded from the analysis presented below. Of the 2,898 FIA plots, 98 burned during the June-July period in the SJRWMD and 2800 did not; of the 1,346 forested plots, 81 burned and 1,255 did not. Within the 1,255 unburned plots were all of the 23 forested plots in the SJRWMD that had experienced a wildfire between the 1987 and 1995 FIA surveys. Also within the 1,255 unburned plots were all of the 280 forested plots classified by FIA as xeric. A tentative conclusion, therefore, is that xeric sites and sites that have experienced a wildfire within approximately 13 years of an extreme ENSO period had zero likelihood of burning during the ENSO wildfire event.

Because xeric physiographic class and previous wildfire perfectly explained a finding of no burn on an FIA plot, the plots with these observations were dropped from the data set. Three xeric plots had experienced a wildfire between FIA surveys, so the number of observations remaining for analysis was 1,346 - (277+23) = 1,046. An additional eighteen of the remaining 1,046 plots had missing data on non-tree vegetation. These plots were also dropped from the analysis. Of those eighteen, one burned and seventeen did not.

Before proceeding with the discussion of the empirical analysis, a quick overview of the data on prescribed burning rates and their relationship to physiographic classification is helpful. Prescribed burning occurred on 113 of the 1,346 plots included in the data set of forested FIA plots in the SJRWMD; of the 1,046 plots remaining for analysis, 86 were prescribed burned between FIA surveys. Of the original 113 plots, four were classified as hydric and twenty-seven as xeric. Given that hydric sites amounted to about 19 percent of all forested FIA plots, it is clear that there is an imbalance in the rates of prescribed burning, which may indicate relative wildfire risks. Specifically, wildfire occurrence between FIA surveys was recorded only for xeric and mesic sites. Further, mesic and xeric sites were more frequently prescribed burned than their representation on the forested landscape while hydric sites were less frequently prescribed burned (Figure 3.6).

Figure 3. 6 Forested area and forested area subjected to prescribed burning by physiographic class. Data from the FIA plots in the SJRWMD.



A tentative conclusion is that both extremes of physiographic classes, xeric and hydric, are not ordinarily at significant risk of wildfire—wildfire risk is normally confined to mesic sites. Hydric sites may ordinarily be at minimal risk due to an abundance of moisture, at least during normal years. Xeric sites may experience fewer fires due to their more limited understory vegetation as shown in the FIA plot data (analysis not shown). In the extreme weather patterns of ENSO cycles however, when hydric sites are drier, the fuel buildup from lower rates of historical wildfire and lower rates of prescribed burning translate into higher wildfire risk.

Table 3.1 presents results of logit equation estimates of wildfire. The logit model was estimated using maximum likelihood and with an assumed heteroscedastic covariance matrix of residuals. Two models were estimated. The first included all variables and is termed the “Full Model” in Table 1; the second, the “Parsimonious model”, included only those variables with t-values in the Full Model greater than unity in absolute value.

Full model estimates show that pine and baldcypress stands were more likely to burn than other forest types. Sites with more 1” to 1.9” dbh trees were more likely to burn than sites with less, ceteris paribus. The cumulative sum of lightning strikes within 0.75 miles of an FIA plot was negatively related to the probability that the site burned during the same period, possibly indicating that high rates of lightning were associated with significant rainfall.

Plots in ecoprovinces 232B and 232C were less likely to burn than those in ecoprovince 232G. Plots with lots of wetland forests near them were more likely to burn. Plots that had been prescribed burned as many as thirteen years previous to the 1998 wildfires were not significantly less or more likely to burn in the 1998 wildfires, although the

parsimonious model estimates show a weak positive relationship. Sites with more nonforest edge were more likely to have burned in 1998 than those in more contiguous blocks of forest, indicating a positive effect of forest fragmentation on wildfire probability during extreme years. Finally, the full model found that sites with more non-tree vegetation near the forest floor were statistically no more or less likely to have burned in 1998 than plots with less lower vegetation, but the parsimonious model estimate showed a positive relationship.

It is noteworthy that measures of actions to reduce fuel buildup were less successful at predicting wildfire risk than more direct measures of their effect. One of the key effects of prescribed burning should be a reduction in the amount of lower vegetation. In our analysis, our two measures of low vegetation—small trees and non-tree vegetation—proved better predictors of fire risk than actual reports of prescribed burning at the stand and landscape levels. This may be due to flaws in the mechanistic relevance of each of the measures used here, but at least in analysis the structure of forests appeared a better predictor of risk than measures of action or intent.

Taken together, several wildfire patterns emerge from our analysis of the extreme fire season observed in 1998.

1. Stands that have experienced a wildfire in the preceding decade's time (up to thirteen years previous) appear to be at little risk of wildfire during an extreme ENSO event.
2. Wetland coniferous sites and sites in the vicinity of wetland forests are at higher risk of wildfire than other sites. In particular, wildfire risks to xeric sites appears to be minimal during such years, and sites in the vicinity of substantial upland forests are at lower risk than other sites during these extreme ENSO events. In contrast, baldcypress and southern pine forest types are at relatively high risk. Upland hardwood types appear to be at lower risk than baldcypress sites and possibly also bottomland hardwood types.
3. Small trees and possibly low-level vegetation are a positive risk factor for wildfire during extreme ENSO events. Although only the count of the smallest trees was correlated positively with wildfires in 1998, trees of 1.9" dbh and smaller might not be the only trees offering a greater wildfire risk: given that up to five years had passed between the last FIA survey in Florida and the 1998 wildfires, many of the trees in the 1.0 to 1.9" dbh class were probably well over 2" in dbh by the time that the wildfire swept through the stand in 1998. The statistically insignificant interaction term between the count of these smallest trees and the count of the largest trees seems to show, as well, that it is immaterial whether the small trees are found beneath an overstory or if they form the canopy of a young stand. The implication here is that vegetation control in mature stands should provide some modest protection against wildfires during ENSO periods.
4. Fragmented landscapes are at higher risk of wildfire during extreme ENSO periods. This may be because fragmented forests are drier or windier (Ranney et al. 1991), or because such locations are at greater risk of arson or other anthropogenic sources of ignition.

Table 3.1 Logit model estimates of 1998 St. John's River Water Management District wildfire occurrence on Forest Inventory and Analysis permanent inventory plots as a function of vegetation, ecoprovince, neighboring forest types, and ignition sources.

Variable	Full Model	Parsimonious Model
Pine Forest Type dummy	1.77 *	1.29 **
	(1.06)	(0.57)
Oak-Pine Forest Type dummy	0.75	
	(1.19)	
Baldcypress Forest Type dummy	1.09 **	1.14 ***
	(0.51)	(0.47)
Bottomland Hardwood Type dummy	1.49	1.02
	(1.11)	(0.67)
Hydric Site dummy	0.08	
	(0.49)	
Count of Trees 1 to 1.9" dbh	0.0016 ***	0.0014 **
	(0.00)	(0.0006)
Count of Trees 2 to 4.9" dbh	-0.00032	
	(0.00)	
Count of Trees 5" dbh and larger	0.00076	
	(0.00)	
Lightning Strike Count (within 0.75 miles)	-0.026	-0.027 *
	(0.02)	(0.016)
Ecoprovince 232B dummy	-2.06 ***	-2.08 ***
	(0.63)	(0.62)
Ecoprovince 232C dummy	-3.82 ***	-3.78 ***
	(1.00)	(0.96)
Upland Forest Area in Section (Acres)	-0.0009	
	(0.00)	
Lowland Forest Area in Section (Acres)	0.01 **	0.0067 **
	(0.00)	(0.0029)
Prescribed burned between FIA surveys	0.59	0.67 *
	(0.42)	(0.38)
Measure of fragmentation, "edge"	0.18 **	0.19 **
	(0.08)	(0.08)
Number of 1 to 1.9" trees times 5" trees	-4.94E-06	
	(4.45E-06)	
Non-tree vegetation 0 to 3' above ground	0.02	0.014 **
	(0.02)	(0.006)
Non-tree vegetation 3 to 8' above ground	-0.01	
	(0.02)	
Neighborhood prescribed burning measure	-0.01	-0.0086
	(0.01)	(0.0077)
Intercept	-5.64 ***	-5.01 ***
	(1.25)	(0.87)
Model Log Ratio Statistic	134.9 ***	133.3 **
Observations	1028	1028

Note: *** indicates statistical difference from zero at 1% significance, ** at 5%, and * at 10%. Eighteen of the 1,046 forested non-xeric and non-previous wildfire plots with missing data on non-tree vegetation were dropped from the analysis.

Discussion

The results presented in this chapter paint a complex roadmap to strategies to minimize economic losses during extreme ENSO periods. The landscape during 1998 may have been significantly different with respect to wildfire behavior than during most years. Because northeast Florida had been experiencing an intense drought, many of the usual barriers to wildfire spread--high moisture content vegetation and standing water--had ceased to be barriers. Areas that could have been subject to regular prescribed burning in the very recent past, including forests managed for timber, were now connected to patches of bottomland forest that had high levels of fuel buildup. Wildfires could ignite and easily spread from these areas into surrounding forests. Controlling fuel buildup in wetlands in ordinary years would seem to be quite difficult, as would controlling risks in young pine stands. Thus it seems unlikely that policies to increase prescribed burning would have substantially affected the risks on the two most troublesome forest types during extreme La Niña years. This suggests that other strategies might be fruitful, such as increased construction and maintenance of firebreaks around high-risk stands, programs to encourage fire-resistant housing near areas at risk, or improved detection and suppression capabilities. An alternative strategy may also be to seek ways, other than prescribed burning, to manage vegetation in bottomland forests and stands with woody undergrowth.

A detailed analysis of ownership in the SJRWMD reveals that 53 percent of baldcypress forests are held by private corporate owners, 16 percent are managed by various government agencies, 23 percent are managed by forest industry, and 11 percent by private individuals. This kind of ownership diversity, illustrating the ownership diversity for all kinds of forests, suggests a diversity in the ownership objectives for managers of high-risk lands. Coordinating wildfire risk reduction strategies would entail working with a diversity of actors in a diversity of settings. Devising a policy that is effective for one group, therefore, may not be effective for another. Further, a policy appropriate for some high-risk stands (e.g., herbicidal treatment of undergrowth, prescribed burning during normal years) may be wholly inappropriate for environmentally sensitive wetlands.

This research suggests several avenues for further investigation. First, detailed wildfire levels in the neighborhood of FIA plots, obtained from Florida Division of Forestry, would enable evaluation of the relationship between wildfire in 1998 and wildfire in the few years previous to the 1998 wildfires—for example, their protective effect. With regard to FIA plots, it is known that FIA attaches locational errors to its geographical coordinates of each FIA plot, to protect the identity of owners and the statistical objectivity of data collected. To the extent of these errors, it is possible that some plots classified as having burned in 1998 were not burned, while some classified as having not burned did in fact burn. Obtaining accurate locations would eliminate this problem and also permit more accurate measures of the neighborhood variables included in the analysis. A fruitful area for further research would be to expand the temporal and spatial scope of the kind of analysis reported in this chapter using past data on wildfire and prescribed burning locations, FIA data on plot vegetation and stand histories, and broader climatic time series data. That kind of analysis would permit a more accurate assessment

of the relationships between weather and climate (e.g., ENSO), stand and site conditions, and the wildfire and prescribed burning history of specific points on the landscape.

Chapter 4: Wildfire Frequency, Temporal Dynamics, and the Relationship of Wildfire to Prescribed Burning

Thomas P. Holmes, Jeffrey P. Prestemon, John M. Pye,

David T. Butry, and D. Evan Mercer

Introduction

In this chapter, we focus attention on the specification and quantification of factors affecting fire production functions in Florida. We propose that, at the landscape-level, "fire production functions" can be estimated using data on wildfire frequency-size distributions over broad geographic areas and long time spans. Such an analysis will help set the context for the 1998 fire season and allow us to test the hypothesis that the 1998 fire regime was statistically different than previous severe fire seasons. We also propose to evaluate fire production functions at a finer geographic scale (the county level) to better understand the temporal dynamics of fire production processes.

Recent research has demonstrated that, in some instances, wildfires in natural forested landscapes follow power-law frequency-size distributions and that the frequency of small and medium size fires can be used to predict the frequency of large fires (Malamud, Morein and Turcotte 1998; Li, Corns and Yang 1999). In contrast, the distribution of California shrubland wildfires does not appear to follow a simple power-function relation, but shows a lesser number of small fires (less than 10 acres) than would be expected in a power-law fire regime (Keeley, Fotheringham and Morais 1999). This "insufficiency" may be due to fire suppression effort or to different fire behavior in grassland and forested ecosystems.

Wildfire production functions in human-dominated landscapes are likely to differ from their size and frequency in natural landscapes due to the influence of three primary types of human-induced "inputs". First, humans affect the amount and distribution of fuel across landscapes by altering total biomass and species mix and by fragmenting spatial fuel configuration through land use changes such as road building, agricultural activities, and housing development. Second, humans change the distribution of wildfire ignition sources away from lightning and toward a variety of anthropogenic causes including intentional (eg., prescribed burning, arson) and unintentional (railroads, escaped fire) causes. Third, suppression activities affect frequency-size distributions. If small fires are easier to control than large fires, for example, then large fires may represent natural ecosystem patterns where small and medium size fire frequencies are less than would be represented in natural ecosystem fire regimes (Moritz 1997).

Over short time spans, suppression may act to limit the size and number of small and medium size fires while having perverse effects over long time spans by allowing fuels to accumulate across the landscape, leading to the occurrence of catastrophic fires during a "severe" fire season. This phenomena, known as the "Yellowstone effect", was postulated to occur when the Yellowstone fires of 1988 burned an estimated 800,000

acres. Note that, if the Yellowstone effect was caused by the accumulation of excess fuel, then increasing costs (leading to increased fuel accumulation) would be associated with an increase in damage – a condition which violates a basic assumption of the standard economic model. A different perspective was offered by Moritz (1997) and Keeley et al (1999) who found no change in the frequency of large fires in a Southern California brushland ecosystem over long time spans. Apparently, fire suppression did not increase the frequency of large fires in that ecosystem. Whether or not accumulation of excess fuel contributed to the severity of wildfires in Florida during 1998 remains an unanswered question.

Forest fuel loads may be reduced through prescribed burning or, in the extreme case, by prior wildfire occurrence. Well replicated studies confirming the effectiveness of prescribed burning programs are difficult to find although both Koehler (1992-1993) and Martin (1988) show promising trends to that effect for areas in and near Florida.

Prescribed burning is not just conducted to reduce wildfire risk. In forestry, prescribed burning is recognized as reducing competing vegetation, preparing sites for planting, and, in some cases, releasing seeds from serotinous cones to ensure proper levels of natural regeneration. Controlled burns also improve access and within-stand visibility, improve nutrient availability, and alter plant species composition and wildlife habitat. Negative effects of prescribed burning can also be identified, including the risk of inadvertent damage to property or surrounding lands, particulate pollution with it's negative human health consequences, and an unsightly scorched understory that may reduce esthetic qualities of the landscape.

Our central interest in this chapter is to evaluate whether or not significant interactions occur between fuel reduction events (i.e. prescribed burning and/or prior wildfire events) and wildfire regimes in Florida. If significant interactions can be identified and quantified, then subsequent research may be meaningfully undertaken to evaluate optimal fire management policies. Below, "fire production functions" are estimated across broad geographic areas but, unfortunately, are subject to limited historical scope regarding fire occurrence. We found some evidence that prescribed burning diminished wildfire frequency and extent during the current year but this effect did not carry-over to subsequent years. Prior wildfire history did, however, have significant influence on current wildfire acres burned, suggesting that temporal dynamics are important characteristics of wildfire production functions. We also found that, in the Atlantic Coast ecoprovince, the frequency-size distribution of wildfires had shifted downwards by about 10% in the 17 years leading up to 1998. Among other things, this trend may represent the effect of fire suppression. However, we found that the 1998 fire season demonstrated statistically significant and highly unusual characteristics relative to earlier years in the historical fire record. The severity of the 1998 fire season, and the preponderance of large fires in that year, may reflect the diminution of the wildfire frequency-size distribution over previous years in combination with extreme ENSO activity.

Empirical Methods

Two "fire production function" models were estimated. The first model estimated fire frequency-size distributions for prescribed and wildfire regimes and was specified at the ecoprovince-level. Correlations between parameters characterizing prescribed and wildfire regimes were evaluated. The second model estimated, at a finer geographic scale, the relationship between fire "inputs" (weather patterns, extent of prescribed burning, past fire history and population density) and wildfire extent. Each model is described below.

Ecoprovince Fire Frequency-Size Model

Ecoprovince fire frequency-size distributions were estimated using the power-law model described by Malamud, Morein and Turcotte (1998) – hereafter MMT. Based on computer simulations and analysis of historical fire records, it was postulated by MMT that wildfires are distributed as a negative exponential function:

$$N_F = a A_F^{-b}$$

where N_F is the number (frequency) of fires, A_F is the fire area burned (size), and á and â are parameters to be estimated. Taking logarithms of both sides of the equation, the resulting function is linear in its arguments and can be estimated using Ordinary Least Squares regression. MMT found that the estimated value of â, the slope of the linear function, varied between 1.31 and 1.49 for selected forest data sets. A value of â = 1 indicates that small and large fires contribute equally to the area burned by wildfires. Consequently, MMT found that small fires contributed more than proportionally to the area burned by wildfires in their data.

Because the Florida forest landscape is subject to significant suppression effort to protect life and property, we anticipate that â < 1 indicating that large fires contribute more than proportionally to the area burned by wildfires. That is, we expect that fire suppression effort is more effective at reducing the frequency of small and medium size fires than in reducing the frequency of large fires. However, whether or not increased ignitions in a human-influenced landscape increase the number of small and medium fires beyond the capacity of suppression efforts to contain them is an empirical question.

Because available fire data on N_F and A_F for Florida apparently contained measurement error, we found it necessary to smooth the data before estimating the linear regressions. In particular, reported fire size frequencies were apparently "binned" during the recording process to correspond with "conventional" fire sizes. Consequently, the number of fires of "conventional" sizes, such as 1 acre or 100 acres, were significantly larger than the number of fires reported for neighboring, but "unconventional", sizes such as 0.9 acres or 101 acres. Data were smoothed using a nonparametric smoothing algorithm with a Gaussian kernel spanning 5 adjacent data points (Hardle; MathSoft). Because smoothing resulted in smoothed values with non-constant variance, all linear regression estimates were corrected for heteroskedasticity (White).

In order to evaluate the frequency-size characteristics of the 1998 fires relative to other fire years in the historical record we modified the MMT model by specifying the following Variable Parameter Model (eg., see Judge et al. 1982):

$$N_{F,t} = a_t A_{F,t}^{-b_t}$$

where *t* refers to the year.

This specification allows the parameters characterizing the fire frequency-size distribution to be estimated relative to a "base" year using "dummy" variables. The base year in our model was 1982 because it is near the beginning of the historical Florida fire data record. The first year in the record, 1981, was not used as the base because it was an unusually severe fire year for the Atlantic Coast of Florida.

The parameters $\forall_t$ and $\exists_t$ form a time-series characterizing the fire frequency-size distribution for each year in the historical fire record. Given these parameter estimates, we were able to evaluate whether there was a significant trend in parameter estimates by regressing them on a time variable. This allowed us to evaluate, for example, the hypothesis that the number of fires was decreasing over time. Second, by including prescribed fires in the Variable Parameter Model, and identifying prescribed from wildfires by using dummy variables, we were able to estimate intercept and slope parameters, by year, characterizing the prescribed fire distribution. These estimates allowed us to evaluate potential correlations between frequency-size distributions for prescribed and wildfire regimes. For example, we were able to test the hypothesis that changes in the size distribution of prescribed fires was correlated with changes in the size distribution of wildfires.

Preliminary analysis showed that the parameters characterizing wildfires frequency-size distributions in ecoprovinces 232C and 232G were not different, so these ecoprovinces were combined, and refer to the Atlantic Coast ecoprovince. Analysis was also conducted for ecoregion 232B, which we refer to as the Interior ecoprovince. A comparison of results between these two ecoprovinces will help place the Atlantic Coast results in perspective. Subsequent analysis could be undertaken to evaluate how fire regimes in the Atlantic Coast ecoprovince compare with fire regimes in Western and Southern Florida ecoprovince.

Wildfire Area Model

The second "fire production function" model we estimated was used to explain the amount of wildfire area burned ("output") as a function of selected "inputs". In particular, we regressed the amount of wildfire area (W_t) per unit of forest area (F_t) in a spatial unit (e.g., county) on lags of that variable, prescribed burning (B_t) in that same and previous periods relative to forest area, a measure of the ecoprovince (Z_t), housing count (H_t) for the spatial unit relative to the forest area, and a measure of El Niño Southern Oscillation (E_t). Suppressing the spatial unit indicator (i), and noting the expected direction of effect, the model was specified as:

$$\frac{W_t}{F_t} = g[\frac{W_{t-k}}{F_{t-k}}(-), \frac{B_t}{F_t}(\pm), \frac{B_{t-k}}{F_{t-k}}(-), \frac{H_t}{F_t}(\pm), Z_t(\pm), E_t(\pm)]$$

Different specifications and functional forms of this equation were evaluated. Because data form a longitudinal series of observations for each observational unit (i.e. county), a

panel model was specified. In particular, we specified a Fixed-Effect Panel Model to capture individual effects characterizing the observational units. The fixed effect model captures heterogeneity between counties by including a fixed term (dummy variable) that is unique for each county. Further, heteroskedasticity was accounted for by using White's method.

Data

Our analyses in this chapter rely on two datasets obtained in summer of 1999 from the Florida Division of Forestry. The first contains records of all wildland fires reported to the State since 1981. Wildfire area over the historical record is shown in Figure 4.1 and wildfire area by year and ecoprovince are shown in Figure 4.3.

Among other variables, data are provided on the date first reported, the county, township, range and section of its origin, the fire's dominant fuel type, and the total area burned. Because of our focus on prescribed burning of forests and its differing spread characteristics, we dropped from this database wildfires whose principal fuel was classed as "grassy". We also dropped from analyses any wildfires reported from sections located in major Federal landholdings, because most fires in these areas are not reported to the State. The Federal areas included Elgin Air Force Base, NASA's Cape Canaveral, Everglades National Park, Big Cypress Wildlife Preserve, and the National Forests of Apalachicola, Osceola, and Ocala.

Our second key dataset for this chapter describes silvicultural burn permits issued by the State. Acres for which prescribed burning permits were issued are shown in Figure 4.1 and acres by year and ecoprovince are shown in Figure 4.4.

The database contains one record per initial permit and includes the day of the permitted burn, a purpose code, the total burn area permitted, and the township, range and section of at least one portion of the intended burn. The records span differing periods depending on the county, extending as far back as 1989 but with statewide coverage not beginning until 1993. Burning permits for agricultural purposes were not used, nor were "silvicultural" permits issued for purposes of site preparation, prior to seed regeneration, or ecology. We assumed that the permit was executed in its entirety on the day of its initial issuance. In other words, continuation permits were ignored. As with the wildfire database, permits from Federal ownerships were excluded to improve data consistency between the two sources.

Ecoregion designations were drawn from Bailey (1995). Ecoprovinces were used for most analyses, and fires or permits were assigned to provinces using the location of section centers. For the size distribution analyses we combined the two northeastern provinces because of the small size of the northern-most one (232G) and its similarity in fire size distribution to its southern neighbor.

Housing distribution data were drawn from county-level projections (Anonymous 1999). ENSO numbers were obtained from anonymous sources at the National Oceanic and Atmospheric Administration (Anonymous 2000b). Earlier studies had indicated the utility of the Niño 3 subsurface temperature anomalies (Niño 3 SST) as particularly useful to

Figure 4. 1 Wildfire area 1981-1999 normalized by section area. Values greater than 1.0 are possible because the area of a wildfire is solely assigned to the section in which it started. Dataset does not include fires in grey areas or the Everglades.

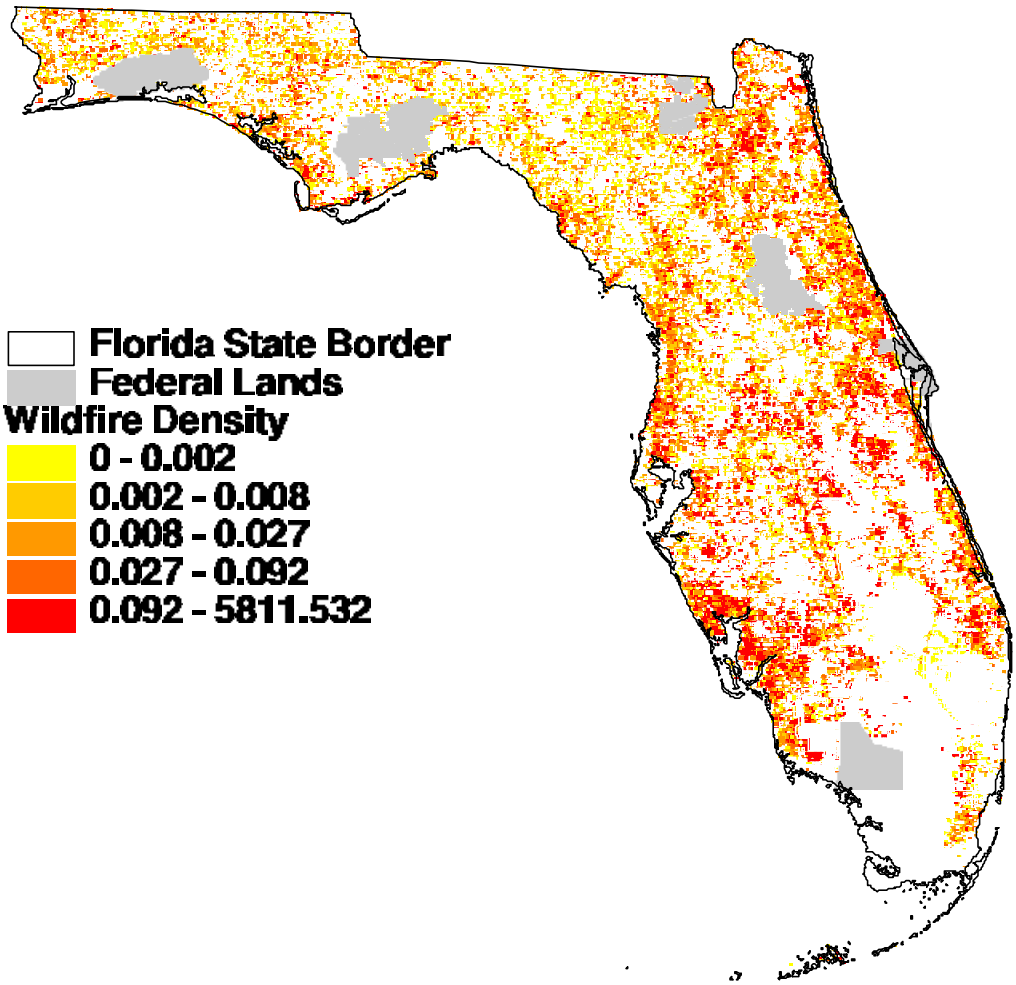


Figure 4. 2 Area of prescribed burn permits 1993-1999 normalized by section area. Values greater than 1.0 are possible because the area of a permit is solely assigned to a single section. Dataset excludes permits in grey areas for compatibility with wildfire data.

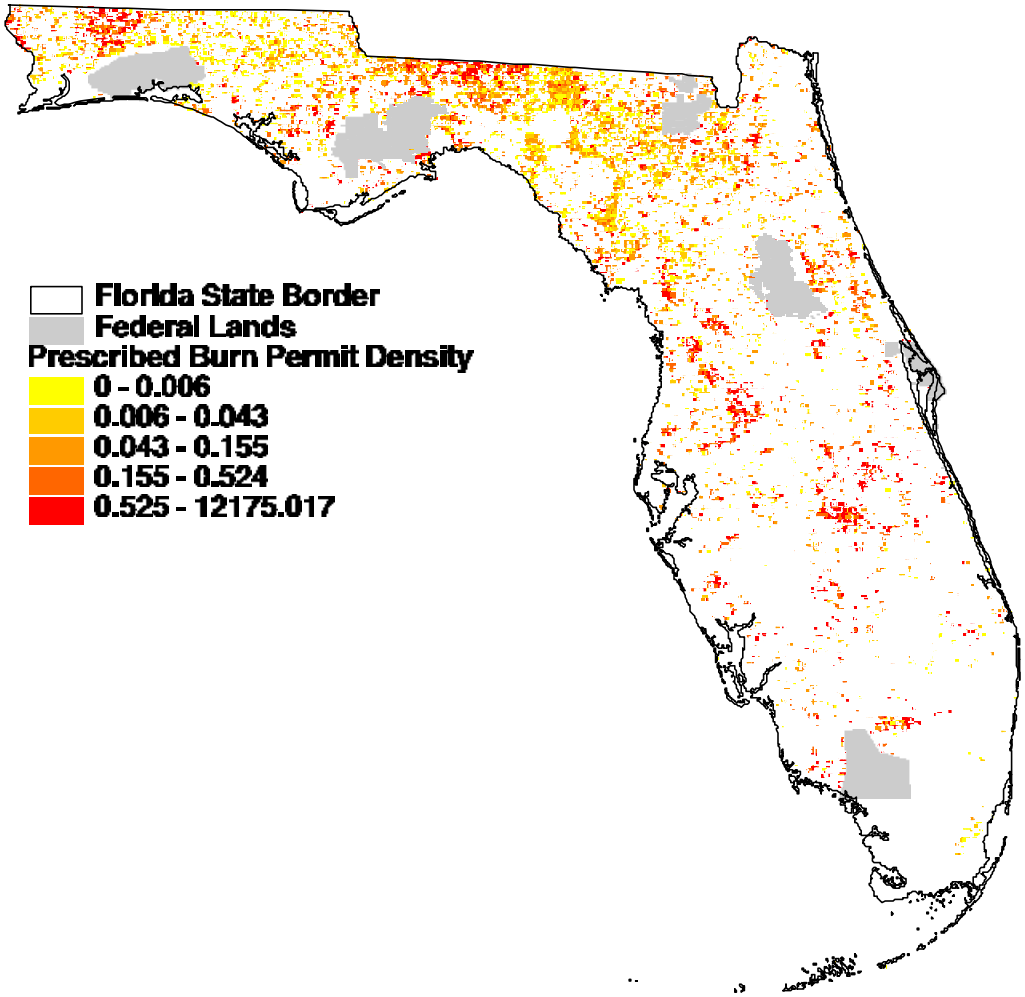


Figure 4.3 Wildfire area by year and ecoprovince. Ecoprovinces are shown in the lower map. Wildfire Unassigned refers to fires which could not be correctly assigned to either a section or ecoprovince. Fire year runs from October of the prior calendar year through September.

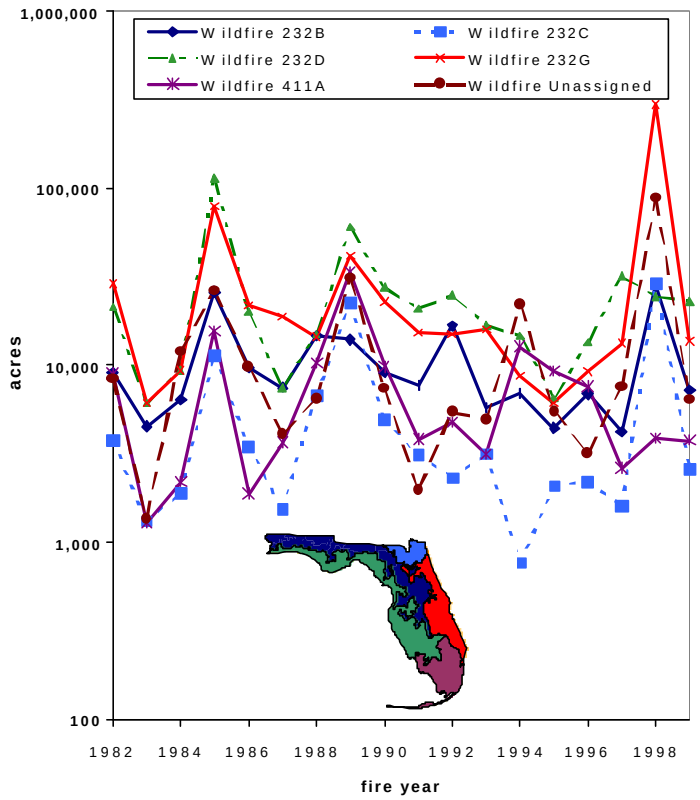
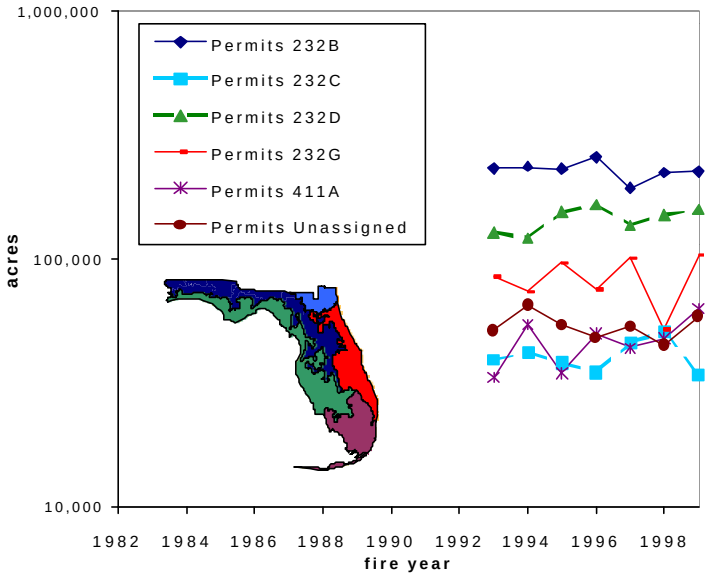


Figure 4.4 Acres for which prescribed burning permits were issued by year and ecoprovince. Ecoprovinces are shown in the map. Permits Unassigned could not be correctly assigned to either a section or ecoprovince. Permit data were only available statewide from 1993 to 1999.



predicting Florida wildfires (Brenner 1991, Barnett and Brenner 1992). To minimize the sensitivity of conclusions to shifts in timing of fires, the analyses of wildfire area used a fire year running from October 1 of the previous year through September 30th of the current year. Preliminary analyses confirmed early fall as a slow period for both wildfires and prescribed burn permits.

Results

Fire Distributions

Table 4.1 shows the results of regressing $\log_{10} N_F$ (fire frequency) on $\log_{10} A_F$ (fire size) for the Atlantic Coast ecoprovince. Recall that the base year in the analysis is 1982. The constant term (1.386) is the vertical intercept and the parameter estimate on $\log_{10} A_F$ (-0.487) is the slope of the log frequency-size distribution for 1982. Other parameter estimates represent deviations from the base year. As anticipated, the slope parameter estimate is larger (less steep) than would be found if small and large fires contributed equally to wildfire area burned. Our results indicate that large wildfires contribute proportionally more to wildfire area burned than do small wildfires. We conjecture that this result is due to fire suppression effort that is more able to control small fires.

For the Atlantic Coast ecoprovince, severe fire years occurred in 1981, 1985, 1989 and 1998. For the first three severe fire years, Table 4.1 shows that the intercept parameter shifted upwards from the base year with statistical significance at the 0.01 level or higher. In none of the three years did the estimate of the slope parameter change in a statistically significant fashion. Consequently, our model indicates that severe fire years are characterized by a parallel upward shift in the log frequency-size distribution. That is, fires of all sizes become more frequent while maintaining the proportion of small to large fires.

This pattern was not replicated for the severe fires in 1998. In that year, the intercept parameter did not change from the base year. However, the estimated slope parameter increased by 0.084 relative to the base slope of –0.487. This effect was significant at the 0.05 level and demonstrates that large wildfires became proportionally more dominant relative to small wildfires during that year.

Examining the parameter estimates for prescribed fires, it is clear from Table 4.1 that the prescribed fire frequency-size distribution is significantly different than the wildfire regime. All estimates of the prescribed fire intercept parameters are statistically smaller than the base year wildfire parameter estimate and all estimates of the slope parameters are larger than the base year wildfire parameter estimates.

Table 4.2 shows the results of regressing $\log_{10} N_F$ (fire frequency) on $\log_{10} A_F$ (fire size) for the Interior ecosystem. The slope of the log size-frequency distribution for the base year in this ecosystem (-0.512) was quite similar to the estimated slope parameter in the Atlantic Coast ecoregion. Significant upward shifts in the intercept parameter were observed for severe fire years occurring in 1981 and 1985. Surprisingly, a downward shift in the intercept was observed in the severe fire year 1992. In none of the years did we find a statistically significant increase in the slope parameter for wildfires. That is the proportion of small to large wildfires did not change over the historical record in this ecoprovince.

The results shown in Table 4.2 indicate that the prescribed burning fire regime in the Interior ecosystem is quite different than for the Atlantic Coast ecoprovince. In the Interior ecosystem, proportionally more small fires occur in the prescribed burning fire regime than in the wildfire regime (the opposite pattern was observed in the Atlantic Coast ecoprovince). In every year for which we have data in the Interior ecoprovince, the estimate for the intercept parameter for the prescribed burn regime is greater than the base intercept parameter and the slope parameters are either not significantly different than zero or are more negative than the base slope parameter.

Regressions of Wildfire Distribution Parameters

To evaluate whether significant interactions occur between wildfire and prescribed fire regimes, parameter estimates from the wildfire frequency-size distributions were regressed on a time trend and on parameter estimates from the prescribed fire frequency-size distributions. It should be kept in mind that such an analysis is exploratory in nature and results should be viewed as testing for correlations, and do not necessarily imply causality.

The regression of intercept parameters from the Atlantic Coast wildfire distributions on the intercept and slope parameters from the prescribed fire distributions and a time trend resulted in the following estimates:

$$\alpha^{wild} = 3.029^{***} - 0.013^{*}(\text{year}) - 0.392^{***}(\alpha^{prescribed}) - 0.064(\beta^{prescribed}) \quad \text{Adj. } R^2 = 0.08$$

(0.585) (0.007) (0.114) (0.208)

where standard errors are shown in parentheses. The parameter estimate on *year* was significantly different than zero at the 0.10 level and indicates that α^{wild} is decreasing over time, that is, the wildfire distribution is shifting downwards. This may be a result of fire suppression effort. We note that, by regressing α^{wild} on year only, and dropping the other variables from the specification, the statistical significance of the year variable increased to the 0.05 level (and increased adjusted R^2 to 0.177), thereby confirming the significance of the time trend.

The parameter estimate on $\alpha^{prescribed}$ was significant at the 0.01 level and demonstrated an inverse relation with α^{wild} . This result indicates that a downward shift in the distribution of prescribed fires was correlated with and upward shift in the distribution of wildfires. The slope of the prescribed fire regime was not statistically related to the intercept of the wildfire regime.

The regression of slope parameters from the Atlantic Coast wildfire distributions on the intercept and slope parameters from the prescribed fire distributions and a time trend resulted in the following estimates:

$$\beta^{wild} = -0.754^{***} + 0.002\,(\text{year}) - 0.185^{***}(\alpha^{prescribed}) - 0.901^{***}(\beta^{prescribed}) \quad \text{Adj. } R^2 = 0.266$$

(0.162) (0.002) (0.048) (0.065)

where standard errors are shown in parentheses. The parameter estimate on *year* was not significantly different than zero and indicates that there has not been a time trend in slope parameters for the wildfire regime. However, parameter estimates on ($\alpha^{prescribed}$) and ($\beta^{prescribed}$) were significantly different than zero at the 0.01 level and showed a strong correlation between parameters of the prescribed burn frequency-size distributions and the slope of the wildfire distributions. A negative sign on these parameter estimates indicates that reductions in both the number and size distribution of prescribed fires increases the proportion of large wildfires.

For the Interior ecoprovince, none of the right hand side variables were significant in explaining variation in the α^{wild} parameters. When we respecified the equation and regressed α^{wild} on *year*, we obtained the following estimates:

$$\alpha^{wild} = 1.967^{***} - 0.006\ (year) \qquad \text{Adj. } R^2 = 0.087$$
$$(0.359) \qquad (0.004)$$

In this case, the parameter estimate on year was negative and significant at the 0.13 level. While not conclusive, this result suggests that the wildfire size-frequency distribution in the Interior ecoprovince may also be shifting down over time.

The regression of slope parameters from the Interior wildfire distributions on the intercept and slope parameters from the prescribed fire distributions and a time trend resulted in the following estimates:

$$\beta^{wild} = -0.456 - 0.0005\ (year) - 0.292\ \alpha^{prescribed}) - 0.890^{***}\ (\beta^{prescribed}) \quad \text{Adj. } R^2 = 0.104$$
$$(0.314) \quad (0.001) \qquad (0.177) \qquad (0.181)$$

where standard errors are shown in parentheses. In this regression, the parameter estimate on ($\beta^{prescribed}$) was different from zero at the 0.01 significance level and shows a statistically significant correlation between the slope of the prescribed fire regime and the slope of the wildfire regime. We note that the value of the parameter estimate in this regression, -0.891, and the value of this parameter estimate in the Atlantic Coast regression, -0.901, are quite similar and close to unity. These results indicate that a downward rotation in the size distribution of prescribed fires is correlated with a nearly equal upward rotation in the size distribution of wildfires.

Regressions of Wildfire Area

County-level regressions were estimated using a fixed-effects error structure in a cross-section panel format, using generalized least squares (White covariance matrix). The fixed effects error structure was imposed on counties, with the model assuming that the relationship between wildfire area and explanatory variables was identical, except for intercepts. All variables except ENSO measures and dummy variables were transformed by the natural logarithm, to minimize potential heteroscedasticity of residuals. Not all Florida counties were included in the data. Thirteen counties that contained some federal forestlands were dropped from the data set because prescribed fire and wildfire records from these lands were not complete; their inclusion in the data set would have produced inconsistencies in the data across counties.

Two versions of the model were estimated and are reported in Table 1. The two versions were meant to reveal the effects of the severe conditions of the 1998 wildfire season on statistical relationships. The first model included one lag of prescribed fire permits and twelve lags of wildfire area, corresponding with wildfire observed during 1994 to 1999. The second had the same specification but was estimated for 1994-1997 and 1999—i.e., it dropped the 1998.

The full data set estimate, first column of parameter estimates shown in Table 1, was statistically significant (F=68, significant at less than 1 percent). This model demonstrates that wildfire in year *t* is negatively related to up to six past years' wildfire areas (*t*-1,…,*t*-6). In effect, and accepting the weak significance of lagged year 3 and 5, each acre of previous six years' wildfire reduces current wildfire by an average of 0.28 acres. In the model estimate that dropped 1998 wildfires, lags 1 to 6 were statistically different from zero at better than 8%, confirming that previous wildfires had a suppressive effect on the extent of wildfires even during the extreme 1998 season.

Prescribed fire, as measured by prescribed silvicultural burn permits, had a statistically weak effect on current wildfire area. The coefficient on current year prescribed fire was about –0.08, significantly different from zero at about 16%, although that effect disappeared for the model estimated without the 1998 data. The coefficient on lagged prescribed fire was not statistically different from zero at any reasonable level of significance. These results imply that, if the coefficient measures the effect of prescribed fires, each acre of silvicultural burn permit issued during the current fire season will reduce current wildfire area by about one-tenth of one acre. The coefficient implicitly contains the effect of non-completed permits, as well; hence, if prescribed burning permits are only carried out on 50% of permitted acres, then the actual effect of prescribed fire is double what the parameter estimate implies—reducing wildfire area by less than two-tenths of an acre. The coefficients on current and lagged prescribed fire in the model without 1998 data were not different from zero, however, which castes doubt on even the weak significance found in the full data model of prescribed fire in reducing wildfire risk. These differing results may be showing, alternatively, that prescribed fire is only effective at reducing wildfire when conditions are particularly severe and not during normal weather patterns.

The chosen measure of El-Niño-Southern Oscillation, El Niño 3 sub-surface temperature anomaly (Niño 3 SST), was a statistically significant explainer of variation in wildfire area. In the current fire year, wildfire area was positively related to positive anomalies. But lagged Niño 3 SST was negatively related to wildfire area, a result that fits with findings of Barnett and Brenner (1992) and Brenner (1991). But when 1998 was dropped from the data, the explanatory effect of the lagged ENSO measure was eliminated.

The number of houses relative to the area of forest in a county was significantly related to wildfire area at only 23% using the full data set but was significantly and negatively related to wildfire area at less than 2% when 1998 was dropped. This result implies that the positive and negative effects of having fires in the urban-wildland interface are not in balance: greater risks of wildfires from human sources are more than offset by greater suppression efforts and greater breaks in vegetative contiguity found in more urbanized counties. The fact that the parameter estimate using the data set that dropped 1998 was larger (and more statistically significant) shows that in normal years, better suppression

efforts and vegetative discontiguities found in more built-up areas serve to reduce risks but that in severe years, such as 1998, these efforts and discontiguities are less effective in reducing wildfire extent.

Discussion

Results of the wildfire frequency-size distributions demonstrated that wildfires in Florida can be modeled using power-functions. Regression results indicated that large fires contributed more than proportionally to the wildfire area burned in both the Atlantic Coast and Interior ecoprovinces. This may be due to fire suppression effort and the ability to control small fires relative to large fires.

We introduced a Variable Parameter model to estimate annual power-function parameters. Using this model, what we discovered for the Atlantic Coastal ecoprovince was that the fires in 1998 did not behave in the same fashion as fires in previous severe fire years. In prior severe fire years, the entire wildfire frequency-size distribution shifted upwards. In 1998, however, the slope of the frequency-size distribution rotated upwards, resulting in an increase in the number of large fires relative to small fires. Also, the number of total acres burned in 1998 exceeded all other years in the historical record.

Can this result be interpreted as a “Yellowstone effect”? That is, was fire suppression in previous years responsible for an “excess” accumulation of fuel that led to and excess of large fires? The results of the regressions of wildfire distribution parameters showed that, in the Atlantic Coast ecoprovince, fire distributions had been shifting downwards over time, resulting in fewer wildfires. This result is consistent with increase in fire suppression and, perhaps, and increase in fuel load. Also, the regressions of wildfire distribution parameters showed that reductions in large prescribed burns was correlated with an increase in large wildfires in both the Atlantic Coast and Interior ecoprovinces. This result may indicate that large prescribed burns reduce the risk of large wildfires by reducing the total fuel load and disrupting the spatial connectivity of fuels. On the other hand, this result may reflect a reduction in prescribed burning permits issued in years when large wildfires are common. Clearly, this is a question that deserves further research.

Results of wildfire area regressions carry with them several conclusions. First, past wildfires have a substantial, and perhaps the primary, suppressive effect on current wildfire area. This suppression persists for six years, and it even persists under conditions found in the most severe years. The finding that one acre of wildfire will suppress future wildfires by a total of more than one acre hints that let-burn strategies may be very effective in reducing future wildfire risks. These results fit weakly with the results found in Chapter 3, where previous wildfires on a particular point in the landscape had a preventive effect on wildfire in 1998. That result, based on fixed plots, indicated that wildfires’ protective effect may have lasted well beyond six years (as many as thirteen). Second, there is little statistical evidence that prescribed fires are effective in reducing wildfire risk. This result may have followed from an implicit assumption in our model that prescribed fire permits were completed at a constant rate over time and across space.

This assumption may be roughly correct, but we have no evidence to support it. Better data on completion rates of prescribed fire permits and an understanding of whether

completion rates vary over space and time could increase the confidence of our current estimates or the precision and accuracy of statistical results in future analyses. Further, the time series of data available in our analysis was short; longer time series of prescribed fire permits could allow the effectiveness of prescribed fires to be revealed. Third, the level of observation in our analysis, the county, may not reveal the true effectiveness of prescribed fire (or other variables). A finer spatial resolution, such as township or section, may allow for a tighter statistical link between prescribed fire and wildfire. Fourth, the urban-wildland interface was not identified in this study as a significant risk factor for wildfire area; in fact, denser development in counties with forests works to reduce the extent of wildfire. But this apparent protective effect of housing development was diminished during extreme years, when vegetative breaks and suppression efforts are less effective in reducing wildfire spread.

Table 4.1 Variable parameter regression model of $\log_{10} N_F$ (fire frequency) on $\log_{10} A_F$ (fire size), Atlantic Coast Ecoregion.

Variable	**Parameter estimate**	***Variable***	**Parameter estimate**
Constant	1.386*** (0.051)		
D81	0.484*** (0.065)	**$\mathbf{Log_{10}A_F}$ 81**	-0.132*** (0.035)
D83	-0.042 (0.074)	**$\mathbf{Log_{10}A_F}$ 83**	-0.012 (0.047)
D84	0.036 (0.070)	**$\mathbf{Log_{10}A_F}$ 84**	-0.029 (0.044)
D85	0.175*** (0.067)	**$\mathbf{Log_{10}A_F}$ 85**	-0.011 (0.037)
D86	0.156** (0.695)	**$\mathbf{Log_{10}A_F}$ 86**	-0.078** (0.040)
D87	0.124* (0.067)	**$\mathbf{Log_{10}A_F}$ 87**	-0.064 (0.040)
D88	0.173*** (0.068)	**$\mathbf{Log_{10}A_F}$ 88**	-0.068* (0.041)
D89	0.224*** (0.066)	**$\mathbf{Log_{10}A_F}$ 89**	-0.053 (0.038)
D90	0.296*** (0.069)	**$\mathbf{Log_{10}A_F}$ 90**	-0.152*** (0.040)
D91	-0.078 (0.070)	**$\mathbf{Log_{10}A_F}$ 91**	0.033 (0.042)
D92	0.015 (0.072)	**$\mathbf{Log_{10}A_F}$ 92**	-0.031 (0.042)
D93	0.139** (0.069)	**$\mathbf{Log_{10}A_F}$ 93**	-0.065 (0.041)
D94	-0.003 (0.072)	**$\mathbf{Log_{10}A_F}$ 94**	-0.088** (0.045)
D95	-0.044 (0.072)	**$\mathbf{Log_{10}A_F}$ 95**	-0.066 (0.045)
D96	-0.0007 (0.071)	**$\mathbf{Log_{10}A_F}$ 96**	-0.043 (0.043)
D97	-0.059 (0.071)	**$\mathbf{Log_{10}A_F}$ 97**	0.004 (0.043)
D98	-0.014 (0.064)	**$\mathbf{Log_{10}A_F}$ 98**	0.084** (0.034)
D93pre	-0.471*** (0.085)	**$\mathbf{Log_{10}A_F}$ 93pre**	0.266*** (0.043)
D94pre	-0.312*** (0.087)	**$\mathbf{Log_{10}A_F}$ 94pre**	0.243*** (0.047)
D95pre	-0.146* (0.085)	**$\mathbf{Log_{10}A_F}$ 95pre**	0.211*** (0.045)
D96pre	-0.229*** (0.087)	**$\mathbf{Log_{10}A_F}$ 96pre**	0.183*** (0.045)
D97pre	-0.344*** (0.083)	**$\mathbf{Log_{10}A_F}$ 97pre**	0.177*** (0.043)
D98pre	-0.268*** (0.078)	**$\mathbf{Log_{10}A_F}$ 98pre**	0.063* (0.034)
$\mathbf{Log_{10}A_F}$	-0.487*** (0.030)		
			N = 2480
			Adjusted $\mathbf{R^2}$ = 0.78

Table 4.2 Variable parameter regression model of $\log_{10} N_F$ (fire frequency) on $\log_{10} A_F$ (fire size), Interior Ecoregion.

Variable	Parameter estimate	Variable	Parameter estimate
Constant	1.337*** (0.051)		
D81	0.284*** (0.067)	**$\mathbf{Log_{10}A_F}$ 81**	-0.057 (0.045)
D83	-0.087 (0.070)	**$\mathbf{Log_{10}A_F}$ 83**	-0.029 (0.050)
D84	0.081 (0.073)	**$\mathbf{Log_{10}A_F}$ 84**	-0.077 (0.052)
D85	0.131** (0.064)	**$\mathbf{Log_{10}A_F}$ 85**	-0.020 (0.045)
D86	0.058 (0.069)	**$\mathbf{Log_{10}A_F}$ 86**	-0.071 (0.051)
D87	0.051 (0.066)	**$\mathbf{Log_{10}A_F}$ 87**	-0.042 (0.048)
D88	0.102 (0.065)	**$\mathbf{Log_{10}A_F}$ 88**	-0.103** (0.048)
D89	0.130** (0.064)	**$\mathbf{Log_{10}A_F}$ 89**	-0.063 (0.047)
D90	0.154** (0.065)	**$\mathbf{Log_{10}A_F}$ 90**	-0.076 (0.048)
D91	0.018 (0.069)	**$\mathbf{Log_{10}A_F}$ 91**	-0.030 (0.052)
D92	-0.110* (0.059)	**$\mathbf{Log_{10}A_F}$ 92**	0.054 (0.044)
D93	0.072 (0.069)	**$\mathbf{Log_{10}A_F}$ 93**	-0.070 (0.048)
D94	-0.042 (0.064)	**$\mathbf{Log_{10}A_F}$ 94**	-0.013 (0.047)
D95	0.018 (0.073)	**$\mathbf{Log_{10}A_F}$ 95**	-0.094* (0.052)
D96	0.012 (0.069)	**$\mathbf{Log_{10}A_F}$ 96**	-0.086* (0.050)
D97	0.039 (0.071)	**$\mathbf{Log_{10}A_F}$ 97**	-0.097* (0.054)
D98	-0.009 (0.063)	**$\mathbf{Log_{10}A_F}$ 98**	0.020 (0.049)
D93pre	0.530*** (0.087)	**$\mathbf{Log_{10}A_F}$ 93pre**	-0.063 (0.048)
D94pre	0.621*** (0.083)	**$\mathbf{Log_{10}A_F}$ 94pre**	-0.083* (0.048)
D95pre	0.491*** (0.094)	**$\mathbf{Log_{10}A_F}$ 95pre**	0.014 (0.053)
D96pre	0.409*** (0.088)	**$\mathbf{Log_{10}A_F}$ 96pre**	0.055 (0.052)
D97pre	0.551*** (0.080)	**$\mathbf{Log_{10}A_F}$ 97pre**	-0.023 (0.054)
D98pre	0.519*** (0.802)	**$\mathbf{Log_{10}A_F}$ 97pre**	-0.108** (0.049)
$\mathbf{Log_{10}A_F}$	-0.512*** (0.036)		
			N = 2361
			Adjusted R2 = 0.733

Table 4.3. Wildfire area relative to forest area as a function of the ratios of past wildfire, past prescribed burning, and housing density to forest area, and of El Niño 3 subsurface temperature anomaly (Niño 3 SST), 1994-1999, and 1994-1997.

	1994-1999 Data	1994-1997, 1999 Data
ln(Wildfire Area$_{t-1}$/Forest Area)	-0.37 ***	-0.23 ***
	(0.06)	(0.06)
ln(Wildfire Area$_{t-2}$/Forest Area)	-0.36 ***	-0.28 ***
	(0.08)	(0.07)
ln(Wildfire Area$_{t-3}$/Forest Area)	-0.14	-0.15 *
	(0.10)	(0.08)
ln(Wildfire Area$_{t-4}$/Forest Area)	-0.37 ***	-0.29 ***
	(0.08)	(0.07)
ln(Wildfire Area$_{t-5}$/Forest Area)	-0.15	-0.31 ***
	(0.10)	(0.06)
ln(Wildfire Area$_{t-6}$/Forest Area)	-0.26 ***	-0.23 ***
	(0.08)	(0.07)
ln(Wildfire Area$_{t-7}$/Forest Area)	-0.10	-0.05
	(0.08)	(0.08)
ln(Wildfire Area$_{t-8}$/Forest Area)	-0.044	0.011
	(0.078)	(0.072)
ln(Wildfire Area$_{t-9}$/Forest Area)	-0.042	0.013
	(0.079)	(0.066)
ln(Wildfire Area$_{t-10}$/Forest Area)	-0.060	0.042
	(0.068)	(0.065)
ln(Wildfire Area$_{t-11}$/Forest Area)	-0.070	0.001
	(0.067)	(0.065)
ln(Wildfire Area$_{t-12}$/Forest Area)	0.089	0.145 **
	(0.061)	(0.058)
ln(Prescibed Permits$_t$/Forest Area)	-0.085	0.017
	(0.061)	(0.049)
ln(Prescibed Permits$_{t-1}$/Forest Area)	-0.002	-0.02
	(0.047)	(0.04)
Nino 3 SST$_t$	0.61 ***	0.33 **
	(0.12)	(0.14)
Nino 3 SST$_{t-1}$	-0.54 ***	0.01
	(0.16)	(0.29)
Ln(Houses$_t$ x 1000/Forest Area)	-2.98	-5.55 **
	(2.45)	(2.20)
Number of Cross-Sections	52	52
Number of Years	6	5
Total Panel (balanced) Observations	292	242
Adjusted R-squared	0.78	0.85
F-statistic	68 ***	86 ***

Notes: Asterisks indicate statistical significance at 1% (***), 5%(**) and 10%(*).

Chapter 5: Summary and Conclusions

The objective of this project was to evaluate the economic effects of catastrophic wildfires and the efficacy of fuel reduction treatment polices and programs for reducing the economic impacts of wildfire in both typical and extreme years. The impetus for the research was Florida's 1998 fire season, which engulfed some 500,000 acres, closed interstate highways, forced evacuations of thousands of Floridians and tourists, and led to a variety of proposed policies and programs to dramatically increase the amount of prescribed burning in Florida. For example, one bill drafted for the Florida legislature would give the Division of Forestry authority to prescribe burn any area of land (including private property) that the Division reasonably determines to be in danger of wildfire. In this report, we present the results of three independent but related studies that assess the damages from the 1998 fires (Chapter 2), identify stand and neighborhood factors associated with forests burned in 1998 (Chapter 3), and perform a longer term, statewide analysis of broad scale factors and climate and the relationship between historical wildfire patterns and the frequency of prescribed burning permits (Chapter 4).

We estimate that the total damages from the 1998 fires in Northeastern Florida range from $622-880 million. The bulk of the losses were incurred by timberland owners ($345-605 million), the tourism industry ($138 million), and the approximately $100 million of resources diverted to fighting the fires. Although the losses from this extraordinary Florida fire season constituted only a small fraction of the Florida's annual Gross State Product of $407 billion in 1998, the effects were (and continue to be) profound in the individual counties and industries most affected. Finally, respiratory problems represent a tangible cost that can exceed thousands of dollars per patient for treatment and traditionally target sensitive populations, such as children and the elderly. Current data availability limited our ability to attach a dollar figure to these costs.

As in any economic disruption, there were both winners and losers. The big losers were the timberland owners whose forests were destroyed and hotel owners and others in the tourist industry. In the short run, timber consumers fared well, as the sudden influx of salvaged timber flooded the market, reducing the price, but only at the expense of timber producers. Now that the supply has declined, those timber producers unaffected by the fires are benefiting while the consumers are losing from the higher price level (prices are above what they *would have* been had there been no wildfire). Although no Hurricane Andrew (which produced losses in the tens of billions of dollars), the $800 million cost represents a large impact on the economy of the SJRWMD and rivals damages from tropical storms and small hurricanes.

Our detailed analysis of the 1998 fire patterns in northeastern Florida (Chapter 3) informed us about two things: the types of forest that were at greatest risk of fire in that season, and the role that fire history played in modifying that risk. Classic distinctions between fuel, ignition and weather factors were not possible in this analysis. Our single attempt to isolate an ignition factor—lightning—did not find a positive effect, and other mesoscale weather factors are reflected in the ecoprovince and physiographic class

measures. Combined with the more direct vegetation measures, they do help forest managers understand what they might expect should such severe fire weather conditions recur and shed some light on what managers might do to mitigate those risks.

The forests at greatest risk under this particularly severe drought were not the forests that ordinarily see the greatest water stress. Rather it was coniferous stands in or near wetland forests that saw the most burning, especially baldcypress. This highlights the unusual nature of the 1998 fire season in northeastern Florida and suggests that different strategies might be needed from those that are effective in more typical fire years. The data also suggest that fragmentation of the forest increases wildfire risk, although this relationship bears further analysis.

Direct statistical confirmation of prescribed burning's role in reducing wildfire risk proved elusive, either through the dated measure from FIA or the more current neighborhood measure, but two other factors suggest its protective effect. First, past wildfires exerted a substantial protective effect against fire in the 1998 season. Both wildfire and prescribed burns reduce fuel for subsequent fires, and both do so to varying degrees. Second, our most direct measure of an effect of prescribed burning—reduced understory vegetation—did show a suppressive effect on wildfire. Perhaps many of the stands with lesser understory had prescribed burns undetectable to FIA crews visiting years later, perhaps other fuel management practices such as herbicide achieved the intended result. Regardless, in lieu of direct measures of litter and downed wood, understory vegetation was our best measure of the fuel to be managed, and reduced understory did indeed reduce wildfire risk.

Controlling understory vegetation in wetland sites poses special difficulties. Conditions favorable for conducting controlled burns are likely to be rare, and herbicide use near open water raises environmental concerns. Other options may prove more attractive: greater use of firebreaks, improved fire resistance for buildings and their surroundings, and better detection and suppression capabilities for when fire conditions become severe, but for this we defer to others more familiar with such technologies.

Our multi-decadal analysis of Florida wildfires since the early 1980's suggests that on average 100,000 acres burn annually resulting in an annual risk of forest wildfires of 0.86 percent, or one acre in every 117. For a typical 30-year slash pine rotation, this translates into an expected risk of 3.16 percent, or one of every 32 acres. This risk of wildfire varies across space and time. County level risks of forest wildfire varied from 0.02 to 6.9 percent. Statewide, wildfires consumed only 0.2 percent (23,600 acres) in 1983 compared to 4.0 percent (472,000 acres) in 1998. Prescribed burning shows a similar temporal and spatial variation with annual prescribed burning rates for counties (percent of the county's forests treated) ranging from 0.2 to 30.8 percent. This spatial and temporal variation in wildfire and prescribed burning led us to perform the detailed statistical analyses (in Chapter 4) of the impact of factors that vary over space and time on the effectiveness of prescribed burning programs.

Chapter 4 focused attention on the specification and quantification of factors affecting fire production functions in Florida. Two fire production function models were estimated. The first model estimated fire frequency-size distributions for prescribed and wildfire regimes and was specified at the ecoprovince level. The second model

estimated, at a finer geographic scale (county), the relationship between fire inputs (weather patterns, extent of prescribed burning, past fire history and housing density) and wildfire extent.

Wildfires in Florida can be reasonably modeled using variable parameter power-functions. Regression results indicated that, over the entire historical record, large fires were responsible for most of the area burned. In addition, wildfire frequency-size distributions shifted downward by about 10% in the 17 years leading up to the 1998 fires. Perhaps this is an indication of increased fire suppression effort over this time period which may suggest an increase in fuel load.

The 1998 fires did not behave in the same fashion as fires in previous extreme fire years. In prior extreme fire years, the wildfire frequency-size distribution *shifted upward* and *rotated downward*, indicating an increase in small fires and a relative reduction of large fires. In 1998, however, the slope of the frequency-size distribution *rotated upward*, resulting in a preponderance of large fires relative to small fires. Consequently, the number of total acres burned exceeded all other years in the historical record. Can this result be interpreted as a "Yellowstone effect"? While it is clearly premature to make this assertion, the wildfire frequency-size distribution analysis suggests this possibility. Clearly, more research targeted at these phenomena is warranted.

Figure 5.1 illustrates this idea of a long-run equilibrium and a tendency of the environment to regain the long-run equilibrium in material build-up through fire. Prescribed fires are ignored in this figure. The forest wildfire area in ecoprovince 232G is typically at a level below that sustainable in the long-run: in normal years, the amount of wildfire is several thousand acres less than the average rate. During extreme years, perhaps when connectivity increases due to dry conditions, wildfire area is substantially above average, in some cases returning the ecoprovince's forests to equilibrium with regard to wildfire area and risk. While this figure describes the Atlantic coastal forests of northern Florida, similar figures can be constructed for other ecoprovinces. Here, it is clear that the province was accumulating a very large wildfire "deficit" in the nine years before the 1998 wildfires. The wildfires observed that year were so large that, in fact, they consumed all of the deficit and more, leaving the region with a wildfire "surplus." That surplus may persist, given average wildfire levels, for up to six years and hopefully indicate a delay of the next extreme wildfire year for a decade or more.

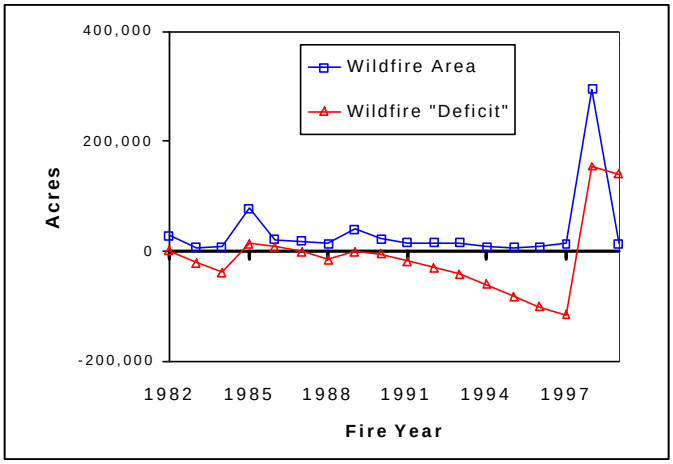


Figure 5. 1 Wildfire area and a hypothetical wildfire "deficit", as calculated from the cumulative sum of wildfire area minus average wildfire area, for the ecoprovince 232G.

Results of wildfire area regressions carry with them several conclusions. First, past wildfires have a substantial, and perhaps the primary, suppressive effect on current wildfire area. These results are further supported by the fixed-plot fire probability model results of Chapter 3. The suppression persists for six years, and it even persists under conditions found in the most severe years. The finding that one acre of wildfire will suppress future wildfires by a total of more than one acre hints that let-burn strategies may be very effective in reducing future wildfire risks. Second, although prescribed burning may make a positive economic contribution to the profitability of timber production (through competition control, reduction of operational expenses, etc.), there is little statistical evidence that prescribed burning is effective in reducing wildfire risk.

The reason for this may be that prescribed burning is taking place in locations on the landscape where its relatively modest fuel reductions (compared with those offered by wildfire) do not contribute substantially to the breaking up of vegetative contiguities or ignition risks. However, this result does not imply that pre-suppression activities in particularly high risk years would not be useful in reducing wildfire risks during those years. Rather, pre-suppression activity that is focused on just those areas with highest risk should have a disproportionate effect on broad scale fire risk. Still, the lack of significance of the prescribed burning area in the model may be suggesting that a more refined level of spatial analysis—such as township or section—may be required. Another possibility is that prescribed burning influences the intensity, but not spatial extent, of wildfires. This hypothesis deserves attention. Fourth, the urban-wildland interface was not identified in this study as a significant positive risk factor for wildfire area; in fact, denser development in counties with forests works to reduce the extent of wildfire. But this apparent protective effect of housing development was diminished in 1998, when vegetative breaks and suppression efforts may have been less effective in reducing wildfire spread. Fully understanding the myriad influences or urban areas on wildfire, however, requires a significant additional research effort.

Our analysis suggests that the Northeast Florida fire season of 1998 was unusual in several ways:

- hydric stands including baldcypress and the forests located near them were at higher risk of burning than other forests, with young pine a close second,
- urbanization had a positive effect on area burned in contrast to other years,
- large fires made up a greater fraction of fires than in even the severest fire years that preceded it,
- accumulated fire deficit was more than surpassed--in other ecoprovinces this has not happened,
- damages were sufficiently severe to draw in fire suppression resources from across the nation and special funding from FEMA, and
- hotel revenues declined in response to the fires, a pattern not seen in previous fire years.

Caveats

The linkages between prescribed burning and wildfire risk are much more complex than can be thoroughly explored in this study. While it is mechanistically apparent that removal of fuel in a stand through prescribed burning must at least in the short run reduce the risk of serious wildfire, various factors complicate detection of this relationship in empirical analyses. Our analyses were seriously limited by data describing prescribed burning activity. Time series were very short and we do not understand how closely actual prescribed burning activity relates to issued permits. There are additional considerations. First, permits for prescribed burning are dependent on fire weather conditions, imposing a spurious inverse relationship between prescribed burns and wildfire when compared within the same short time interval. From a statistical perspective this suggests that prescribed burning and wildfire area may be codetermined to some extent. In our study this problem was mitigated by differences in seasonality—prescribed burns are most frequently conducted in winter to early spring, months before most wildfires. Second, a spatial variation on codetermination is that landowners in areas historically subjected to wildfires might understandably be among those most eager to conduct prescribed burns. This imposes a positive relationship into spatial comparisons despite the depressing effect of fuel management in individual stands.

Finally, all of our analyses focused on wildfire area rather than fire intensity. However, prescribed burning's greatest contribution may be in reducing the intensity rather than the area of wildfires. For example, prescribed burning may reduce the numbers of trees killed and thereby landowner losses and may reduce suppression costs by preventing crowning out. None of these effects are observable in the data we used as we were only able to examine the probability of a wildfire rather than the intensity or type of fire. However, extending our analysis to include these effects should be a fruitful area of additional research. Finally, we should also re-state that we ignored grassy fires as our focus was on forest fires and the role forest management may play in ameliorating the potentially devastating impacts of wildfire.

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