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Economically Optimal Wildfire Intervention Regimes

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Paper Presented at the American Agricultural Economics Association Annual Meeting, Chicago, IL, August 5-8, 2001.

Abstract

Wildfires in the United States result in total damages and costs that are likely to exceed billions of dollars annually. Land managers and policy makers propose higher rates of prescribed burning and other kinds of vegetation management to reduce amounts of wildfire and the risks of catastrophic losses. A wildfire public welfare maximization function, using a wildfire production function estimated using a time series model of a panel of Florida counties, is employed to simulate the publicly optimal level of prescribed burning in an example county in Florida (Volusia). Evaluation of the production function reveals that prescribed fire is not associated with reduced catastrophic wildfire risks in Volusia County Florida, indicating a short-run elasticity of -0.16 and a long-run elasticity of wildfire with respect to prescribed fire of -0.07. Stochastic dominance is used to evaluate the optimal amount of prescribed fire most likely to maximize a measure of public welfare. Results of that analysis reveal that the optimal amount of annual prescribed fire is about 3 percent (9,000 acres/year) of the total forest area, which is very close to the actual average amount of prescribed burning (12,700 acres/year) between 1994-99.

Keywords: wildfire, prescribed burning, damages, stochastic dominance, Florida

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Economically Optimal Wildfire Intervention Regimes

Introduction

The United States spends millions of dollars annually to suppress wildfires that continue to produce millions of dollars in damages to the U.S. economy each year. For example, the 2000 wildfire season in the United States burned over 7 million acres and resulted in federal direct wildfire suppression expenditures of nearly \$900 million (National Interagency Fire Center). The recent amount of wildfire exceeds the 40-year average, and some industry, environmental and land management experts claim is the result of misguided government wildfire suppression and vegetation management policies. Land managers and policy makers have proposed a number of actions to reduce damages from catastrophic fires (USDA Forest Service). Proposals to reduce risks of future catastrophic losses from wildfire include recommendations that land management agencies increase rates of prescribed burning, mechanical thinning, and timber harvesting over those observed in recent years. These proposals carry with them many economic questions, few of which have been rigorously analyzed.

One of the principal economic questions is whether the resources expended to reduce wildfire risk result in net economic gains. Previous analyses of vegetation management have recognized that the site level and short-term net benefits of such intervention may be positive (e.g., González-Cabán and McKetta). Yet, little work has been done to evaluate whether this is true at broader spatial and temporal scales. For example, how does vegetation management in a landscape (e.g., a county or other large spatial unit) affect wildfire patterns in the landscape? Answering this question requires evaluating dynamic wildfire patterns in the context of a mosaic of human settlements, varying ecological conditions, alternative vegetation management treatments, stochastic weather, and a combination of random and nonrandom ignition risks. In other words, until we understand how wildfire patterns respond to intervention, statements about whether more (or less) vegetation management is “better” is premature.

This paper develops a method for identifying publicly optimal levels of prescribed fire and wildfire. We explicitly ignore the private decision of how much prescribed fire to apply to an individual forest stand and focus instead on how prescribed fire can be used to maximize the sum of discounted expected producer and consumer surplus (Samuelson 1954, 1955) for a region. We report an empirical wildfire production function, apply assumed prices of wildfire output and prescribed fire input, simulate

wildfire over time given alternative stationary prescribed fire policies, and use stochastic dominance techniques (Hadar and Russell) to compare the discounted net present value of public welfare of each prescribed fire policy. After the best rate of vegetation management intervention into the wildfire regime is determined, we evaluate the welfare effects of deviating from the optimal policy.

Literature and Methods

Economists have outlined many of the economic principles of wildfire management policy over the past eighty years (Headly; Lovejoy; Sparhawk; Davis; Gamache; Gorte and Gorte; Mills and Bratten; Bellinger, Kaiser and Harrison; Teeter and Dyer; Rideout and Omi 1990; Hesseln). The more recent descriptions framed the problem as akin to profit maximization given prices or as a problem of minimizing the sum of the net value change from wildfire and the costs of suppression (firefighting activities) and presuppression (activities that reduce wildfire risk, including vegetation management) (Rideout and Omi 1990). Previous research did not recognize that for large spatial units, wildfire in period t could affect wildfire in that same spatial unit in subsequent periods. Only Donoghue and Main took a broad scale approach in their evaluation of wildfire, although their model did not recognize that presuppression activities could have effects that extend beyond the current time period and the immediate location of the activities. Because wildfires consume flammable vegetation and because vegetation management can affect fire fuel levels, it is reasonable to expect that the effects of fire and vegetation management can operate across a range of scales of space and time.

In general, determining the publicly optimal amount of vegetation management requires a solution to a stochastic dynamic optimization problem. To find the optimal levels of vegetation management inputs, we maximize the sum of expected current and future net present value of welfare:

$$(1) \quad \max_{\mathbf{x}_t} A = E \left\{ VW_t - \mathbf{v}' \mathbf{x}_t + \sum_{i=t+1}^T e^{-ri} (VW_i - \mathbf{v}' \mathbf{x}_i) \right\}$$

$$s.t. W_t = W(\mathbf{Z}_t, \mathbf{W}_{t-j}, \mathbf{x}_{t-k}) + \varepsilon_t, \mathbf{x}_t \geq \mathbf{0} (\forall t)$$

where A is the maximization criterion (a welfare measure), V is the net value change per unit area of

wildfire, W_t is current wildfire area for the spatial unit of observation in year t , \mathbf{v} is a vector of the prices per unit area of suppression and presuppression inputs¹, $\mathbf{x}=(x_t, x_{t+1}, \dots, x_T)$ is a vector of areas of these inputs for year t through T (the planning horizon), \mathbf{Z}_t are exogenous inputs to wildfire production including a stochastic climate variable, $\mathbf{W}_{t,j}$ is a vector of j lags of wildfire area, and r is the discount rate. The result of this analysis is a $T \times 1$ vector of optimal input quantities and a $T \times 1$ vector of wildfire quantities over time. The uncertainty associated with random events (errors in prediction of weather, for example) means that $W(\cdot)$, is known only with error, complicating the solution process. In the presence of such error, simulation techniques may be used to identify, for example, the amounts of vegetation management most likely to maximize the welfare criterion. Hadar and Russell described how to evaluate these kinds of uncertain prospects.

Vegetation management is already conducted on private lands in the U.S. with little or no inducement by public agencies, at least partly motivated by a desire to reduce risks of catastrophic wildfire. Indeed, if landowners are rational, and in the absence of subsidy or mandatory prescribed burning laws, those who manage vegetation and thereby reduce wildfire risk perceive that the private benefits of vegetation management exceed their private costs. However, vegetation management affects some public values; for example, prescribed fire generates smoke that crosses property boundaries. Also, because wildfires and escaped prescribed fires (one kind of vegetation management) cross property boundaries, private behavior affects the wildfire risks experienced by others. For these reasons, it may be informative for policy makers to better understand the publicly optimal rates of vegetation management and how they may differ from the apparently privately optimal rates. Once the differences between privately and publicly optimal rates of vegetation management are better understood, policy makers and analysts can identify methods of bridging the apparent gaps between these rates.

Optimization models such as (1) may involve as many choice variables as periods in the simulation², so they can be difficult to solve even with currently available computing power. An alternative, consistent with any utility function that demonstrates nonincreasing marginal utility, is to find the single optimal (stationary) policy that would yield the highest expected net welfare benefits out of the

¹ The “price” to the economy would be the net welfare changes arising from the diversion of resources to vegetation management and away from other economically productive activities in the economy.

² The number of periods could be specified as infinite. Discounting would, of course, place a practical limit on the number of periods that need to be considered.

set of possible policies. In this case, the quantities in the vector x in (1) would be constant (i.e., $x_t = x_{t+1} = \dots = x_T$).

In this research, we apply first-degree stochastic dominance (FSD), second-degree stochastic dominance (SSD), and third-degree stochastic dominance (TSD) concepts to evaluate alternative stationary policies for one kind of vegetation management, levels of prescribed fire applied annually in the spatial unit (one county in northeastern Florida). We simulate the empirical cumulative value function for wildfire. In the parlance of Hadar and Russell, g is at least as large as f if and only if $G(x_i) \leq F(x_i)$ for all x_i contained in X . Using the wildfire optimization model, a single distribution of the welfare criterion (A) is generated for a given level of prescribed fire, x_i . Additional distributions of A are generated under alternative levels of prescribed fire. Then, all of the distributions are compared under FSD.

The possibility that the probability distributions cross (i.e., FSD does not hold) requires that SSD be applied. Under SSD, if the area under one cumulative distribution G is always less than or equal to the area under another cumulative distribution F , then G has SSD over F . That is (Hadar and Russell),

$$(2) \quad \int_{x_1}^x G(y)dy \leq \int_{x_1}^x F(y)dy \quad \text{for all } x \in I$$

If FSD holds, then SSD automatically holds. If neither SSD nor FSD holds, the analyst is forced to compare the value of entire cumulative distributions (e.g., Levy and Kroll). This is the essence of third-degree stochastic dominance. Here, G has TSD over F if:

$$(3) \quad \int_{x_1}^x \int_0^t [G(y) - F(y)]dydt \text{ for all } x \in I \text{ and } \int_0^1 [G(t) - F(t)]dt \geq 0$$

Wildfire Production, Prices, and Data

The wildfire production function used in this research was estimated from an annual time series of wildfire for a cross-section of 39 counties in Florida for the period 1994-1999 (Prestemon et al.). The model was estimated as a wildfire risk function, using a fixed-effects panel approach assuming

heteroscedastic errors:

$$(4) \quad \ln\left(\frac{W_{i,t}}{F_i}\right) = \sum_{i=1}^I a_i d_i + \sum_{j=1}^J b_j \ln\left(\frac{W_{i,t-j}}{F_i}\right) + c \ln\left(\frac{B_{i,t}}{F_i}\right) + \sum_{m=1}^M f_m \ln\left(\frac{P_{i,t-m}}{F_i}\right) + g_1 E_t + g_2 E_{1998} + \omega_{i,t}$$

where: \ln is the natural logarithm operator, $W_{i,t}$ is wildfire area (acres) in county i in year³ t , F_i is the area of forest (acres) in the county, the d_i 's are dummies for the various counties to control for the fixed effects of counties on the error term, $B_{i,t}$ is the amount (acres) of prescribed burning⁴ in year t , $P_{i,t-m}$ is the amount (million ft³) of small diameter materials (trees with diameters at breast height less than 9 inches) removed from forests of county i in period $t-m$, E_t is the Niño 3 sea surface temperature (Niño 3 SST) anomaly (departure from a long-run moving average) in degrees centigrade, and E_{1998} is a dummy variable corresponding to 1998, allowing the effect of the Niño 3 SST anomaly for 1998⁵ to be different from all other years, and $\omega_{i,t}$ is a randomly distributed error term with variance 0.80 (see the equation (5) estimate). This equation forces the structural relationship between wildfire area and right-hand-side variables shown in (2) and (3) to be identical across all counties, although the intercept-shifting county dummies allow endemic levels of wildfire to vary across counties. Note that, except for the coefficients on the Niño 3 SST variables, which are not in logarithms, the significance of the lags of the dependent variable imply that the coefficients in this formulation amount to short-run elasticities. Long run elasticities (in this case, the “long

³ The year we refer to is the “fire year,” October 1-September 30. Hence, fire year 1994 was October 1, 1993, to September 30, 1994. The fire year was defined as such because September and October are typically months with the least wildfire activity. The typical wildfire season is from January-July, with the worst fires in April-July. Prescribed fire usually is done (depending on the county) in December-March.

⁴ Prescribed burning area is defined here as the sum of the permitted prescribed fire permits issued in the county in that fire year. In an initial model estimate, two lags were included, to account for lingering effects of prescribed fire. However, only current year prescribed fire was statistically related to wildfire at traditional levels of significance. Equation (3) is the more parsimonious model used in the optimization modeling. Also, prescribed fire in period t always precedes wildfire in period t because the prescribed burning season ends before the wildfire season begins in each fire year and each county. Counties do not issue permits once wildfires begin burning in that county for the wildfire season, and very little prescribed fire occurs in the fire year after the wildfire season is over.

⁵ The 1998 value of the temperature anomaly was modeled as a separate variable because 1998 marked the end of a “super” El Niño, in which the magnitude of the cycle of the El Niño Southern Oscillation was of a scale not before observed. We allowed the effect of the “super” El Niño to be different in the modeling.

run is J years, the number of significant lags of the dependent variable) are a function of the short run elasticity and the coefficients on the lagged dependent variable. For example, the long-run elasticity of

wildfire area with respect to prescribed fire area is $c/(1 - \sum_{j=1}^J b_j)$.

Our production function estimate forced wildfire to behave similarly in response to climatic and human influences, and it forced wildfire regimes to be identical across forest stands. Most counties included in our analysis were in northern Florida, but the forests of northern Florida vary ecologically, and they are subject to differing levels of wildfire ignition risks⁶. The observed wildfire area implicitly contains the effects of efforts by humans to limit its extent through suppression. In econometric estimates we attempted to include a proxy for suppression, housing count divided by forest area, but the coefficient estimate on that variable was not statistically different from zero. Finally, although we used wildfire area as the measure of wildfire damages, wildfires differ in their intensity, some being more damaging than others, and wildfire intensity may be related to the amount of prescribed fire in a way that differs from how wildfire area is related to prescribed fire. A better model might relate explanatory variables to the amount of destroyed timber and nontimber capital.

The cost of prescribed fire varies by the size of the burn and a variety of operational variables (Cleaves and Brodie; Bellinger, Kaiser, and Harrison; González-Cabán and McKetta; Rideout and Omi 1995). However, in our spatially aggregated model, we assume that the average cost per acre does not change according to the scale of prescribed burning within a spatial unit. We use a prescribed fire “price” of \$25/acre, which is actually the private price of obtaining prescribed fire services. This is not the general equilibrium welfare effect on the economy of diverting resources away from other economic activities and to prescribed fire (see Thurman and Thurman and Easley); rather, the prescribed fire “price” of \$25/acre is a first approximation of the public price of prescribed burning.

The net value change of wildfire was based on findings of Butry et al. The Butry et al. research reported welfare effects on timber markets and expenditures on suppression, costs of evacuations, and changes in spending in other sectors. The point estimate of timber market welfare impacts caused by the 1998 wildfires amounted to approximately \$750/acre. The welfare effects of resource diversions away from

⁶ Ignition sources include arson, various accidents (sparking from vehicle accidents, debris burning, campfires, etc.), and lightning.

other economic sectors and the destruction of resource inputs into production would only add to that figure. However, we conservatively use the \$750/acre in our modeling.

Results

The wildfire production function in equation (5) shows those variables whose coefficients were significant at the 10% level, but suppressing for parsimony the estimates of county dummy variables (there were 39 dummy variables, most of which were statistically significantly different from zero at traditional significance levels) and the effects of small-diameter timber harvests (also statistically significantly different from zero).

$$(5) \quad w_{i,t} = \sum_{i=1}^I a_i d_i - 0.12w_{i,t-1} - 0.29w_{i,t-2} - 0.19w_{i,t-3} - 0.33w_{i,t-4} - 0.23w_{i,t-5} - 0.17w_{i,t-6} - 0.07w_{i,t-7} - 0.16b_{i,t} + \sum_{m=1}^M f_m p_{i,t} - 0.38E_t + 1.82E_{1998} + \omega_{i,t} \quad R^2 = 0.81, s = 0.91$$

where w_i is the natural logarithm of wildfire area divided by forest area, b_i is similarly defined for prescribed fire.

Equation (5) shows that only the current year's prescribed fire area is a statistically significant explainer of wildfire risk (no lags of this measure were significant at 10 percent significance). The estimated long-run elasticity of wildfire with respect to current year prescribed fire is therefore $-0.16/[1-(-0.12-0.29-0.19-0.33-0.23-0.17-0.07)]=-0.07$. In other words, each 1 percent increase in prescribed fire area leads to a seven-year reduction in wildfire area by 0.07 percent. Also important in the model are the estimates of coefficients on lagged wildfire risk. Implied by (5) is that each 1 percent increase in current wildfire area leads to a 1.4 percent $(-0.12-0.29-\dots-0.07=-1.4)$ decrease in future wildfire area over the ensuing seven years. Similarly, the ENSO measure was negatively related to wildfire area, except in 1998, when the direction of influence appeared to be opposite of usual. The sign difference, however, illustrates an apparent imprecision in measurement of the effect of ENSO in 1998: the average of the ENSO measure was positive over the 12 months of the fire year, reflecting what historically would have been considered indicative of wet conditions, while during the fire season the measure was negative, consistent with dry

conditions and the historical relationship between wildfire area in Florida and ENSO (Brenner, Barnett and Brenner).

The software package @Risk® was used to conduct 20,000 Monte Carlo simulations of 50-years of wildfire area in 1,000-acre/year increments of prescribed fire, ranging from 1,000 acres/year to 20,000 acres/year in Volusia County, in northeast Florida, one of the counties of the St. John's River Water Management District that in 1998 experienced catastrophic wildfires (Butry et al.) (Figure 1 and Table 1). Small-diameter timber harvests, variables in the equation estimate, were held constant over the entire simulation periods, so their effects were not directly explored. The simulated distributions of the objective function were compared across prescribed burning policies using stochastic dominance to identify the “best” level. The model (5) was converted to a wildfire area model for wildfire in Volusia County in year t by taking the exponential of the predicted w_t for Volusia County and multiplying by the area of forest in the county (313,035 acres). The randomness requiring simulation using @Risk® was from two sources: the equation standard error of estimate and the simulated values of E_t . ENSO was simulated by adding to a historical 50-year realization of the Niño 3 SST anomaly (National Oceanic and Atmospheric Administration) a normally distributed random error whose standard deviation was determined from first-differences of the 50-year Niño 3 SST anomaly realization⁷. Wildfire price per acre was negative (i.e., -\$750/acre), while the cost per acre of prescribed fire was positive (+\$25/acre). Because of that, as specified, the modified objective function (1) seeks to maximize, given a stationary prescribed fire policy, a welfare measure that is always negative (see Rideout and Omi 1990).

Stochastic Dominance Results

Simulation results show that, in the range of alternative stationary prescribed fire policies considered, no policy has FSD or SSD over all alternatives; probability distributions of the objective function values cross in the ranges from 8,000 acres/year to 12,000 acres/year. Only using TSD can an optimal policy be identified: 9,000 acres/year. This figure is close to the 1994-1999 average actually done

⁷ Another strategy for simulating ENSO was also tried, with essentially identical results regarding the optimal prescribed fire policy. In this other strategy, for each simulated 50-year period, a 50-year span of the Niño 3 SST anomaly was sampled randomly from a combination of proxy and actual data. The proxy record (Woodruff et al.) runs from 1864 to 1949; actual data run from 1950-2000 (National Oceanic and Atmospheric Administration).

in Volusia County (12,700 acres/year). Differences in cumulative value functions between 7,000 acres/year and 11,000 acres/year were very small (Figure 2). In short, once the stationary policy is found within half an order of magnitude of the best level, expected discounted net welfare is approximately maximized.

The mean value of the objective function for 9,000 acres/year is -\$34.22 million, for 7,000 acres/year of prescribed fire is -\$34.28 million, and for 11,000 acres/year is -\$34.24 million. When the level of prescribed fire is set at 100,000 acres/year (near the highest rate observed in the panel of prescribed fire observations in Florida and amounting to burning one-third of the forest in the county in the same year), the mean value of the objective function is -\$56.70 million, a \$22.38 million difference from the 9,000 acres/year policy. Part of the explanation for the small differences among stationary policies in the 1,000-20,000 acres/year range is the small differences in the realized average wildfire areas: prescribe burning 20,000 acres/year only reduces wildfire area an average of 900 acres/year for the county compared to the 1,000 acres/year policy. Nevertheless, because of the small cost of prescribed fire, the returns from doing the identified “best” level of prescribed burning compared to the smallest level consistent with the data are large: to prescribe burn 9,000 acres/year costs \$200,000 more than to burn 1,000 acres/year, while the net value change saved amounts to +\$3.6 million—a marginal benefit to marginal cost ratio of 18. Of course, beyond 9,000-acre/year, given the prices considered the marginal benefits are less than the marginal costs of conducting more prescribed burning.

The prices assumed for wildfire output and prescribed fire input were merely educated guesses, so it is important to understand how such guesses would affect the optimal rates of prescribed fire. Principles of profit maximization (e.g., Varian, p. 25-28) offer an understanding of the optimal levels of prescribed fire input: the marginal product (wildfire) should equal the ratio of the output (wildfire output) price to the input (prescribed fire) price. In our setting of stochastic wildfire and long-run effects of prescribed fire that differ from short-run effects, this condition basically holds. At 9,000 acres of prescribed fire, the marginal product average over 20,000 simulations is about -0.032, while the price ratio is -0.033. The effect on optimal prescribed fire input of changing the price ratio depends on the shape of the wildfire production function. We explored the effects of doubling and halving ratios of wildfire output and prescribed fire input. Doubling the ratio approximately doubles the best rate of prescribed burning (found through stochastic dominance), and halving it reduces the identified best rate of prescribed fire by about half.

Implications

The modeling and simulations reported here describe how to identify an economically optimal level of vegetation management in a forested landscape. Our production function estimate, applicable only to Florida, suggests that prescribed fire is not a major force determining the area of wildfire in that state in any given year. More important are weather conditions linked to ENSO and the apparent randomness in wildfire ignition and extent. For example, the most negative value of the Niño 3 SST anomaly would result in expected wildfire area 60% greater than average, while the most positive value of Niño 3 SST would force expected wildfire to be 32% below average. Changing the amount of prescribed fire across observed levels in Florida would only change expected wildfire area by a few percentage points from the levels forced by climatic conditions—prescribed fire merely chips away at the margins. Indeed, previous wildfires are much more effective at reducing wildfire in the current period, so prescribed fire’s effectiveness is severely dampened in the long-run even if it appears somewhat effective at reducing wildfire peaks in the short-run.

Future research in this area seems nearly unlimited in scope, but following this approach, needed improvements would focus on obtaining more precise estimates of the prices of wildfire output and vegetation management inputs and on refining estimates of wildfire production functions for Florida and other fire-prone regions of the U.S. and elsewhere. Research should fully account for benefits of prescribed fire on timber growth, timber production costs, and nontimber outputs of private forests, and it should account for nontimber and non-market public and private values affected by both wildfire and vegetation management activities. Improved production function modeling would explore wildfire production at alternative scales of spatial resolution, allow wildfire production to vary by forest types and other ecological and fuel conditions, include all potential vegetation management inputs, recognize differences in intensity of individual wildfires, and seek to understand how wildfire intensity is related to climatic and weather conditions.

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Table 1. Statistics on discounted net value change minus costs (net discounted public welfare) generated for 20,000 fifty-year simulations for each of 20 stationary prescribed fire policies in Volusia County, Florida.

Prescribed Fire (Thousand Acres/Year)	95% Probability of Being Greater Than (\$ million)	5% Probability of Being Greater Than (\$ million)	Mean NVCMC (\$ million)	Std Deviation (\$ million)	Mean Wildfire (Thousand Acres/Year)
1	-52.53	-31.73	-40.17	6.79	4.73
2	-49.93	-30.46	-38.36	6.35	4.50
3	-48.78	-29.83	-37.51	6.21	4.38
4	-47.73	-29.50	-36.98	5.97	4.29
5	-47.37	-29.36	-36.68	5.92	4.22
6	-47.03	-29.15	-36.49	5.86	4.17
7	-46.67	-29.27	-36.37	5.67	4.12
8	-46.54	-29.15	-36.32	5.71	4.09
9	-46.43	-29.23	-36.30	5.62	4.05
10	-46.51	-29.41	-36.35	5.58	4.02
11	-46.31	-29.51	-36.34	5.53	3.99
12	-46.36	-29.52	-36.42	5.53	3.97
13	-46.21	-29.71	-36.53	5.45	3.95
14	-46.53	-29.73	-36.54	5.49	3.95
15	-46.54	-30.02		5.37	3.91
16	-46.62	-30.07	-36.88	5.52	3.89
17	-46.76	-30.31	-37.01	5.37	3.87
18	-46.73	-30.50	-37.16	5.35	3.86
19	-46.94	-30.70	-37.32	5.37	3.85
20	-47.10	-30.92	-37.49	5.27	3.84

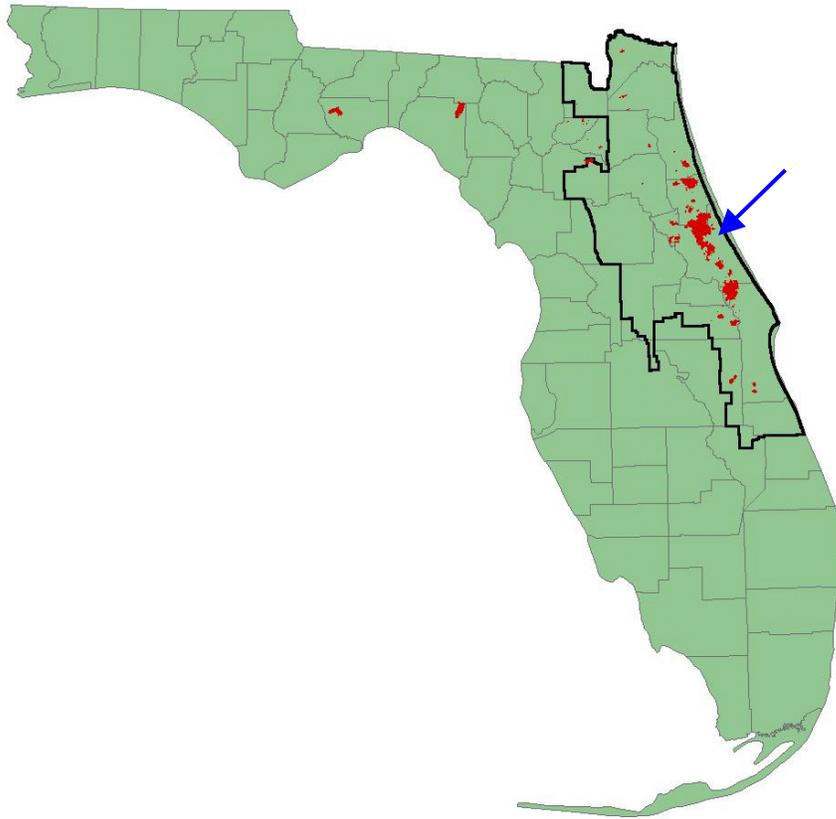


Figure 1. Florida and the Saint John's River Water Management District (outlined in black). Red polygons are the locations of catastrophic wildfires of June-July, 1998. Volusia County is indicated by the arrow.

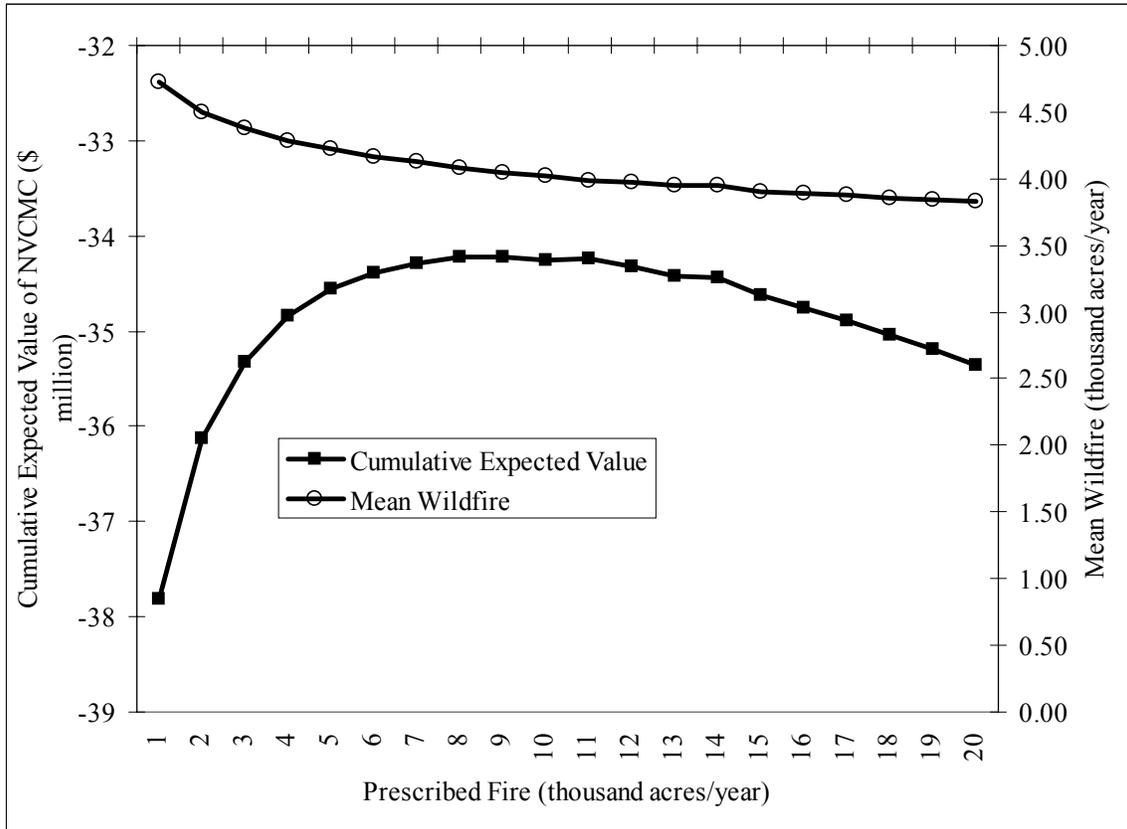


Figure 2. Cumulative expected value of net discounted public welfare (NVCMC, the objective function value) and mean expected wildfire acres, 20,000 Monte Carlo simulations of fifty-year wildfire realizations, for each of 20 alternative stationary prescribed burning policies, Volusia County, Florida.