CHAPTER 13

ANALYZING TRADE-OFFS BETWEEN FUELS MANAGEMENT, SUPPRESSION, AND DAMAGES FROM WILDFIRE

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1. INTRODUCTION

With expenditures to suppress wildfires in the United States increasing rapidly during the past couple of decades[1], fire managers, scientists, and policy makers have begun an intense effort to develop alternative approaches to managing wildfire. One alternative is "fuels management,"[2] which typically uses prescribed fire or mechanical methods (or both) to reduce fuel loads in dense, overstocked forests. Despite meeting strong resistance from many wildland policy makers and resource managers throughout much of the 20th century (Yoder et al. 2003), within the past decade prescribed fire has become one of the most frequently promoted approaches to reducing wildfire risk and intensity (Bell et al. 1995, Haines and Cleaves 1999, Hesseln 2000). For example, the Healthy Forests Restoration Act of 2003 called for dramatic increases in the use of fuel treatments to reduce hazardous fuel loads and the economic costs of wildfire, and one of the main objectives of the National Fire Plan (USDI/USDA 1995) is reducing fuels on 3 million acres annually. Graham et al. (2004) estimated that 100 million acres of forest lands historically burned by frequent surface fires in the western United States may benefit from surface fire restoration and 11 million acres need to be treated to protect communities (Graham et al. 2004), while Rummer et al. (2003) calculated that 66 million acres could benefit from fuels reduction. Progress has been slow, however. Obstacles include public resistance to smoke, planning and regulatory review difficulties, potential impacts on threatened and endangered species, budgetary limitations, risk of escaped fires, and lack of incentives (Stephens and Ruth 2005).

[1] Fire suppression expenditures by the USDA Forest Service rose from $160 million in 1977 to $760 million in 2005, when adjusted to 2003 dollars (Mercer et al. 2007).

[2] Fuels management is defined in the USDA Forest Service Manual as the "practice of controlling flammability and reducing resistance to control of wildland fuels through mechanical, chemical, biological or manual means, or by fire, in support of land management objectives." (USDA 1995).

T. P. Holmes et al. (eds.), The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species, 247–272.

The objectives of this chapter are to (1) characterize the overall problem of economically rational interventions into wildfire processes, (2) describe how economists and other analysts have evaluated the efficacy of fuel treatments, and (3) provide some empirical examples of how we have evaluated the trade-offs among fuel treatments, wildfire suppression, and wildfire damages. A goal of the chapter, however, is also to provide an overall characterization for the many complexities of the problem, due to its spatial and temporal dimensions and its need to account for the multiple impacts of both wildfire and proposed interventions.

2. LITERATURE REVIEW

Conventional wisdom suggests that reducing fuel loads may enhance wildfire management efficiency by reducing the resources needed for fire suppression, increasing fire fighter safety, and allowing more flexibility for suppression strategies. All too often, however, fuels management advocates promise an array of benefits yet to be validated by science. For example, fuels reduction has been promoted to restore forest structure and function, eliminate today's out of control wildfire behavior, and reduce suppression costs, acres burned, and economic and ecological damages (Finney 2003). Several recent studies, however, provide evidence that reducing fuel loads may have only a short-lived effect on wildfire spread rates (Fernandez and Botelho 2003).

The effectiveness of fuels management for reducing wildfire risk varies by ecosystem, fuel type, and weather. Although reducing fuel loads may facilitate wildfire management during most weather conditions, Graham et al. (2004) suggest that placing too much emphasis on fuels treatments for reducing the risk of catastrophic wildfire may underestimate the more important role played by weather. Under extreme weather conditions (low fuel moisture, low humidity, high winds), intense wildfires often burn through or breach most fuel treatments (Fernandez and Botelho 2003). For example, in the Southern Canadian Rockies, Graham et al. (2004) found surface fire intensity and crown fire initiation were affected more by weather rather than fuel loads. Crown spread, however, was slightly more dependent on fuels.

Piñol et al. (2005) examined the effectiveness of fuels treatments using simulation models and fire history data from Tarragona, Spain and Coimbra, Portugal. They found that the total amount and proportion of large fires decreased with increasing prescribed fire while the total area burned was not affected by fire suppression or prescribed fire. Suppression slightly enhanced dominance of large fires and prescribed fire reduced the importance of large fires. Finney (2003) concludes that changes in fire behavior associated with reduced fuel loads may enhance the effectiveness of fire suppression tactics, but it is impossible for fuel treatments alone to stop fires from burning or spreading. A more realistic objective for fuel treatments may be to reduce the risk of crown fires that tend to produce higher economic and ecological damages (Graham et al. 2004).

Research on the operational effectiveness of fuels management has been primarily based on anecdotal case studies, most of which only report on areas recently prescribed burned (i.e., within 4 years prior to the wildfire). However, since wildfires are produced from a combination of several random events (e.g., weather, ignition sources, ecological conditions) the usefulness of conclusions drawn from even the best of case studies is limited and needs to be validated with statistical analyses across a variety of spatial and temporal scales (Fernandez and Botelho 2003).

We know of only two studies (Prestemon et al. 2002, Mercer et al. 2007) that have rigorously subjected time-series data to statistical analyses of the impact of fuels management on wildfire risk. Both studies used data on wildfires and prescribed fire in Florida from 1994-1999 (Prestemon et al. 2002) and 1994-2001 (Mercer et al. 2007) and reported similar results. Mercer et al.'s more recent analysis showed that prescribed burning reduces wildfire risk for at least three years. Averaged over three years, each percentage increase in prescribed burned area in a county reduced wildfire area by 0.27 percent. In the short run (0-2 years), a 1 percent increase in prescribed burning acreage reduced the areal extent of wildfire by 0.65 percent and, when acres burned were weighted by fire intensity, by 0.71 percent (Mercer et al. 2007).

Scant research addresses the economic success of fuels management programs (Hesseln 2000). The focus of most economics research on fuels management has been on estimating per acre costs of prescribed burning or identifying factors that affect those costs (González-Cabán et al. 2004, González-Cabán and McKetta 1986, Rideout and Omi 1995). Following an in-depth review of the economics literature on prescribed burning, Hesseln (2000) concluded that existing economic research and methodology is insufficient for implementing cost-effective fire management programs based on sound economic principles. Two of the most important unanswered economic questions are whether the resources expended to reduce wildfire risk result in net economic gains and how to quantify the tradeoffs between increasing expenditures on suppression and fuels management.

Although some previous analyses have found that fuel treatments may produce positive short-term net benefits, most of the studies were site-specific (González-Cabán and McKetta 1986). Little work has evaluated whether this holds for larger geographic areas (e.g., a county) and over longer time frames (greater than two years); for example, how prescribed burning in a landscape affect subsequent wildfire patterns across the landscape (Prestemon et al. 2002). We need comprehensive risk research that focuses on stochastic processes, investment-return relationships, and changes in wildfire risk as a result of fire management activities (Hesseln 2000). This requires evaluating the effects of management activities on physical and financial outcomes over time.

Previous research, however, has tended to ignore the dynamic and spatial aspects of wildfire. Although Donoghue and Main (1985) evaluated wildfire on a broad scale, they did not consider the dynamic effects of presuppression activities that extend beyond the current time period or the immediate location of the activities. Since wildfires affect fuel levels by consuming and fragmenting flammable vegetation, the effects of wildfire and fuels management are expected to operate across a range of scales of space and time (Prestemon et al. 2002).

Although an increasing body of evidence supports the efficacy of using prescribed fire and other fuels management methods to reduce the extent and especially the intensity of wildfires (Brose and Wade 2002, Butry 2006, Davis and Cooper 1963, Hesseln 2000, Koehler 1992-93, Martin 1988, Stephens 1997, Wagle and Eakle 1979), economic analyses of the effectiveness of fuel treatment programs and of the tradeoffs between fuel treatments, wildfire suppression efforts, and economic impacts are rare (Kline 2004). The absence of trade-off analyses between fuels treatments and wildfire suppression has been attributed to problems specifying production functions for fuel treatments (Prestemon et al. 2002), lack of knowledge of the rates of technical substitution between treatment alternatives, and lack of fuel treatment data, which typically have not been collected or reported in formats that allow analysis of relative returns to treatments (Omi 2004).

One recent exception to the lack of analyses of economic efficacy of fuels management is a study by Butry (2006). Butry uses propensity score techniques to identify the individual effects of suppression and prescribed fire on wildfire activity in Florida. The analysis shows that a reduction in the suppression response time of firefighters to a reported wildfire has a large, negative impact on the resulting intensity-weighted acres burned—with an elasticity of about 0.40—implying that a 1 percent reduction in response time yields a 0.40 percent reduction in intensity-weighted acres burned. Similarly, prescribed fire in a section[3] and its neighboring sections has a significant negative impact on observed intensity-weighted acres burned, although the current-year elasticity, generally no larger than –0.05, is smaller than the long-run effect identified by Mercer et al. (2007). Nevertheless, Butry (2006) found that the benefit-cost ratio of damages averted per dollar spent in prescribed fire is about 1.5. Because little is known about the cost of reducing suppression response times, a similar ratio could not be found for wildfire suppression.

Next, we present two case studies for applying economic models to analyze the tradeoffs involved in fuels management for both strategic and tactical management applications. The first case study develops a dynamic stochastic programming and Monte Carlo simulation model to evaluate the tradeoffs between fuels management (prescribed fire) and resulting economic damages from wildfires. This approach is directed at strategic decision-making for wildfire management: how to allocate fuels management resources across regions in a way that maximizes societal welfare in the long-run. The second case study uses operations research methods (linear-integer optimization) to examine the tradeoffs between

[3] A "section" is a geographic area in U.S. land surveying. Sections are one mile square, containing 640 acres (2.6 km^2). Thirty-six sections make up a survey township on a rectangular grid.

investments in fuels management and wildfire suppression resource deployment within a fire planning unit. The second analysis is based on a tactical decision model, and includes assumptions about how fuel treatments affect the ability of initial attack resources to contain fire ignitions. Scaling up the analysis through a set of assumptions about landscapes and costs and losses associated with fires could permit a strategic analysis to identify societal net benefit of spending on both fuels management and initial attack resource deployment.

The first case study shows, for one county in Florida, that prescribed fire does pay off for society, in terms of damages averted compared to the costs of prescribed fire. The second study shows that there is a trade-off between investing in initial attack resource deployment and fuels management and that some combination of the two should yield a globally optimal outcome.

3. CASE STUDIES

3.1. A Stochastic Programming Simulation of Fuel Treatment Effects on Wildfire in Florida[4]

Government agencies commonly intervene in wildfire processes through prescribed burning and other types of fuel treatments. In Florida, managers conduct and encourage landowners to reduce the risks of catastrophic wildfires through prescribed fire. Little is known about the overall efficacy of prescribed burning in reducing catastrophic wildfire damages, often because data are lacking and because wildfire processes are inherently spatial and intertemporal and proposed interventions have similar dimensional complexities. Because of this lack of information, decision makers find it difficult to evaluate how large scale programs of prescribed fire may result in net public benefits. Recently, several studies have quantified the net effects of both wildfire (Butry et al. 2001) and prescribed fire and other factors on wildfire in Florida (Prestemon et al. 2002, Butry 2006, Mercer et al. 2007). The following analysis summarizes the research of Mercer et al. (2007), who investigated how prescribed fire may affect wildfire activity and net economic benefits over the long run in Florida.

In general, determining the publicly optimal amount of prescribed burning requires solving a stochastic dynamic optimization problem. Therefore, to find the optimal levels of prescribed fire (or other vegetation management) inputs for wildfire risk reduction, we maximize the sum of expected current and future net present value of welfare[5]:

$$\max_{x_t} A = E\left\{VW_t - \mathbf{v(x)'x_t} + \sum_{m=t+1}^{T} e^{-ri}(VW_i - \mathbf{v(x)'x_m})\right\}, \tag{13.1}$$

$$\text{subject to} \quad W_t = W(\mathbf{Z_t}, \mathbf{W_{t\text{-}j}}, \mathbf{x_{t\text{-}k}}) + \varepsilon_t, \mathbf{x_t} \geq 0(\forall t)$$

[4] This section is derived from Mercer et al. (2007).

[5] This is a type of cost plus net value change model discussed in Chapter 16.

where A is the maximization criterion (a welfare measure), V is the net value change per unit area of wildfire, W_t is area (acres) burned by wildfire[6] in year t for the spatial unit of observation, $\mathbf{v}$ is a vector of the costs per unit area of suppression, pre-suppression, and vegetation management inputs[7], $\mathbf{x} = (\mathbf{x}_t, \mathbf{x}_{t+1}, \ldots, \mathbf{x}_T)$ is a vector of the amount of suppression, pre-suppression, and vegetation management inputs for year t through T (the planning horizon), $\mathbf{x}_{t-k}$ is a vector of k lags of prescribed burn area, $\mathbf{Z}_t$ are exogenous inputs to wildfire production including stochastic climate variables, $\mathbf{W}_{t-j}$ is a vector of j lags of wildfire area, and r is the discount rate. Solving this optimization problem produces a Tx1 vector of optimal input quantities, $\mathbf{x}$, and a Tx1 vector of wildfire quantities, W_t, 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 prescribed burning most likely to maximize the welfare criterion. Hadar and Russell (1969) describe how to evaluate these types of uncertain prospects.

Optimization models like equation (13.1) may involve as many choice variables as periods in the simulation[8], making them difficult to solve. Alternatively, the problem can be simplified to identifying the single optimal (stationary) policy from the set of possible policies that yields the highest expected net welfare benefits and which is consistent with any utility function that demonstrates non-increasing marginal utility.

3.1.1 The simulation model

Identifying the long-run expected impact of prescribed fire requires accounting for variable weather and the uncertainties associated with the "true" form of equation (13.1). While equation (13.1) was estimated using historical data on fire output and wildfire production inputs, observed wildfire output always differs from that predicted by an empirical model because of the random nature of the phenomenon and the imprecision of model specification. To identify the "best" level of prescribed fire to apply in a fire-prone landscape, Mercer et al. (2007) first estimated two versions of equation (13.1)—one expressing wildfire output in area burned and one in intensity-weighted area burned (tables 13.1 and 13.2).

[6] W_t could, alternatively, be expressed as a quantity measure of resources "saved" by applying resource inputs. In that case, V would be a positive number, reflecting positive values. As currently expressed in (1), V would be a negative value per unit, measuring damages per unit of wildfire realized.

[7] The "price" to the economy would be the net welfare change arising from the diversion of resources to vegetation management and away from other economically productive activities in the economy; in other words, this is the opportunity cost of foregone uses of these resources in the economy.

[8] 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.

Research has shown that wildfire intensity is closely related to the resulting damages to forests (Kennard 2004). So, measuring how prescribed fire affects the intensity of wildfire output should provide a more accurate prediction of the impacts of prescribed fire on wildfire damages.

Next, the results from the empirical estimates of equation (13.1) were used to forecast the expected damages from wildfire under different prescribed fire scenarios for Volusia County, which is representative of the fire-prone landscape of Florida. Forecasts of annual wildfire activity were made for 100 years into the future. The 100-year realization of wildfire output was done by (1) selecting a fixed level of prescribed fire to apply every year; (2) randomly selecting the values of two climate variables found to influence wildfire in Florida (a measure of El Niño and a measure of the North Atlantic Oscillation); (3) randomly selecting a forecast error for wildfire area burned and wildfire intensity-weighted area burned from the historical distribution of weather factors and from prediction errors; and then (4) calculating the total annual expected wildfire damages and suppression costs and the annual cost of applying the fixed amount of prescribed fire to the county. In the final step, we varied the amount of prescribed fire chosen in step 1 and then repeated steps 2-4. This process was continued, starting from 5,000 acres prescribed burned per year, up to about 100,000 acres per year (out of 313,000 acres of forest in the county). After all of these simulations were completed, the total, long-run discounted cost plus losses associated with wildfire and prescribed fire were compared across all levels of prescribed fire to identify the level of prescribed fire where the costs and losses were smallest.

Data were obtained from the Florida Division of Forestry, the Florida Bureau of Economics and Business Research, the National Oceanic and Atmospheric Administration (NOAA), and federal agencies. The Florida fire data on state and private lands, 1981-2001, included daily records of the location and the features of the wildfire, sufficient information to construct a damage measure of fire intensity-weighted acres burned per year in each county. Data on wildfires on Federal lands were obtained from the U.S. Forest Service, U.S. Fish and Wildlife Service, and the U.S. Park Service. The prescribed fire data, 1994-2001, were derived from permits granted by the State of Florida for prescribed fire. The National Oceanic and Atmospheric Administration (2003a) provided data on the Niño-3 SST (sea surface temperature) anomaly, 1994-2001, a measure of the strength of El Nino (fires burn more in Florida when the Niño-3 SST anomaly is negative). NOAA (2003b) also provided the values of the North Atlantic Oscillation, 1994-2001, another ocean temperature measure linked to wildfire in Florida. The U.S. Forest Service provided information on the amount of forest in each county. The Florida Bureau of Economics and Business Research (2002) provided information on housing counts in each county, our instrument for measuring the impact of available wildfire suppression resources.[9]

[9] We assume that counties with more housing units will have larger fire departments than counties with fewer housing units.

The wildfire intensity-weighted risk variable was calculated from observations of the average flame length for each fire. We summed (for each county) the acres of fire for each flame length category and calculated the fireline intensity with Byram's (1959) equation, $FI = 259.833(L)^{2.174}$, where FI is fireline intensity (kW/m) and L is flame length in meters. The annual intensity-weighted risk was derived by summing for each county the product of the annual acres burned in each intensity class times the average intensity for that class divided by the county's total forest area.

Two county fixed-effects time series models[10] were estimated: (1) intensity-weighted area burned and (2) area burned. The dependent variables for the two models were: (1) intensity-weighted acres per acre of forest area in the county in the year and (2) total wildfire area burned per acre of forest area in the county.

The calculations of losses associated with wildfire were based on the 1998 wildfires (Butry et al. 2001). Two versions of losses were generated. One version assembled timber and housing losses and suppression expenditures in terms of market values—prices times quantities. The second version assembled losses in terms of social welfare—consumer plus producer surplus changes. Due to data limitations, suppression expenditures were not included in the social welfare analysis.

3.1.2 Results

The original statistical models, relating fire area burned and fire intensity-weighted area burned, show that prescribed burning at the county level has a large, statistically significant effect on both intensity-weighted area burned and on area burned in the county (tables 13.1 and 13.2). The elasticity of intensity-weighted area burned with respect to prescribed fire was –0.9 in the short-run (0 to 2 years) and –0.31 in the long-run (greater than 2 years). The elasticity of wildfire area burned with respect to prescribed fire was –0.72 in the short-run and –0.28 in the long-run.

We also estimated a model describing the supply of prescribed fire services[11] and found that prescribed fire services had a long-run elasticity of about 0.54. This indicates that the cost of prescribed fire per acre would increase twice as fast as the increase in the areal extent of prescribed fire. This extra cost associated with higher levels of prescribed fire was included in the cost plus loss simulations.

The simulations showed that the optimal levels of prescribed fire depend on whether wildfire is measured in area burned or in intensity-weighted acres. Figure 13.1 shows the impact of prescribed fire on both wildfire intensity-weighted acres

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[10] A "fixed effects" time series regression model assumes that differences across units (counties in our case) can be captured in the constant term.

[11] Prescribed fire services refer to the human and capital inputs required for peforming prescribed burns.

Table 13.1. Model Parameter Estimates of Fully Specified and Parsimonious Forms of Intensity-Weighted Risk Functions (Source: Mercer et al. 2007).

Explanatory Variables	Full Model		Parsimonious Model	
	Parameter	Z value	Parameter	Z value
ln (*Prescribed Burn Area/ Forest Area*)	0.323***	-2.51	-0.388***	-3.29
ln (*Prescribed Burn Area$_{t-1}$/ Forest Area*)	-0.161	-0.096	----	----
ln (*Prescribed Burn Area$_{t-2}$/ Forest Area*)	-0.395***	-2.44	-0.513***	-3.13
ln (*Wildfire Area$_{t-1}$/Forest Area*)	-0.333***	-4.19	-0.314***	-4.64
ln (*Wildfire Area$_{t-2}$/Forest Area*)	-0.276***	-3.50	-0.308***	-4.53
ln (*Wildfire Area$_{t-3}$/Forest Area*)	-0.217***	-2.56	-0.292***	-3.95
ln (*Wildfire Area$_{t-4}$/Forest Area*)	-0.302***	-3.11	-0.318***	-3.95
ln (*Wildfire Area$_{t-5}$/Forest Area*)	-0.152*	-1.56	-0.171**	-2.05
ln (*Wildfire Area$_{t-6}$/Forest Area*)	-0.266***	-2.92	-0.309***	-4.11
ln (*Wildfire Area$_{t-7}$/Forest Area*)	0.816	0.84	----	----
ln (*Wildfire Area$_{t-8}$/Forest Area*)	0.174*	1.67	----	----
ln (*Wildfire Area$_{t-9}$/Forest Area*)	-0.081	-0.84	----	----
ln (*Wildfire Area$_{t-10}$/Forest Area*)	-0.239***	-2.70	-0.191***	-2.62
ln (*Wildfire Area$_{t-11}$/Forest Area*)	0.004	0.04	----	----
ln (*Wildfire Area$_{t-12}$/Forest Area*)	-0.001	-0.01	----	----
ln (*Pulpwood Harvest$_{t-1}$/ Forest Area*)	0.483**	1.81	----	----
ln (*Pulpwood Harvest$_{t-2}$/ Forest Area*)	0.075	0.27	----	----
ln (*Pulpwood Harvest$_{t-3}$/ Forest Area*)	-0.813***	-3.25	-0.932***	-5.65
ln (*Housing Density/Forest Area*)	-0.342	-0.17	----	----
ENSO	-0.633***	-3.20	-0.703***	-4.99
NAO	1.700***	4.47	1.256***	3.88
1998 Dummy	4.291***	10.10	3.986***	12.06
Number of Cross Sections	48		48	
Number of Years	7		7	
Total panel observations	275		285	
Wald Chi^2	2,681***		1,673***	
Log Likelihood	-334.2644		-382.1589	

Notes: * indicates statistical significance at 10%, ** at 5%, and *** at 1%. The dependent variable is the ratio of the log of sum of number acres burned at each intensity level times the intensity level per county per year relative to total forest area. Equation estimates reported here exclude estimates of 48 county dummies, which are available from the authors.

Table 13.2. Model Parameter Estimates of Fully Specified and Parsimonious Forms of Areal Risk Functions (Source: Mercer et al. 2007).

Explanatory Variables	Full Model		Parsimonious Model	
	Parameter	Z value	Parameter	Z value
ln (*Prescribed Burn Area/ Forest Area*)	-0.262***	-3.17	-0.284***	-3.60
ln (*Prescribed Burn Area$_{t-1}$/ Forest Area*)	-0.051	-0.46	----	----
ln (*Prescribed Burn Area$_{t-2}$/ Forest Area*)	-0.373***	-3.32	-0.432***	-3.61
ln (*Wildfire Area$_{t-1}$/Forest Area*)	-0.266***	-4.73	-0.209***	-4.28
ln (*Wildfire Area$_{t-2}$/Forest Area*)	-0.239***	-4.42	-0.229***	-4.61
ln (*Wildfire Area$_{t-3}$/Forest Area*)	-0.186***	-3.62	-0.176***	-3.34
ln (*Wildfire Area$_{t-4}$/Forest Area*)	-0.238***	-3.77	-0.255***	-4.49
ln (*Wildfire Area$_{t-5}$/Forest Area*)	-0.193***	-3.12	-0.223***	-3.87
ln (*Wildfire Area$_{t-6}$/Forest Area*)	-0.160***	-2.78	-0.164***	-3.21
ln (*Wildfire Area$_{t-7}$/Forest Area*)	-0.013	-0.21	----	----
ln (*Wildfire Area$_{t-8}$/Forest Area*)	0.066	0.99	----	----
ln (*Wildfire Area$_{t-9}$/Forest Area*)	-0.149**	-2.25	-0.153**	-2.62
ln (*Wildfire Area$_{t-10}$/Forest Area*)	-0.197***	-3.19	-0.149***	-2.91
ln (*Wildfire Area$_{t-11}$/Forest Area*)	-0.104*	-1.61	----	----
ln (*Wildfire Area$_{t-12}$/Forest Area*)	-0.054	-0.93	----	----
ln (*Pulpwood Harvest$_{t-1}$/ Forest Area*)	0.421**	2.29	----	----
ln (*Pulpwood Harvest$_{t-2}$/ Forest Area*)	0.376*	1.89	----	----
ln (*Pulpwood Harvest$_{t-3}$/ Forest Area*)	-0.509***	-2.97	-0.470***	-3.77
ln (*Housing Density/Forest Area*)	0.834	0.59	----	----
ENSO	-0.312***	-2.51	-0.262***	-2.67
NAO	0.934***	3.81	0.906***	4.10
1998 Dummy	2.268***	8.22	2.310***	10.09
Number of Cross Sections	48		48	
Number of Years	7		7	
Total panel observations	275		285	
Wald Chi^2	2,960***		1,645***	
Log Likelihood	-228.0352		-276.6049	

Notes: * indicates statistical significance at 10%, ** at 5%, and *** at 1%. Dependent variables are natural logs of each county's annual total areal extent (acres) of wildfire (areal risk model) and the natural logs of sum of area burned (acres) at each intensity level times the intensity level per county per year. Equation estimates reported here exclude estimates of 48 county dummies, which are available from the authors.

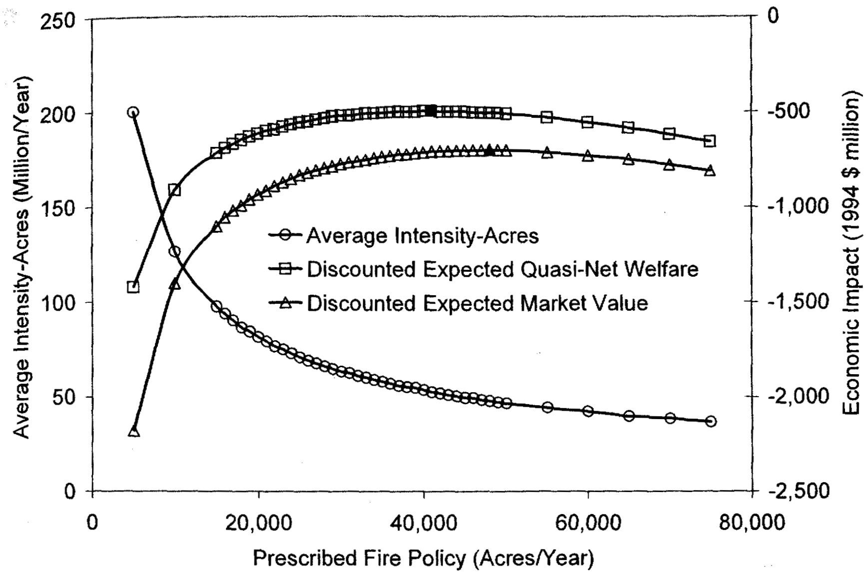

Figure 13.1. The simulated schedule of input-output combinations derived from the intensity-weighted risk model; amounts of prescribed burning yielding the maximum of net value change minus cost (symbols shaded black) are 41,000 acres/year for the quasi-net welfare analysis and 48,000 acres/year for the market value analysis (Source: Mercer et al. 2007)

and on the losses and costs associated with wildfire and prescribed fire. Figure 13.2 shows the same, but in terms of area burned related losses instead of intensity-weighted area burned related losses. Figure 13.1 shows that the expected value of losses plus costs in welfare terms is minimized when prescribed fire is set at about 41,000 acres per year and minimized in market value terms at 48,000 acres per year in Volusia County, Florida. Figure 13.2 shows that the prescribed fire area of 17,000 acres per year minimizes net value change plus costs in welfare terms and 19,000 acres per year in market value terms. The curves shown in Figure 13.1 are flatter than those shown in Figure 13.2 because the efficacy of prescribed fire on area burned and therefore economic damages is greater when the fire intensity is accounted for in the modeling. That is, the costs of progressively greater levels of prescribed burning increase at close to the same rate that wildfire damages decrease when intensity is accounted for, resulting in flatter curves in Figure 13.1. From 1994-2001, Volusia County treated about 13,000 acres per year with prescribed fire, or about 30 percent less than the optimal amount based on the area burned effect of prescribed fire and 70 percent less than the optimal amount based on the intensity-weighted area burned measure.

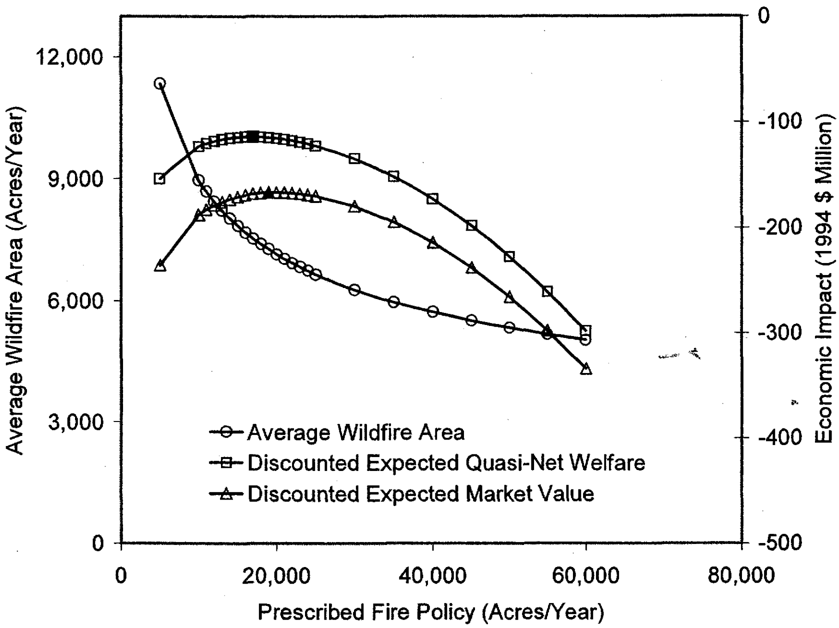

Figure 13.2. The simulated schedule of input-output combinations derived from the areal risk model; amounts of prescribed burning yielding the maximum of net value change minus cost (symbols shaded black) are 17,000 acres/year for the quasi-net welfare analysis and 19,000 acres/year for the market value analysis. (Source: Mercer et al. 2007)

3.1.3 Summary

This analysis documented that large scale programs of prescribed fire produce net economic benefits (at least in Florida). The empirical analysis of wildfire showed that the efficacy of prescribed fire appears to be greater when the effects of fuel treatments on fire intensity are accounted for. The study documented that prescribed fire levels in an already heavily treated landscape could be up to four times higher and still yield significant positive net benefits. The study also contributed to our understanding of the role of fuel treatment markets in influencing prescribed fire programs. As the amount of treatment practiced on the landscape grows, prices of prescribed fire services rise with it. Government-sponsored treatment programs on land managed by the government run the risk that they could squeeze out prescribed fire conducted on private lands. Land managers should be cognizant of these kinds of off-site impacts when making decisions about fuels management on the lands they manage.

3.2 Assessing Tradeoffs Between Fuel Treatment and Initial-Attack Investments

The following case study seeks to model the relative impacts of investments in fuel treatment and fire suppression resources. In contrast to the statistical approach taken above, the following case presents an engineering model to determine levels of investment in fuel treatment and initial attack resource deployment that minimize the expected cost of escaped wildfires. The model is based on predictions of the likelihood that a fire ignition will escape as a function of the level of fuel treatment and the number of initial attack resources that are dispatched to the fire. Results of the optimization model can be used to estimate the efficiency of fuel treatment and the tradeoffs between investments in fuel treatment and initial attack resource deployment. It provides a framework for a new kind of analysis that could be done in Florida or elsewhere, where sufficient data exist to quantify the effect of fuels management on both the cost of suppression and the losses associated with wildfire.

Fuel treatments may change wildfire behavior and enhance the effectiveness of fire suppression tactics (Finney and Cohen 2003). Deploying initial-attack resources to meet expected demands for fire suppression in the coming days, weeks, or months is an important part of wildland fire planning (Martell 1982). Deployment decisions have been incorporated in optimization models that minimize operating costs while meeting pre-defined demands for initial attack (Hodgson and Newstead 1978, MacLellan and Martell 1996) or minimize area burned or number of escapes subject to budget constraints that limit the size of the initial-attack force (Kirsch and Rideout 2005, Haight and Fried 2007). These latter models include relationships between fire behavior and fire suppression. If those relationships could be extended to include the impacts of fuel treatment, then optimization models could be used to analyze the cost-effectiveness of fuel treatment and suppression.

To demonstrate this potential, we modified the standard-response model of Haight and Fried (2007) to include the effects of fuel treatment. Their model determines where to deploy a fixed number of initial-attack resources to minimize the expected number of fires that do not receive a standard response, defined as the number of resources that must reach the fire within a maximum response time (Marianov and ReVelle 1991). The idea is that if a fire receives the standard response, the likelihood of escape is low. We modified the model to minimize the expected cost of escapes with assumptions about how fuel treatments and the number of resources dispatched affect the probability of escape. We demonstrate how the model can be used to construct cost curves for the relationship between initial attack resources in position to respond and expected cost of escapes, with and without fuel treatments. The cost curves can be used to estimate the cost savings associated with fuel treatment, in terms of reduction in expected cost of escaped fires under a given level of initial attack force.

3.2.1 A risk-of-escape model for initial attack

The optimization model is a linear-integer formulation with two objective functions: the cost of deploying initial-attack resources and the expected cost of fires that escape initial attack. A weighted sum of the objective functions is minimized, and the weight is ramped from large to small to generate a tradeoff curve showing how different levels of investment in initial attack resources affect subsequent costs of suppressing escaped fires. The model is for a single fire planning unit. The data include the locations of fire stations and representative fires. Each station has a capacity to house initial attack resources, and the time required for resources to reach each representative fire location is known. The data also include fire scenarios, each representing a set of fire locations during a single day. The model includes integer decision variables for the number of suppression resources deployed to each station and the number of resources dispatched from each station to each fire in each scenario. The probability of escape decreases with the number of resources that are dispatched to the fire within a maximum response time. Therefore, each fire is characterized by a set of parameters representing escape risk reduction for increasing numbers of resources dispatched for initial attack. In our application, the values of parameters of the risk-reduction function depend on the level of fuel treatment. The model is formulated with the following notation:

Indices:
i, I = index and set of fire stations,
j, J = index and set of potential fire locations,
k, K = index and set of suppression resource dispatch classes,
s, S = index and set of fire scenarios,

Objective functions:
Q_1 = cost of deploying suppression resources,
Q_2 = expected cost of escaped fires,

Parameters:
λ = objective weight; $0 \leq \lambda \leq 1$,
a_{jk} = escape risk reduction parameter (≤ 0) for fire location j dispatch class k,
b_i = upper bound on number of resources deployed at station i,
c^1_i = fixed cost of opening station i,
c^2_i = cost of deploying a resource at station i,
c^3_j = cost of containing an escaped fire at location j,
f_{js} = 0-1 parameter; 1 if fire occurs in location j scenario s; 0 otherwise,
p_s = probability that scenario s occurs,
t_{ij} = response time from station i to location j,
T = maximum response time,
N_j = set of stations from which resources can reach location j within the maximum response time; i.e., $N_j = \{i \mid t_{ij} < T\}$.

Variables:

v_{js} = probability of escape for fire in location j scenario s,

w_i = 0-1 variable; 1 if station i is open, 0 otherwise,

x_i = number of resources deployed at station i,

y_{ijs} = number of resources at station i dispatched to location j during scenario s,

z_{jks} = 0-1 variable; 1 if dispatch class k is used at fire location j scenario s, 0 otherwise.

The model is formulated as follows:

$$\text{Minimize}: \lambda Q_1 + (1-\lambda)Q_2 \quad (13.2)$$

subject to:

$$Q_1 = \sum_{i \in I} c_i^1 w_i + c_i^2 x_i \quad (13.3)$$

$$Q_2 = \sum_{s \in S} p_s \sum_{j \in J} f_{js} v_{js} c_j^3 \quad (13.4)$$

$$x_i \le b_i w_i \qquad \text{for all } i \in I \quad (13.5)$$

$$\sum_{j \in J} y_{ijs} \le x_i \qquad \text{for all } i \in I \text{ and } s \in S \quad (13.6)$$

$$\sum_{k \in K} z_{jks} = \sum_{i \in N_j} y_{ijs} \qquad \text{for all } j \in J \text{ and } s \in S \quad (13.7)$$

$$v_{js} = 1 + \sum_{k \in K} a_{jk} z_{jks} \qquad \text{for all } j \in J \text{ and } s \in S \quad (13.8)$$

The objective (equation 13.2) is to minimize the weighted sum of the two objective functions: the cost of deploying initial-attack resources to stations prior to the occurrence of fires (equation 13.3) and the expected cost of fires that escape initial attack (equation 13.4). The weight λ represents the decision maker's preference for the two objectives. When λ is closer to one, more weight is put on minimizing the cost of deploying initial attack resources. When λ is closer to zero, more weight is put on minimizing the expected cost of escaped fires. In equation (13.4), the inside summation is the expected cost of escapes during scenario s, where each product includes three terms: f_{js} is a 0-1 parameter for whether or not a fire occurs at location j, v_{js} is the probability of escape at location j, and c^3_j is the cost of containing an escape. In the outside summation of equation (13.4), each expectation is weighted by p_s, the probability of scenario occurrence. Equation (13.5) defines the capacity of each station, which is greater than zero only if the station is open. Equation (13.6) requires that the number of resources dispatched from each station does not exceed the number of resources deployed to the station.

Equations (13.7) and (13.8) calculate v_{js}, the probability of escape of a fire at location j, and require a bit of explanation. We assume that escape probability equals one when no resources are dispatched and approaches zero as the number of resources dispatched increases. The probability of escape is modeled as a decreasing, convex, piecewise-linear function of the number of resources dispatched so that the slope is negative and closer to zero with each additional resource dispatched. The 0-1 variables z_{jks}, $k = 1,\ldots,K$, represent resource dispatch classes where $z_{jks} = 1$ means at least k resources have been dispatched. As a result, the sum of these 0-1 variables must equal the number of resources dispatched to the fire from stations within the required response time (equation 13.7). The parameter a_{jk} is the slope of the function for probability of escape and represents the escape risk reduction ($a_{jk} \leq 0$) for dispatch class k. Because the function is convex, $a_{j1} \leq a_{j2} \leq \ldots \leq a_{jK}$. If the model dispatches any resources to fire j, the model will choose the dispatch variables z_{jks} with the most negative risk reduction parameters first to minimize probability of escape. As a result, for any k such that $z_{jks} = 1$, $z_{jts} = 1$ for all $t < k$.

It is important to recognize that the decision variables of the model take place in different time periods. Resource deployment decisions take place in the first period to meet possible resource demands in the coming days. Dispatching decisions take place in the second period once the locations of fires are known. The dispatching decisions assume that fires in a single day occur close enough in time to compete for the same resources.

The model's objectives and data requirements differ from other optimization models for initial-attack resource deployment and dispatching. Kirsch and Rideout's (2005) model has an objective of minimizing area burned and includes binary containment variables for fires based on the ratio of fire line to fire perimeter in discrete time intervals (e.g., hours) after ignition. With an objective of minimizing area burned, the model dispatches resources to contain fires as soon as possible within a budget constraint. Further, the Kirsch and Rideout model requires rates of fire line production and fire area and perimeter growth. In contrast, our model has an objective of minimizing the expected cost of escapes. As a result, a single variable representing escape risk, v_{js}, is defined for each fire along with parameters, a_{jk}, representing the reduction in escape risk per unit increase in resources dispatched to the fire. The escape risk reduction parameters are proxies for fire line production and spread rates.

The probability-of-escape model for initial attack does not explicitly include fuel treatment. In practice, fuel treatment may reduce the risk of escape by reducing fire intensity. In our model, the risk-reduction parameters, a_{jk}, will be greater in locations with fuel treatment. Making a_{jk} depend on a fuel treatment variable in equation (13.8) would create a nonlinear equation because a_{jk} is already multiplied by a variable z_{jks} representing the number of resources dispatched to the fire. To maintain linearity, we solved the probability-of-escape model for various assumptions about fuel treatment to investigate the tradeoffs between investments in fuel treatment, initial attack resources, and cost of containing escaped fires.

3.2.2 *Application*

The model was applied to a hypothetical problem involving a 10 X 10 grid of forest districts, each covering 6170 acres (25 km^2) and belonging to one of three fire risk classes based on daily ignition probability (fig. 13.3). Classes 1, 2, and 3 had ignition probabilities of 0.10, 0.06, and 0.02, respectively. The analysis focused on deploying fire engines in 10 stations. Each station had a capacity of 4 engines, and each engine costs $10,000 to base. Assuming that each engine traveled 31 miles/hour (50 km/hour) and the distance separating each district was a straight line between district midpoints, we calculated the time required to travel between each station and each district. Assuming a maximum response time of

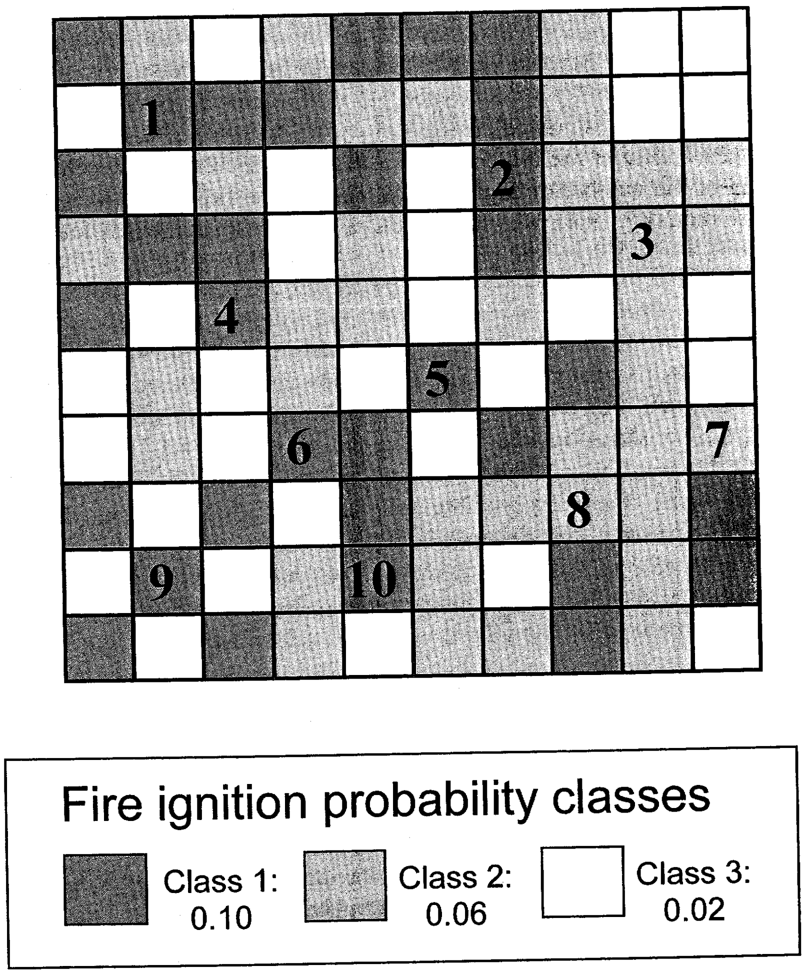

Figure 13.3. Fire districts (shaded according to probability of fire occurrence) and stations (represented by numbers) in a hypothetical planning unit.

20 minutes, we constructed a set of stations that were within 20 minutes of each potential fire location. We selected this response time threshold because fast-spreading fires tend to escape initial attack if firefighting is not well-underway within 20 minutes following a fire report.

We formulated the optimization model to determine the engine locations for days during the "high" fire season when multiple fires occur. We focused on days with multiple fires because draw-down of suppression resources on such days increases the likelihood that fires escape initial attack. We used the daily fire probabilities to construct 100 fire scenarios representing days with multiple fires. Each scenario is a list of districts in which fires occur. Each scenario, f_{js} j = 1,...,100, is a vector of 0-1 parameters where parameter $f_{js} = 1$ means that a single fire ignites in district j under scenario s. The value of each parameter f_{js} was determined by comparing a uniform 0-1 random number with the probability of ignition in district j. Because ignitions were determined randomly, each scenario had the same probability of occurrence, $p_s = 0.01$. Mean daily number of fires per scenario was 6.04 with range 2-14.

The probability of fire escape was modeled as a decreasing, piecewise-linear function of the number of engines dispatched to the fire within the 20-minute response time (fig. 13.4). We assumed that a standard response was four engines

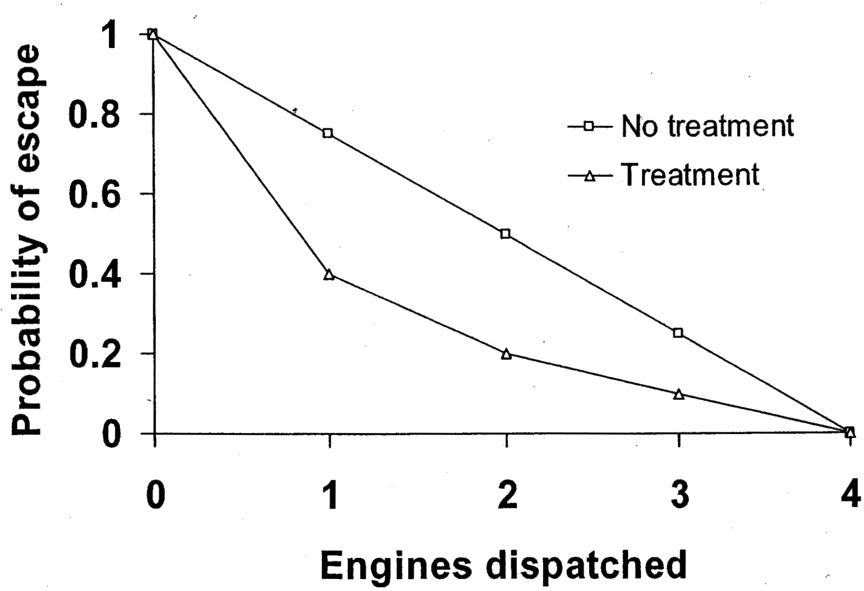

Figure 13.4. Probability of fire escape as a function of the number of engines reaching the fire within the standard response time (20 minutes) in areas with and without prior fuel treatment.

reaching the fire within 20 minutes and the probability of escape associated with the standard response was zero. The shape of the relationship between escape risk and response depended on fuel treatment. Without fuel treatment, the relationship was linear with a constant risk reduction parameter of 0.25. With fuel treatment, the relationship was piecewise linear with risk reduction parameters that decreased as the number of engines responding increased (0.6, 0.2, 0.1, 0.1). In this case, probabilities of escape are lower for each engine response category; however, the standard response of four engines is still required to achieve zero probability of escape.

The costs of escaped fires were based on observations of emergency suppression costs of 13 large fires (>300 acres) in national forests in the southeastern United States in years 2000-2003. Six fires had containment costs less than $50,000, five had containment costs of $100,000-500,000, and two had costs greater than $1,000,000. We assigned an average cost to escaped fires in each of the three risk classes in figure 13.3. Costs of escaped fires in districts with ignition probabilities of 0.10, 0.06, and 0.02 were $50,000, $100,000, and $500,000, respectively.

Our analysis focused on the trade-off between the cost of deploying initial-attack engines and the expected cost of fires that escape initial attack. We computed optimal engine locations for problems in which the objective function weight λ was decreased from 1.0 (minimize cost of deploying engines) to 0.0 (minimize expected cost of escaped fires) in increments of 0.02 subject to a capacity constraint of 4 engines per station. The baseline analysis was conducted assuming no fuel treatment. Then, trade-off curves were constructed with fuel treatment performed in districts belonging to each of the three fire risk classes.

The spatial optimization problems were solved on a Dell Pentium 4 laptop computer (CPU 2.4 GHz) with the integrated solution package GAMS/Cplex 9.0 (GAMS Development Corporation 1990), which is designed for large and complex linear and mixed-integer programming problems. Input files were created in GAMS (General Algebraic Modeling System), a program designed to generate data files in a format that standard optimization packages can read and process. Cplex solves a mixed-integer programming problem using a branch and cut algorithm, which solves a series of linear programming sub-problems.

3.2.3 Results

In the baseline case without fuel treatment, the curve showing the tradeoff between the cost of deploying engines and expected cost of escaped fires had a convex shape in which cost of escapes decreased at a decreasing rate as the total cost of engine deployment ($10,000 times the number of engines deployed) increased (fig. 13.5). The points on the curve represent non-dominated solutions and their relative performance with respect to the two objectives. For each non-dominated solution, improvement in one objective cannot be achieved without simultaneously causing degradation in the value of the other objective. As a result, the points represent a frontier below which there were no better solutions.

The best deployment of engines depended on the objective function weight. If minimizing the cost of basing engines is most important (i.e., $\lambda = 1$), the choice is solution A in which no engines are deployed and the expected number of escapes equals the average daily fire frequency of 6.04 with expected cost of $705,000 (fig. 13.5). As more weight is given to minimizing the cost of escapes, more engines are deployed resulting in higher engine deployment costs and lower costs from escapes. For example, with 24 engines deployed at a cost of $240,000 (solution B), the expected cost of escapes was $90,000, 13 percent of the expected cost of escaped fires with no engines deployed. Increasing the number of engines from 24 to 40 for a deployment cost of $400,000 (solution C) reduced the expected cost of escaped fires to $11,000, 2 percent of the expected cost with no engines deployed.

The slope of the tradeoff curve is a benefit/cost ratio showing the reduction in expected cost of escapes per increase in cost of engines deployed for initial attack. The slope was relatively steep between solutions A and B (< -1) indicating that benefits of deploying more engines exceeded costs. Between solutions B and C, the slope was relatively flat (> -1) indicating that deploying more engines was not cost-effective in terms of reducing the expected cost of escapes. The slope of the tradeoff curve was -1 at solution B, which minimizes the sum of the costs of engine deployment and escapes.

When fuel treatment was applied in risk classes 1 and 2, the curves showing the tradeoff between cost of engines deployed and expected cost of escapes were

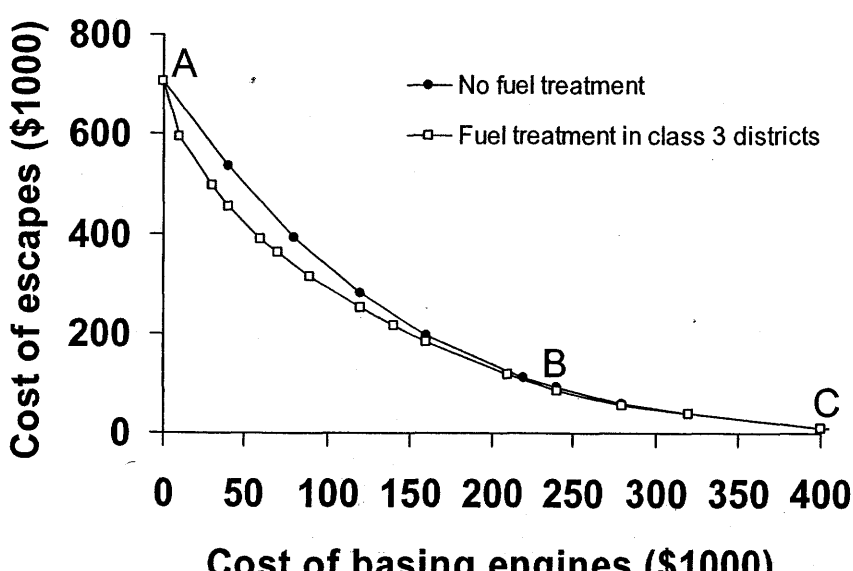

Figure 13.5. Tradeoffs between the cost of deploying initial-attack engines ($10,000 per engine) and the expected cost of fires that escape initial attack.

slightly lower than the baseline tradeoff curve computed without fuel treatment. Even though fuel treatment lowered the probability of escape, the relatively low costs of escapes ($50,000 and $100,000 per fire) in these risk classes made the economic impacts of fuel treatment relatively small.

When fuel treatment was applied in each district in risk class 3, which had a relatively high cost of escape ($500,000 per fire), the curve showing the tradeoff between cost of engines deployed and expected cost of escapes was significantly lower than the baseline curve computed without fuel treatment, especially when 1-15 engines were deployed at a cost of up to $150,000 (fig. 13.5). Fires in areas with fuel treatment have lower probabilities of escape than fires in areas without fuel treatment, especially when one or two engines are dispatched for initial attack (fig. 13.4). As a result, the greatest gain from fuel treatment in terms of reducing the expected cost of escape occurs when there are relatively small numbers of engines available for initial attack.

The tradeoff curves in fig. 13.5 can be used to evaluate the economic effectiveness of fuel treatment in districts in risk class 3. The vertical distance between points on the curves represents the reduction in expected cost of escapes resulting from fuel treatment while maintaining a given engine force. With more than 15 engines deployed at a cost of > $150,000, fuel treatment produced very little reduction in expected cost of escape because there were enough engines deployed to dispatch 3-4 engines to most fires, which resulted in a relatively low probability of escape regardless of fuel treatment. With fewer than 15 engines deployed, fuel treatment had a bigger effect. For example, with 12 engines deployed at a cost of $120,000, applying fuel treatment to risk class 3 resulted in a $32,000 reduction in expected cost of escapes. This cost saving can be compared with fuel treatment cost to determine whether this particular fuel treatment activity is cost effective. In this example, fuel treatment was applied in 31 districts (191,000 acres), and the break-even fuel treatment cost was $0.17 per acre. This is considerably lower than actual treatment costs which can be up to $250 per acre. As a result, the fuel treatment activity in this case is not cost-effective. It should be noted that this break-even analysis assumes that fuel treatment only affects the expected cost of escapes during the upcoming fire season. If the effects last more than one year, this analysis underestimates the benefits of fuel treatment.

4. CONCLUSIONS

In this chapter we have presented two case studies illustrating innovative approaches to analyzing the impacts of fuels management on wildfire outcomes and for predicting the tradeoffs between expenditures for fuels management and suppression resources. The first case study examining tradeoffs between prescribed fire treatments and damages from wildfire shows that fuels management (prescribed fire in this case) does appear to pay off, at least in Florida. At the current prescribed fire levels in Volusia County, Florida, the long-run benefit-cost ratio of prescribed fire is close to or greater than unity. This analysis, however, leaves out some additional benefits associated with prescribed fire—such as the beneficial impacts on ecosystems that depend on wildfire for their health and increased productivity of the remaining stand of timber. At the same time, the analysis omits some of the costs of prescribed fire, in terms of the risk of escape and some of the negative health impacts associated with the smoke from prescribed fires. Butry et al. (2001) showed that the asthma-related impacts of wildfire are not large, in economic terms. In contrast, Rittmaster et al. (2006), who accounted for both respiratory and cardiac-related effects, characterize the human health related losses associated with one large wildfire in Alberta, Canada, to have been substantial and far reaching spatially, with economic impacts second only to those associated with timber. But neither of these studies quantified the losses associated with the averting behavior of individuals who flee when wildfires burn near their homes. It is not clear whether individuals with respiratory problems also flee locations undergoing active prescribed fire; this is an area worthy of additional research.

The Florida case study, however, was unable to detect a significant impact of wildfire suppression on observed wildfire, because the statistical models of wildfire activity (area burned, intensity-weighted area burned) omitted a direct measure of wildfire suppression. Further research, such as that done by Butry (2006), could help to clarify those suppression impacts. Mercer et al. (2007) did not find a significant impact of housing density (a proxy for the availability of suppression resources) on observed wildfire activity; therefore, the simulation analysis simply assumed that a constant level of fire suppression is applied per unit of wildfire output, effectively assuming away any trade-off between suppression and fuels management. Butry (2006) did find that suppression could trade off for prescribed fire, but he did not attempt to quantify that trade-off in a simulation as done by Mercer et al. (2007).

The second case study examined short run tradeoffs between investments in fuels management versus increased initial-attack resources on the ground. The case study shows that decisions for basing and dispatching initial-attack resources can be formulated as a mixed-integer programming model that minimizes the cost of deploying initial-attack resources and the expected cost of suppressing fires that escape initial attack. The model is well suited to determining the tradeoffs between these objectives given uncertainties in the number and location of fires that may occur during the fire season. A key component is the relationship between the number of resources that reach a fire within a maximum response time and the probability of escape. The case study was based on a hypothetical relationship because empirical analyses of the likelihood of escape as a function of initial attack force and fuel treatment are rare. Butry (2006) identified the individual effects of suppression and prescribed fire on wildfire activity in a case study in Florida, and more work is needed to empirically model of these relationships.

Fuel treatments may increase the probability of containment of a fire during initial attack. This effect was incorporated in the model by adjusting the slope of the relationship between the number of resources dispatched to an ignition and the probability of escape. To maintain linearity of the initial-attack model, the effects of alternative levels and locations of fuel treatments were determined as one-at-a-time changes in model parameters. Analysis of these changes allows determination of the cost-effectiveness of case-specific fuel treatment activities. Given the structure of the initial-attack model, determining optimal levels and locations of fuel treatment would require a non-linear formulation and heuristic rather than exact optimization methods.

The strengths of the initial-attack model include spatial detail (e.g., locations of fire stations, suppression resources, and potential fires) and practical decision criteria (e.g., minimizing the expected cost of escape). However, this detail makes it difficult to reach general conclusions about optimal levels of investment in fuel treatment and initial attack. The results will depend on case-specific model parameters, including the number and location of fire stations, probabilities of fire occurrence, and relationship between probability of escape and resources dispatched during initial attack. Nevertheless, incorporating fuel treatment into an initial-attack optimization model is a first step toward evaluating the cost-effectiveness of these two important fire preparedness activities.

In this chapter we presented two methods for examining the strategic and tactical tradeoffs between fuels management and wildfire suppression. Separately, each approach provides essential insights into the economics of wildfire management. However, to make the most effective use of these analyses requires combining the approaches so that both the tradeoffs between fuels management and suppression expenditures and the tradeoffs between fuels management, suppression and the economic damages from subsequent wildfires can be examined simultaneously. This will require a wide array of additional research in the economics of wildfire.

At the same time, the case studies highlight the complexity of the problem of wildfire management. Wildfire management can be approached from many different angles, from fire prevention, fuels management (as described in our first example), resource pre-placement (as described in our second example), wildfire suppression (our second example, as well). Wildfires occur in time and space, and wildfire occurrence is driven by both natural and human factors. Wildfire management actions have intertemporal effects across multiple spatial scales and are inherently uncertain. Therefore, simulation models are not able to account for all the ways that managers can intervene in wildfire processes and can only roughly approximate the spatial and temporal interdependencies among both wildfire and management efforts. Likewise, economic analyses are limited by a lack of understanding of the full economic effects of wildfires on society, including public health and secondary impacts on economic sectors beyond forests. The research presented in this chapter demonstrates advancements in our understanding of the problem of designing better combinations of interventions, but they should be followed by modeling that can better account for other forms of management (e.g., fire prevention, mechanical fuel treatments) and for the interactions between fuel treatment design, fire suppression, and the landscape and how actions may affect risks in both spatial and temporal dimensions.

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