Evaluating Alternative Prescribed Burning Policies to Reduce Net Economic Damages from Wildfire

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We estimate a wildfire risk model with a new measure of wildfire output, intensity-weighted risk and use it in Monte Carlo simulations to estimate welfare changes from alternative prescribed burning policies. Using Volusia County, Florida as a case study, an annual prescribed burning rate of 13% of all forest lands maximizes net welfare; ignoring the effects on wildfire intensity may underestimate optimal rates of prescribed burning. Our estimated supply function for prescribed fire services is inelastic, suggesting that increasing contract prescribed fire services on public lands may produce rapidly escalating costs for private landowners and unintended distributional and "leakage" effects.

Key words: policy, prescribed fire, stochastic dominance, wildfire.

Expenditures to prevent, control, and suppress wildfire in the United States have been expanding rapidly (Mutch 2002). For example, fire suppression expenditures by the USDA Forest Service rose from $160 million in 1977 to $760 million in 2005, when adjusted to 2003 dollars. Increases in wildfire costs have been attributed to: (1) increased wildfire severity and extent, caused by changes in weather and climate patterns; (2) aggressive wildfire suppression,[1] resulting in fuel buildups in fire-prone landscapes; and (3) greater expenditures to protect a growing wildland–urban interface from wildfire (Aplet and Wilmer 2003; The White House 2002; USDA Forest Service 2000, 2004). One of the more controversial means of reducing wildfire damages, as outlined in the Federal Wildland Fire Policy of 1995 (USDI/USDA 1995) and the President's 2002 Healthy Forests Initiative (The White House 2002), is to reduce wildland fuels through prescribed fire. Although many wildland policy makers and resource managers strongly resisted the use of prescribed fire throughout much of the twentieth century (Yoder et al. 2003), prescribed fire has more recently been promoted to mitigate the impacts of increased fuel loads on wildfire probability and intensity (Bell et al. 1995; Haines and Cleaves 1999; Hesseln 2000).

While some research supports the efficacy of prescribed fire for reducing wildfire risk (Brose and Wade 2002; Davis and Cooper 1963; Hesseln 2000; Koehler 1992–93; Martin 1988; Stephens 1997; Wagle and Eakle 1979), scant research addresses the economics of prescribed fire programs or the tradeoffs between prescribed fire, suppression, and wildfire costs (Hesseln 2000). Most economic research has focused on understanding the financial costs of prescribed burning (González-Cabán and McKetta 1986; Rideout and Omi 1995).

One unanswered economic question is whether fuels management efforts result in net economic benefits. Previous analyses of prescribed fire have found that site-specific and short-term net benefits may be positive (e.g., González-Cabán and McKetta 1986).

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[1] Suppression is defined as "all the work of extinguishing or confining a fire beginning with its discovery"; presuppression refers to "activities in advance of fire occurrence to ensure effective suppression … [which] includes planning the organization, recruiting and training, procuring equipment and supplies, maintaining fire equipment and fire control improvements"; and fuels management is defined 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" (National Wildfire Coordinating Group 1996).

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However, little work has evaluated whether this holds true at the broader spatial and temporal scales relevant to regional and national policies. Prestemon et al. (2002) were the first to empirically estimate broad-scale wildfire production functions (including fuels management treatments as predictors) and quantify the degree of stochasticity present in wildfire production in Florida. However, their measure of wildfire output, area burn probability, did not include a direct measure of wildfire damages, nor did they evaluate economic tradeoffs between fuels management and wildfire.

Our research advances and expands Prestemon et al.'s (2002) wildfire risk analysis in several ways. First, we estimate a statistical wildfire *damage* risk model whose dependent variable, fireline intensity-weighted area burned divided by forest area, is more directly linked to economic damages from wildfire.[2] This linkage allows us to detect a statistically significant and theoretically consistent effect of prescribed fire on observed wildfire damages across a broad spatial scale. The linkage also reveals the potential shortcoming of relying on area burned to predict economic damages. Second, our analysis includes the effect of the randomness of wildfire and uncertainties inherent in the relationships between prescribed fire and wildfire and between climate and wildfire. Third, our analysis is long-run, measuring the long-run economic consequences of alternative prescribed fire policies in the context of a range of possible climate scenarios. Thus, we demonstrate how uncertainties can be included in a long-run analysis of fuels management actions evaluated at a policy relevant spatial and temporal scale.

Our model of economic tradeoffs is applied specifically to estimate the economically best amount of prescribed fire to apply in Volusia County, Florida. The simulation model uses the estimated wildfire production models, an estimate of a model of prescribed fire services supply, information about the patterns of fire-related climate processes (ocean temperatures), and information from the published literature on prices of wildfire output and prescribed fire inputs to simulate the net economic outcomes from wildfire over a 100-year future. Stochastic dominance (Hadar and Russell 1969) is used to compare the discounted net present values resulting from a range of prescribed burn policies. Comparison of the expected values from current and simulated policies provides a measure of how publicly optimal behavior may differ from privately optimal behavior.

Prescribed burning is widely conducted on private lands in the Southern United States, particularly in Florida (Wade and Lunsford 1988). With almost a half million acres of forest treated annually (table 1), Florida has one of the most active prescribed burning programs in the nation (Florida Department of Agriculture and Consumer Services 2005). Prescribed burning on private forestlands often addresses a diversity of objectives, including reducing wildfire risk, preparing sites for tree regeneration, controlling disease and tree competition, disposing of logging debris, improving wildlife habitat, improving understory forage for grazing, enhancing aesthetics, perpetuating fire-dependent species, and managing endangered species (Wade and Lunsford 1988). However, wildfire risk reduction is frequently cited as an important objective. In the absence of subsidies or mandatory prescribed burning laws, we assume that those who prescribe burn believe that the private benefits of such burnings exceed their private costs. However, because prescribed fire also affects public values, privately optimal behavior may not match publicly optimal behavior. For example, the effects of smoke on air quality extend far beyond the burned area. Also, because wildfires and escaped prescribed fires often cross property boundaries, private behavior can affect the wildfire risks experienced by others (Yoder et al. 2003). Identifying gaps between the sum of private actions and optimal levels for society is key to enhanced policy making.

We do not analyze the mechanics of private decision making over how much prescribed fire to apply to an individual forest stand. Instead, we adjust prescribed burning for an entire region to maximize the sum of discounted expected producer and consumer surplus (Samuelson 1954, 1955) associated with future wildfire. As such, this analysis represents an initial step in responding to Hesseln's (2000) call for economics research to define and characterize wildfire production functions and to use these production functions to evaluate the returns to alternative wildfire risk reduction strategies.

[2] Fireline intensity, the rate of heat energy released per unit time per unit length of fire front, is the product of available fuel energy and the fire's rate of advance. Because it correlates well with crown damage, lethal scorch height, and expected temperature above surface fires, fireline intensity is one of the best predictors of the effects of fire on forests and the damages associated with fires (Kennard 2004).

Table 1. Summary Statistics of Wildfires and Prescribed Burning in Florida and Volusia County, 1994–2001

Fire Year	Forests (Acres)	Wildfire Area (Acres)	Wildfire Areal Risk	Wildfire Intensity-Weighted Area (kW-Acres/m)	Prescribed Burn Acres	Prescribed Burn Acres (% of Total Forest Area)	Pulpwood Harvest (m^3 per Acre)
Volusia County, Florida							
1994	313,035	1,318	0.42	2,181,228	9,696	3.10	20.58
1995	313,035	3,038	0.97	13,700,000	9,385	3.00	32.11
1996	313,035	1,284	0.41	2,043,996	33,511	10.71	31.74
1997	313,035	878	0.28	4,048,271	9,590	3.06	30.99
1998	313,035	157,006	50.15	681,000,000	6,760	2.16	26.18
1999	313,035	1,712	0.54	10,000,000	6,713	2.14	28.82
2000	313,035	1,657	0.53	21,600,000	15,625	4.99	19.78
2001	313,035	303	0.09	1,436,865	n/a	n/a	17.79
Total 1994–2001	–	167,199	53.41	736,010,360	91,283	–	–
Average 1994–2001	313,035	20,899	6.68	92,001,295	13,040	4.17	26.00
Average 1987–2001	313,035	12,126	3.87	53,600,000	n/a	n/a	n/a
All Counties in Florida							
1994	11,846,599	31,903	0.27	126,609,063	501,331	4.23	27.01
1995	11,846,599	19,989	0.17	57,112,614	593,443	5.01	26.58
1996	11,846,599	33,710	0.28	115,207,246	527,154	4.45	29.76
1997	11,846,599	47,124	0.40	193,903,395	602,146	5.08	27.97
1998	11,846,599	429,427	3.62	2,301,048,181	453,359	3.83	28.01
1999	11,846,599	59,359	0.50	277,267,446	667,307	5.63	28.92
2000	12,112,181	108,227	0.89	572,711,949	307,408	2.54	25.45
2001	12,535,308	94,309	0.75	530,586,429	235,497	1.88	25.46
Total 1994–2001	–	824,053	6.89	4.17E+09	3,887,644	–	–
Average 1994–2001	11,965,885	103,793	0.86	524,815,379	485,955	4.06	27.39

Methods

Economic analyses of wildfire management policy have been based primarily on two models: Least Cost plus Loss (LC + L) and Cost plus Net Value Change (C + NVC) minimization (Bellinger, Kaiser, and Harrison 1983; Davis 1965; Gamache 1969; Gorte and Gorte 1979; Headly 1916; Lovejoy 1916; Mills and Bratten 1982; Sparhawk 1925; Teeter and Dyer 1986). More recent analyses have framed the problem as either maximizing profit given prices, or minimizing the sum of the net value change from wildfire plus the costs of suppression and presuppression (Donovan and Rideout 2003; Rideout and Omi 1990). Because fires affect fuel levels by consuming and fragmenting flammable vegetation, the effects of wildfire and fuels management (e.g., prescribed fire) are expected to operate across a range of temporal and spatial scales (Prestemon et al. 2002). Prestemon et al. (2002) was unusual in its explicit examination of the dynamics of wildfire for large spatial units, that is, wildfire in period t can affect wildfire in subsequent periods on the same spatial unit.

Determining the publicly optimal amount of prescribed burning usually requires stochastic, dynamic optimization. To find the optimal annual acreage of prescribed fire for wildfire risk reduction, an analyst would maximize the sum of expected current and future net present value of welfare:

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

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

where A is the maximization criterion (a welfare measure), V is the net value change per unit area of wildfire, which can take on either negative or positive values, W_t is area burned by wildfire for the spatial unit of observation in year t, $\mathbf{v}$ is a vector of the prices per unit area of suppression, presuppression, and fuels management inputs,[3] $\mathbf{x} = (\mathbf{x_1}, \mathbf{x_2}, \dots, \mathbf{x_T})$ is a matrix describing the amounts of suppression, presuppression, and fuels management inputs applied annually for year 1 through T (the planning horizon), $\mathbf{Z}_t$ contains exogenous inputs to wildfire production including stochastic climate variables, $\mathbf{W}_{t-j}$ is a vector of j lags of wildfire area burned, and r is the discount rate.

Solving this optimization problem produces a T-dimensional matrix of optimal input quantities and a T $\times$ 1 vector of wildfire quantities over time. The uncertainty associated with random events (e.g., weather prediction errors) means that $W(\cdot)$ is the predicted amount of wildfire in any year t and is made with error, complicating the solution process. In the presence of such error and with risk-averse decision makers, simulation techniques may be used to identify the amounts of prescribed burning most likely to maximize the welfare criterion and stochastically dominate (Hadar and Russell 1969) other levels of prescribed burning.

Optimization models, such as equation (1), may involve as many choice variables as periods in the simulation, making them difficult to solve. Alternatively, one can identify the policy that yields the highest expected net welfare from the set of all possible stationary policies and that is consistent with any utility function that demonstrates nonincreasing marginal utility. Stationarity means that the quantities in the vector $\mathbf{x}$ in equation (1) are constant (i.e., $\mathbf{x_1} = \mathbf{x_2} = \cdots = \mathbf{x_T}$). We use this more tractable analysis.

We simulate empirically derived cumulative value functions for wildfire under various prescribed burning regimes and use stochastic dominance analysis to evaluate alternative stationary policies for annual prescribed fire. Using the model described by equation (1), we generate distributions of the welfare criterion, A, for alternative levels of prescribed fire, x_i. Then, we compare the distributions for each prescribed burn policy under first-degree (FSD), second-degree (SSD), and third-degree (TSD) stochastic dominance. FSD obtains if and only if $G(x_i) \leq F(x_i)$ for all x_i contained in X (Hadar and Russell 1969). When probability distributions cross (i.e., FSD does not hold) SSD is 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, when (Hadar and Russell 1969)

$$\int_{x1}^{x} G(y)\,dy \leq \int_{x1}^{x} F(y)\,dy \quad \text{for all} \quad x \in I \tag{2}$$

where $I = x_1 - x_n$, and x_n is the largest value taken by the random variable.

If FSD holds, then SSD automatically holds, as does TSD. If neither SSD nor FSD hold, third-degree stochastic dominance, TSD, is used to compare the value of the entire cumulative distribution (e.g., Levy and Kroll 1979). The cumulative distribution, G, has TSD over F if

$$\int_{x1}^{x} \int_{0}^{t} [G(y) - F(y)]\,dy\,dt \geq 0 \quad \text{for all} \quad x \in I \quad \text{and} \quad \int_{0}^{1} [G(t) - F(t)]\,dt \geq 0. \tag{3}$$

In equation (3), TSD occurs only if the first condition holds with inequality for at least one value of x. Note that if FSD or SSD holds, then TSD also automatically holds.

Wildfire Production Functions

The first step in the optimization process is to estimate the wildfire production function, $W(\mathbf{Z_t}, \mathbf{W_{t-j}}, \mathbf{x_{t-k}})$ in equation (1). We estimate two double-(natural) log wildfire production functions using an annual time series (1994 to 2001) of wildfire for a cross-section of 48 counties in Florida. The dependent variable in the areal risk model is the ratio of forest wildfire area burned in county i in year t to total forest area in county i. The corresponding dependent variable for the wildfire intensity-weighted risk model is the sum of wildfire area burned in year t in county i in each fireline intensity class times their intensities, divided by the total forest area in county i.

[3] The "price" to the economy would be the net welfare change arising from the diversion of resources to fuels 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.

The form of our empirical model is

$$(4)\quad \ln\left(\frac{W_{i,t}}{F_i}\right) = a_i d_i + \sum_{j=1}^{J} b_j \ln\left(\frac{W_{i,t-j}}{F_i}\right) + \sum_{k=0}^{K} c_k \ln\left(\frac{B_{i,t-k}}{F_i}\right) + \sum_{m=1}^{M} f_m \ln\left(\frac{P_{i,t-m}}{F_i}\right) + g_1 E_t + g_2 E_{1998} + hG_t + k \ln H_{i,t} + \omega_{i,t}.$$

As shown, the dependent variable in equation (4), $W_{i,t}$, is either wildfire area burned (in acres) or intensity-weighted area burned ($\sum$(acres) $\times$ (kW/m)) in county i in year t, while in the lagged position, $W_{i,t-j}$ is the lag j of (strictly) wildfire area burned (in acres) in county i. F_i is the area of forest (acres) in the county; the d_i's are county dummies; $B_{i,t-k}$ is lag k of the area of prescribed burning (in acres); $P_{i,t-m}$ is lag m of the volume (in million cubic feet) of pulpwood removed from forests of county i; E_t is the Niño-3 sea surface temperature (Niño-3 SST) anomaly in degrees centigrade, which predicts wildfire through its influence on precipitation and drought (Barnett and Brenner 1992; Brenner 1991; Westerling et al. 2002); E_{1998} is a dummy variable for the year 1998 to account for the unusual Niño-3 SST anomaly in 1998[4]; G_t is the sea surface temperature anomaly for the North Atlantic Oscillation (NAO); $H_{i,t}$ is the housing stock (a proxy for the wildland–urban interface) in county i in year t; and $\omega_{i,t}$ is a randomly distributed error term; ln is the natural logarithm operator.

The fixed effects, time series cross-sectional modeling framework in equation (4) implies that the relationships between the dependent and independent variables vary across counties only by a proportional factor. In log–log space this is captured by a vector of intercept-shifting constants. Also contained in this vector of intercepts is the proportional (constant) effect of fire suppression on the dependent variable. The intercept-shifting vector in this model allows endemic or average levels of wildfire to vary across counties such as might result from spatially varying but temporally static ecological, land management, and land use factors. Equation (4) is not explicitly spatial although the cross-sectional units used in its empirical estimation are spatially arranged. Statistical tests for underlying spatially autocorrelated wildfire production models are discussed in the Results and Discussion section.

Seemingly unrelated regression (SUR) methods were used to simultaneously estimate generalized least squares (GLS) areal risk and intensity-weighted risk models of equation (4). This approach provides information on cross-equation error and parameter correlations needed in the simulation (see below). We also estimated parsimonious versions of the areal wildfire risk and intensity-weighted risk models for the simulation analyses by dropping all variables statistically significant at 20% or larger in two estimation iterations. This yielded the final, parsimonious equation estimates reported in the Results section.

Simulation Models and Prices

Parsimonious forms of the fire areal risk and intensity-weighted risk models (equation 4) estimated with SUR-GLS were used as inputs for Monte Carlo simulations of the effects of varying prescribed fire policies (annual acreage prescribed burned) on wildfire outcomes. Simulated fire outcomes were generated annually from 2002 to 2101 and for annual prescribed fire ranging from 5,000 to 60,000 acres in increments of 1,000 or 5,000 acres. This range of prescribed fire corresponds to 1.6% to 33% of the forested landscape in Volusia County. The period of 100 years was simulated 50,000 times for each level of prescribed fire. The economic impacts of wildfire outcomes were summarized by discounting the sum of quasi-net welfare (QNW) associated with different prescribed fire policies.

Simulations accounted for three sources of uncertainty: (1) parameter uncertainty, incorporating multivariate-normally distributed random errors about model parameter estimates; (2) random errors in wildfire outcomes, bivariate-normally distributed about zero, with variances and covariances derived from the jointly estimated areal risk and intensity-weighted risk equations; and (3) climate variation in the form of the El Niño-Southern Oscillation measure (Niño-3 SST anomaly, variable E_t) and the North Atlantic Oscillation (NAO, A_t), as described by historical data.

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[4] The 1998 value of the temperature anomaly was modeled as a separate variable because 1998 marked the end of a "super" El Niño. The magnitude of the cycle of the "super" El Niño had not previously been observed.

We used Krinsky and Robb (1986) techniques to capture cross-equation parameter and error correlations resulting from the use of lags of areal risk as inputs (regressors) in the intensity-weighted risk model when generating random sets of parameters and equation errors for each Monte Carlo simulation. Specifically: let $\hat{\mathbf{B}}$ be a $1 \times (K_1 + K_2)$ vector of K_1 parameters from the areal risk model and the K_2 parameters from the intensity-weighted risk model, estimated in a simultaneous system of seemingly unrelated, fixed effects equations. The $(K_1 + K_2) \times (K_1 + K_2)$ covariance matrix of these parameter estimates is $\mathrm{Cov}(\hat{\mathbf{B}})$. Given a $1 \times (K_1 + K_2)$ standard normal variate, $\mathbf{Q_B}$, a simulated set of parameter estimates for each iteration of the Monte Carlo is calculated as $\hat{\hat{\mathbf{B}}} = Q_B \times \mathrm{Cholesky}[\mathrm{Cov}(\hat{\mathbf{B}})] + \hat{\mathbf{B}}$, where $\mathrm{Cholesky}[\mathrm{Cov}(\hat{\mathbf{B}})]$ is the $(K_1 + K_2) \times (K_1 + K_2)$ Cholesky decomposition of the covariance matrix of parameter estimates. Simulations based on the areal risk model involved only the $K_1 \times K_1$ submatrix of $\mathrm{Cov}(\hat{\mathbf{B}})$and required a $1 \times K_1$ normal variate to generate random parameter values. The sum of the constant and fixed effect dummies was calibrated so that the prediction errors (observed minus predicted natural logarithms of areal risk and/or intensity-weighted risk) for 1994–2001 summed to zero for each simulated set of parameter estimates.

Random equation errors for every year in each 100-year Monte Carlo simulation were produced similarly to random parameter error generation. Let s_1 be the standard error of the regression of the areal risk model, s_2 be the standard error of the regression of the intensity-weighted risk model, $\mathrm{Cov}(s_1, s_2)$ be the 2×2 cross-equation regression error covariance matrix, $\mathrm{Cholesky}[\mathrm{Cov}(s_1, s_2)]$ be the 2×2 Cholesky decomposition of this cross-equation regression error covariance matrix, and $\mathbf{Q}_{\mathbf{e},t}$ be a 1×2 standard normal variate generated for each year t of a 100-year simulated future. A pair of random equation errors for each year of a 100-year simulated future, $\hat{\mathbf{s}}_t = [\hat{s}_{1,t}, \hat{s}_{2,t}]$, is produced by $\hat{\mathbf{s}}_t = \mathbf{Q}_{\mathbf{e},t} \times \mathrm{Cholesky}[\mathrm{Cov}(s_{1,t}, s_{2,t})]$.

Random Niño-3 SST anomaly values for each year of the 100-year simulated future were created by sampling randomly from both historical proxy and actual data. The proxy record ran from 1864 to 1949 (Woodruff et al. 1987), while actual data ran from 1950–1999 (National Oceanic and Atmospheric Administration 2003a). The North Atlantic Oscillation (NAO) was simulated by adding normally distributed random errors to its historical 50-year (1950–1999) annual mean observed value; the variance of that univariate distribution was taken to be the 50-year sample variance (National Oceanic and Atmospheric Administration 2003b).

The ranked 50,000 Monte Carlo simulated values of the discounted welfare change minus prescribed fire cost distributions were used to assess stochastic dominance. Note that because the wildfire "price per acre" was a change from a no-fire counterfactual, it was always negative. In contrast, the cost per acre of prescribed fire was always positive. Therefore, the modified objective function in equation (1) maximizes a welfare measure that is always negative, given a stationary prescribed fire policy (Rideout and Omi 1990). To calculate the discounted QNW generated by each of the 50,000 sets of 100-year wildfire simulations, wildfire outcomes, $\hat{w}_{i,\tau}$, for each future year for each fire output equation were converted from natural logarithm per-acre predicted values. This was calculated as $\hat{W}_{i,\tau} = 313035 \times \exp(\hat{w}_{i,\tau} + 0.5s_i^2)$, where i indexes the simultaneously estimated areal risk ($i = 1$) and intensity-weighted risk ($i = 2$) model estimates, τ indexes the future year ($\tau = 1, \ldots, 100$), and the constant is the total forest area in Volusia County.

The net value change of wildfire was based on Butry et al.'s (2001) study of Florida's 1998 wildfire season. Butry et al. (2001) reported welfare effects of wildfires on timber markets and on costs of damages to structures, expenditures on suppression, costs of evacuations, and changes in spending in other sectors. The point estimate of Volusia County's timber market welfare loss from the 1998 wildfires was \$163 million. Approximately \$0.5 million in welfare losses are attributable to damaged or destroyed structures in Volusia County.[5] The market value of wildfire suppression services in 1998 was approximately \$42 million for Volusia County, while the county's hotel and

[5] Applying the PriceWaterhouseCoopers' estimates of structure loss and damage (Butry et al. 2001), we calculate that 5.5 house-equivalents were lost in Volusia county in 1998. With a replacement value of \$77,922/structure, the aggregate market replacement value of \$428,572 produced a total welfare loss of \$446,500. We estimated linear approximations of Volusia County housing supply and demand curves. The position of these curves in price-quantity space was based on data from the Florida Bureau of Economic and Business Research (2002) and two surveys of housing market supply and demand elasticities. The new construction supply elasticity of 5.0 is based on Blackley (1999, p. 32, in her table 2), and our housing services demand elasticity estimate of 0.2 is derived from Zabel (2004, p. 29, his table 2, models 2 and 4).

tourism sector lost an estimated $20 million in revenues.

A full computable general equilibrium analysis would be required to fully quantify the welfare impacts of suppression expenditures and changes in spending in the tourism and hotel industries. In lieu of such a prohibitive addition to this analysis we performed a sensitivity analysis using Monte Carlo simulations based on (1) the quantified welfare losses only (timber and housing, about $164 million), and (2) the market values of commodities or services lost (including timber, housing, hotel and tourism sector revenues, and suppression costs, for a total of about $251 million) in the 1998 wildfires. Quantified welfare losses from wildfires in Volusia County were $1,012/acre (for the wildfire areal risk model) and $0.56/kW-acres/meter (for the intensity-weighted risk model). Using quantified market values, these figures are, respectively, $1,558/acre and $0.88/kW-acres/meter for the areal risk and intensity-weighted risk models.

The cost of prescribed fire varies with the size of the burn and various operational variables (Cleaves and Brodie 1990; Bellinger, Kaiser, and Harrison 1983; González-Cabán and McKetta 1986; Rideout and Omi 1995). For example, Cleaves, Martinez, and Haines (2000) estimated average prescribed burn costs/acre for nine regions in the United States and found that the costs ranged from $10.70 to $344.46 per acre, with an average for the Southeast of $26.30 per acre. We expect that increasing demand for prescribed fire services would result in higher per acre costs, given a fixed supply curve. Factors contributing to higher prescribed fire costs as larger percentages of a county are treated might include: (1) an inadequate (inelastic) supply of qualified prescribed fire technicians, (2) higher expenses for treating progressively more complicated land blocks, (3) rising public costs in terms of health impacts and escape risks, and (4) higher costs associated with less accessible and more difficult to treat forest ecosystem types (e.g., bald cypress [*Taxodium distichum*] and water tupelo [*Nyssa aquatica*]). Although the supply of qualified technicians is a short-run problem, the other factors are expected to worsen in the long run with continued population growth. So, we expect increases in prices of prescribed fire services in both the short and the long run.

To estimate the elasticity of prescribed fire service supply with respect to price, we used 1984–1994 data obtained from Cleaves, Martinez, and Haines' (2000) survey of National Forests. Data on total forest acres by National Forest or District were obtained from the National Forest System.[6] We estimated long run prescribed fire service supply as a double-log cross-sectional model, expressing the quantity of acres treated as a function of prescribed fire price per acre (the sum of weighted average planning plus project costs in real 1996 dollars), agricultural sector wages by state, and National Forest System Region dummies. The estimated supply function is inelastic with respect to prescribed fire price per acre, with a constant elasticity estimate of 0.54 (standard error of 0.23), significantly different from zero at 2% and from unity at 5%. The elasticity of supply with respect to real wages is also significantly different from zero, at 3% (elasticity $= -1.51$), while planning and project costs and four out of six regional dummies are significant at 2%.

Using the estimated supply elasticity of 0.54, we calibrated the prescribed fire supply function over the average amount of prescribed fire observed between 1994 and 2001 in Volusia County. Using the observed average cost of $25/acre and actual average quantity burned as points of departure for calibrating prices per acre for alternative prescribed fire amounts, prescribed fire prices varied from $11/acre at 5,000 acres per year to $298/acre for 75,000 acres per year.[7]

The real discount rate was set at 5%; results were not highly sensitive to the discount rate. Because small-diameter timber harvests were held constant and fire suppression resource efficiency was unchanged over the entire simulation period, their effects were not directly explored. While fuel reductions in the form of both timber harvesting (or thinning) and prescribed burning could make suppression more cost-effective, their total effects on suppression costs are uncertain (Donovan and Rideout 2003). Thus, their effects on subsequent fire suppression costs were also assumed constant. This implies that the change in welfare in the theoretical model (equation (1)) results exclusively from changes in prescribed fire costs and net value change (net damages from wildfire).

[6] Data were obtained from http://www.fs.fed.us/land/staff/lar/LAR94/lartab3.htm or directly from District or National Forest personnel.

[7] A lower bound of $10.70 per acre, the minimum observed by Cleaves, Martinez, and Haines (2000), was impose on prescribed fire price. Hence, amounts above 7,700 acres per year had prices higher than $10.70 at the base case elasticity of supply with respect to prescribed fire price.

For each simulation, we essentially estimated one curve in the envelope of C+NVC curves described by Donovan and Rideout (2003).

Data

The Florida Division of Forestry provided detailed records for all wildland fires on nonfederal lands reported to the Division of Forestry between 1981 and 2001. These records included the fire's county of origin, date first reported, dominant fuel type, flame length, and total area burned. Fires whose dominant fuel type was "grassy" were dropped, as our interest was in forest fires. Data on wildland fires on federal lands were obtained from the USDA Forest Service, U.S. Fish and Wildlife Service, and the U.S. Park Service. Because wildfire data were unavailable for the Department of Defense (DOD) and NASA lands, counties containing DOD or NASA lands were dropped from the analysis.

The wildfire intensity-weighted risk variable was calculated from observations of the average flame length for each fire.[8] For the 3% of fires lacking observations on flame length, we applied a weighted average of acres of fires with different flame lengths for each county in each. Next, we summed (for each county) the acres of fire for each flame length category[9] 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 number of acres burned in each intensity class times the average intensity for that class divided by the county's total forest area.

Data on silvicultural burn permits covering all ownerships were obtained from the Florida Division of Forestry. The permit data base consists of one observation for each permit and includes the date, purpose, total permitted burn area, and the location (township, range, and cadastral section) of at least one portion of the treated area. We assumed all burns were completed as described in the permit database. Burns for agricultural and rangeland purposes were dropped. Although permit data for some counties began in 1989, full statewide coverage was not available until 1993. Therefore, we used 1993 as the first valid start year. Table 1 provides summary statistics for wildland fires and prescribed burn permits for Volusia County and all of Florida for 1993–2001.

Data on annual softwood and hardwood pulpwood harvests by county were obtained from the USDA Forest Service Forest Inventory and Analysis unit in Asheville, NC. Since pulpwood removal data were only available for the calendar year and harvests occur both before and after the start of the fire year, we reduced potential simultaneity bias by including only lagged pulpwood variables in the regressions. Data for the Niño-3 SST anomaly and the NAO (our proxies for annual variation in fire climate) were obtained from the National Oceanic and Atmospheric Administration (2003a, b). Data on annual housing counts were provided by the Florida Bureau of Economics and Business Research (2002).

Results and Discussion

Wildfire Production Functions

The parameter estimates for the full specifications of both the areal and intensity-weighted risk functions (tables 2 and 3) reveal that both models are broadly significant, with most variables significant at 1% and all with signs in the expected directions. Moran's I tests detected no statistically significant spatial autocorrelation in either model.[10] The parsimonious versions of these two models used in the simulations are also shown in tables 2 and 3. Compared to previous literature, our results show that prescribed fire produces a larger risk reduction for a longer time and that prescribed burning significantly reduces both areal risk and intensity-weighted risk for at least three years.

With a few minor exceptions, the parameter estimates in the intensity-weighted risk model are larger in absolute terms than those estimated in the areal risk model. Notably, the effectiveness of prescribed fire is greater in

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[8] The Florida Division of Florida's flame length categories were 0–2 feet, 3–4 feet, 5–8 feet, 9–10 feet, or greater than 10 feet in height.

[9] Average flame length for each category and 15 feet as the average for the greater than 10-feet category were used for the calculations.

[10] We constructed a row-standardized inverse distance spatial weights matrix (275 × 275) of Florida counties by fire year (October–September). A county could only be a neighbor of another if both had an estimated residual in the same year. For the fully specified intensity-weighted risk model, the Moran's I is 0.004 with a variance of 0.00029, producing a Z-score of 0.450, which results in a (two-sided test) probability of 0.653 of spatial autocorrelation. For the full specification of the areal risk model, the Moran's I is 0.019 with a variance of 0.00026, producing a Z-score of 1.402 and a 0.160 probability of autocorrelation.

Table 2. Model Parameter Estimates of Fully Specified and Parsimonious Forms of Intensity-Weighted Risk Functions

	Full Model		Parsimonious Model	
Explanatory Variables	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 (prob > Chi^2 = 0.000)		1,673 (prob > Chi^2 = 0.000)	
Log likelihood	−334.2644		−382.1589	

Notes: Single (*), double (**), and triple (***) asterisk denote significance at 0.10, 0.05, and 0.01 levels, respectively. 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.

the intensity model than in the simple area model, implying that prescribed fire reduces both wildfire area and wildfire intensity. In the intensity-weighted risk regression, each percentage increase in prescribed burn area (averaged over three years) reduces wildfire intensity-weighted risk by 0.27% compared to 0.23% for the areal risk model. In the short-run (0 to 2 years), a 1% increase in prescribed burning acreage reduces the areal risk of wildfire by 0.65% and the intensity-weighted risk by 0.71%.

Our results also suggest that the impacts of prescribed burning and past wildfire are similar, at least for the first few years. The shorter time series for prescribed burning only allowed identification of the effects of the current year and two years of lagged prescribed fire, but this period is consistent with the period over which prescribed fire was found to reduce tree mortality from wildfire (Brockway and Outcalt 2000; Outcalt and Wade 2004). Our results show that past wildfire continues to reduce the risk of current wildfire up to ten or eleven years later.

Prescribed Burn Simulations

Results from the 100-year simulations of wildfire under a range of prescribed burn policies for Volusia County are presented in figures 1 (the intensity-weighted risk model) and 2 (the areal risk model). Each figure depicts both the market value and QNW economic impacts associated with a range of stationary prescribed burn policies. The welfare values are based on predicted impacts on the timber and housing sectors, while the market value curves use market values for the timber and housing sectors, suppression costs, and changes in expenditures in the travel and hotel sector. The models perform as expected, with increasing amounts of prescribed fire leading to lower area burned and intensity-weighted area

Table 3. Model Parameter Estimates of Fully Specified and Parsimonious Forms of Areal Risk Functions

	Full Model		Parsimonious Model	
Explanatory Variables	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 (prob > Chi^2 = 0.000)		1,645 (prob > Chi^2 = 0.000)	
Log likelihood	−228.0352		−276.6049	

Notes: Single (*), double (**), and triple (***) asterisk denote significance at 0.10, 0.05, and 0.01 levels, respectively. 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.

burned and lower overall net economic losses and costs. Greater amounts of prescribed fire lead to rising per-unit prescribed fire costs and marginally smaller gains in damages averted. Together these produce the inverse-U shaped QNW curves in figures 1 and 2.

The intensity-weighted risk model predicts that an annual rate of prescribed fire of 41,000 acres (welfare analysis) or 48,000 acres (market value analysis) would maximize discounted net value change minus costs.[11] The additional 7,000 acres treated in the market analysis results from accounting for expenditures on fire suppression and wildfire impacts on the hotel and tourism sector. Comparing figures 1 and 2, the annual prescribed fire amount that maximizes QNW is about 33% lower in the areal risk model than in the intensity-weighted risk model, regardless of which damage measures are used. Although the stochastic dominance analyses fail to identify specific policy solutions, they do provide a range of treatments that dominate all other policies tested. Using the intensity-weighted risk model and welfare

[11] The optimal amount of fuel treatment for a county may also depend on how the treatments are allocated spatially. Although some anecdotal evidence supports this, empirical evidence is not yet available to validate this claim. However, if it turns out to be true, our approach may underestimate the damage-cost reductions of prescribed fire, suggesting that higher rates of prescribed fire may be optimal. Nevertheless, we do not expect that explicit spatial analysis would substantially affect our results on optimal levels of aggregate treatments across a county. In this paper, we assume that the actions of managers in the historical data were optimal, in the sense that prospective areas to burn were identified spatially and then prioritized (burned first) with an (constrained) economic optimization model in mind. When the budget or institutional constraints are removed, we expect landowners to use the same criteria for locating treatments on the landscape. Consistent with our log–log model parameter estimates, the marginal effect of each additional acre prescribed burned declines with the absolute level of prescribed burn area in the county.

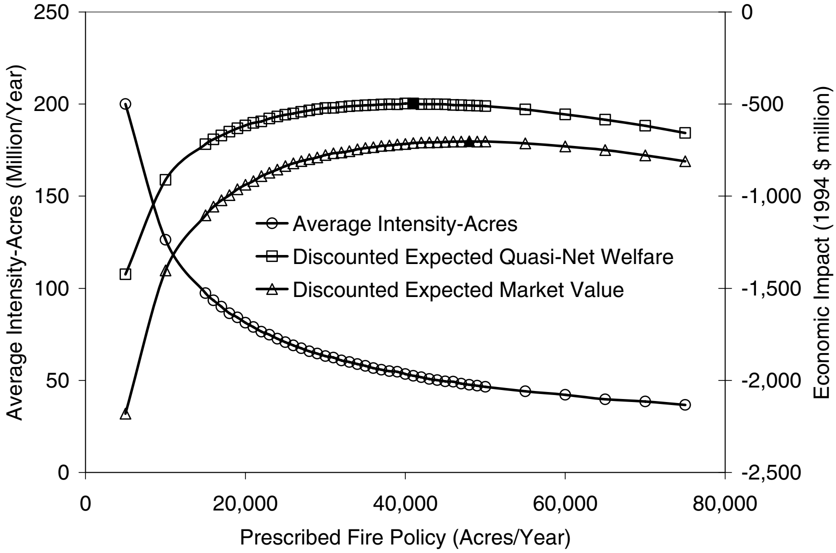

Figure 1. The simulated schedule of input–output combinations derived from the intensity-weighted risk model; amounts of prescribed burning yielding the maximum of net value change minus cost (symbols shaded black) are 41,000 acres/year for the QNW analysis and 48,000 acres/year for the market value analysis

analysis (figure 1), prescribed fire treatments between 37,000 and 43,000 acres per year dominate all other prescriptions by TSD. Using the market value analysis, including the hotel and tourism sector and suppression costs, the equivalent TSD range is 45,000 to 51,000 acres/year. For the areal risk model, prescribed fire treatments between 15,000 and 19,000 acres per year (welfare analysis) and 17,000 and 21,000 acres/year (market analysis)

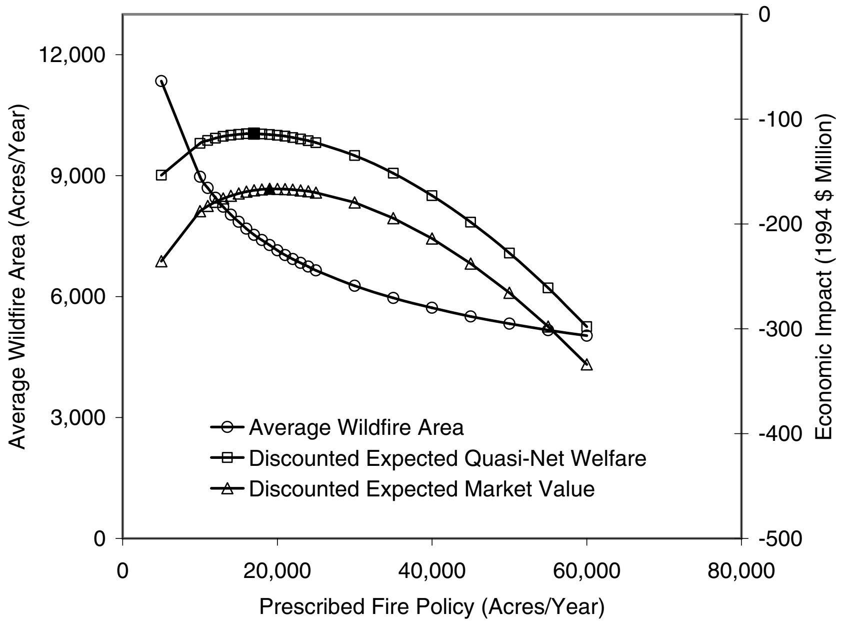

Figure 2. The simulated schedule of input–output combinations derived from the areal risk model; amounts of prescribed burning yielding the maximum of net value change minus cost (symbols shaded black) are 17,000 acres/year for the QNW analysis and 19,000 acres/year for the market value analysis

dominate all other prescriptions by TSD. Both the discounted QNW and market value analyses produce maxima in the middle of the ranges identified by the stochastic dominance analysis.

The values for economic damages from wildfire in our Monte Carlo simulations are point estimates that do not vary. Therefore, we also evaluated how the prescribed fire level with the maximum QNW varies across a range of assumed per-unit net value changes. We varied the net value change from $0.28/kW-acres/meter to $1.12/kW-acres/meter, keeping wildfire production parameters constant while including random equation errors and Niño-3 SST and NAO values. The results presented in figure 3 show that reducing the net value change from wildfire by half lowers the prescribed fire amount yielding the highest expected value by about 27%. Doubling the net value change per unit increases the prescribed fire amount with the highest expected value by about 34%.

Between 1994 and 2001, landowners in Volusia County requested permits to prescribe burn an average of 13,040 acres per year, or about 4.17% of all forested acres (table 1). Our results suggest that increasing the amount of prescribed burning in Volusia County would reduce both the areal risk and intensity-weighted risk of subsequent wildfires and associated damages. Because the intensity of a fire is strongly correlated with the damages observed (Kennard 2004) and prescribed burning reduces wildfire intensity in addition to area, using a strictly areal approach to modeling wildfire production will underestimate the true impact of prescribed fire on subsequent wildfire damages and hence underestimate the "optimal" rate of prescribed fire for a landscape. For example, the areal risk model suggests that the current rate of prescribed burning in Volusia County is close to the amount that maximizes long-run discounted QNW (17,000 acres per year or 4.8% of the forest area). Using the intensity-weighted risk model, however, the preferred rate of prescribed fire is about 214 percent higher than current rates, 41,000 acres per year, or 13% of the county's forest.

Conclusions

Although the economic theory of wildfire management has been the subject of considerable study, empirical economic analysis of wildfire is still in its infancy. Using panel data from the State of Florida from 1994 to 2001, we extend previous wildfire production function analyses by estimating a wildfire risk model that incorporates both the areal extent and the intensity of wildfire in a new measure of wildfire output, intensity-weighted risk. We then develop an approach for incorporating wildfire production functions into simulation models that identify the rate of prescribed burning that maximizes a net welfare criterion.

The amount of prescribed fire that minimizes the net economic losses from wildfire depends strongly on the chosen measure of damages from wildfire. Because net economic damages from fires are related both to the size and the intensity of the fires, ignoring intensity and relying on a strictly areal risk expression of wildfire output may lead to an underapplication of prescribed fire on a landscape. This finding is supported by our results from Volusia County, Florida, where accounting for wildfire intensity resulted in a one-third increase in the amount of prescribed fire required to minimize aggregate economic impacts from wildfire, compared to a strictly areal risk alternative.

This research represents an initial step toward developing cost-effective wildfire management programs through improved understanding of the economic tradeoffs between fuels management and wildfire suppression efforts. However, before our approach is applied broadly, models should be estimated and evaluated for the entire range of ecosystems where prescribed fire is being considered. For example, fuel treatments in dry, slow growing pine forests in the western United States may produce very different wildfire risk reductions, both in absolute amounts and in terms of the length of their effective duration.

We also caution that our approach is scale dependent. Findings at the county level may not hold for specific land holdings within a county. As such, our research represents a strategic approach for wildfire policy and management, helping policy makers determine appropriate budgets, programs, and incentives for fuels management to reduce the societal impacts of wildfires. Additional work will be needed to determine how such resources should be applied tactically and strategically.

Despite some of these potential shortcomings, this research advances economic theory through empirical analysis. Our results document a new understanding of how wildfire should be measured when evaluating the

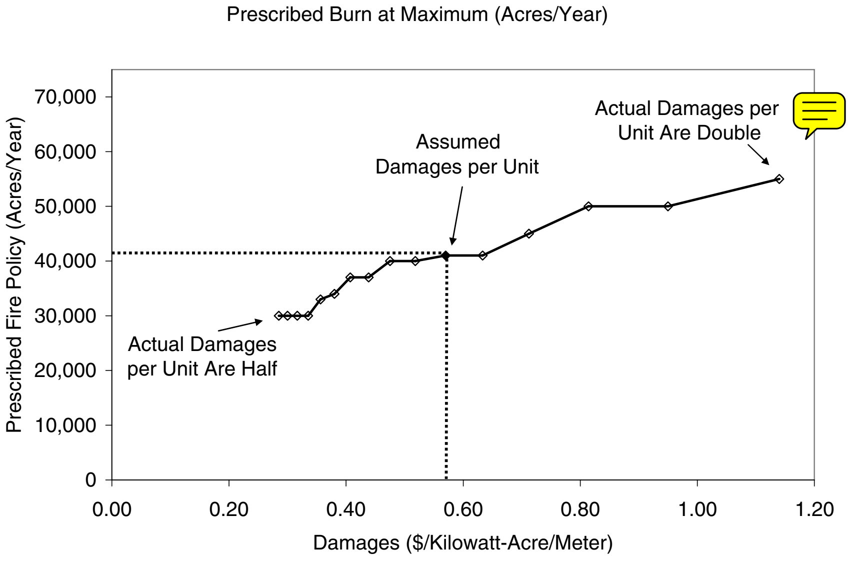

Figure 3. Simulated schedule of prescribed fire policies yielding the highest expected values, identified by varying assumed wildfire damages per unit, using the intensity-weighted risk model and quasi-net welfare losses from wildfire

efficacy of wildfire management inputs. Our results suggest that wildfire prevention and management activities have an effect on damages that exceed those reflected in simple measures of area burned. Additionally, our finding that the national supply of prescribed fire services responds inelastically to price should be a warning that the cost of prescribed fire services may increase rapidly with expanded prescribed fire use in the United States. Our estimated prescribed fire supply function implies that if programs like the President's Healthy Forests Initiative succeed in increasing contracts for prescribed fire on public lands, private landowners may face higher costs for similar services. Therefore, an unintended consequence of expanded use of fuel treatments on public lands may be a reduction in prescribed fire on private lands.

Our research suggests the need for additional research in several areas. First, a better understanding of the supply of prescribed fire services would allow more realistic simulations of nonmarginal changes in prescribed fire inputs. Second, identification of the envelope of economically optimal levels of any particular input needs to account for substitutability across inputs. Mechanical fuel treatments may interact with prescribed burning, such that the "best" prescribed fire levels identified without such interactions may differ from those found when other approaches are included in estimating optimal combinations of treatments. Similar cautions exist with respect to fire suppression. It is possible that fire suppression resource efficiencies may be changed by fuels management, but data limitations precluded identification of such changes. Finally, both wildfire and prescribed fire provide a suite of public and private goods and bads that go beyond the economic damages and market prices of direct inputs described in this study. Although considerable research is needed to quantify the values of these nonmarket impacts of wildfire, including these other values in optimization models could lead to a more accurate assessment of public and private policy choices for wildfire management.

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