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Comparing production function models for wildfire risk analysis in the wildland–urban interface

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Abstract

Wildfires create damages in the wildland–urban interface (WUI) that total hundreds of millions of dollars annually in the United States. Understanding how fires are produced in built-up areas near and within fire prone landscapes requires evaluating and quantifying the roles that humans play in fire regimes. We outline a typology of wildfire production functions (WPFs) and empirically estimate three broad classes of WPFs: fire event (ignitions), fire aggregate extent, and a combination function of fire effect and aggregate extent (an intensity-weighted aggregate extent model). Our case study is Florida, which contains an abundance of both wildland and human populations. We find that socio-economic variables play statistically significant roles in all three estimated production functions. At the county level, we find that population and poverty are usually positively related to annual wildfire area and intensity-weighted fire area, while unemployment is negatively related to ignitions, area, and intensity-weighted wildfire area. Poverty is found to be negatively related to wildfire ignitions, while the number of police are correlated with fewer ignitions. These results suggest that managers and decision makers should be aware of socio-economic variables and consider them in their wildland fire management decisions in the wildland–urban interface. Our results also emphasize the importance of including such variables in statistical models of wildfire risk in the WUI.
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1. Introduction

Expenditures by federal, state and local governments on wildfire prevention, control, and suppression have expanded rapidly over the past 10 years (Mutch, 2002). A chief cause of these increased expenditures has been the rapid population growth in the wildland–urban interface (WUI), which has placed more citizens and property at risk of wildfire and prompted wildfire managers and policymakers to expend all resources necessary to protect them when wildfire breaks out (Aplet and Wilmer, 2003; The White House, 2002; United States Department of Agriculture (USDA) Forest Service, 2000, 2004). Indeed, wildfire is one of the most daunting, urgent, and visible problems forest managers face in the WUI (Duryea and Hermansen, 2002). Consequently, federal, state,

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and local governments have initiated plans, studies, and initiatives to reduce the impacts of wildfire in the WUI by identifying, quantifying, and prioritizing communities at risk (e.g., Glickman and Babbitt, 2001; Governor's Wildfire Response and Mitigation Review Committee, 1998; Steelman and Kunkel, 2004; USDA Forest Service, 2000, 2004). These efforts have had mixed results. While significant progress has been made in assessing wildfire risks at fine spatial scales (e.g., the Florida Fire Risk Assessment System (McLellan and Brenner, 2003)), most risk assessments have paid scant attention to social and economic factors influencing wildfire risk. Solving the WUI wildfire problem requires research to identify linkages among ecological, social, and physical factors affecting wildfire and develop a better understanding of how social policies and socioeconomic conditions alter those linkages at different spatial and temporal scales (Zipperer, 2002).

Recent research suggests that wildfire patterns are linked to human activities and land use, including vegetation management (Prestemon et al., 2002). For example, many wildfire ignitions (e.g. arson, accidents, those relating to transportation) are human caused. To the degree that human activities are statistically related to wildfire, a portion of wildfire variability may be explained using socioeconomic variables. From a statistical perspective, failure to account for the effects of socioeconomic variables on wildfire activity may lead to biases and inconsistencies in model estimation. Inclusion of these factors can help managers and decision makers better understand why wildfire activity varies across space and time. Models that include socio-economic variables can help in the design of more effective and efficient wildland fire management and public policy.

A central problem facing managers, policy makers, and economists is measuring the effects of wildfire management interventions at different spatial and temporal scales. Wildfire production functions (WPFs) (Rideout and Omi, 1990; Prestemon et al., 2002) are a way of revealing these effects, in addition to the effects of non-management variables. WPFs are quantitative models that explain the spatial and temporal variability in wildfire activity, given different ecological, social, and economic conditions and management inputs. Thus, wildfire production function modeling allows empirical analysis of the relative impacts of human and non-human factors on wildfire in a unified framework. An estimated wildfire production function can provide a rigorous means for evaluating trade-offs among alternative wildfire intervention programs and policies and for forecasting risks. In this context, wildfire production functions are closely patterned after production functions in classical economic analysis (Rideout and Omi, 1990). Depending on the empirical specification, WPFs can provide critical information for allocating resources across the full suite of inputs to wildfire management: wildfire awareness programs, fuel treatments, preparedness (pre-suppression), and suppression. They can also serve to predict the spatial and temporal spillovers from wildland fire management across ownerships and ecosystems. Finally, wildfire production modeling can also be used to develop actuarial tables for property or economic losses in wildland settings. Nevertheless, we have found nothing in the literature that provides a typology of WPFs or outlines the diverse set of empirical methods available for estimating them.

Therefore, our objectives for this paper are to: (1) review and compare WPFs; (2) describe some published examples and report our own empirical examples of WPFs; and (3) assess the impact of WUI variables on wildfire risk. We illustrate empirical approaches appropriate to WPF analyses in the WUI, using data from Florida as a case study. We contend that wildfire production analysis will promote our ability to answer questions such as: (a) Where in the WUI are wildfires most likely to occur?; (b) What is the distribution of the extent and intensity of wildfires within the WUI?; (c) What are the characteristics (ecological, economic, demographic, and social) of the WUI that are more likely to be associated with wildfire?; (d) How can we predict which communities in the WUI are most at risk? In this paper, we provide examples of answers for some of these four questions. Additional WPF analysis would be required to develop answers for the full suite of questions for different ecologic and socio-economic conditions.

2. Wildfire production functions

Wildfire production functions (WPFs) are quantitative models that explain the variability in wildfire activity across spatial and/or temporal units of analysis. WPFs are usually represented as parametric relationships between wildfire output and a set of inputs. The inputs or covariates include: (1) ecological variables such as weather, climate, ecosystem type and characteristics; (2) management variables such as fuels management, pre-suppression and suppression activities; and (3) socioeconomic variables such as housing density, income, and employment. Time series, cross-sectional, and panel data sets can be used to statistically relate a variety of measures of wildfire output to these covariates.

We classify WPFs into four general categories: fire event, individual fire extent, aggregate fire extent, and fire effects models. Combining WPFs to incorporate elements of at least two of the four listed categories is also possible. Table 1 presents an overview of our typology of wildfire production function models, including references to published studies. Each type of model is discussed below.

2.1. Event models

The most common wildfire event models analyze ignitions as counts or occurrences within discrete units of time and/or space. When described as point processes, ignitions can be related to conditions surrounding the ignition point. Using covariates and events arranged in spatial–temporal units, event models can incorporate spatially dependent or spatially autoregressive relationships with other events that occur in regular patterns. Counts of events can additionally be related to counts in previous time periods, incorporating temporally autoregressive patterns that characterize contagion over time.

Wildfire ignition processes can be modeled in several ways. Most common are the Poisson approaches (Poisson, negative binomial, etc.), which relate the observed counts of ignitions to a set of covariates based on a Poisson process (Greene, 1997). Point process models relate individual events to spatially arranged covariates. The advantage of the point process model is its explicit joint use of local and non-local covariate information, which can improve the statistical efficiency of some parameter estimates and increase the explanatory power of the event model, compared to available non-spatial alternatives. Point process models, which shrink the size of the wildfire to a specific point and then relate the occurrence to spatially arranged variables, may be useful for identifying times and places of high wildfire ignition risks, thereby aiding in raising initial attack success rates through prepositioning of suppression resources.

Nonparametric methods for modeling counts have not been widely applied in wildfire research and are ripe for future research. Survival models relate a set of covariates to the length of time until an event occurs. Common in epidemiology and actuarial science, an example is the Cox Proportional Hazards Model (Cox, 1972), which relates the covariates associated with one spatial–temporal unit to the probability of an event occurring in that unit relative to some baseline probability of the event.

Event models are useful when ignitions are important in economic optimization models involving wildfire. For example, if wildfire suppression costs include a cost associated with ignitions in addition to costs that vary with the extent and intensity of wildfires, then the occurrence of an ignition or rate of ignitions in a spatial–temporal aggregate is of economic interest. In arson modeling, the occurrence is the criminal act, while the damages from the fire are the measure of its effect. Both occurrence and damage (or area burned) might be described separately. The likelihood of ignition can be related to law enforcement and to wildfire awareness and prevention campaigns (Donoghue and Main, 1985).

Gill et al. (1987) estimated models of two kinds of wildfire ignitions in Australia, lightning and ‘people’, relating them to indices of wildfire danger and a set of dummy variables that accounted for systematic differences in ignition rates according to day of the week, public holidays, and calendar months, all of which were found to correlate significantly with the daily count of ignitions. A logit model estimated by Vega Garcia et al. (1995) to model human-ignited wildfires in Canada is another example of the use of daily information on wildfire conditions. This model was structured in a manner similar to the modeling from Australia, except that wildfire occurrence in Canada was indexed as a binary event.

2.2. Individual fire extent models

Individual fire extent models relate the area or change in area per unit time for a single wildfire to

Table 1
Typology of wildfire production function models

Model	Dependent variable(s)	Common types	Advantages	Disadvantages	Examples
Fire event models	Ignitions	Statistical: Probit/logit Poisson Negative binomial Point process Non-parametric Survival models	1. Can incorporate spatially and temporally dependent or autoregressive relationships. 2. Useful when suppression includes costs associated with ignitions. 3. Can identify time and location of high wildfire risk.	1. Low statistical power. 2. Underdeveloped statistical methods.	1. Cox (1972) 2. Donoghue and Main (1985) 3. Gill et al. (1987) 4. Vega Garcia et al. (1995) 5. Pye et al. (2003)
Individual fire extent	Area burned or not burned by a single fire	FARSITE BEHAVE Statistical: Distance function (multi-output) Least squares (single output)	1. Useful for evaluating influence of suppression resources, fuels levels, and weather on burned area.	1. May be unsuitable for statistical analyses. 2. Often ignore spatial and temporal spillovers of resource decisions.	1. Davis and Cooper (1963) 2. Finney (1998) 3. Andrews and Bevins (1999) 4. Finney and Andrews (1999)
Aggregate fire extent	Area burned or not burned by multiple fires	Statistical: Principal components Canonical correlation Least squares	1. Can be a collective risk model. 2. Useful for evaluating impact of large-scale management on wildfire. 3. Can be used to quantify pre-suppression resource needs.	1. Not applicable for economic optimization models at fine spatial or temporal scales.	1. Barnett and Brenner (1992) 2. Armstrong (1999) 3. Westerling et al. (2002a,b) 4. Prestemon et al. (2002)
Fire effects	Intensity Damage Fuel consumed Severity	Statistical: Ordered logit/probit Least squares	1. Most useful when combined with other model types. 2. Can statistically relate fire intensity to area burned. 3. Can create total damage or aggregate heat output functions.	1. Discrete nature of some measured effects leads to low powered statistical models.	1. Rideout and Omi (1990)
Combination models	Wildfire area given successful ignition	Statistical: Heckman Tobit Extreme value Pareto distributions Least squares	1. Able to combine event and extent models. 2. Useful for size-frequency distribution analysis. 3. Useful for forecasting wildfire extent for spatial–temporal units. 4. Provides more complete characterization of aggregate wildfire activity.	1. Large data requirements. 2. May be difficult to identify influences. 3. Spatio–temporal population of fires may be difficult to identify.	1. Strauss et al. (1989) 2. Malamud et al. (1998) 3. Li et al. (1999) 4. Keeley et al. (1999) 5. Holmes et al. (2004) 6. Cumming (2001)

hypothesized covariates. These models either relate the total extent of the fire to a set of hypothesized explanatory variables or relate the area burned or not burned within a temporal unit (e.g., a day) to variables expected to affect the rate of wildfire spread.

Individual fire extent models are useful for evaluating the influences of suppression resources, weather, and fuels on realized wildfire or area unburned. These models are best suited for identifying the effectiveness of wildfire suppression resources and fuel conditions on wildfire extent. As such, they complement aggregate fire extent models (described below), whose imprecise description of suppression resources means that wildfire output and wildfire suppression inputs are often highly positively correlated. The individual extent models may be further complicated by multiple production aspects. Suppression resources are applied to protect resources (e.g., timber and habitat), property, and people. Because efforts to protect resources, property and people can be substitutes or complements, models need to account for the multiple effects of wildfire suppression on individual fire extent. The multi-output feature of wildfire can be an important barrier to properly identifying wildfire production functions. However, methods (such as distance functions) exist that could enable their identification (Färe and Grosskopf, 1990; Grosskopf et al., 1995).

One way to model individual fire extent would be to statistically relate the daily change in wildfire area burned (or saved from burning) to available suppression resources, weather, fuels, and other covariates. Specifying a distance function, two outputs of wildfire production–e.g., the area burned and the structures destroyed–would be related simultaneously to the inputs. Parameters from this analysis could inform analysts using larger-scale modeling frameworks (e.g., estimating aggregate extent models) on the effects of suppression and the relationships between suppression, vegetation management, and non-purchased inputs such as weather. It could also support optimization modeling of wildfire suppression at the individual fire level (Donovan and Rideout, 2003).

The FARSIGHT Fire Area Simulator (Finney, 1998; Finney and Andrews, 1999) and BEHAVE (Andrews and Bevins, 1999) are examples of simulation models that provide insights and predictions into how factors such as fuel, wind, topography, and moisture affect fire behavior. These models have enabled a deep understanding of fire behavior and have been useful in tactical applications, evaluating the effects of suppression inputs and nonpurchased inputs (weather, fuels, landscape features) on the spread of individual fires. Fire risk (defined as the probability that a particular location will burn during a discrete time period) is related to many of the same factors used in models such as FARSITE and BEHAVE. However, these simulation models are necessarily very short run and are not amenable to identifying the broad spatial and long temporal scale dynamic effects of fire, fire suppression, vegetation management, weather patterns, and socio-economic modulators of fire occurrence. As an economic tool, FARSIGHT and BEHAVE are difficult to employ in economic analyses concerned with large spatial and long temporal scales.

2.3. Aggregate extent models

The aggregate extent WPF generalizes the individual fire model, utilizing many of the same factors expected to affect the extent of the individual fire. These can include measures of aggregate quantities of suppression resources, weather and climate, ecological conditions, and fuels. When expressed relative to the size of the spatial unit, a fire extent model becomes a collective risk model.

Collective wildfire risk and aggregate extent models are useful for evaluating how large-scale management activities affect observed amounts of wildfire. Such models can potentially measure the tradeoffs across different kinds of wildfire interventions. Backward-looking models or those that include forecastable covariates can be used to predict collective risk or aggregate extent. Such forecasts can be used for preparedness planning and firefighting resource allocation decision making.

Westerling et al. (2002a,b) outlined a U.S. West-wide model of aggregate wildfire area for the fire season for one-degree grid cells, as related to the Palmer Drought Severity Index (PDSI). These authors used principal components and canonical correlation analysis to relate wildfire area in each cell to the PDSI's across all cells. Prestemon et al. (2002) estimated models relating the amount of wildfire per unit of forest area (collective risk), to prescribed fire, lagged wildfire, a measure of the El Niño-Southern Oscillation, small diameter timber removals, and housing density. Four kinds of models were estimated, one for each of three kinds of ignitions (arson, lightning, and accidents [all others]), and one for all ignition sources combined. These were estimated separately, using panel data methods.

2.4. Effects models

WPF effects models relate non-extent descriptions of wildfire, such as intensity, damage, fuel consumed, severity, or ecological benefit, to covariates. Dividing by time allows the models to relate measured rates of output to covariates. A potential example of these statistical versions of effects models would relate the average observed flame length of a fire (e.g., 0.5, 1.0, 2.0 m, etc.) to hypothesized explanatory variables. Given a sample of individual wildfires and an effect measured in discrete classes, probit, logit, or ordered versions of these could be used as estimation frameworks for effects models. An effect measured as a continuous variable could be modeled using generalized least squares techniques.

Because effects models as described here would be limited in spatial and temporal scope, they have many of the same inferential limitations as individual fire effects models. For this reason, effects models are probably most useful in combination with other kinds of WPFs. For example, wildfire effects can be aggregated across large spatial and temporal scales and related to similarly aggregated explanatory variables.

2.5. Combination models

Combination wildfire production models incorporate elements of at least two of the four categories of wildfire production listed above. For example, a wildfire spread model describes the size of a wildfire, given a successful ignition or start. These models combine an event model with an individual fire extent model. Econometric frameworks for these models include the Heckman and Tobit models. Another approach uses information on the sizes and the counts of all wildfires within a spatial–temporal aggregate, to create a probability density function (pdf) of fire sizes (size-frequency distributions and extreme value functions) within the aggregate. If replicated across many spatial–temporal units, the estimated parameters of the size-frequency distribution (slope and intercepts) or the extreme value function, at least in principle, could be compared quantitatively or statistically related in an auxiliary regression to covariates, using multivariate statistical techniques.

Individual or collective wildfire damage extent models are also combination models, incorporating elements of wildfire character and extent. These models can be estimated for individual fires or for large spatial–temporal units, relating the amount of damage to a set of hypothesized covariates.

In Section 3, we provide an example of one approach for combining effects (fire intensity) and aggregate extent (wildfire area) models. Intensity, developed from a flame height measure for each fire, is multiplied by the size of the fire, and the "intensity-acres" measure is then aggregated across all fires. This aggregation is defined as an expression of aggregate damage in the spatial–temporal unit of interest (a county over a year). Wildfire intensity-acres per unit of forest area are then related to covariates. This kind of 'damage' model is akin to one described by Rideout and Omi (1990).

The main uses of combination models include forecasting aggregate wildfire extent or expected damages for particular spatial–temporal units. Models of intensity-area, damage-area, or models of the parameters of size-frequency distributions or extreme values can also be used to more completely characterize aggregate wildfire activity. The distribution function models provide estimates of how covariates affect both the amount of non-extreme (low damage) and extreme (high-damage) fire. These models fit well within the Rideout and Omi (1990) or Donovan and Rideout (2003) frameworks.

One example of this type is by Holmes et al. (2004) plotted wildfires in Florida in nearly log–linear size class–frequency space. The Holmes et al. (2004) study estimated the slope and intercepts of smoothed functions relating size class to frequency of fires in each size class. Observed kinks in the distribution for fires beyond certain size classes (i.e., the function had a different slope and intercept), revealed potential regime changes beyond a threshold.

3. Wildfire production in the Florida wildland–urban interface

In this section, we use a Florida case study to provide examples of applying production functions to wildfire risk analysis and assess the impacts of WUI variables on wildfire activity. We estimated three wildfire production functions: (1) a fire event model of wildfire ignitions, (2) an aggregate fire extent model, and (3) a combined fire effect and aggregate extent WPF. Each model was estimated with a cross-sectional time series panel data set with the cross-sections defined by counties in Florida and the time series running from 1995 to 2001. Model estimates provide insights into how physical, managerial, and socioeconomic factors affect fire occurrence, area burned, and damages across broad spatial and temporal scales.

The fire event model relates total wildfire ignitions per county per year to 10 years of previous wildfire extent, weather variables (the sea surface temperature anomalies El Niño and North Atlantic Oscillation), three years of past prescribed burns, and WUI-related socioeconomic measures (population, poverty rates, unemployment, housing density, and number of police). Justification for inclusion of these variables is provided by wildfire ignition models of human-ignited wildfires estimated by Donoghue and Main (1985), Gill et al. (1987), Vega Garcia et al. (1995); by aggregate wildfire extent research published by Prestemon et al. (2002); and by research from the criminology literature that relates crime patterns to socioeconomic variables (e.g., Arthur, 1991; Corman and Mocan, 2000; Gould et al., 2002; Burdett et al., 2003). The fire event model is estimated with a conditional fixed effects Poisson panel model. Mathematically the fire event (ignition) model is described as:

Fire event model

$$S_{it} = \sum_{i=1}^{I} a_i d_i + \sum_{j=1}^{J} b_j \left(\frac{W_{i,t-j}}{F_i} \right) + \sum_{k=0}^{K} c_k \ln\left(\frac{B_{i,t-k}}{F_i} \right) + e_1 E_t + e_2 E_{1998} + f G_t + g H_{i,t} + h U_{it} + l P_{it} + m O_{it} + \omega_{i,t} \tag{1}$$

S_{it} is the count of the number of ignitions in county i in fire year t; W_{it-j} is the areal extent (acres) of wildfire in county i in fire year $t-j$; F_i is the area of forest (acres) in the county; the d_i's are dummies for the various counties (which control for temporally static but spatially variable un-modeled factors); $B_{i,t-k}$ is the total area (acres) of prescribed burning permits issued in county i in year $t-k$; E_t is the Niño-3 sea surface temperature (Niño-3 SST) anomaly (departure from a long-run moving average) in degrees centigrade (see Brenner, 1991; Barnett and Brenner, 1992); E_{1998} is a dummy variable corresponding to 1998 to allow the effect of the Niño-3 SST anomaly for 1998 (given its extreme, 'Super El Niño', characteristics) to be different from other years; G_t is the sea surface temperature anomaly in degrees centigrade for the North Atlantic Oscillation (NAO); $H_{i,t}$, $U_{i,t}$, $P_{i,t}$, $O_{i,t}$ are the housing density, unemployment rate, poverty rate, and number of police officers, respectively, in county i in year t; and $\omega_{i,t}$ is a randomly distributed error term.

The fire extent and aggregate fire effect models only differ in the definition of the dependent variable. Following Prestemon et al. (2002), both utilize a general least squares, fixed effects panel approach assuming heteroscedastic errors to estimate log–log production functions. The basic structures are:

Fire extent model:

$$\ln\left(\frac{W_{i,t}}{F_i} \right) = \sum_{i=1}^{I} a_i d_i + \sum_{j=1}^{J} b_j \ln\left(\frac{W_{i,t-j}}{F_i} \right) + \sum_{k=0}^{K} c_k \ln\left(\frac{B_{i,t-k}}{F_i} \right) + e_1 E_t + e_2 E_{1998} + f G_t + g H_{i,t} + h U_{it} + l P_{it} + m O_{it} + \omega_{i,t} \tag{2}$$

Fire effect model:

$$\ln\left(\frac{X_{i,t}}{F_i} \right) = \sum_{i=1}^{I} a_i d_i + \sum_{j=1}^{J} b_j \ln\left(\frac{W_{i,t-j}}{F_i} \right) + \sum_{k=0}^{K} c_k \ln\left(\frac{B_{i,t-k}}{F_i} \right) + e_1 E_t + e_2 E_{1998} + f G_t + g H_{i,t} + h U_{it} + l P_{it} + m O_{it} + \omega_{i,t} \tag{3}$$

Independent variables are defined as in the ignition model (1) except that the natural log operator (ln) is applied to the past wildfire extent ($W_{i,t-j}/F_i$) and prescribed burning ($B_{i,t-k}/F_i$) variables. For the fire extent model, the dependent variable is the natural log of the acreage of wildfire in county i in year t as a proportion of the total forest area. The dependent variable in the fire effect model is the natural log of wildfire intensity-acres (X_{it}) as a proportion of the total forested area in the county. The intensity-acres variable was constructed by multiplying the number of acres burned at different fireline intensities by those intensity levels, summing these, and then dividing by the total forest area in county i in year t. Fireline intensity is defined as the rate of heat energy released per unit time per unit length of the fire front (Kennard, 2004). Fireline intensity is one of the best descriptors of fire behavior and correlates well with expected temperatures at different heights above surface fires, crown damage, and lethal scorch height. Fireline intensity is often used to compare fires and assess the effects of prescribed burns (Kennard, 2004).

4. Data

Data for this study were collected from several sources. The Florida Division of Forestry (FDF) provided detailed records for all wildland fires on all non-Federal lands reported to the FDF between 1981 and 2001 and included location of the fire (cadastral section and county of origin), date the fire was first reported, dominant fuel type, flame length, and total area burned. Fires whose dominant fuel type was "grassy" were dropped from the data set, as we were strictly interested in forest fires. We obtained data on wildland fires on federal lands from the USDA Forest Service, US Fish and Wildlife Service, and the US Park Service. Data were unavailable for Department of Defense (DOD) and NASA lands; so counties containing DOD or NASA lands were dropped from the analysis.

We used areal extent and flame length data for each fire to calculate the wildfire intensity-acres variable. The Florida Division of Forestry assigned each fire an average flame length category. Flame length categories were: 0–2, 3–4, 5–8, 9–10 ft, and greater than 10 ft in height. There were also a large number of fires in which the flame length was not reported; we used a weighted average of acres of fires with different flame lengths for each county and each year to account for missing observations. To calculate an intensity measure from the flame length data, we first summed the acres of fire for each flame length category (using the average flame length for each category and 15 ft as the average for the greater than 10 ft category) for each county. We then applied the following equation to convert flame length to Byram's fireline intensity (Kennard, 2004): $I=259.833\ (L)^{2.174}$, where I is fireline intensity (kW/m) and L is flame length in meters. Finally, we calculated the variable "intensity-acres" for each county for each year by summing the product of the annual number of acres burned in each intensity class times the average intensity for that class for each county.

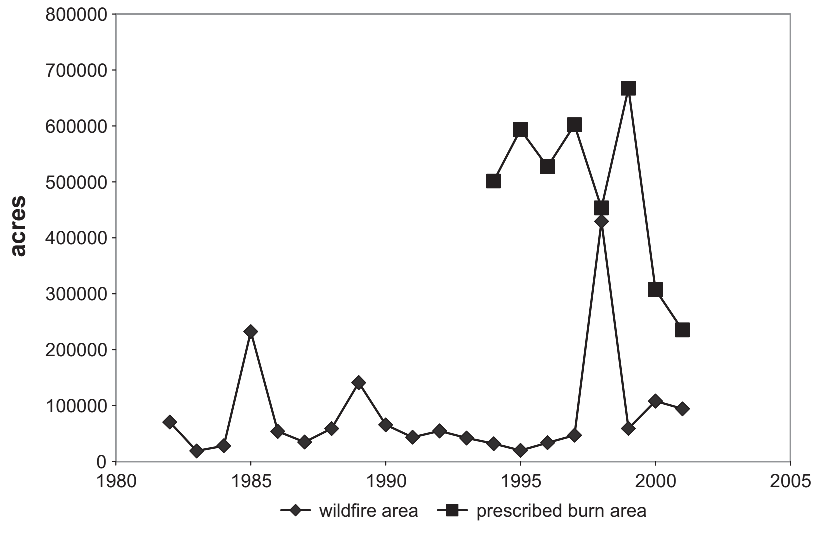

Fig. 1. Area burned by wildfire and area of permitted prescribed fire in Florida, 1982–2001 (prescribed fire data not available prior to 1994).

Data on silvicultural burn permits issued by the State of Florida were also obtained from the FDF and covered all ownerships. The permit database consists of one observation for each permit and includes the date, purpose, total permitted burn area, and the location (cadastral section and county) 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 not included in our analysis. Although some counties have permit data beginning in 1989, full statewide coverage was not available until 1994.

Plots of statewide wildfire acreage (1982–2001) and permitted prescribed burn acreage (1994–2001) illustrate their temporal variability (Fig. 1). Total wildfire ranged from a low of about 20,000 acres in 1983 and 1995 to a high of 429,000 acres in 1998.

Table 2
Maximum likelihood estimates of three wildfire production/risk functions (Event, Area, and Effect)

Independent variables	Event (ignitions)		Area (ln area)		Effect (ln intensity)	
	Coefficient	*P*-value	Coefficient	*P*-value	Coefficient	*P*-value
Wildfire lag 1	**−0.386**	**0.00**				
ln wildfire lag 1			**−0.282**	**0.00**	**−0.336**	**0.00**
Wildfire lag 2	**−0.500**	**0.01**				
ln wildfire lag 2			**−0.266**	**0.00**	**−0.230**	**0.00**
Wildfire lag 3	−0.990	0.25				
ln wildfire lag 3			**−0.201**	**0.00**	**−0.227**	**0.01**
Wildfire lag 4	−0.804	0.74				
ln wildfire Lag 4			**−0.217**	**0.00**	**−0.254**	**0.01**
Wildfire lag 5	−2.448	−0.37				
ln wildfire lag 5			**−0.213**	**0.00**	**−0.153**	**0.08**
Wildfire lag 6	**−7.234**	**0.00**				
ln wildfire lag 6			**−0.199**	**0.00**	**−0.308**	**0.00**
Wildfire lag 7	−1.954	0.17				
ln wildfire lag 7			0.165	0.77	**0.176**	**0.04**
Wildfire lag 8	2.589	0.12				
ln wildfire lag 8			0.103	0.11	0.144	0.13
Wildfire lag 9	−2.054	0.17				
ln wildfire lag 9			**−0.132**	**0.04**	−0.096	0.28
Wildfire lag 10	1.392	0.17				
ln wildfire lag 10			**−0.136**	**0.02**	**−0.205**	**0.01**
Pres. burn current	**−1.515**	**0.00**				
ln pres. burn current			**−0.199**	**0.03**	**−0.389**	**0.00**
Pres. burn lag 1	**−0.644**	**0.01**				
ln pres. burn lag 1			−0.102	0.356	−0.217	0.17
Pres. burn lag 2	−0.247	0.23				
ln pres. burn lag 2			**−0.509**	**0.00**	**−0.658**	**0.00**
Housing density (dwellings/for. ac)	**−1022.68**	**0.05**	**−7224.31**	**0.00**	**−6006.95**	**0.03**
Unemployment rate (%)	**−7.103**	**0.00**	**−9.937**	**0.06**	**−29.032**	**0.00**
Poverty rate (%)	**−2.122**	**0.00**	**3.654**	**0.07**	**4.640**	**0.10**
Population	**7.953**	**0.01**	**33.639**	**0.00**	5.166	0.70
Police	**−1.795**	**0.01**	−1.89	0.41	**6.978**	**0.10**
Niño-3 SST anomaly (°C)	**−0.334**	**0.00**	**−0.310**	**0.01**	**−0.658**	**0.00**
NAO anomaly (°C)	**0.294**	**0.00**	**0.883**	**0.00**	**1.149**	**0.01**
1998 dummy	**0.979**	**0.00**	**2.200**	**0.00**	**3.753**	**0.00**
Log-likelihood	−1359.79		−275.62		−387.72	
Observations	297		289		289	
Wald test statistic	1800.82		2611.98		1261.7	
Wald significance	0.00		0.00		0.00	

Statistically significant results are in bold type.

Several years of relatively low wildfire activity were typically followed by high wildfire years (e.g. 1985, 1989, 1998). Except for 1998, permitted area of prescribed burning was higher than the observed area of wildfire. From 1994–1997, permitted prescribed fire area was 12–29 times the annual area of wildfire in Florida. During the catastrophic 1998 wildfire season, permitted prescribed fire and wildfire accounted for about the same acreages, (453,359 and 429,427 acres, respectively). Immediately following the 1998 season, permitted prescribed fire area jumped to 667,307 acres.

Climate data (the Niño-3 SST anomaly and the NAO) were obtained from the National Oceanic and Atmospheric Administration (2003a,b). These two measures were our proxies for annual variation in fire climate. Data for annual housing counts and population for the estimation period were provided by the Florida Bureau of Economic and Business Research (2002). Poverty data were provided by the United States Department of Commerce, Bureau of the Census (2002). Data on police in each county were provided by the Florida Department of Law Enforcement (2002). Unemployment data were provided by the United States Department of Labor and Bureau of Labor Statistics (2002).

5. Results

The parameter estimates for the ignitions, area and intensity production functions in Table 2 reveal that each of the three models are broadly significant, with most parameter estimates different from zero at 1% significance and most signs in the expected directions. The size of the coefficients are not directly comparable for the three models because the area and intensity models are specified as log–log while the Poisson ignition model is by necessity a linear in parameters model. The wildfire area model predicts the size and direction of effects of the independent variables based strictly on the areal extent of wildfire, while the intensity model's dependent variable captures the combined impact on both areal extent and fireline intensity. Thus, with a few exceptions, the intensity model's parameter values tend to be slightly larger (i.e., more negative or more positive) than the strictly areal model.

Results are slightly different for the three estimated production/risk functions. However, all models generally confirm results from previous studies (e.g., Prestemon et al., 2002). Our models suggest that the impacts of prescribed burning and wildfire are similar, at least for the first few years. We faced a trade-off between information (long series) and the potential for model misspecification and hence statistical inconsistency with respect to the number of included lags of prescribed burning variables. Adding more lags in these fixed-effects panel models would have had the effect of shortening the time series and reducing information. Hence, our choice of allowing only 2 years of prescribed burning variables limited our ability to fully evaluate whether the risk reduction impacts of wildfire and prescribed fire operate over similarly long time scales. Prestemon et al. (2002) showed that prescribed fire impacts are modest, compared to wildfire. Past wildfire seems to have had a long lasting effect in our models, especially on wildfire acreage and intensity, less so on ignitions. Past wildfire appears to reduce current ignitions for only 5 years while wildfire acreage and intensity are reduced for 10 years.

WUI variables included population, poverty, unemployment, housing density, and police, almost all of which were highly significant in each of the three models. Table 3 compares the direction of the impacts of the WUI variables for each model. Unemployment, housing density, and population have similar results in all three models. Lower unemployment and housing density are consistently associated with statistically significant lower risks of ignition and areal extent and intensity of wildfire.

Table 3
Direction of impact of wildland–urban interface variables on wildfire ignitions, acreage, and intensity

	Wildfire ignitions	Wildfire area	Wildfire intensity-area
Population	+	+	+ (insignificant)
Poverty	–	+	+
Unemployment	–	–	–
Housing density	–	–	–
Police	–	– (insignificant)	+

Increased population had a statistically significant and strongly positive impact on the risk of ignition and areal extent of wildfire. Although positive, population was not significant in the intensity model. Poverty rates and number of police in the county produce opposite impacts on ignitions and wildfire area and intensity. The higher the poverty rate in the county the lower the probability of ignition, but once ignited the resulting wildfires appear to be larger and more intense in counties with higher population.

6. Discussion

At first glance some of the results from our analysis may seem contradictory. For example, although unemployment, housing density, and population are related to the dependent variables in the same direction in all three models, poverty has a negative impact on the number of ignitions but a positive impact on wildfire acreage and intensity. The number of police in a county was correlated with reduced ignitions, but the resulting wildfires in those counties were more intense and therefore, perhaps more damaging. Statistical relations in these cases are more likely to be correlative rather than causal.

Butry et al. (2002) used Geographic Information Systems (GIS) overlay and correlation techniques to characterize and compare fire-affected zones in Florida by population demographics, road density, forest stand attributes, forest fragmentation and sources and frequency of wildfire ignition. They found that areas that had more prescribed burning and lower amounts of wildfire tended to be characterized by younger, less educated, and lower income populations. These areas occurred predominately in more rural areas with predominately slash pine forest stands managed relatively intensively for timber production by federal and state agencies in the north central and panhandle regions of Florida. In contrast, regions of Florida with less prescribed burning and more wildfire tended to be dominated by privately owned, highly fragmented bald cypress–water tupelo forests located on more valuable properties near water dominated by older, wealthier populations and higher housing prices, i.e., the WUI. These less managed forests tend to provide more amenity benefits, greater forest access, and more "natural" undisturbed conditions than their highly managed and less risky slash pine counterparts. Indeed, 75% of all wildfires in Florida occur in these WUI areas where there has been no recorded prescribed burning in recent decades.

In this context, our results can be more easily interpreted. Unemployment in the county may be serving as a proxy for economic activity. All three of our models predict that areas with high unemployment and lower economic activity experience fewer wildfire ignitions and lower amounts of area burned at lower intensities by wildfire. These tend to be in the rural areas of the Panhandle and North Central Florida dominated by forests managed for timber production undergoing high rates of prescribed burning. In contrast, areas with lower unemployment and higher economic activity, corresponding more closely with the WUI, tend to have more wildfire and less prescribed burning. These WUI areas also tend to have higher populations, which our models also suggest are correlated with more ignitions, wildfire acreage, and more intense wildfire. Increased housing density was correlated with fewer ignitions and fewer wildfires with lower intensities, which reflects the fact that densely populated urban areas (as opposed to the less densely populated WUI areas) tend to have less risk of wildfire.

Our analysis suggests that, the more poverty in a county the lower the rate of wildfire ignitions but the larger the subsequent area of wildfire once ignition occurs (intensity was statistically insignificant). The lower ignition rate is consistent with the findings of Butry et al. (2002). The higher acreage burned once ignition occurs is likely due to fewer fire fighting resources being available for initial attack in poorer counties. The number of police in a county was correlated with fewer ignitions for perhaps two reasons. First, counties with large cities and urban populations, such as Miami-Dade, will tend to have more police and also less wildfire. Second, in the WUI, police have a negative impact on arson related wildfire ignitions (Donoghue and Main, 1985), a common cause of wildfire ignition in Florida (Florida Protection Bureau, 2004). However, the WUI areas of Florida described in Butry et al. (2002) have less prescribed burning. Therefore, once an ignition occurs, the resulting wildfire may tend to be more intense because of greater fuel accumulations.

7. Conclusions

We have described the principal categories of wildfire production functions and illustrated their estimation with a case study of the Florida WUI. Our results suggests that, in addition to the ecological and climate variables that are typically used in wildfire risk analysis, the socioeconomic conditions of communities included in fire prone landscapes also influence wildfire risk. Disregarding these variables in wildfire risk analysis may result in inefficient allocation of wildfire management resources.

Our empirical estimates of wildfire production functions that include WUI variables, placed in the context of the analysis by Butry et al. (2002), suggest that the more rural end of the WUI had fewer wildfire ignitions and lower aggregate wildfire extent. This is probably because the more rural portions of the WUI in Florida occur in areas of more highly managed forests, where prescribed burning is common and where other managerial inputs to production forestry tend to lower risks of catastrophic wildfire. Moving along the WUI continuum to more densely populated areas with more valuable properties located near water resources, the forests are less intensively managed. There, prescribed burning is rare, and the number of ignitions and the area burned per unit of space and time are higher. Prescribed burning rates may be lower because of a combination of population resistance to smoke impacts and the public's desire to have more 'natural' forests. Rates are also lower because the forests are more likely to be bald cypress–water tupelo ecosystems, which are difficult to prescribe burn but are highly flammable in extreme drought years.

One overall implication of our research is that wildfire production models that are estimated for regions with high populations and varying economic indicators are improved by including socioeconomic factors in addition to physical variables. Omissions of such variables can lead to mischaracterizations of the factors underlying wildfire production, especially when attempting to explain wildfire production variations across time and space. Because management factors are linked to observed fire patterns, it makes sense that policy makers evaluate wildland management solutions to lowering the costs and losses attributable to wildfire. Likewise, fire managers and decision makers should recognize the critical role that humans play in affecting wildfire risk aside from forest management. Humans set fires, put out fires, construct barriers to fire spread (e.g., roads), and socioeconomic variables related to economic conditions affect the degree to which these kinds of intentional and unintentional interventions into fire regimes are manifested. Unemployment and poverty are indicators of the resources available for fire suppression and perhaps directly related to the effectiveness of fire awareness programs, the frequency of arson, and economic activities that might be linked to accidental ignitions (e.g., rail and automotive traffic). Policy makers seeking ways to minimize damages and restore ecosystems in places where people live should be aware of these effects and seek solutions that account for the many ways that people affect wildfire risk.

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