Spatio-Temporal Wildland Arson Crime Functions

David T. Butry and Jeffrey P. Prestemon

*Respectively, Economist and Research Forester, Southern Research Station of the USDA Forest Service, PO Box 12254, Research Triangle Park, NC 27709. David T. Butry is the corresponding author: e-mail dtbutry@fs.fed.us, tel. 919-549-4037.

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, July 24-27, 2005.

Abstract

Wildland arson creates damages to structures and timber and affects the health and safety of people living in rural and wildland urban interface areas. We develop a model that incorporates temporal autocorrelations and spatial correlations in wildland arson ignitions in Florida. A Poisson autoregressive model of order *p*, or PAR(*p*) model, is estimated for six high arson Census tracts in the state for the period 1994-2001. Spatio-temporal lags of wildland arson ignitions are introduced as dummy variables indicating the presence of an ignition in previous days in surrounding Census tracts and counties. Temporal lags of ignition activity within the Census tract are shown to be statistically significant and larger than previously reported for non-spatial variants of the PAR(*p*) model. Spatio-temporal lagged relationships with current arson that are statistically significant show that arson activity up to a county away explains arson patterns, and spatio-temporal lags longer than two days were not significant. Other variables showing significance include weather and wildfire activity in the previous six years, but prescribed fire and several variables that provide evidence that such activity is consistent with an economic model of crime were less commonly significant.

Keywords: Arson, Poisson, Spatial, Temporal, Crime, Wildfire

JEL Codes: Q230, K490, C220, C250

Introduction

Wildland arson creates damages to structures and timber and affects the health and safety of people living in rural and wildland urban interface areas. Wildland arson is the single leading cause of wildfire on private lands in several heavily populated states, including California and Florida. Wildland managers and law enforcement agencies seek to predict wildland arson occurrence, and they could benefit from new information that enables more effective strategies and tactics for reducing risks and damages from such firesetting. Published time series event models of wildland arson have been static and nonspatial, relating ignition events to weather, seasonal trends, and law enforcement. These models therefore have ignored the role of some socioeconomic variables that can predict crime. Additionally, if a time series process is autoregressive and spatial, then such static, non-spatial models could produce biased and inconsistent parameter estimates, or their estimators may be inefficient.

The objective of this research is to more completely explain the spatio-temporal nature of wildland arson ignitions, in the context of an economic model of property crime. To do this, we outline a Poisson autoregressive model of order p, as first described by Brandt and Williams. Different from previous research on wildland arson (Prestemon and Butry), the model includes information on recent and spatially distant wildland arson ignitions. Also unique is the spatial resolution, with observations deriving from ignitions in individual Census tracts. Because wildland arson is an infrequent activity, in order to identify parameters of the extended PAR(p) model of wildland arson, we limit our analysis to six Census tracts in Florida where arson has been historically highest. Our model is similar to work by Prestemon and Butry, relating criminal activity to variables associated with opportunity costs of crime; these include economic measures as well as measures associated with likely high arson success (weather, fuels) and free time (holidays and weekends).

Methods

Theoretical Development

Wildland arson has been the cause of major wildfire disasters in recent history. In 2002, the Hayman Fire, which burned southwest of Denver, burned 138,000 acres and created costs and losses totaling well over $100 million (Kent et al.). Other recent fires include part of the Rodeo-Chediski fire in Arizona in 2002, which burned nearly a half-million acres. Similarly damaging arson events occurred in the Black Hills of South Dakota in 2000. Butry, Pye and Prestemon described how arson wildfire in Florida more commonly occurred near built-up areas of the state, hinting that the potential damages from these fires are higher than they are for other principal ignition sources (e.g., lightning).

In spite of these damages, research that has sought to explain or predict wildland arson is limited to only a few studies (e.g., Donohue and Main, Prestemon and Butry). In a technical advance in the area of wildland arson prediction, Prestemon and Butry found that in Florida, significant autocorrelation of wildland arson ignitions exist, lasting up to eleven days. Missing from all analyses, however, has been specific attention to using recent crime information in nearby locations to explain arson events. Such research has been done to help explain urban crime patterns (e.g., Bowers and Johnson; Corcoran, Wilson and Ware; Deadman), indicating its potential for wildland arson prediction. In fact, crime prediction using spatial and temporal data is a relatively new topic in criminology (Gorr and Harries; Gorr, Olligschlaeger and Thompson), enabled by better data gathering, processing, and statistical modeling techniques (e.g., Liu and Brown, Ratcliffe and McCullagh).

The spatio-temporal modeling of crime adds to a larger literature that has sought to understand some of the underlying causes of crime. That research has sought to link economic conditions and law enforcement with criminal activity, many in the context of an economic model of crime (Becker). Studies include those by Arthur, Brotman and Fox, Hannon, Hershbarger and Miller, and Neustrom and Norton examining poverty's link; Burdett, Lagos and Wright, and Gould, Weinberg and Mustard linking crime to working conditions; and Corman and Mocan and Di Tella and Schargrodsky, and Marvell and Moody, who have examined the effectiveness of law enforcement at reducing crime incidences.

Statistical Approach to Wildland Arson Modeling

Following Prestemon and Butry's approach to modeling an autoregressive crime function, we begin from Becker's model of person *i*'s decision on crime commission:

$$(1) \qquad O_i = O_i(\pi_i, f_i, u_i)$$

where O_i is the number of offenses committed, π_i is the probability of being caught and convicted, f_i is the wealth loss experienced by the criminal if caught and convicted, and u_i measures other factors influencing the decision and success of completion of the crime. The first derivatives of O_i with respect to π_i and f_i are negative. Next, consistent with

Becker, we describe the arsonist's psychic and income benefits from illegal firesetting as g_i and the production cost for the firesetting as c_i.[1] The loss from being caught and convicted of the crime is a positive function of income while employed: $f_i = f_i(w_i, W_i)$, where w_i are wages (Burdett, Lagos and Wright; Gould, Weinberg and Mustard) and W_i is the employment status. The prospective arsonist's expected utility from successfully[2] starting a wildland arson fire may be expressed as (Becker):

$$(2) \qquad EU_i(O_i) = \pi_i U_i(g_i - c_i - f_i(W, w)) + (1 - \pi_i) U_i(g_i - c_i)$$

As wages rise, for example, the expected net utility from arson declines, lowering the probability that an arson fire will be set: $\partial EU_i(O_i) / \partial w_i = \pi(\partial EU_i / \partial f_i)(\partial f_i / \partial w_i) < 0$.

---

[1] Arsonists could gain income in several possible ways: First, if the firesetter is the owner of the property, and timber is insured (or other buildings burned by the fire are insured), then an income benefit could accrue. Second, if the firesetter is also a paid firefighter who earns more when fighting fires, then starting a fire can provide employment and income. Third, because it is possible to salvage burned timber, burning timber can provide an economic benefit to nearby sawmill owners, potentially serving as an inducement to set fires if the mill owner has a chance of buying fire-salvaged wood. Indeed, Prestemon et al. (forthcoming) have shown how fires can benefit timber consumers.

[2] A "successful" ignition is one in which arson is reported to have occurred. In our empirical analysis, this matters: a "successful" ignition appears in our dataset.

The production cost of firesetting, c_i, is a function of time available (Jacob and Lefgren), fuels and weather (Gill et al., Vega Garcia et al., Prestemon et al. 2002), employment status, and information on other arson wildfires. An arsonist who observes other successful ignitions in the vicinity could conclude that conditions are favorable for an ignition, effectively lowering the per-ignition production cost by raising the success rate. Anything that raises the crime production cost will lower the expected utility of the crime: $\partial EU_i(O_i)/\partial c_i = \pi(\partial U_i/\partial c_i) + (1-\pi)(\partial U_i/\partial c_i) < 0$.

π can be expressed as a function of law enforcement effort (Burdett, Lagos and Wright). Analysts have long claimed that aggregate crime may be simultaneously determined with law enforcement (Becker, Fisher and Nagin). Not accounting for simultaneity would distort statistical inference (Cameron; Marvell and Moody; Eck and Maguire). Recent research has hinted that simultaneity is not a serious issue in many statistical analyses, as law enforcement agencies find it difficult to quickly respond to rising crime (Corman and Mocan; Gould, Weinberg and Mustard). Following Prestemon and Butry, we also assume exogeneity.

A PAR(p) Model of Daily Wildland Arson Ignitions

The PAR(p) model (Brandt and Williams) can be used to model a Poisson process in the presence of an underlying autoregressive event process. Here, in the case of wildland arson, the daily arson decisions made by all persons (i=1 to I) in location j on day t, culminates in a day's count of arson ignitions, $y_{j,t}$. The PAR(p) model hypothesizes that the observed count is drawn from a Poisson distribution conditional on $m_{j,t}$,

$$\text{(4)} \qquad \Pr[y_{j,t} \mid m_{j,t}] = \frac{m_{j,t}^{y_{j,t}} e^{-m_{j,t}}}{y_{j,t}!}$$

where $m_{j,t}$ = E[$y_{j,t}$|$Y_{j,t}$] is the conditional mean of a linear AR(p) process. The expected count is:

$$\text{(5)} \qquad E[y_{j,t} \mid Y_{j,t-1}] = \sum_{i=1}^{p} \rho_{j,i} y_{j,t-i} + \left(1 - \sum_{i=1}^{p} \rho_{j,i}\right) \exp(\mathbf{x}'_{j,t} \boldsymbol{\beta}_j)$$

where: $\mathbf{x}_{j,t}$ is a vector of independent variables (including a constant), $\boldsymbol{\beta}_j$ is a vector of associated parameters, and the $\rho_{j,i}$'s are the autoregressive parameters.

The likelihood equation associated this model is (suppressing the location subscript j):

$$\text{(6)} \qquad \begin{aligned} &\ell(m_{t-1}, \sigma_{t-1}^2 \mid y_t, \ldots, y_T; Y_{t-1}) = \ln \prod_{t=1}^{T} \Pr(y_t \mid Y_t) = \sum_{t=1}^{T} \ln \Gamma(\sigma_{t-1}^2 m_{t-1} + y_t) - \\ &\Gamma(y_t + 1) - \Gamma(\sigma_{t-1}^2 m_{t-1}) + \sigma_{t-1}^2 m_{t-1} \ln(\sigma_{t-1}^2) - (\sigma_{t-1}^2 m_{t-1} + y_t) \ln(1 + \sigma_{t-1}^2) \end{aligned}$$

where $m_{j,t-1}$ and the variance $\sigma_{j,t-1}^2$ are both positive, $\Gamma(\cdot)$ is the gamma distribution, and $m_{j,t-1} = E[y_{j,t} \mid Y_{j,t-1}]$ *and* $\sigma_{j,t-1}^2 = V[y_{j,t} \mid Y_{j,t-1}]$.

Data and Empirical Application

Wildfire and prescribed fire permit data were obtained directly from the Florida Division of Forestry. Arson wildfires were those deemed by the Division as likely arson, but uncertainty means that an unknown number of fires were misclassified.[3] Local population estimates were from the Florida Bureau of Economic and Business Research, while annual poverty data were from the United States Department of Commerce, Census Bureau. The Florida Department of Law Enforcement provided data on the mid-year count of full-time equivalent police officers in each county. The retail wage rate in our models was the state-level average for the year, from the United States Department of Labor (2004). County unemployment data were from the United States Department of Labor (2002). The current day's Keetch-Bryam Drought Index (KBDI), a measure of fire weather, was constructed using an algorithm (Keetch and Byram) from representative weather station data in the study area, which were collected by the National Climatic Data Center and provided by EarthInfo, Inc.

We examine six Census tracts across Florida, residing in the counties of Charlotte, Duval, Santa Rosa, Sarasota, Taylor, and Volusia (figure 1). These areas were indicated by the Florida Department of Forestry has having high arson activity. Given the apparent clustering of arson activity, we allow for the count of arson ignitions in a Census tract to be correlated with neighborhood arson (figure 2). We define two measures of neighborhood—local and regional—that allow us to evaluate whether repeat arson is a very localized phenomenon (perhaps indicative of a serial arsonist) or is part of a broader pattern (perhaps suggesting copycatting). The local neighborhood includes those Census tracts that surround (share a common border) the Census tract under study. The regional

[3] Division personnel claim a high degree of accuracy in fire cause attribution. Nevertheless, classification errors would result in some statistical inconsistency in our model parameter estimates.

neighborhood includes all other Census tracts that reside in the same county, as the Census tract under study, plus those within the surrounding counties. Summary statistics are provided in table 1.

Models are estimated for each of the six locations. Due to data constraints, many of the models have been shortened (variables dropped) in order to attain convergence in maximum likelihood estimation. Consequently, there are inferential limitations associated with individual location models. To gain some inferential ability, we also estimate a pooled version of the individual location models. The pooled version interacts the Census tracts' populations with all explanatory variables except for neighborhood ignition measures; the autocorrelation parameters are unitless and so also are not interacted with population. Because our individual location models do not contain population as an explanatory variable, the pooled model did include population, as an interaction with the intercept. Note that a single, un-interacted intercept is also included to allow for statistical consistency.

Results

Our spatially augmented PAR(p) models, all significantly different from a null model (table 2), broadly support a contention that the arson ignition process is temporally as well as spatially autocorrelated. In four cases out of six, restricting the neighborhood variables to zero is rejected at better than 10 percent significance. Daily autocorrelation parameters (p_i) are typically significant and range from one to four; longer autocorrelations are not estimable because of data constraints. Neighborhood variables are statistically related to arson ignitions, and they are generally large: both local and regional arson ignitions are usually positively related to one to two days' lags. This combination is evidence that arson wildfires serve as a copycat stimulus and favorable evidence that the temporal autocorrelation found by Prestemon and Butry in their county level analysis is generated by serial arson behavior.

Socioeconomic factors are sometimes significant explainers of wildland arson ignitions, consistent with an economic model of wildland arson crime, but the evidence is weak. Significant variables include unemployment (positively, in one case), wages (conflicting signs in the two significant cases), poverty (anomalously negative), and police (conflicting signs).

Only one other variable linked to the opportunity cost of crime, the Saturday dummy, is significantly related to arson. It is significantly different from zero at 5 percent in two cases—one positively, one negatively. Other locations have insignificant relationships at traditional statistical thresholds, but two are positive and different from zero at 10 percent. Broadly, however, this replicates some of the results shown in Prestemon and Butry. Saturdays are frequently not days of work and so serve as days when the opportunity costs of firesetting are lower—no wages are lost by spending time starting fires. Holidays and Sundays are not statistically different from other days of the week in their influence on arson, however, except for one case for which the Sunday dummy has a negative sign. Prestemon and Butry found holidays to be positively linked to arson in some county aggregates, but low information content in Census tract-level data (few ignitions) forced us to drop this variable in estimation, implying that we cannot test for its significance in our individual location models, here.

Wildland management and weather variables are usually significant in ways consistent with other research and with our theory. Recent wildfires in the Census tract are negatively related to arson ignition, indicating that lower fuels increase the costs of firesetting. Prescribed fire, done to specifically reduce fuels, is found in only one case (Sarasota County) to be correlated with less arson. Dry weather conditions, as measured by the KBDI, are related to wildland arson in ways expected from theory: droughtier weather leads to more ignitions, implying that the success rates are higher or costs of firesetting are lower when fuels are dry.

The pooled model estimate (Table 3) supports the findings of the individual location models with respect to the autoregressive nature of wildland arson and the statistical influence of neighborhood ignitions. In this case, more information allows for the estimation of an eleventh-order PAR model, with autoregressive parameters p_1 to p_{10} significantly different from zero at 5 percent and p_{11} significant at 20 percent. This closely matches the findings of the county level pooled daily model estimated by Prestemon and Butry. The Wald test that all neighboring ignitions have no statistical influence is rejected at smaller than 1 percent significance. Supporting an economic model of ignitions, arson ignition rates are higher during droughty weather, during the high fire season months, and on Saturdays. However, this pooled specification is not able to identify statistical linkages to socioeconomic variables, previous wildfire, or prescribed fire in a manner expected from theory.

Conclusions

Our research extends work by previous authors and supports hypotheses that spatial as well as temporal information can be incorporated into a daily arson expected count (risk) measure for spatio-temporal units, a statistical approach to wildland arson crime hotspotting (e.g., Bowers and Johnson). We have four principal conclusions, which may be used to further research on wildland arson.

First, at finer spatial scales than examined by all previous work, law enforcement and wildland managers can use information on arson ignitions to update expectations of arson in concentrated spatial zones. In our subject locations of Florida, spatio-temporal lags include areas as far away as to include Census tracts in adjacent counties and up to two days; arson ignitions in one Census tract usually foretell future ignitions in the same tract over the coming days and nearby tracts for one or two or more days. Managers could use that information, then, to preposition law enforcement and firefighting personnel, potentially reducing expected damages and enhancing arrest rates. However, further analysis would be needed to assess whether such a strategy would be economically efficient. For example, if law enforcement resources available are fixed, then reallocations would imply trade-offs. Greater success in limiting arson in high-arson risk locations through reallocation could lead to lower success in limiting other criminal activities in areas that lose law enforcement resources as a consequence.

Second, in the context of arson modeling, identifying the links to socioeconomic variables is very difficult in a daily time series of wildland arson ignitions. We found this to be true even for Census tracts with the highest arson activity levels, and the hoped for additional information provided by a pooled estimate could not reveal these links, either. Aside from the obvious possibility that socioeconomic variables do not affect wildland arson, sparse arson activity could imply merely statistically weak models or models whose spatial and temporal resolution is inappropriate for detecting effects of such variables. On the other hand, our specifications were linear and did not include lags of socioeconomic variables; further efforts to identify the influence of socioeconomic variables could therefore focus on possible nonlinear and lagged relationships. But whatever the statistical challenges remaining in fine time scale arson ignition modeling, as demonstrated by Prestemon and Butry and shown by Donohue and Main, identification of links between these variables and arson might be better accomplished by modeling the process with observations specified at larger spatial and temporal units of aggregation.

Third, although we have identified spatio-temporal relationships in wildland arson, we did not prove that these statistical results map to the actions of individual arsonists. Research is needed on the actual behavior of known arsonists, which could alleviate this limitation in further analyses. In criminology, one kind of study is on self-reported criminal activity. This type of study, focused on convicted wildland arsonists, could enhance our understanding about their actual spatial and temporal patterns of firesetting. Such knowledge could aid in defining statistical model functional forms and the best levels of spatial and temporal resolution needed to identify the statistical linkages that we seek to measure.

Fourth, our modeling has revealed a need to extend statistical results to investigations into model usefulness on the ground. A first stage in on-the-ground implementation is to test their predictive ability out of sample. The ability of such models to provide usable results would also have to be weighed against the returns to better predictive information. The returns should include the trade-off analysis outlined in our first listed conclusion, above. One feature to consider in the development of better predictive models of wildland arson activity would be to strike a balance between spatial and temporal scales of prediction that would be most useful to law enforcement and wildland managers and those scales that allow for statistically robust predictive models.

Literature Cited

Arthur, J.A. "Socioeconomic Predictors of Crime in Rural Georgia." *Criminal Justice Review* 16(1991):29-41.

Becker, G.S. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76(1968):169–217.

Bowers, K.J., and S.D. Johnson. "The Stability of Space-Time Clusters of Burglary." *British Journal of Criminology* 44(2004):55–65.

Brandt, P.T., and J.T. Williams. "A Linear Poisson Autoregressive Model: The Poisson AR(p) model." *Political Analysis* 9(2001):164–84.

Brotman, B.A., and P. Fox. "The Impact of Economic Conditions on the Incidence of Arson: Comment." *Journal of Risk and Insurance* 55(1988):751-54.

Burdett, K., R. Lagos, and R. Wright. "Crime, Inequality, and Unemployment." *American Economic Review* 93(2003):1764–77.

Butry, D.T., J.M. Pye, and J.P. Prestemon. “Prescribed Fire in the Interface: Separating the People from the Trees.” In K.W. Outcalt, ed. Proceedings of the 11th Biennial Southern Silvicultural Research Conference. Asheville NC: U.S. Department of Agriculture, Forest Service General Technical Report SRS-48, 2002, pp. 132–36.

Cameron, C.A., and P.K. Trivedi. *Regression Analysis of Count Data*. Cambridge: Cambridge University Press, 1998.

Corcoran, J.J., I.D. Wilson, and J.A. Ware. “Predicting the Geo-Temporal Variations of Crime and Disorder.” *International Journal of Forecasting* 19(2003):623–34.

Corman, H., and H.N. Mocan. “A Time Series Analysis of Crime, Deterrence, and Drug Abuse in New York City.” *American Economic Review* 90(2000):584-604.

Deadman, D. “Forecasting Residential Burglary.” *International Journal of Forecasting* 19(2003):567–78.

Di Tella, R., and E. Schargrodsky. “Do Police Reduce Crime? Estimates Using the Allocation of Police Forces after a Terrorist Attack.” *American Economic Review* 94(2004):115–33.

Donoghue, L.R., and W.A. Main. “Some Factors Influencing Wildfire Occurrence and Measurement of Fire Prevention Effectiveness.” Journal of Environmental Management

20(1985):87–96.

Eck, J., and E. Maguire. “Have Changes in Policing Reduced Violent Crime? An Assessment of the Evidence.” *The Crime Drop in America.* A. Blumstein and J. Wallman, eds., pp. 207-65. New York: Cambridge University Press, 2000.

Fisher, F., and D. Nagin. “On the Feasibility of Identifying the Crime Function in a Simultaneous Model of Crime Rates and Sanction Levels.” In A. Blumsten, J. Cohen, and D. Nagin, eds. *Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates*. Washington, DC: National Academy of Sciences, 1978, pp. 361-99.

Florida Department of Law Enforcement. Data on full-time equivalent officers per county per year obtained by special request, 2002.

Gill, A.M., K.R. Christian, P.H.R. Moore, and R.I. Forrester. “Bush Fire Incidence, Fire Hazard and Fuel Reduction Burning.” *Australian Journal of Ecology* 12(1987):299-306.

Gorr, W., and R. Harries. “Introduction to Crime Forecasting.” *International Journal of Forecasting* 19(2003):551–55.

Gorr, W., A. Olligschlaeger, and Y. Thompson. “Short-term Forecasting of Crime.” *International Journal of Forecasting* 19(2003)579–94.

Gould, E.D., B.A. Weinberg, and D.B. Mustard. "Crime Rates and Local Labor Market Opportunities in the United States: 1979-1997." *The Review of Economics and Statistics* 84(2002):45-61.

Hannon, L. "Criminal Opportunity Theory and the Relationship between Poverty and Property Crime." *Sociological Spectrum* 22(2002):363-81.

Hershbarger, R.A., and R.K. Miller. "The Impact of Economic Conditions on the Incidence of Arson." *Journal of Risk Insurance* 45(1978):275-90.

Jacob, B.A., and L. Lefgren. "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration, and Juvenile Crime." *American Economic Review* 93(2003):1560-77.

Keetch, J.J., and G.M. Byram. *A Drought Index for Forest Fire Control*. Asheville, NC: Southeast Forest Experiment Station Research Paper SE-38, 1968.

Kent, B., K Gebert, S. McCaffrey, W. Martin, D. Calkin, E. Schuster, I. Martin, H.W. Bender, G. Alward, Y. Kumagai, P.J. Cohn, M. Carroll, D. Williams, and C. Ekarius. "Social and Economic Issues of the Hayman Fire." *Hayman Fire Case Study*, USDA Forest Service General Technical Report RMRS-GTR-114 (Revision), R.T. Graham, ed., p. 315-95. Fort Collins, CO: USDA Forest Service, 2003.

Liu, H., and D.E. Brown, “Criminal Incident Prediction Using a Point-Pattern-Based Density Model” *International Journal of Forecasting* 19(2003):603–22.

Marvell, T., and C. Moody. “Specification Problems, Police Levels, and Crime Rates.” *Criminology* 34(1996):609-46.

Neustrom, M.W., and W.M. Norton. “Economic Dislocation and Property Crime.” *Journal of Criminal Justice* 23(1995):29-39.

Prestemon, J.P., and D.T. Butry. “Time to Burn: Modeling Wildland Arson as an Autoregressive Crime Function.” *American Journal of Agricultural Economics* (forthcoming).

Prestemon, J.P., J.M. Pye, D.T. Butry, T.P. Holmes, and D.E. Mercer. “Understanding Broad Scale Wildfire Risks in a Human-Dominated Landscape.” *Forest Science* 48(2002):685-93.

Prestemon, J.P., D.N. Wear, T.P. Holmes, and F. Stewart. “Wildfire, Timber Salvage, and the Economics of Expediency.” *Forest Policy and Economics* (forthcoming).

Ratcliffe, J.H., M.J. McCullagh, “Hotbeds of Crime and the Search for Spatial Accuracy.” *Journal of Geographic Systems* (1999):385-98.

United States Department of Commerce, Census Bureau. “Small Area Income and Poverty Estimates, State and County Estimates.” Available at <http://www.Census.gov/hhes/www/saipe/estimatetoc.html>. Accessed by authors on September 3, 2002.

United States Department of Labor. “Local Area Unemployment Statistics.” Available at <http://www.bls.gov/>. Accessed by authors on October 31, 2002.

United States Department of Labor. “Quarterly Census of Employment and Wages: Retail Trade.” Available at <http://www.bls.gov/>. Accessed by authors on July 12, 2004.

Vega Garcia, C., P.M. Woodard, S.J. Titus, W.L. Adamowicz, and B.S. Lee. “A Logit Model for Predicting the Daily Occurrence of Human Caused Forest Fires.” *International Journal of Wildland Fire* 5(1995):101-11.

Table 1. Summary statistics

	Santa Rosa County Census Tract 101	Sarasota County Census Tract 2712	Dixie County Census Tract 9802	Charlotte County Census Tract 204	Volusia County Census Tract 83204	Taylor County Census Tract 9504
Arson Ignitions/Day						
Mean	0.11	0.09	0.06	0.04	0.04	0.03
Maximum	8	5	10	4	14	7
Minimum	0	0	0	0	0	0
Standard Deviation	0.51	0.39	0.44	0.26	0.34	0.26
Census Tract Neighborhood, 1 Day Lag Dummy						
Mean	0.05	0.07	0.05	0.10	0.05	0.08
Maximum	1	1	1	1	1	1
Minimum	0.00	0	0	0	0	0
Standard Deviation	0.21	0.25	0.21	0.30	0.22	0.27
County Neighborhood, 1 Day Lag Dummy						
Mean	0.30	0.27	0.22	0.31	0.49	0.21
Maximum	1	1	1	1	1	1
Minimum	0	0	0	0	0	0
Standard Deviation	0.33	0.32	0.30	0.37	0.45	0.30
KBDI						
Mean	212	434	324	432	293	320
Maximum	681	783	749	783	694	749
Minimum	0	4	0	4	1	0
Standard Deviation	180	194	211	194	181	211
Unemployment Rate (%)						
Mean	3.89	2.80	6.78	3.85	4.05	8.78
Maximum	5.70	4.70	10.90	5.90	6.88	14.12
Minimum	2.81	1.60	3.90	2.40	2.70	5.70
Standard Deviation	0.49	0.70	1.49	0.89	1.03	1.80
State-Level Wage Rate ($/year)						
Mean	16,871	16,836	16,832	16,844	16,831	16,819
Maximum	17,803	17,727	17,689	17,727	17,727	17,689
Minimum	16,146	16,146	16,146	16,146	16,146	16,146
Standard Deviation	582	563	552	562	564	553
Poverty Rate (%)						
Mean	10.96	8.47	23.29	9.46	13.32	20.08
Maximum	12.49	9.70	25.76	10.20	15.24	22.00
Minimum	7.30	7.30	20.00	8.60	11.10	17.80
Standard Deviation	1.43	0.72	1.93	0.39	1.45	1.59

Table 1. Continued

Police Officers (County Full-time Equivalent)						
Mean	642	194	15	203	1,022	33
Maximum	730	234	17	214	1,135	34
Minimum	554	162	12	177	921	31
Standard Deviation	53	19	1	11	64	1
Population of the Census Tract						
Mean	3,365	5,433	3,605	4,725	14,959	4,826
Maximum	3,812	7,701	3,705	5,409	17,621	5,558
Minimum	2,994	3,264	3,510	4,068	12,448	4,149
Standard Deviation	232	1,357	57	409	1,590	421
Wildfire Lag 0-2 years (Acres)						
Mean	3,338	1,478	875	1,653	19,400	809
Maximum	6,380	3,625	2,448	2,653	43,892	1,303
Minimum	808	562	338	719	1,692	541
Standard Deviation	1,952	686	425	466	19,300	143
Wildfire Lag 3-5 years (Acres)						
Mean	2,157	1,460	722	1,219	5,279	1,574
Maximum	4,888	3,607	1,099	2,358	43,640	5,949
Minimum	808	562	338	332	2,266	541
Standard Deviation	985	978	160	539	6,150	1,832
Prescribed Fire 0 years (Acres)						
Mean	59,482	1,651	9,046	95	2,831	2,574
Maximum	118,484	8,250	25,185	450	6,825	10,226
Minimum	11,805	0	0	0	209	0
Standard Deviation	20,282	2,526	7,777	161	1,669	2,625
Prescribed Fire Lag 1 year (Acres)						
Mean	62,838	1,685	10,643	84	3,183	2,414
Maximum	118,484	8,250	25,196	450	6,915	10,433
Minimum	11,805	0	485	0	729	151
Standard Deviation	23,444	2,516	7,087	160	1,600	2,634
Observations	2,909	2,771	2,642	2,763	2,792	2,694

Table 2. Poisson Autoregressive Models of Maximum Order Estimable, Six Study Areas in Florida, Daily Counts of Wildland Arson Ignitions, 1994-2001 (Standard Errors in Parentheses).

	Model Locations					
Variables	Charlotte	Dixie	Santa Rosa	Sarasota	Taylor	Volusia
Constant	43.41	-64.55	-16.87	44.34	-64.44 **	0.43
	(32.99)	(57.93)	(11.29)	(33.93)	(32.59)	(15.76)
KBDI	0.50 ***	0.23 **	0.28 ***	0.31 ***	0.14 **	0.10
	(0.15)	(0.09)	(0.10)	(0.08)	(0.06)	(0.11)
Local Neighbors t-1	-0.16		0.79	-0.76	-0.85 *	-0.14
	(0.45)		(0.49)	(0.55)	(0.51)	(0.47)
Local Neighbors t-2	0.42		0.90	1.62 ***	0.09	-0.27
	(0.40)		(0.64)	(0.49)	(0.66)	(0.56)
Local Neighbors t-3 to -11	0.69 **		0.17	-0.08	0.20	0.43
	(0.34)		(0.24)	(0.31)	(0.16)	(0.35)
Local Neighbors t-1 to -4		-0.11				
		(0.40)				
Local Neighbors t-5 to -11		0.27				
		(0.44)				
Regional Neighbors t-1	0.28		0.14	0.93 **	1.10 **	1.07 ***
	(0.37)		(0.37)	(0.36)	(0.51)	(0.33)
Regional Neighbors t-2	0.76 **		-0.56	-0.47	0.18	0.32
	(0.37)		(0.44)	(0.47)	(0.66)	(0.34)
Regional Neighbors t-1 to -4		0.78 **				
		(0.31)				
Regional Neighbors t-5 to -11		-0.02				
		(0.49)				
Saturday	-0.16	0.69	0.64	-0.86 **	0.051	1.10 ***
	(0.42)	(0.42)	(0.39)	(0.41)	(0.080)	(0.36)
Sunday	-0.27	0.24	-0.60	-0.95 ***	0.25	0.33
	(0.37)	(0.37)	(0.37)	(0.36)	(0.09)	(0.43)

Table 2. Continued

January		0.45	2.4 ***	-0.13	0.766	0.5755
		-0.45	-0.65	-0.52	-0.5	-0.64
February	0.83 *	1.61 ***	2.97 ***	-0.75	1.70 ***	0.34
	(0.46)	(0.43)	(0.61)	(0.58)	(0.32)	(0.65)
March	1.06 **	0.86 *	1.70 ***	0.44	2.01 ***	0.40
	(0.44)	(0.45)	(0.59)	(0.57)	(0.35)	(0.59)
April	0.65		1.93 ***	0.00	-0.03	0.68
	(0.48)		(0.51)	(1.10)	(0.61)	(0.48)
May	0.87 **		1.33 ***	0.65	-0.32	0.06
	(0.44)		(0.45)	(0.57)	(0.49)	(0.54)
October			0.94 **	1.37 ***		
			-0.46	-0.50		
November			1.77 ***	0.73		
			-0.43	-0.58		
Poverty Rate	0.48	0.23	-0.38	-1.63	-0.74 ***	-0.12
	(0.60)	(0.49)	(0.26)	(1.66)	(0.29)	(0.52)
Unemployment Rate	-0.61	0.15	0.22	-0.36	0.54 ***	-0.04
	(0.37)	(0.19)	(0.27)	(0.55)	(0.09)	(0.36)
State-wide Retail Wage	-0.03 *	0.03	1.69	-0.14	0.03 *	0.00
	(0.02)	(0.03)	(1.61)	(0.14)	(0.01)	(0.01)
Police/Census Tract Pop.	0.05	1.13	-4.18	-1.77 *	40.06 ***	-0.57
	(1.83)	(11.03)	(9.71)	(1.06)	(9.83)	(1.57)
Wildfire Area Years 0 to -2	0.28	-0.72	-7.88 *	-2.18 ***	-1.56	-0.03
	(0.34)	(0.86)	(4.27)	(0.64)	(1.53)	(0.02)
Wildfire Area, Years -3 to -5	1.33	2.38	-8.34 **	0.73 **	-0.47 ***	-0.07
	(0.90)	(1.61)	(4.25)	(0.35)	(0.18)	(0.09)
Haz. Red. PB Years 0 to -1	1.28	0.09	0.16 *	-0.16	0.05	0.15
	(2.50)	(0.06)	(0.09)	(0.12)	(0.09)	(0.13)
Haz. Red. PB Years -1 to -2	0.85	0.03	-0.01	-0.36 ***	-0.11	0.18
	(1.98)	(0.05)	(0.06)	(0.14)	(0.10)	(0.13)
p_1	0.52 ***	0.30	0.32 ***	0.23 ***	0.02	0.51 ***
	(0.13)	(0.19)	(0.07)	(0.08)	(0.11)	(0.14)

Table 2. Continued

p_2	0.32	***	0.22		0.14	**	0.12	*			0.14		0.32
	(0.11)		(0.20)		(0.06)		(0.07)				(0.12)		(0.11)
p_3					0.12	**	0.20	***			0.21		
					(0.06)		(0.07)				(0.12)		
p_4					0.13	**	0.10						
					(0.06)		(0.07)						
Number of Observations	2763		2642		2909		2771		2694		2792		
LL PAR(p)	-438.84		-473.33		-799.04		-735.91		-381.35		-364.22		
LL PAR(p), All Neighbors=0	-450.57	***	-477.02		-803.71	*	-747.23	***	-385.41		-370.91	**	
LL Null Model	-527.18	***	-650.23	***	-1124.67	***	-915.33	***	-432.73	***	-465.14	***	

***Asterisks correspond to the significance level of the parameter estimates: for 1%, ** for 5%, * for 10%.

Table 3. Poisson Autoregressive Model of 11th-Order, Pooled Across Six Study Areas in Florida, Daily Counts of Wildland Arson Ignitions, 1994-2001.

Variables	Parameter Estimate (Standard Error)	
Constant	-0.89	***
	(0.31)	
KBDI x Census Tract Population	0.17	***
	(0.06)	
Local Neighbors$_{t-1}$	0.13	
	(0.23)	
Local Neighbors$_{t-2}$	0.58	**
	(0.23)	
Local Neighbors$_{t-3 \text{ to } -11}$	0.50	***
	(0.13)	
Regional Neighbors$_{t-1}$	0.58	***
	(0.19)	
Regional Neighbors$_{t-2}$	0.24	
	(0.20)	
Saturday x Census Tract Population	0.47	**
	(0.22)	
Sunday x Census Tract Population	-0.22	
	(0.27)	
January x Census Tract Population	1.27	***
	(0.34)	
February x Census Tract Population	1.10	***
	(0.35)	
March x Census Tract Population	0.85	**
	(0.36)	
April x Census Tract Population	1.03	***
	(0.34)	
May x Census Tract Population	0.84	**
	(0.35)	
June x Census Tract Population	-0.09	
	(0.44)	
October x Census Tract Population	0.51	
	(0.48)	
November x Census Tract Population	0.92	**
	(0.41)	
Census Tract Population	3.25	
	(4.77)	
Poverty Rate x Census Tract Population	-0.02	
	(0.04)	
Unemployment Rate x Census Tract Population	0.04	
	(0.09)	
State-wide Retail Wage x Census Tract Population	-0.28	
	(0.26)	

Table 3. Continued

Police	4.44	
	(5.79)	
Wildfire Area Years 0 to -2 x Census Tract Population	-0.0064	
	-0.0073	
Wildfire Area, Years -3 to -5 x Census Tract Population	-0.11	
	(0.10)	
Haz. Red. PB Years 0 to -1 x Census Tract Population	0.033	***
	(0.011)	
Haz. Red. PB Years -1 to -2 x Census Tract Population	-0.010	
	(0.010)	
p_1	0.21	***
	(0.03)	
p_2	0.086	***
	(0.024)	
p_3	0.11	***
	(0.03)	
p_4	0.072	***
	(0.022)	
p_5	0.11	***
	(0.03)	
p_6	0.074	***
	(0.023)	
p_7	0.067	***
	(0.023)	
p_8	0.052	**
	(0.021)	
p_9	0.069	***
	(0.022)	
p_{10}	0.066	***
	(0.023)	
p_{11}	0.024	
	(0.019)	
Number of Observations	16,571	
LL PAR(*p*)	-3,245	
LL PAR(*p*), All Neighbors=0	-3,279	***
LL Null Model	-4,194	***

***Asterisks correspond to the significance level of the parameter estimates: for 1%, ** for 5%.

Figure 1. The locations of the six individual Census tracts in Florida.

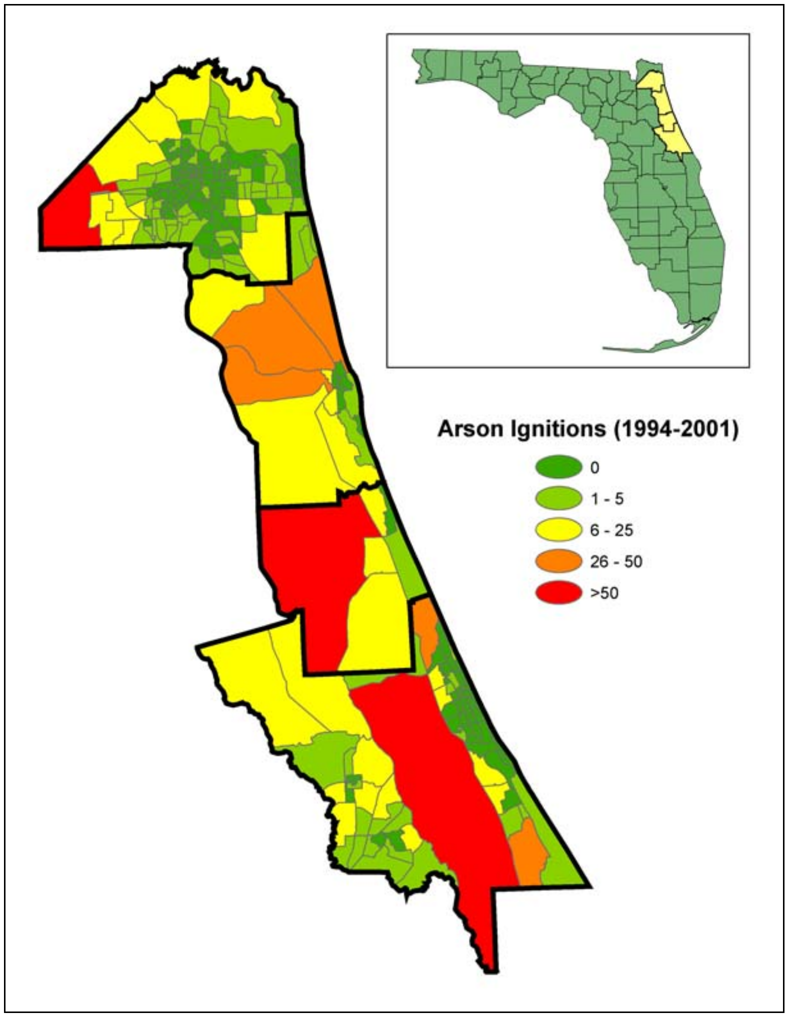

Figure 2. A close-up of the arson activity (1994-2001), by Census tract, in Duval, St. Johns, Flagler, and Volusia County.