Wildland Arson: A Research Assessment

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Abstract

Wildland arson makes up the majority of fire starts in some parts of the United States and is the second leading cause of fires on Eastern United States Federal forests. Individual arson fires can cause damages to resources and communities totaling over a hundred million dollars. Recent research has uncovered the temporal and spatial patterns of arson fires and their long- and short-term drivers. In statistical analyses, explanatory variables include those associated with general economic conditions and law enforcement. Research findings indicate that wildland arson ignitions are consistent with other kinds of crimes, in terms of their relationships to hypothesized factors. Arson is predictable in short and long timespans, as its rate is heavily influenced by weather, climate, fuels, and recent information on other nearby and recent arson fires. These results could be used to enhance the effectiveness of law enforcement and wildfire management resources.

Keywords: Arson, autocorrelation, crime, spatio-temporal, wildfire prevention.

Introduction

Over 0.5 million fires are set by arsonists each year in the United States, resulting in over $3 billion in damages (Tri-Data Corporation 1997). Arson is a leading cause of wildfire in several heavily populated States, including California and Florida. Furthermore, arson fires are concentrated in urban interface areas (Butry and others 2002), where values at risk are likely to be high. Several recent large wildfires were intentionally set, including the Hayman Fire near Denver in 2002, which caused damages exceeding $100 million (Kent and others 2003). In the Eastern United States, wildland fire is primarily a human-initiated phenomenon. Data provided by Schmidt and others (2002) show that for 92 percent of the area burned 1986-1996 in 18 Eastern U.S. States, the causes were attributed to human-related ignition sources. During the same period, 74 percent of area burned on all Eastern Federal forests was from human-related ignition sources (18 percent by arsonists). Wildland arson ignitions in Florida compose a quarter of all fire starts. Arson fires are set for a variety of reasons, but a primary feature of these fires is that they are ignited close to high values at risk, and, hence, also threaten human safety. In spite of the potentially large economic losses associated with such events, wildland arson has received scant attention in the refereed literature, with some exceptions (e.g., Donoghue and Main 1985, Prestemon and Butry 2005). The vast majority of research into wildland fire management and policy in the United States has been concerned with wildfire suppression, fuel treatments, fire physics, and overall economic efficiency questions.

Worldwide, wildland fire setting has been a common practice of rural residents for centuries (Gamst 1974), and at least in the 20th century in parts of the United States South (Doolittle and Lightsey 1979, Kuhlken 1999). In early parts of the European settlement of America, fires were often set intentionally, for prescriptive purposes. Fires were set to shape vegetation communities, enhance forage for grazing animals, reduce pests, and clear land for agriculture (Doolittle and Lightsey 1979). However, some fires were set in the same context as many are today—for revenge against a landowner, as an act of protest, as an attempt to cover up another crime, or as vandalism. It is unclear whether the kind of relatively innocuous, managerial-type fire setting persists today in the United States. However, as we explain in this article, current wildland arson ignition patterns appear to closely align with certain behavioral patterns found with other criminal activities.

Long-term studies of intentionally set fires are nonexistent. Instead, the analyst has to resort to statistical tests based on short time series to establish the validity of proposed theories. Here, we attempt to provide an overview of what is known about wildland arson today, as it has manifested itself since 1970, based on such research. We focus on wildland arson within the context of crime, generally describing how it follows patterns similar to violent and nonviolent crimes. In this, we exclude consideration of fires ignited by children, which we consider accidental (although this carries with it several assumptions that we leave for other analysts for the moment).

Wildland Arson Background

Spatial and Temporal Scope of the Wildland Arson Problem at the National and State Levels in the United States

Wildland arson fires on national forests have exhibited conflicting trends. Arson ignitions on national forests clearly trended downward from the mid-1980s to 2004 (Figure 1), but no identifiable trend exists on the area burned by wildland arson (Figure 2). The ignition share of arson (proportion of all ignitions attributed to arson) appears to be less correlated with the ignition shares of lightning and other fire sources than those sources are to each other (Figure 3). There is, however, no research that provides statistical evidence that the apparent decline in arson ignitions has led to an overall decline in wildfire activity. Prestemon and others (2002) showed how wildfire area burned in Florida by wildland arson responds to the same kinds of factors as do fires started by other means. But Mercer and Prestemon (2005) indicate that wildfire ignitions by arsonists respond differently to influential factors—especially socioeconomic variables—compared to other fire causes. The overall decline in the trend of arson fire ignitions and nontrending area burned, however, translates into a relative decline in arson area burned compared to other fire sources (Figure 4), as total area burned by all causes has apparently trended upward.

Information from the State of Florida, which includes fires on both public and private lands, also demonstrates that arson appears to be on a negative time trend. Prestemon and Butry (2005) suggested that rising policing levels, rising wage rates, and falling poverty rates explain some of the negative trend. However, more research is needed to establish the general validity of such findings.

Wildland Arson in the Context of Crime

Crime and Criminology

Wildland arson is classified as one subset of arson, a serious crime that is tracked by State and national authorities. Icove and Estepp (1987) reported that wildland arson is the third most common type of arson behind arson in residential and educational structures. These crime categories are each summarized at local, State, and national levels into an index of the number of crimes of each type per 100,000 individuals in the reporting location. Indices reported across States (and smaller geographical and political jurisdictions) include the violent crimes of murder, rape, robbery, and aggravated assault and the property crimes or nonviolent crimes of burglary, larceny, motor vehicle theft, and arson. Historically, arson has not been consistently tracked across States, so a long-term nationwide picture of arson is not available. However, a nationwide picture is available for all index crimes besides arson.

National Crime Trends

Between 1972 and 2004, nationwide index crimes have undergone a rise and then a fall (Figure 5). Crime trends have been used to empirically test economic theories of crime and to uncover the primary drivers of the observed, aggregate time trends, and the reasons for differences in rates across space (e.g., Burdett and others 2003; Corman and Mocan 2000; Gould and others 2002; Grogger 1995, 1998). Beginning from foundational work on the economics of crime by Becker (1968), research has shown that aggregate crime rates follow socioeconomic and law enforcement variables, which are linked to the opportunity costs experienced by criminals. Thus, crime-rate fluctuations are related to changing wage rates, unemployment rates, intensities of law enforcement, length of prison sentences, and the proportion of the population incarcerated.

Criminology Theories

Many theories have been used to explain levels of crime and their variations, and an extensive review of these is not possible here. Instead, we mention Becker's (1968) crime

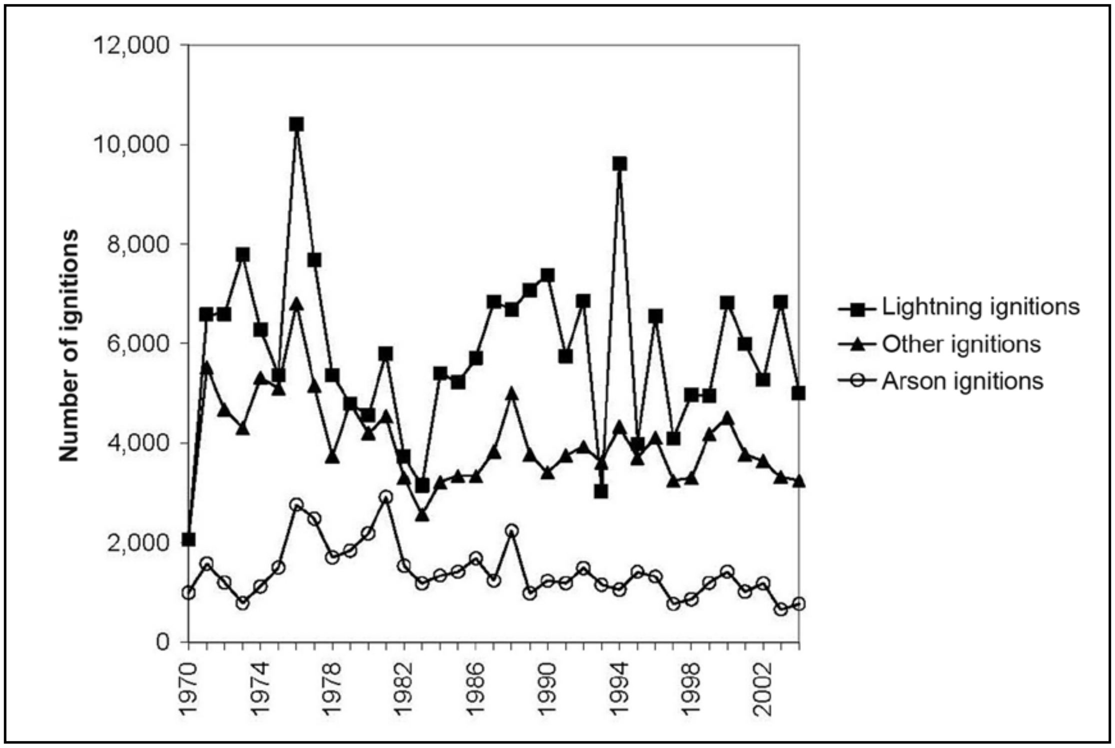

Figure 1—Wildland arson and other wildland fire ignitions on all national forests, 1970-2004. (Source: USDA Forest Service 2007)

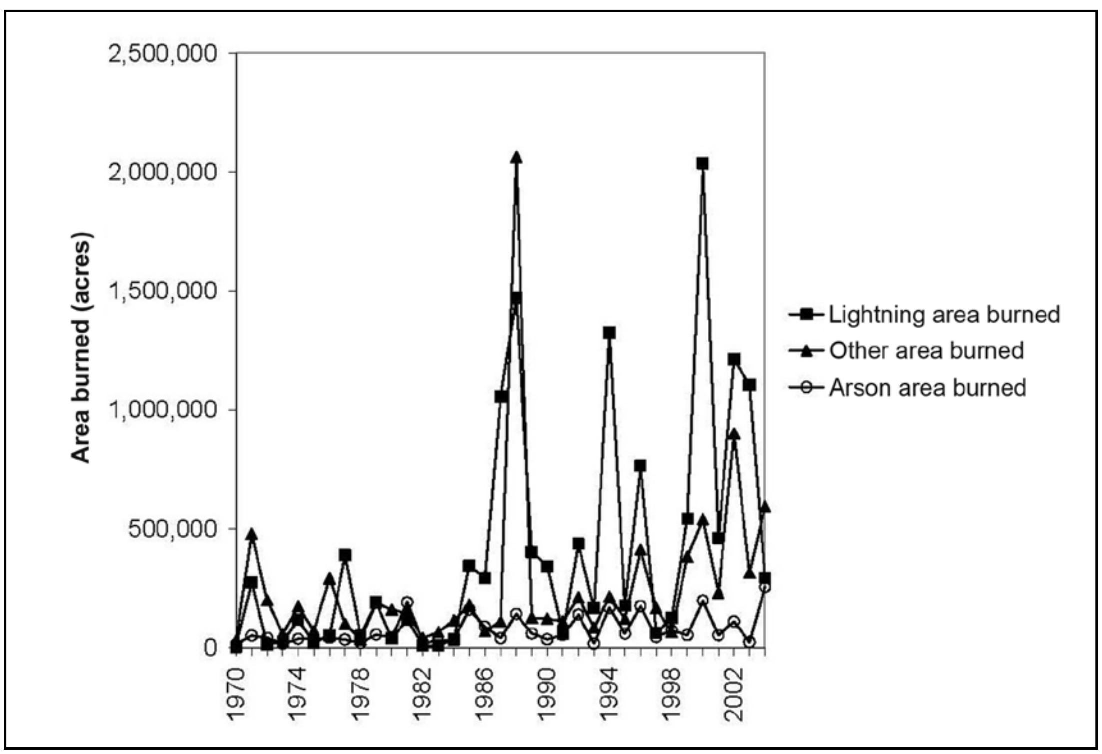

Figure 2—Wildland arson and other wildland fire areas burned on national forests, 1970-2004. (Source: USDA Forest Service 2007)

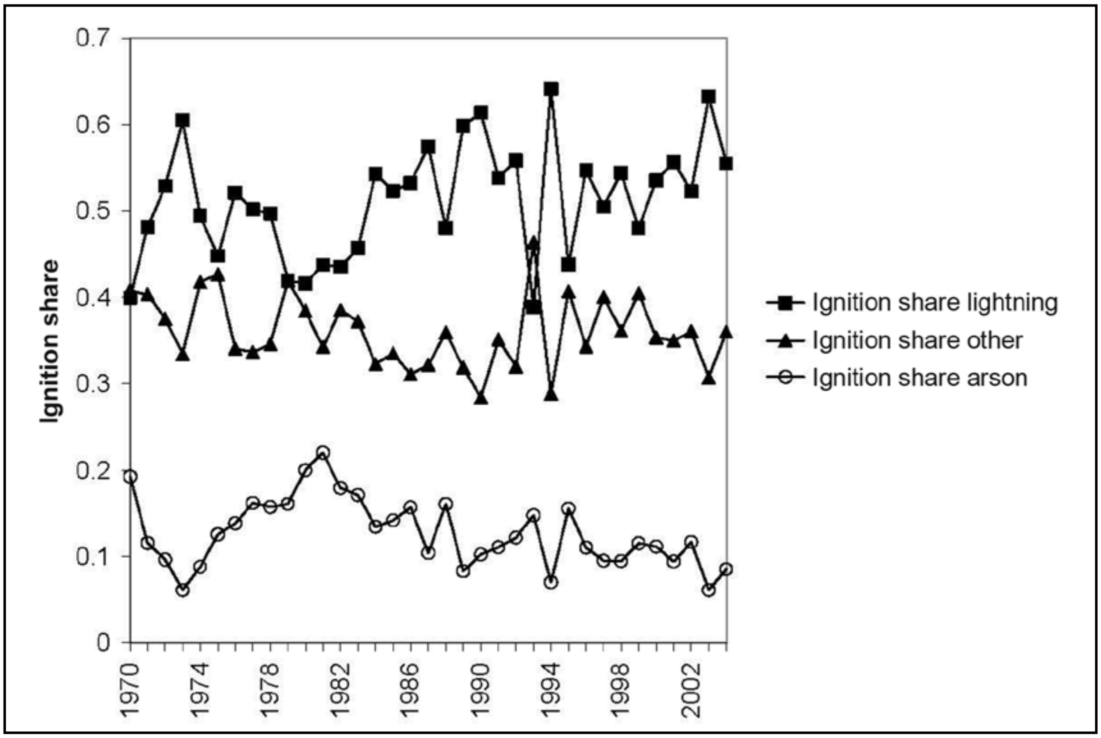

Figure 3—Share of wildland arson, lightning, and other wildfire ignitions on national forests, 1970-2004. (Source: USDA Forest Service 2007)

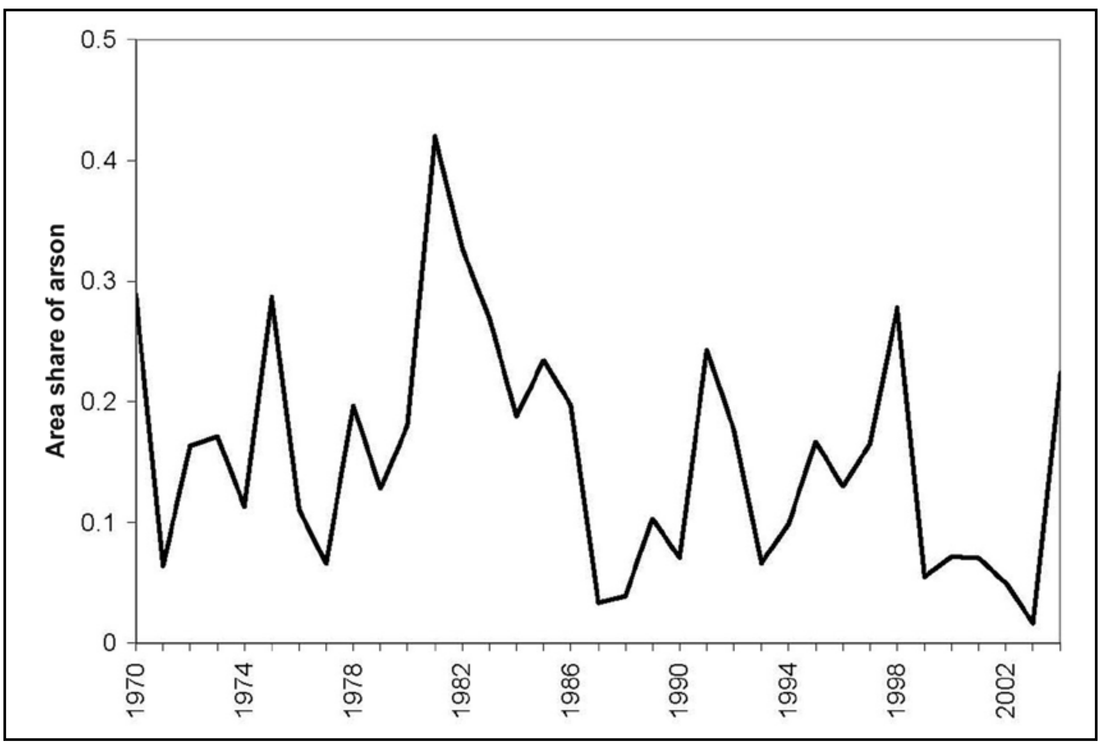

Figure 4—Share of wildfire area burned attributed to arson on national forests, 1970-2004. (Source: USDA Forest Service 2007)

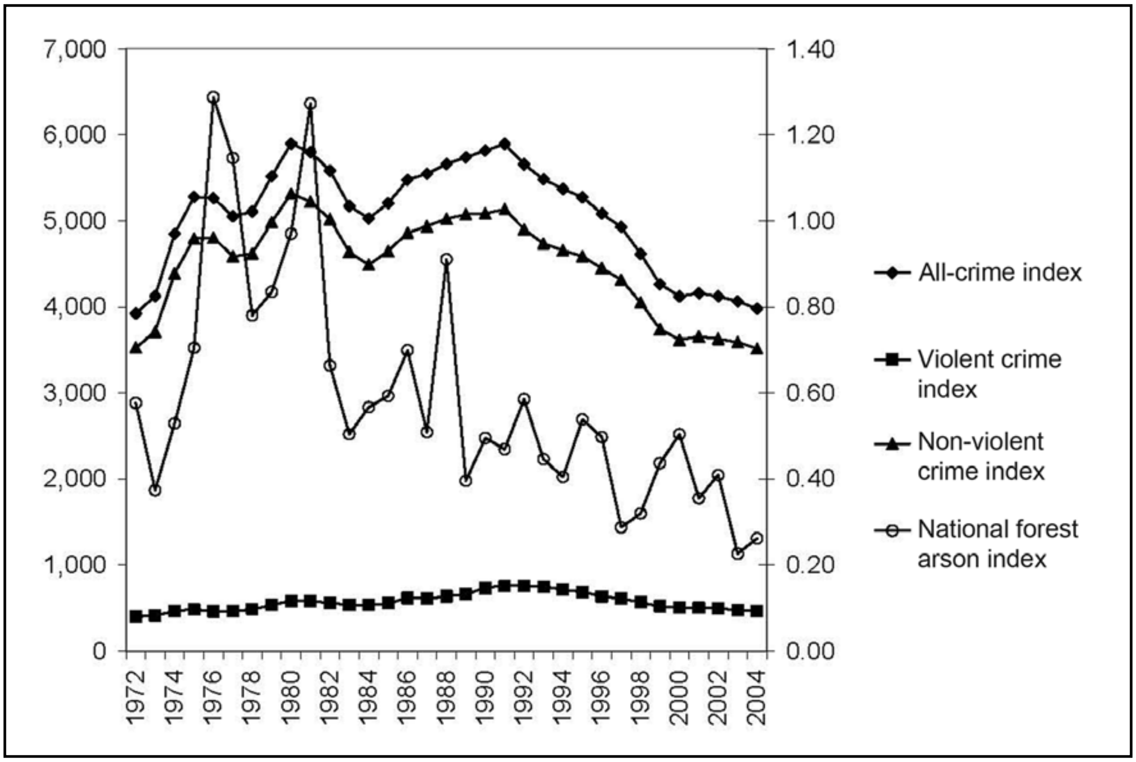

Figure 5—Nationwide index crimes (left-hand scale) and a national forest arson ignition index (right-hand scale), 1972-2004. (Sources: Federal Bureau of Investigation 2005, USDA Forest Service 2007)

function and what Cohen and Felson (1979) labeled "Routine Activity Theory." Becker's seminal work conceptualized the decision to commit a crime as:

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

where O_i is the number of offenses committed, $\boldsymbol{\pi}_i$ 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 to attempt and success in completion of the crime. From this, Becker (1968) expressed crime commission as generating positive utility (welfare), through either wealth generation or some enhancement of psychic pleasure for the perpetrator. Think of this as, for example, the expected utility generated from successfully igniting an arson wildfire:

(2) $E[U_i(O_i)] = \pi_i, U_i(g_i - c_i - f_i(W_i, w_i)) + (1 - \pi_i)U_i(g_i - c_i)$

where E is a mathematical expectations operator, U_i is the criminal's utility function, g_i is the criminal's psychic and income benefits from the illegal activity (e.g., fire setting), c_i is the production cost for the activity, $f_i(W_i,w_i)$ is the loss from being caught and convicted of the crime (a positive function of income while employed), W_i is the employment status, and w_i is the wage rate. This theory has been tested by economists and criminologists in analyses of many kinds of crimes, and it has generally held up well. Prestemon and Butry (2005) were the first to successfully test the theory in the case of wildland arson in Florida.

In routine activity theory, crime is committed when a set of necessary conditions coincide: an offender, a target, and a lack of capable guardians (e.g., police or neighborhood watch groups). The routine activities approach explains that crime varies across space and over time according to how everyday human activities vary in response to seasonal or economic differences across space and time. Variations in the crime rate across space and time in the United States, then, can be explained by variations in the convergence or the availability of all necessary ingredients. It would be possible to express wildland arson as deriving from routine activity theory by recognizing that the "target" is wildland (or property owned by a target); it would have to be augmented, however, to accommodate weather and fuel conditions.

A challenge of all theories of crime is applying the results of the research to decisionmaking. One way that criminologists have done this is by developing computer-based tools that are derived from mathematical models of criminal activity. The mathematical models are loosely based on statistical representations of routine activity theory and the economics of crime in the context of Becker (1968). These models can identify crime hotspots, or crime intensity maps, in space and time. Hotspotting crime research is concerned with developing mapping tools for law enforcement and other authorities that can be used to identify crime hotspots and therefore aid in crime control (Bowers and Johnson 2004, Johnson and Bowers 2004). The idea of crime hotspots in space and time is not new. Lottier (1938) pointed out how crime is concentrated in locations across space, which is useful for targeting law enforcement. Boggs (1966) evaluated urban crime patterns and how they tend to be concentrated in space-time dimensions. It seems likely that law enforcement has recognized this kind of clustering for as long as crime has existed. For wildland arson, few efforts have been made to understand the spatial and temporal extent of clustering. However, Butry and Prestemon (2005) developed a preliminary statistical tool for hotspotting of wildland arson, specified at the census tract level and on daily arson ignitions.

Spatio-Temporal Crime Processes—

Crime as a Spatio-Temporal Process

Butry and Prestemon (2005) and Prestemon and Butry (2005) found that wildland arson is a crime that may be particularly suited to hotspotting. Wildland arson, like other crimes, is concentrated in space and in time, due to concentrations of criminals and fuel quantities in space and the concentration of amenable fire-setting weather and dry fuel in time. Genton and others (2006) showed how this clustering in space can last many years, whereas Prestemon and Butry (2005) showed concentrations at the daily time scale, and Butry and Prestemon (2005) showed concentrations at the daily time scale in relatively limited geographical areas.

Wildland Arson as a Spatio-Temporal Process

Prestemon and Butry (2005) found that, for small county aggregates in Florida, wildland arson is concentrated in time, with an elevated risk for more such ignitions for up to 11 days after an initial ignition. This kind of temporal clustering is consistent with models of serial and copycat criminal activity, patterns, and behaviors observed for other crimes (Brandt and Williams 2001, DiTella and Schargrodsky 2004, Surrette 2002). Also important are weather, as measured by the Keetch-Byram Drought Index, which indexes fuel conditions on fine temporal scales and captures the effect of fuel moisture on ignition success rates or the cost of igniting a wildfire; historical wildfires and prescribed fire in the location, which reduce fuels and usually reduce arson risk by making fire setting more difficult or costly; and intra-annual patterns of weather, as measured by month dummy variables, which are probably also related to fuel conditions and therefore fire setting cost or success. Other explanatory variables, which fit an economic model of crime, include police per capita, the retail wage rate, and poverty. Daily variations were also found to matter, with arson more common on Saturdays and sometimes holidays.

Butry and Prestemon (2005) evaluated wildland arson patterns in Florida, where ignitions were geolocated to the census tract. This analysis related wildland arson ignitions in a single day to, in addition to the same set of variables used in Prestemon and Butry (2005) at the county level, wildland arson ignitions in previous days in the same and neighboring census tracts in six high-arson tracts in the State. Their analysis found that wildland arson ignitions in the census tract are related positively to ignitions in the same tract in the previous several days and in local (immediately surrounding) and regional (an outer shell of) neighboring tracts in the previous 11 days. They found that a current day's count of ignitions could be explained by local neighbors for up to 11 days, regional neighbors for up to 4 days, and ignitions in the same tract for up to 10 days. Thus, it appears that short-term arson ignition process propagates like a contagion (although the exact pattern in space-time was not identifiable).

In research similar to that reported by Prestemon and Butry (2005), we report here an analysis of arson ignitions

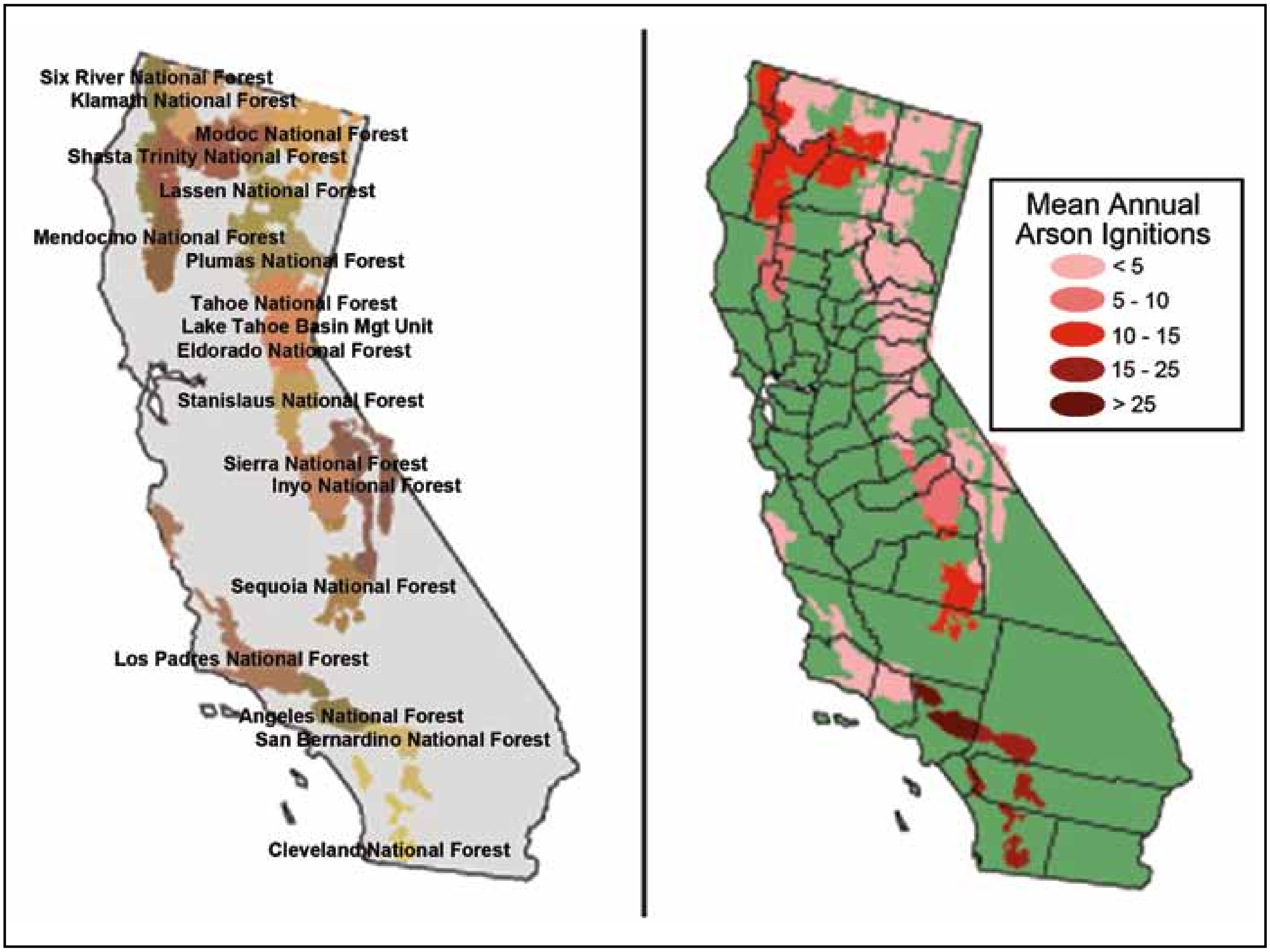

Figure 6—National forests and wildland arson on national forests in California, 1970-2003.

on national forests in California (Figure 6). We estimate daily and annual models of arson fires at the national forest level. Models use wildfire data from the USDA Forest Service National Interagency Fire Management Integrated Database (NIFMID) (USDA Forest Service 2004), unemployment and population data from the California Department of Finance (2005), law enforcement data from the California Department of Justice (2005), and climate and weather data from the National Oceanic and Atmospheric Administration (2005) and the National Climatic Data Center (2004). The models are generally specified as in Prestemon and Butry (2005), capturing temporal autocorrelation and not directly quantifying spatio-temporal patterns, but omit information on wages and poverty. Also, unlike in Prestemon and Butry (2005), the number of sworn full-time equivalent police officers, a measure of law enforcement effort, is lagged one year to avoid issues of simultaneous determination with crime and to allow for lagged perceptions among potential arsonists on arrest probability (Lochner 2007). As in Prestemon and Butry (2005), a Poisson autoregressive model of order p (Brandt and Williams 2001) is specified for the daily ignitions for the San Bernardino, Sierra, Cleveland, and Angeles National Forests, 1994-2002 (Table 1). An annual panel fixed-effects Poisson model (Greene 2003) is specified using data from all 18 national forests in the State, 1993-2002 (Table 2).

In the daily model, significant variables (at five percent) influencing arson ignitions on the two national forests studied include up to five ignition lags (positively); alternative models that drop these lags (i.e., non-autoregressive

Table 1—Poisson autoregressive models of order p of daily wildland arson fire occurrences for selected high-arson California National Forests, 1994-2002

	San Bernardino N.F.	Sierra N.F.	Cleveland N.F.	Angeles N.F.
Intercept	-1.49	26.97	-1.73	34.65***
Average annual Palmer drought severity index, t	0.93	3.11	-0.65	0.24
Weekday	-0.66***	-0.35	0.16	-0.12
Saturday	-0.74**	1.22**	0.66*	0.40
Sunday	-0.47	-0.54	0.76**	0.15
Holiday	-0.36	1.57**	0.35	0.17
January	-0.20	n.p.	-0.73	0.37
February	1.07	n.p.	-1.18	0.87
March	-0.72	1.97	-0.36	0.20
April	-0.62	1.62	0.22	1.15**
May	1.46*	0.55	0.66	1.55***
June	1.72**	0.96	1.22*	1.57***
July	1.62*	1.72	1.32*	2.04***
August	1.96**	0.96	1.36**	2.16***
September	2.02**	-0.25	1.72***	1.75***
October	1.84**	-0.30	0.87	1.37**
November	0.82	1.26	0.46	0.81
Law Enforcement Officers Per Capita, t-1	-1.90	13.67 *	-17.09*	-1.75
Population, t	n.p.	-0.088	5.6549	-0.0028*
Unemployment, t	4.76*	-6.37**	10.39***	-3.71*
Wildfire, t-1 to t-3	0.02	-1.12	-0.37**	-0.08*
Wildfire, t-4 to t-6	0.01	0.59	-0.14	-0.11
Wildfire, t-6 to t-9	0.06	0.77	0.03	-1.02**
Wildfire, t-10 to t-12	-0.23	0.06	0.02	-1.09**
Wildfire, t-13 to t-15	-0.05	0.75	-0.27**	-0.04
AR(1)	0.29***	0.49**	0.37***	0.26***
AR(2)	0.38***	n.p.	0.60***	0.16***
AR(3)	0.24**	n.p.	n.p.	0.17***
AR(4)	n.p.	n.p.	n.p.	0.21***
AR(5)	n.p.	n.p.	n.p.	0.16***
n	3,089	3,090	3,091	3,103
Likelihood ratio statistic, model all AR terms are zero (df = p)	38.37***	7.47***	70.77***	142.32***
Log likelihood, model	-651.60	-257.29	-566.56	-896.62

Note: ***indicates significance at 1 percent, **at 5 percent, and *at 15 percent; "n.p." indicates that models with this variable included would not converge in maximum likelihood estimation.

alternative versions) explain significantly less variation in daily wildfire at high significance (last row of Table 1). This result is consistent with serial or copycat fire setting activity. The model also found that many month dummy variables are significant, which indicates that arson, like other fire causes, has a seasonal pattern that may be related to seasonal weather and fuel moisture variations that affect the difficulty or costs of successfully igniting arson fires. Also, for these national forests, the coefficient on the Saturday dummy is significant and positive in two cases (Sierra N.F. and Cleveland N.F.) and the coefficient on the holiday dummy variable is significant and positive in one

Table 2—Fixed-effects panel Poisson model of wildland arson fire occurrences, 18 California National Forests, 1993–2002

Variable	Coefficient	Standard Error
Population, t	-7.89E-07	3.11E-07**
Unemployment percent, t	4.81E-02	3.05E-02*
Per capita sworn law enforcement officers, t-1	-655	195***
Pacific decadal oscillation, t	0.50	0.09***
Palmer drought severity index, January-March, t	-0.21	0.05***
Palmer drought severity index, April-June, t	0.13	0.04***
Palmer drought severity index, July-September, t	9.1E-02	2.8E-02***
Palmer drought severity index, October-December, t	-9.8E-02	2.5E-02***
Nino-3 SST anomaly, t	-0.43	0.07***
Wildfire area, t-1	-2.14E-06	1.35E-06*
Wildfire area, t-2	4.78E-06	1.10E-06***
Wildfire area, t-3	3.47E-06	1.27E-06***
Wildfire area, t-4	-7.21E-06	2.37E-06***
Wildfire area, t-5	-1.03E-06	2.44E-06
Wildfire area, t-6	-2.07E-06	1.49E-06
Wildfire area, t-7	6.16E-07	1.58E-06
Wildfire area, t-8	-3.57E-06	1.66E-06**
Wildfire area, t-9	-9.96E-07	1.46E-06
Wildfire area, t-10	-2.44E-06	1.66E-06*
Wildfire area, t-11	2.58E-06	1.23E-06**
Wildfire area, t-12	4.72E-06	1.42E-06***
Observations	180	
Number of cross-sections (18 national forests)	8	
Number of periods (10 years, 1993-2002)	10	
Log-likelihood model	-521.96	
Likelihood ratio statistic, model versus intercept only (21 d.f.)	1,559.56***	

Note: ***indicates significance at 1 percent, **at 5 percent, and *at 15 percent.

case (Sierra N.F.), both results indicating higher arson fire probability, which, in the context of an economic model of crime, is consistent with lower opportunity costs of time faced by arsonists those days. In contrast, dummy variables for weekdays are not significant, indicating that those days of the week have the same arson probabilities as Mondays. We also find that the average annual Palmer Drought Severity Index is not significantly related to fires. The unemployment rate is negatively related to arson ignitions in two cases (Sierra N.F. and Angeles N.F.), which conflicts with our expectation, but positive in two cases (San Bernardino N.F. and Cleveland N.F.), which does fit with our expectation. A similar conflicting result occurs for law enforcement: higher law enforcement levels are significantly and negatively related to arson rates in one case (the Cleveland N.F.) but are positively related to arson in another (Sierra N.F.). The latter finding is not expected and could be a consequence of omitted variables related to wages or other justice-related expenditures (e.g., sanction levels). But, the former finding for the Sierra N.F. would be expected based on the opportunity costs of being caught and convicted of setting an arson wildfire. Finally, lagged wildfire area (the running total of the area burned by wildfire in the national forest in previous years) is negatively related to arson wildfire in all cases where statistical significance is found. This is consistent with our expectations, as wildfires can reduce landscape fuels, providing the prospective arsonists with greater difficulty or higher costs of successful arson fire setting. In summary, the majority of these findings are consistent with those of Prestemon and Butry (2005), supporting an economic model of crime and one that confirms the temporal clustering of arson ignitions on these forests. However, some conflicting results lead us to conclude that further research into the daily arson fire setting process for California National Forests is necessary.

In contrast with our uncertainty about the role of law enforcement and socioeconomic factors in wildland arson, the annual models provide results consistent with expectations (Table 2). Here, law enforcement officers per capita are significantly and negatively related and unemployment is significant and positively related to wildland arson ignitions. The finding of the deterrent (negative) effect of policing on wildland arson is entirely consistent with crime theory, indicating that either (i) arsonists perceive higher opportunity costs of being caught, or (ii) more arsonists are caught and convicted and, hence, are removed from the arson fire setting population.

Biophysical variables also explain significant variation in annual levels of wildland arson ignitions on national forests: lagged wildfire (positively for 2-, 3-, 11-, and 12-year lags and negatively for 1-, 4-, 8-, and 10-year lags); the Pacific decadal oscillation (positively); the Palmer Drought Severity Index (positively for 2- and 3-quarter lags and negatively for 1- and 4-quarter lags); and the Niño-3 SST anomaly (negatively) (Table 2). Population is negatively related to wildland arson risk, a finding that we cannot fully explain, except in the context of omitted variable bias. Nor can we explain the unusual statistical correlations between arson ignitions and longer lags of wildfire activity, so we leave this to future research.

What these results for the California National Forests show is broad consistency with the results found for Florida: wildland arson ignitions are clustered in time (5 days in two high-arson national forests in California, up to 11 days in Florida); law enforcement is generally negatively related to arson rates; climate and weather variables matter, in a more complex intra-annual pattern in California than in Florida; and fuel levels matter, although in a more complicated way in California than in Florida. Left uninvestigated are the influences of other labor market variables, poverty, and other measures of criminal sanctions.

Summary and Conclusions

Law Enforcement Lessons and Programs

Beginning with initial studies by Donoghue and Main (1985) through studies by the authors reported here, it seems clear that law enforcement deployment and other efforts to apprehend and incarcerate arsonists work to reduce wildland arson in the long run in high-arson locations in the United States. As found by Prestemon and Butry (2005) and Butry and Prestemon (2005), wildland arson appears to be clustered in time and space. Law enforcement personnel could use these results to advance hotspotting models for wildland arson or develop tactical responses to reducing the number of such ignitions in such outbreaks or both. Although it may not be clear that reducing wildland arson ignitions results in large-scale and long-run reductions in the amount of area burned on an annual basis, reducing such ignitions could have significant benefits for society, especially in places where arsonists tend to set fires: closer to built-up areas with greater values at risk (Butry and others 2002, Genton and others 2006). The results of more recent research indicate that it might be worthwhile to redirect law enforcement efforts to certain locations during periods of weak labor markets and even higher poverty rates. In this case, however, we caution that careful analysis is needed that would quantify the tradeoffs of redirection away from other policing activities. During certain months of the year and also during droughts, arsonists are more active, so law enforcement could also pay special attention to weather and fire season variations. As well, from a strategic standpoint, authorities could also monitor trends in climate variables or their predictions (Ji and others 1998) as indicators of broad trends in climatic factors that create conditions favorable for fire setting. Special attention to weather and climate is important, as conditions favorable to ignitions may also favor large and intense fires once they are successfully ignited.

Wildland Manager Lessons

Wildland managers can use the same lessons as indicated for law enforcement. There is a distinct degree of seasonality in arson wildfire ignitions, and firefighting resource allocations can conform to this seasonality. Arson ignitions are correlated with dry weather in ways similar to other ignition types, so wildland managers should be ready for these kinds of fires, even in times when fires are banned (perhaps reducing accidental ignitions) or when lightning storms are not occurring. In time scales longer than days or weeks, managers can also pay attention to forecasts of ocean temperatures (e.g., Ji and others 1998), which might foretell upcoming drought situations that would raise future arson risks and therefore plan firefighting resource allocations accordingly. Finally, wildland managers might be able to reduce landscape fuel levels in ways that reduce wildland arson opportunities.

Future Research and Development Needs

Modern studies of the spatial and temporal patterns of wildland arson are few, and much remains to be investigated. In our view, key needs include understanding how wildland arson fits within the larger picture of structural arson and other crime. The research results reported in this paper are only suggestive of similarities between wildland arson and other crimes, but real connections have not been identified and quantified. Many criminals commit multiple crimes of different types, and it is possible that wildland arsonists do the same. Hence, it may be possible to include information on structural arson or other crimes to improve the accuracy of statistical models of wildland arson.

Another need is to develop hotspotting models of wildland arson that would be applicable in different locations and useful for wildland managers and law enforcement. Before operational models are developed, more work needs to be done to understand the spatio-temporal patterns of wildland arson. To date, these patterns fit with spatio-temporal crime functions found by other criminologists and modelers. A key challenge in development of hotspotting tools is operational usefulness. The hotspotting tools envisioned may require real-time data updating that may not be possible for law enforcement agencies or land management organizations with tight budgets. However, if such tools bring long-term savings for fire and police organizations through reduced firefighting and fire investigation activities and lower property losses, investments would lead to net societal and agency budgetary gains.

Literature Cited

Becker, G.S. 1968. Crime and punishment: an economic approach. Journal of Political Economy. 76(2): 169–217.

Boggs, S.L. 1966. Urban crime patterns. American Sociological Review. 30(6): 899–908.

Bowers, K.J.; Johnson, S.D. 2004. The stability of space-time clusters of burglary. British Journal of Criminology. 44(1): 55–65.

Brandt, P.T.; Williams, J.T. 2001. A linear Poisson autoregressive model: the Poisson AR(p) model. Political Analysis. 9(2): 164–184.

Burdett, K.; Lagos, R.; Wright, R. 2003. Crime, inequality, and unemployment. American Economic Review. 93(5): 1764–1777.

Butry, D.T.; Prestemon, J.P. 2005. Spatio-temporal wildland arson crime functions. Paper presented at the annual meeting of the American Agricultural Economics Association. Providence, RI: American Agricultural Economics Association. 18 p.

Butry, D.T.; Pye, J.M.; Prestemon, J.P. 2002. Prescribed fire in the interface: separating the people from the trees. In: Outcalt, K.W., ed. Proceedings of the 11th biennial southern silvicultural research conference. Gen. Tech. Rep. SRS–48. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station: 132–136.

California Department of Finance. 2005. Data obtained by special request (May 2005).

California Department of Justice. 2005. Data obtained by special request (May 2005).

Cohen, L.E.; Felson, M. 1979. Social change and crime rate trends: a routine activity approach. American Sociological Review. 44(4): 588–608.

Corman, H.; Mocan, H.N. 2000. A time series analysis of crime, deterrence, and drug abuse in New York City. American Economic Review. 90(3): 584–604.

DiTella, R.; Schargrodsky, E. 2004. Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack. American Economic Review. 94(1): 115–33.

Donoghue, L.R.; Main, W.A. 1985. Some factors influencing wildfire occurrence and measurement of fire prevention effectiveness. Journal of Environmental Management. 20(1): 87–96.

Doolittle, M.L.; Lightsey, M.L. 1979. Southern woods-burners: a descriptive analysis. Res. Pap. SO-151. New Orleans: U.S. Department of Agriculture, Forest Service, Southern Forest Experiment Station. 6 p.

Federal Bureau of Investigation. 2005. Crime in the U.S. index offenses, 1972-2004. Data downloaded from http://www.fdle.state.fl.us/fsac/Crime_Trends/download/excel/fed_ucr.xls. [Date accessed: December 30, 2005].

Gamst, F.C. 1974. Peasants in complex society. New York: Holt, Rinehart, and Winston. 82 p.

Genton, M.G.; Butry, D.T.; Gumpertz, M.; Prestemon, J.P. 2006. Spatio-temporal analysis of wildfire ignitions in the St. Johns River Water Management District. International Journal of Wildland Fire. 15(1): 87–97.

Gould, E.D.; Weinberg, B.A.; Mustard, D.B. 2002. Crime rates and local labor market opportunities in the United States: 1979-1997. The Review of Economics and Statistics. 84(1): 45–61.

Greene, W.H. 2003. Fixed and random effects in nonlinear models. Available at http://pages.stern.nyu.edu/~wgreene/panel.pdf. [Date accessed: March 29, 2003].

Grogger, J. 1995. The effect of arrest on employment and earnings of young men. Quarterly Journal of Economics. 110(1): 51–72.

Grogger, J. 1998. Market wages and youth crime. Journal of Labor Economics. 16(4): 756–791.

Icove, D.J.; Estepp, M.H. 1987. Motive-based offender profiles of arson and fire-related crimes. FBI Law Enforcement Bulletin. 56(4): 17–23.

Ji, M.; Behringer, D.W.; Leetmaa, A. 1998. An improved coupled model for ENSO prediction and implications for ocean initialization: Part 2 - the coupled model. Monthly Weather Review. 126(4): 1022–1034.

Johnson, S.D.; Bowers, K.J. 2004. The burglary as a clue to the future: the beginnings of prospective hot-spotting. European Journal of Criminology. 1(2): 237–255.

Kent, B.; Gebert, K.; McCaffrey, S. [and others]. 2003. Social and economic issues of the Hayman fire. In: Graham, R.T., ed. Hayman fire case study. Gen. Tech. Rep. RMRS-114 (Rev.). Fort Collins, CO: U.S. Department of Agriculture, Forest Service: 315–395.

Kuhlken, R. 1999. Settin' the woods on fire: rural incendiarism as protest. The Geographical Review. 89(3): 343–363.

Lochner, L. 2007. Individual perceptions of the criminal justice system. American Economic Review. 97(1):444–460.

Lottier, S. 1938. Distribution of criminal offenses in sectional regions. Journal of Criminal Law and Criminology. 29(3): 329–344.

Mercer, D.E.; Prestemon, J.P. 2005. Comparing production function models for wildfire risk analysis in the Wildland-Urban Interface. Forest Policy and Economics. 7(5): 782–795.

National Climatic Data Center. 2004. Summary of the day. Boulder, CO: EarthInfo, Inc. [Number of pages unknown].

National Oceanic and Atmospheric Administration. 2005. Historical Palmer drought severity indices by Climate Division. Available at http://www.cpc.ncep.noaa.gov/products/monitoring_and_data/drought.shtml. [Date accessed: May 4, 2005].

Prestemon, J.P.; Butry, D.T. 2005. Time to burn: modeling wildland arson as an autoregressive crime function. American Journal of Agricultural Economics. 87(3): 756–770.

Prestemon, J.P.; Pye, J.M.; Butry, D.T. [and others]. 2002. Understanding broad-scale wildfire risks in a human-dominated landscape. Forest Science. 48(4): 685–693.

Schmidt, K.M.; Menakis, J.P.; Hardy, C.C. [and others]. 2002. Development of coarse-scale spatial data for wildland fire and fuel management. Gen. Tech. Rep. RMRS-87. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 41 p. [CD-ROM].

Surrette, R. 2002. Self-reported copycat crime among a population of serious and violent juvenile offenders. Crime and Delinquency. 48(1): 46–69.

Tridata Corporation. 1997. Arson in the United States. National Fire Data Center Pub. FA174. [Number of pages unknown].

USDA Forest Service. 2004. National Interagency Fire Management Integrated Database. Washington, DC: USDA Forest Service. [Date accessed: May 28, 2004].

USDA Forest Service. 2007. National Interagency Fire Management Integrated Database. Washington, DC: USDA Forest Service. [Date accessed: January 5, 2007].

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