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Effect of fire prevention programs on accidental and incendiary wildfires on tribal lands in the United States

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Abstract. Humans cause more than 55% of wildfires on lands managed by the USDA Forest Service and US Department of the Interior, contributing to both suppression expenditures and damages. One means to reduce the expenditures and damages associated with these wildfires is through fire prevention activities, which can include burn permits, public service programs or announcements, outreach efforts to schools, youth groups and equipment operators, and law enforcement. Using data from 17 US Bureau of Indian Affairs tribal units, we modelled the effect of prevention programs and law enforcement on the number of human-caused ignitions. We also included weather and lagged burned area in our estimation of fixed-effects count models. The results show that prevention activities led to significant reductions in wildfires caused by escaped campfires, juveniles, fire-use (e.g. escaped debris burns) and equipment. Increased law enforcement resulted in fewer incendiary- and equipment-caused wildfires. Using average suppression expenditures by wildfire and our estimate of avoided wildfires per additional year of prevention, we estimate partial benefit–cost ratios of greater than 4.5 for all Bureau of Indian Affairs regions for the continuation of the prevention program.

Additional keywords: arson wildfires, instrumental variables methods, intervention analysis, law enforcement, wildfire suppression.

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Introduction

Wildfire prevention programs have a long history in the United States and include the iconic Smokey Bear reminding us that 'Only you can prevent forest fires'. In spite of its long presence, however, only recently have the effects of prevention programs on human-caused wildfires been quantified. Human-caused wildfires can be classified as either accidental (unintentional) or incendiary (intentional, also called arson). Accidental wildfires include wildfires started by children (juveniles), escaped campfires, escaped debris burns or other fire uses, equipment, smoking materials and railroads. The general trend in all of these wildfire categories on federal lands is downward (Prestemon *et al.* 2013), and although it is often assumed that prevention is a contributor, the statistical evidence to document the effects of prevention programs or law enforcement efforts in reducing the number of human-caused wildfires had, until recently, been missing. A recent set of studies in the state of Florida showed wildfire prevention programs reduce wildfire occurrence and thus reduce damages and suppression expenditures (Butry *et al.* 2010; Prestemon *et al.* 2010). These studies also concluded that the marginal benefits of the prevention programs outweighed the marginal costs, and generally found that although the programs were most effective immediately before a fire season, there were also longer-term effects that could be seen up to 6 months later. We add to this literature by evaluating the effects of starting and continuing wildfire prevention programs on a subset of Bureau of Indian Affairs (BIA) tribal units across the United States. We also test the impact of law enforcement presence on both accident- and incendiary-caused wildfires. For these wildfire causes, we calculated a narrowly defined benefit–cost ratio, where benefits are calculated for suppression expenditures averted and costs are the cost of maintaining a prevention program. This is different from the partial benefit–cost ratios reported by Prestemon *et al.* (2010), for example, who included as benefits not only suppression expenditures but also quantifiable economic damages averted (e.g. timber, structures, evacuation-related economic losses).

We assume, following the conceptual wildfire model developed in Prestemon *et al.* (2013), that the number of wildfires are a function of biophysical inputs (including fuels and weather), societal factors (including population, income and access) and interventions. Interventions in this case include (1) the number of months a prevention program has been in place, and (2) the number of sworn law enforcement officers. Duration of prevention is hypothesised to reduce the number of accidental wildfires, and the number of sworn law enforcement officers is hypothesised to reduce the number of incendiary wildfires.

Biophysical inputs

For human-caused wildfires, weather has two potential impacts – drier and warmer weather will increase the number of people likely to be out in wildlands (opportunity), and will also increase the probability that an accidental or incendiary ignition will turn into a wildfire (probability). Ignitions that go out before they become a wildfire are not reported as wildfires. Thus, we would expect that, all else held constant, a rainy day will have fewer reported wildfires than a sunny day because the opportunity to start fires is reduced because fewer people are outside and because the probability that an ignition will develop into an observed wildfire is smaller. Although not all studies of wildfire occurrence include weather or fire danger indices, many of those that do find some significance in the fire danger indices and in measures of temperature, relative humidity, wind speed and precipitation (Haines *et al.* 1983; Martell *et al.* 1987; Garcia *et al.* 1995; Cardille *et al.* 2001; Preisler *et al.* 2004; Butry and Prestemon 2005; Prestemon and Butry 2005; Preisler *et al.* 2008; Butry *et al.* 2010; Prestemon *et al.* 2010; Vilar *et al.* 2010; Prestemon *et al.* 2012).

The probability that an ignition will become a recorded wildfire is also influenced by the abundance, location and structure of fuels. Fuel treatments, whether specifically designed to reduce or alter available fuels for wildfires, such as prescribed fire or mechanical thinning, or inadvertent treatments that result from previous wildfires or timber harvests, are hypothesised to be negatively correlated with the number of wildfires. The empirical results regarding the response of wildfires to lagged prescribed fire, lagged area burned and lagged harvest are mixed, with most of the studies addressing the state of Florida (Prestemon *et al.* 2002; Butry and Prestemon 2005; Prestemon and Butry 2005; Mercer *et al.* 2007; Butry *et al.* 2010; Prestemon *et al.* 2010). Topography, elevation and seasonality also influence fuel dryness, and thus the probability of ignition success (Preisler *et al.* 2004; Vilar *et al.* 2010).

Societal factors

The societal factors affecting the number of wildfires also include opportunity, which occurs whenever people have access to wildlands. This access is facilitated by roads, trails and campgrounds, though the empirical evidence regarding the effect of these features on the number of wildfires is mixed (Garcia *et al.* 1995; Syphard *et al.* 2007; Yang *et al.* 2007; Calef *et al.* 2008). Access is also increased by people living in or adjacent to wildlands, for which the following can act as proxies: population level, population density, housing density and wildland–urban interface status. The influence of these factors is slightly more consistent, with many of the studies showing significance, and nearly all showing a positive relationship with number of wildfires (Donoghue and Main 1985; Butry and Prestemon 2005; Prestemon and Butry 2005; Mercer *et al.* 2007; Syphard *et al.* 2007; Butry *et al.* 2010; Prestemon *et al.* 2010, 2012).

A second factor hypothesised to affect the number of human-caused wildfires, especially incendiary wildfires, is the level of economic wellbeing. This hypothesis is consistent with overall crime literature and we hypothesise that the number of incendiary wildfires will be higher when wellbeing is lower. Thus, lower income, higher unemployment and lower wages could be expected to increase the number of incendiary wildfires. The results to date are mixed, and weak, but have not been examined in many studies (Butry and Prestemon 2005; Prestemon and Butry 2005; Prestemon *et al.* 2012). Positive community attitudes towards accident prevention and safety have been shown to be correlated with fewer unintentional wildfires. Economic wellbeing is thought to incentivise the implementation of safeguards (Thomas *et al.* 2012), although, again, the results are mixed.

Interventions

The interventions we examine are (1) duration of the prevention program in months, and (2) number of full-time sworn law enforcement officers by year. Prevention programs have been empirically evaluated in a set of studies in Florida (Butry *et al.* 2010; Prestemon *et al.* 2010), and the marginal benefits of the programs were found to exceed the marginal costs. These analyses also included the number of law enforcement officers, but the studies found an unexpected positive relationship between the number of wildfires and the number of officers. This could be due to an increased level of fire reporting resulting from having more law enforcement personnel to investigate and report fires. Also in Florida, a set of studies addressing arson (Butry and Prestemon 2005; Prestemon and Butry 2005) found mixed effects of law enforcement presence on incendiary wildfire occurrences, whereas Prestemon *et al.* (2012) found strong effects when enforcement was measured by arson arrests. Donoghue and Main (1985) found a significant effect of law enforcement on arson wildfires, but not other wildfire causes, in a highly aggregated study of these fires in the eastern United States.

We include both interventions in all types of human-caused wildfires, though there is no reason to expect that prevention affects incendiary wildfires and little evidence – other than speculative or anecdotal (see Prestemon *et al.* 2013), related to burn permit enforcement – that law enforcement affects accidental wildfires. Our prevention variable accounts for the presence of a program, while allowing for its effect to vary by experience, with length of time used as a proxy for experience. The law enforcement variable is a proxy for police effort (e.g. increased patrol and arrest ability), which has been found to be correlated with the number of arson wildfires (e.g. Thomas *et al.* 2011; Prestemon *et al.* 2012). Because we assume the staffing of full-time, sworn law enforcement officers is a decision made at the beginning of the funding year, the potential for endogeneity with the number of wildfire starts is limited.

However, reflecting assertions by Prestemon *et al.* (2013), data to fully parameterise this conceptual wildfire occurrence model are not available for our study area. To compensate for some of the missing factors, we model wildfires by cause using fixed effects for years, months and tribal units to account for the societal effects present on each of the units and to account for month and year patterns in wildfires. We include tribal unit-specific weather variables (precipitation, relative humidity, temperature and various index variables) to capture both the probability and opportunity effects of weather on ignitions.

Lagged area burned is also included to account for some of the time-related variability in the condition and abundance of fuels that cannot be captured by the tribal unit fixed effect.

We use data collected from 17 US BIA tribal units to capture the cumulative impacts of prevention programs instituted in the mid-2000s. These tribal units are used because they responded to a data request from fire specialists at the National Interagency Fire Center regarding fire prevention programs, and provided enough information to confirm that the programs were functional through 2011.[1] Table 1 provides a list of included units, along with the acronym and tribal unit name used in the wildfire data (National Wildfire Coordinating Group 2012). A description of the general wildfire causes used by the US Department of the Interior, as well as the percentage of wildfires on these 17 tribal units assigned to each wildfire cause are shown in Table 2. Three of the agencies dominate the wildfire data – San Carlos (AZSCA), Pine Ridge (SDPRA) and Red Lake (MNRLA), representing a total of 52% of the included wildfires. In total, we obtained 2901 observations for the 17 tribal unit months beginning in January 1996 and ending in December 2011, with

Table 1. US Bureau of Indian Affairs (BIA) tribal units used in the analysis and percentage of wildfires and area burned on each unit

Fire data identifier	Fire data name	State	Fiscal year when funded prevention began	Percentage of fires in our data[A]	Percentage of area burned in our data[A]
AZSCA	San Carlos Agency	Arizona	2001	14.5	0.9
IDNPT	Northern Idaho Agency	Idaho	2005	1.3	1.4
KSHOA	Horton Agency	Kansas	2006	0.5	0.5
MNMNA	Minnesota Agency	Minnesota	2006	5.6	0.8
MNRLA	Red Lake Band of Chippewa Indians	Minnesota	2001	20.5	11.8
MTFHA	Flathead Agency	Montana	2005	2.7	1.4
NDTMA	Turtle Mountain Agency	North Dakota	2005	9.0	2.2
OKANA	Anadarko Agency	Oklahoma	2006	3.4	4.2
OKCHA	Chickasaw Agency	Oklahoma	2005	2.9	10.4
OKOSA	Osage Agency	Oklahoma	2005	4.1	15.7
OKTLA	Talihina Agency	Oklahoma	2004	4.4	8.8
OKWEA	Wewoka Agency	Oklahoma	2004	1.2	2.6
ORWSA	Warm Springs Agency	Oregon	2005	3.4	12.9
SDPRA	Pine Ridge Agency	South Dakota	2008	18.0	8.3
WACOA	Colville Agency	Washington	1996	3.8	12.8
WASPA	Spokane Agency	Washington	2004	1.8	0.7
WAYAA	Yakama Agency	Washington	2004[B]	2.8	4.5

[A]Source: National Wildfire Coordinating Group (2012) (pchaffp.txt files).
[B]The Yakama Nation website (Yakama Nation 2015) on fire prevention indicates the presence of a program in existence for 30 years. Our data, however, show that funding for the Yakama program began in 2004. To account for the presence of an unfunded effort on prevention by the Yakama Nation, we also include a dummy variable for WAYAA for the years 1996–2004.

Table 2. Description of Department of the Interior (DOI) general causes and percentage by cause of all DOI wildfires and the percentage by cause for tribal land units in the present study

DOI general cause number	General cause	Specific cause	Percentage by cause (all DOI 2000–08)	Percentage by cause (17 BIA tribal units used in the present study 1996–2011)
1	Natural	Lightning, volcanic	37	17
2	Campfire	Cooking or warming fires	3	2
3	Smoking	Smoking	2	2
4	Fire use	Trash burning, burning dump, field burning, land clearing, slash burning, right-of-way, resource management	8	16
5	Incendiary	Trash burning, field burning, grudge fire, recurrent, employment, blasting, fireworks	15	26
6	Equipment	Aircraft, vehicle, exhaust, brakes, blasting, power-line	8	6
7	Railroads	Exhaust, brakes	0	0
8	Juveniles	Recurrent, fireworks, ignition devices	7	14
9	Miscellaneous	Burning building, adult fireworks	19	16

Source: National Wildfire Coordinating Group (2012).

[1]Data are available from Samuel Scranton, BIA (samuel.scranton@bia.gov).

1587 tribal unit months having prevention programs and 1314 tribal unit months having no prevention program.

The wildfire data included all fires of Type 1 and 2, where Type 1 fires include all fires that are suppressed by BIA employees or contractors and Type 2 includes 'natural outs', or fires that self-extinguish. This allowed us to later compare fire prevented with BIA program and suppression expenditures.

The wildfire data include the number of wildfires for all causes, including natural, railroad and miscellaneous. We excluded natural-, railroad- and miscellaneous-caused fires from our modelling. There is no reason to expect that either prevention or law enforcement would affect the number of naturally ignited wildfires, and the number of railroad-caused wildfires was insufficient for our modelling. Miscellaneous wildfires include several distinct causes, as well as wildfires that could not be identified by cause. We elected to not model this category of wildfires as we had conflicting *a priori* expectations of the effects of prevention and law enforcement. Increased funding for these two activities is expected to improve the assignment of wildfire causes, which would perversely lead to increases in the miscellaneous-cause wildfires, while at the same time, the typical effects of these interventions would be expected to reduce the number of wildfires in this category.

Empirical model estimation

We model the rate of human-started wildfires per month as a function of biophysical inputs, socioeconomic factors and interventions for 17 BIA agencies over the years 1996 to 2011. The rate of wildfires is assumed to follow a negative binominal distribution:

$$w_{i,t,c} = e^{\delta_c{}'\mathbf{z}_{i,t}+\beta_c{}'\mathbf{x}_{i,t}+\varepsilon_{i,t,c}} \tag{1}$$

where $w_{i,t,c}$ is the number of wildfires recorded in location i, in month t, by cause c, $\mathbf{z}$ are the biophysical and socioeconomic inputs, $\mathbf{x}$ are interventions, δ_c and β_c are parameters (and vary by cause), and ε is an error term, which follows a gamma distribution, $e^{\varepsilon_{i,t}} \sim \text{gamma}(1/\alpha, \alpha)$, with α as a parameter. Maximum likelihood estimation is used to parameterise Eqn 1. The log-likelihood function is defined as:

$$\begin{aligned}\ln L = \sum_{i=1}^{n} \Big[& \ln\{\Gamma(\alpha^{-1} + w_{i,t,c})\} - \ln\{\Gamma(w_{i,t,c}+1)\} \\ & - \ln\{\Gamma(\alpha^{-1})\} + \alpha^{-1}\ln((1+\alpha\{e^{\delta_c{}'\mathbf{z}_{i,t}+\beta_c{}'\mathbf{x}_{i,t}}\})^{-1}) \\ & + w_{i,t,c}\ln(1-(1+\alpha\{e^{\delta_c{}'\mathbf{z}_{i,t}+\beta_c{}'\mathbf{x}_{i,t}}\})^{-1})\Big]\end{aligned}$$

where Γ denotes the gamma distribution.

Six models are estimated, one for each wildfire cause – campfire, fire-use, smoking, juveniles, equipment and incendiary. The interventions ($\mathbf{x}$) include: (1) the number of months a wildfire prevention program has been in place, and (2) the number of full-time sworn law enforcement officers active in the tribal unit.

The biophysical and socioeconomic inputs ($\mathbf{z}$) that we directly include in the models are the weather variables for the tribal unit and previous wildfire activity, which we hypothesise is a partial proxy for available fuels. The weather variables include: average monthly maximum temperature in degrees Celsius, number of days per month with wind speed in excess of 24 km h^{-1}, number of days with precipitation, average monthly Keetch–Byram Drought Index (KBDI; Keetch and Bryam 1968), average monthly Fire Weather Index (FWI; Goodrick 2002), the number of days per month with a high daily FWI (17–31), and the number of days per month with an extreme daily FWI (>31).

Direct measures of fuel availability are difficult to obtain, but available fuels are reduced when a wildfire occurs. Thus, we use previous wildfire area burned as a proxy for fuel conditions. To account for previous wildfire activity, we calculate the area burned over the previous (1) 1 to 12 months, (2) 13 to 24 months, (3) 25 to 36 months, (4) 37 to 48 months, and (5) 49 to 60 months. Area burned, in thousands of hectares, was derived from all fires of Types 1 and 2, to be consistent with our data on ignitions. We hypothesised that an increase in lagged wildfire area burned would be related to fewer reported wildfires of any cause. Note that the lagged wildfire area burned did not include prescribed fire area burned, which could affect ignitions, but we did not have a consistent dataset that included both fire cause and prescribed fire for the years of our prevention data.[2]

In addition, in part to account for fuel differences across units, but also to account for differences in tribal unit size and other biophysical and socioeconomic variables, we estimate the model using fixed effects, with a dummy variable entered for each tribal unit (except one, which is accounted for in the intercept term). Although socioeconomic conditions are a likely factor in increased human-caused wildfires, a time series of these data is not available for all tribal units, and because most of these agencies include parts of several counties, some of which include large non-Indian populations, county-level data are also inadequate.

We also include year and month dummy variables to account for time-related fixed effects. A time trend or seasonal variables could be included, but a preliminary examination of the data did not reveal any simple linear trends. The inclusion of the single year and single month dummy variables allows for more complex trends and patterns over years and within years. Although our data indicate that the Yakama Nation began a prevention program in 2004, the Yakama Nation website on fire prevention claims that a program has existed for 30 years (Yakama Nation 2015). To ensure that we captured the possibility of a program before 2004, we included a dummy variable in our estimations (dummy = 1 if the observation is Yakama Nation and the date is before 2004, the time when other units began prevention programs).

The wildfire data (including ignitions and area burned by tribal unit by year by cause) were assembled from the National Wildfire Coordinating Group (2012). All fires of Type 1 and 2

[2]Data on prescribed fire are available from one of the two data sources at FAMWEB; however, there are two issues we encountered: (1) the source with the prescribed fire data does not include the general cause we needed for this analysis, and more importantly, (2) the prescribed fire data are largely blank for the years prior to 2002. It is possible, if unlikely, that there were no prescribed fires in these years. In addition, there are many years after 2002 for these units that have no record of prescribed fire. Fire specialists for BIA indicated that these data may be incomplete.

(regardless of whether the fire began on BIA land or not – provided the BIA was involved in the suppression) were included for the selected human causes.

The weather and fire-weather data were obtained from Fire and Aviation Management Web (FAMWEB) data for the Remote Automated Weather Stations (RAWS) (National Wildfire Coordinating Group 2012), and processed through software as described in Prestemon *et al.* (2012) that uses all available RAWS weather station data to create an area-specific set of daily, monthly and yearly weather averages. This is a spatially referenced program that accounts for all RAWS stations and creates a weather 'surface' from which the specific tribal unit averages are computed.

The wildfire prevention data were assembled through special requests by one of the authors made directly to tribal authorities. The law enforcement data were assembled from the data provided by the Directory of Law Enforcement Agencies (US Department of Justice 1998) and the Census of State and Local Law Enforcement Agencies in 2000, 2004 and 2008 (US Department of Justice 2009, 2011*a*, 2011*b*). Law enforcement data are periodic and represent a single year, so month-to-month variation is not included. We used linear interpolation to estimate the number of law enforcement officers between the survey years, and where observations for a particular survey or tribal unit were missing.[3]

Descriptive statistics are shown in Table 3. Of the ignition causes examined, incendiary-caused fires were the most common (2.5 per tribal-unit-month), followed by fire-use-caused wildfires (2.2 per tribal-unit-month), juvenile-caused wildfires (2.1 per tribal-unit-month), equipment-caused (0.6 per tribal-unit-month), escaped campfire-caused (0.3 per tribal-unit-month) and smoking-caused (0.2 per tribal-unit-month). The average length of a wildfire prevention program was 29 months, and all the tribal lands averaged a total of 31 full-time sworn law enforcement officers per month.

All of these agencies have active programs and participated in data collection for the present study, so all of them have some commitment to prevention activities, which could skew the results if these agencies chose to participate in the prevention program and data collection because they were likely to gain more benefits from the program. Because it seems unlikely that tribal unit personnel could correctly anticipate the effects of a program, we assume that the results are not skewed as a result of our modelling of only the tribal units who responded to the initial data request.

Table 3. Descriptive statistics for the dependent and continuous explanatory variables (*n* = 2901)

KBDI, Keetch–Byram drought index; FWI, Fire Weather index

Variable	Mean	s.d.	Min.	Max.
Campfire-caused wildfires	0.32	1.59	0.00	31.00
Smoking-caused wildfires	0.15	0.78	0.00	22.00
Fire-use-caused wildfires	2.22	9.14	0.00	225.00
Juvenile-caused wildfires	2.11	10.94	0.00	244.00
Incendiary-caused wildfires	2.53	10.83	0.00	194.00
Equipment-caused wildfires	0.64	1.63	0.00	32.00
Prevention duration	29.11	38.14	0.00	192.00
Full-time sworn law enforcement officers	30.56	23.23	3.00	110.00
Temperature (°C)	16.74	11.13	−14.71	39.82
Days with wind >24 km h^{-1}	5.37	4.08	0.00	25.00
Percentage relative humidity	40.07	12.79	9.51	72.14
Average monthly KBDI	146.12	164.02	0.00	731.50
Average monthly FWI	18.19	5.19	4.29	38.50
Days with precipitation	6.77	4.32	0.00	23.00
Days FWI high	12.03	4.57	0.00	26.00
Days FWI extreme	3.44	3.60	0.00	19.00
Area burned (10^3 ha)[A]				
Previous 1–12 months	2.81	5.65	–	50.11
Previous 13–24 months	2.80	5.60	–	50.11
Previous 25–36 months	2.80	5.58	–	50.11
Previous 37–48 months	2.65	5.50	–	50.11
Previous 49–60 months	2.44	5.37	–	50.11

[A]Note that the maximum and minimum span the entire dataset because of the cumulative lag – for example, the largest accumulation of 50.11×10^3 ha for 1 month in one unit is included in all five of the lag periods.

Results

The results of the six model estimations are shown in Tables 4 through 9. The negative binomial models were all significantly different from a null intercept-only model. Each table shows model estimates described in the form of the incident rate ratio (the factor of increase or decrease in the rate of wildfire ignitions due to a one-unit increase in a regressor). In four of the models, the presence of a prevention program is significantly, and negatively, related to the wildfire cause (campfire, fire-use, juveniles and equipment). Two of the wildfire causes are significantly, and negatively, related to the number of law enforcement officers (incendiary and equipment). Only equipment-caused wildfires are affected by both prevention and law enforcement.

Escaped campfire-caused wildfire model (Table 4)

The number of campfires that escape to become wildfires was significantly reduced statistically by each additional month of a prevention program. The WAYAA dummy variable, which is used to account for this tribal unit's pre-2004 prevention program, however, shows that their program was not effective (statistically) in the early years in reducing escaped campfires. The second intervention we examine, the number of law enforcement officers, was not shown to influence the number of these wildfires. As hypothesised, increased temperature and decreased relative humidity were related to increased numbers of escaped campfires. Warm and dry conditions are likely to increase the number of people in wildlands (increasing opportunity to start wildfires) as well as increasing the success rate for wildfires to become established, warrant action and thus be reported. Wind speed was not a statistically significant explainer of campfire-caused wildfires. A higher FWI is expected to increase the number of wildfires, but the coefficient on FWI was negative, whereas the number of days with high or extreme FWI

[3]The law enforcement data include responses from the 28 law enforcement groups on the 17 tribal units, and 23% of these observations were missing and had to be estimated.

Table 4. Count model of escaped campfire-caused wildfires
*indicates significance at the 5% level. KBDI, Keetch–Byram drought index; FWI, Fire Weather index

Variable	Incidence rate ratio	s.e.	Z		$P>\|z\|$
Intercept	2.82	3.13	0.94		0.35
Prevention duration in months	0.99	0.00	−2.21	*	0.03
Full-time sworn law enforcement officers	0.99	0.01	−0.83		0.41
Average monthly temperature (°C)	1.09	0.03	3.06	*	0.00
Days with wind >24 km h^{-1}	1.03	0.04	0.75		0.45
Percentage relative humidity	0.93	0.01	−6.85	*	0.00
Average monthly KBDI	1.00	0.00	−0.38		0.71
Average monthly FWI	0.82	0.05	−3.21	*	0.00
Days with precipitation	0.98	0.02	−1.10		0.27
Days with FWI high	1.08	0.03	2.37	*	0.02
Days with FWI extreme	1.20	0.08	2.87	*	0.00
Area burned (10^3 ha)					
Previous 1–12 months	1.01	0.01	0.80		0.42
Previous 13–24 months	0.99	0.00	−1.17		0.24
Previous 25–36 months	1.02	0.01	2.62	*	0.01
Previous 37–48 months	1.03	0.01	2.69	*	0.01
Previous 49 – 60 months	1.01	0.01	0.62		0.53
Pre-2004 WAYAA	0.65	0.30	−0.94		0.35
Year fixed effects (base = 1996)					
1997	0.61	0.24	−1.25		0.21
1998	0.99	0.35	−0.03		0.97
1999	0.99	0.34	−0.04		0.97
2000	0.80	0.29	−0.63		0.53
2001	1.86	0.60	1.93		0.05
2002	2.33	0.74	2.65	*	0.01
2003	1.35	0.46	0.89		0.38
2004	1.33	0.48	0.80		0.43
2005	1.24	0.47	0.58		0.57
2006	1.88	0.72	1.66		0.10
2007	2.32	0.95	2.04	*	0.04
2008	3.99	1.72	3.22	*	0.00
2009	4.81	2.23	3.39	*	0.00
2010	5.07	2.53	3.25	*	0.00
2011	3.07	1.75	1.97	*	0.05
Month fixed effects (base = January)					
February	0.41	0.25	−1.49		0.14
March	1.08	0.52	0.15		0.88
April	0.91	0.52	−0.16		0.87
May	0.88	0.58	−0.19		0.85
June	0.56	0.42	−0.77		0.44
July	0.47	0.39	−0.91		0.36
August	0.36	0.30	−1.23		0.22
September	0.43	0.31	−1.19		0.24
October	1.11	0.62	0.19		0.85
November	2.57	1.22	2.00	*	0.05
December	0.52	0.36	−0.95		0.34
Tribal unit fixed effects (base = AZSCA)					
IDNPT	0.77	0.38	−0.53		0.60
KSHOA	0.00	0.00	0.00		1.00
MNMNA	4.94	5.01	1.58		0.12
MNRLA	2.92	1.49	2.09	*	0.04
MTFHA	17.73	6.86	7.43	*	0.00
NDTMA	2.44	1.07	2.02	*	0.04
OKANA	0.37	0.18	−1.99	*	0.05
OKCHA	0.23	0.12	−2.69	*	0.01
OKOSA	0.72	0.37	−0.66		0.51
OKTLA	0.42	0.21	−1.70		0.09
OKWEA	0.28	0.20	−1.75		0.08
ORWSA	1.15	0.38	0.43		0.66
SDPRA	0.66	0.31	−0.90		0.37
WACOA	6.42	2.70	4.43	*	0.00
WASPA	0.94	0.39	−0.16		0.87
WAYAA	0.92	0.40	−0.19		0.85

was positively correlated with escaped campfires. Lagged area burned was found to be positively and significantly related to the count of campfire-caused wildfires for only 2 of the preceding 5 years. Some of the fixed effects are significant (6 years; 1 month; 6 tribal units).

Smoking-caused wildfire model (Table 5)

Wildfires ignited by smoking materials were shown to respond only weakly (at the 8% level) to law enforcement levels, and not to the prevention program, except that the WAYAA dummy indicates that their program did reduce smoking-caused wildfires pre-2004. Lower temperatures, higher humidity and higher precipitation significantly reduced smoking-caused wildfires. None of the fire indices were significant explainers of smoking-caused wildfires, and only one of the lagged area burned variables was significant. Some of the fixed effects are significant (1 year; 2 months; 8 units).

Fire-use-caused wildfire model (Table 6)

Prevention duration had a significant and negative effect on the number of fire-use-caused wildfires. The WAYAA dummy variable indicated that the presence of a pre-2004 program also effectively reduced the number of fire-use-caused wildfires. As hypothesised, the number of sworn law enforcement officers did not affect the number of fire-use-caused wildfires. Except for wind speed, response to weather was as expected, with higher temperatures, and lower precipitation and relative humidity, correlated with higher numbers of fire-use-caused wildfires. Increases in wind speed were correlated with fewer fire-use-caused wildfires. The number of days with high FWI correlated with a higher monthly number of fire-use-caused wildfires. Three of the lagged area burned variables were significant. Many of the fixed effects were significant (6 years; 8 months; 10 tribal units).

Juvenile-caused wildfire model (Table 7)

Prevention duration significantly reduced the number of wildfires caused by juveniles, as did the pre-2004 WAYAA prevention program. More wildfires occurred when temperatures were higher and precipitation and relative humidity were lower, but average wind speed did not influence the number of these wildfires. None of the fire weather indices or lagged area burned

Table 5. Count model of smoking-caused wildfires

*indicates significance at the 5% level. KBDI, Keetch–Byram drought index; FWI, Fire Weather index

Variable	Incidence rate ratio	s.e.	Z		$P > \|z\|$
Intercept	0.62	0.86	−0.35		0.73
Prevention duration in months	0.99	0.01	−1.37		0.17
Full-time sworn law enforcement officers	0.98	0.01	−1.75		0.08
Average monthly temperature (°C)	1.06	0.04	1.82		0.07
Days with wind >24 km h^{-1}	1.02	0.05	0.36		0.72
Percentage relative humidity	0.94	0.02	−3.78	*	0.00
Average monthly KBDI	1.00	0.00	1.08		0.28
Average monthly FWI	1.05	0.08	0.59		0.56
Days with precipitation	0.90	0.03	−3.45	*	0.00
Days with FWI high	1.03	0.04	0.75		0.45
Days with FWI extreme	1.00	0.08	0.01		1.00
Area burned (10^3 ha)					
Previous 1–12 months	1.02	0.01	1.66		0.10
Previous 13–24 months	1.00	0.01	0.05		0.96
Previous 25–36 months	1.03	0.01	2.31	*	0.02
Previous 37–48 months	1.00	0.02	0.27		0.79
Previous 49–60 months	1.00	0.01	−0.15		0.88
Pre-2004 WAYAA	0.24	0.18	−1.90		0.06
Year fixed effects (base = 1996)					
1997	0.75	0.28	−0.77		0.44
1998	1.44	0.48	1.10		0.27
1999	0.63	0.23	−1.28		0.20
2000	0.43	0.17	−2.16	*	0.03
2001	1.65	0.54	1.53		0.13
2002	1.16	0.41	0.43		0.67
2003	0.50	0.21	−1.67		0.10
2004	1.14	0.51	0.31		0.76
2005	1.32	0.60	0.62		0.54
2006	1.45	0.71	0.75		0.45
2007	0.83	0.47	−0.32		0.75
2008	0.81	0.51	−0.33		0.75
2009	0.45	0.35	−1.02		0.31
2010	0.81	0.67	−0.25		0.80
2011	0.29	0.29	−1.24		0.22
Month fixed effects (base = January)					
February	0.35	0.18	−2.06	*	0.04
March	0.72	0.33	−0.71		0.48
April	0.39	0.23	−1.57		0.12
May	0.48	0.35	−1.01		0.31
June	0.32	0.27	−1.35		0.18
July	0.40	0.38	−0.97		0.33
August	0.34	0.31	−1.17		0.24
September	0.20	0.16	−1.98		0.05
October	0.37	0.23	−1.62		0.11
November	0.26	0.15	−2.34	*	0.02
December	0.15	0.11	−2.70		0.01
Tribal unit fixed effects (base = AZSCA)					
IDNPT	1.58	0.84	0.85		0.39
KSHOA	0.00	0.00	−0.01		0.99
MNMNA	1.78	1.83	0.56		0.57
MNRLA	0.37	0.32	−1.14		0.25
MTFHA	0.27	0.16	−2.18	*	0.03
NDTMA	0.11	0.09	−2.59	*	0.01

(*Continued*)

Table 5. (Continued)

Variable	Incidence rate ratio	s.e.	Z		$P > \|z\|$
OKANA	0.12	0.08	−3.25	*	0.00
OKCHA	0.22	0.13	−2.52	*	0.01
OKOSA	0.00	0.00	−0.02		0.98
OKTLA	0.24	0.16	−2.17	*	0.03
OKWEA	0.24	0.20	−1.69		0.09
ORWSA	0.58	0.25	−1.27		0.20
SDPRA	5.52	2.40	3.94	*	0.00
WACOA	0.39	0.23	−1.61		0.11
WASPA	0.18	0.10	−3.03	*	0.00
WAYAA	0.28	0.18	−1.96	*	0.05

Table 6. Count model of fire use-caused wildfires

*indicates significance at the 5% level. KBDI, Keetch–Byram drought index; FWI, Fire Weather index

Variable	Incidence rate ratio	s.e.	Z		$P > \|z\|$
Intercept	0.29	0.22	−1.63		0.10
Prevention duration in months	0.98	0.00	−5.63	*	0.00
Full-time sworn law enforcement officers	1.00	0.01	−0.67		0.50
Average monthly temperature (°C)	1.07	0.02	4.31	*	0.00
Days with wind >24 km h^{-1}	0.95	0.02	−2.08	*	0.04
Percentage relative humidity	0.96	0.01	−4.84	*	0.00
Average monthly KBDI	1.00	0.00	3.08	*	0.00
Average monthly FWI	1.02	0.05	0.54		0.59
Days with precipitation	0.96	0.01	−3.10	*	0.00
Days with FWI high	1.05	0.02	2.31	*	0.02
Days with FWI extreme	1.08	0.05	1.69		0.09
Area burned (10^3 ha)					
Previous 1–12 months	1.03	0.01	3.63	*	0.00
Previous 13–24 months	1.02	0.01	2.68	*	0.01
Previous 25–36 months	1.02	0.01	1.78		0.08
Previous 37–48 months	1.02	0.01	2.35	*	0.02
Previous 49 – 60 months	1.00	0.01	0.56		0.58
Pre-2004 WAYAA	0.10	0.03	−6.98	*	0.00
Year fixed effects (base = 1996)					
1997	0.89	0.19	−0.53		0.60
1998	0.85	0.19	−0.72		0.47
1999	1.22	0.26	0.92		0.36
2000	0.78	0.17	−1.13		0.26
2001	0.81	0.19	−0.90		0.37
2002	0.82	0.18	−0.90		0.37
2003	1.45	0.32	1.67		0.10
2004	1.86	0.43	2.68	*	0.01
2005	1.60	0.38	1.97	*	0.05
2006	1.01	0.27	0.03		0.98
2007	1.49	0.43	1.40		0.16
2008	2.48	0.77	2.92	*	0.00
2009	2.22	0.75	2.34	*	0.02
2010	3.25	1.21	3.15	*	0.00
2011	2.77	1.13	2.49	*	0.01
Month fixed effects (base = January)					

(*Continued*)

Table 6. (Continued)

Variable	Incidence rate ratio	s.e.	Z		$P > \|z\|$
February	0.82	0.19	−0.88		0.38
March	1.73	0.41	2.30	*	0.02
April	1.81	0.53	2.00	*	0.05
May	0.72	0.27	−0.90		0.37
June	0.23	0.10	−3.36	*	0.00
July	0.18	0.09	−3.55	*	0.00
August	0.10	0.05	−4.71	*	0.00
September	0.11	0.05	−5.12	*	0.00
October	0.51	0.16	−2.10	*	0.04
November	0.69	0.18	−1.44		0.15
December	0.48	0.12	−2.90	*	0.00
Tribal unit fixed effects (base = AZSCA)					
IDNPT	4.10	1.29	4.50	*	0.00
KSHOA	1.24	0.50	0.52		0.60
MNMNA	10.09	5.15	4.53	*	0.00
MNRLA	22.85	7.25	9.86	*	0.00
MTFHA	1.62	0.50	1.55		0.12
NDTMA	11.03	3.38	7.83	*	0.00
OKANA	0.88	0.28	−0.40		0.69
OKCHA	1.03	0.30	0.10		0.92
OKOSA	3.01	1.03	3.21	*	0.00
OKTLA	0.82	0.26	−0.63		0.53
OKWEA	2.01	0.74	1.88		0.06
ORWSA	0.55	0.16	−2.12	*	0.03
SDPRA	19.53	5.22	11.12	*	0.00
WACOA	16.80	5.31	8.93	*	0.00
WASPA	4.49	1.28	5.27	*	0.00
WAYAA	7.24	2.34	6.13	*	0.00

Table 7. Count model of juvenile-caused wildfires

*indicates significance at the 5% level. KBDI, Keetch–Byram drought index; FWI, Fire Weather index

Variable	Incidence rate ratio	s.e.	Z		$P > \|z\|$
Intercept	2.74	2.58	1.07		0.28
Prevention duration in months	0.99	0.00	−2.72	*	0.01
Full-time sworn law enforcement officers	0.99	0.01	−0.83		0.41
Average monthly temperature (°C)	1.11	0.02	5.21	*	0.00
Days with wind >24 km h^{-1}	1.02	0.03	0.62		0.54
Percentage relative humidity	0.92	0.01	−6.93	*	0.00
Average monthly KBDI	1.00	0.00	1.14		0.25
Average monthly FWI	1.00	0.06	0.02		0.98
Days with precipitation	0.90	0.02	−5.86	*	0.00
Days with FWI high	1.01	0.03	0.50		0.62
Days with FWI extreme	0.98	0.05	−0.34		0.74
Area burned (10^3 ha)					
Previous 1–12 months	1.00	0.01	0.08		0.93
Previous 13–24 months	1.00	0.01	−0.45		0.65
Previous 25–36 months	1.01	0.01	0.53		0.59
Previous 37–48 months	0.99	0.01	−0.60		0.55
Previous 49–60 months	0.99	0.01	−1.31		0.19

(*Continued*)

Table 7. (Continued)

Variable	Incidence rate ratio	s.e.	Z		$P > \|z\|$
Pre-2004 WAYAA	0.32	0.12	−3.14	*	0.00
Year fixed effects (base = 1996)					
1997	1.04	0.28	0.10		0.92
1998	1.41	0.38	1.23		0.22
1999	1.26	0.33	0.88		0.38
2000	1.15	0.31	0.55		0.58
2001	0.90	0.25	−0.42		0.68
2002	0.99	0.28	0.00		1.00
2003	1.03	0.29	0.07		0.94
2004	1.14	0.34	0.45		0.65
2005	1.00	0.31	0.06		0.95
2006	1.38	0.45	1.18		0.24
2007	1.27	0.45	0.88		0.38
2008	2.78	1.06	2.90	*	0.00
2009	3.51	1.48	3.24	*	0.00
2010	2.83	1.30	2.54	*	0.01
2011	2.45	1.23	2.10	*	0.04
Month fixed effects (base = January)					
February	0.47	0.17	−2.08	*	0.04
March	1.43	0.48	1.10		0.27
April	2.60	1.04	2.41	*	0.02
May	1.02	0.50	0.05		0.96
June	0.96	0.53	−0.06		0.95
July	1.03	0.62	0.05		0.96
August	0.16	0.10	−2.97	*	0.00
September	0.17	0.09	−3.32	*	0.00
October	0.49	0.21	−1.63		0.10
November	0.85	0.31	−0.34		0.73
December	0.52	0.20	−1.66	*	0.10
Tribal unit fixed effects (base = AZSCA)					
IDNPT	0.68	0.26	−1.15		0.25
KSHOA	0.06	0.05	−3.52	*	0.00
MNMNA	7.77	4.26	4.16	*	0.00
MNRLA	39.62	13.91	10.50	*	0.00
MTFHA	0.18	0.07	−4.51	*	0.00
NDTMA	3.46	1.24	3.38	*	0.00
OKANA	0.16	0.06	−4.83	*	0.00
OKCHA	0.05	0.03	−6.22	*	0.00
OKOSA	0.16	0.08	−3.91	*	0.00
OKTLA	0.02	0.02	−5.59	*	0.00
OKWEA	0.06	0.04	−4.31	*	0.00
ORWSA	0.46	0.15	−3.05	*	0.00
SDPRA	22.64	6.81	9.92	*	0.00
WACOA	0.74	0.26	−1.06		0.29
WASPA	0.15	0.06	−5.15	*	0.00
WAYAA	0.63	0.24	−1.44		0.15

values were statistically significant. Some of the time fixed effects were significant (4 years; 5 months), whereas nearly all of the tribal unit fixed effects were significant (13 units).

Incendiary-caused wildfire model (Table 8)

As hypothesised, the number of sworn law enforcement officers was found to significantly reduce incendiary wildfires, but prevention program duration was not shown to have any effect.

Table 8. Count model of incendiary-caused wildfires

*indicates significance at the 5% level. KBDI, Keetch–Byram drought index; FWI, Fire Weather index

Variable	Incidence rate ratio	s.e.	Z		$P > \lvert z \rvert$
Intercept	2.90	2.59	1.19		0.24
Prevention duration in months	1.00	0.00	1.03		0.30
Full-time sworn law enforcement officers	0.97	0.01	−3.53	*	0.00
Average monthly temperature (°C)	1.08	0.02	3.77	*	0.00
Days with wind >24 km h^{-1}	0.96	0.03	−1.43		0.15
Percentage relative humidity	0.94	0.01	−5.98	*	0.00
Average monthly KBDI	1.00	0.00	1.95	*	0.05
Average monthly FWI	1.04	0.05	0.81		0.42
Days with precipitation	0.93	0.02	−4.37	*	0.00
Days with FWI high	1.02	0.03	0.75		0.45
Days with FWI extreme	1.07	0.06	1.22		0.22
Area burned (10^3 ha)					
Previous 1–12 months	0.98	0.01	−2.00	*	0.05
Previous 13–24 months	0.97	0.01	−2.66	*	0.01
Previous 25–36 months	0.98	0.01	−1.81		0.07
Previous 37–48 months	0.98	0.01	−2.16	*	0.03
Previous 49–60 months	1.00	0.01	−0.04		0.97
Pre-2004 WAYAA	2.15	0.99	1.67		0.10
Year fixed effects (base = 1996)					
1997	0.56	0.17	−1.91		0.06
1998	1.10	0.32	0.32		0.75
1999	0.51	0.15	−2.32	*	0.02
2000	0.56	0.17	−1.95		0.05
2001	1.41	0.41	1.21		0.23
2002	0.85	0.25	−0.55		0.58
2003	0.79	0.23	−0.82		0.42
2004	0.82	0.24	−0.69		0.49
2005	2.79	0.81	3.53	*	0.00
2006	3.83	1.21	4.24	*	0.00
2007	4.64	1.63	4.36	*	0.00
2008	4.87	1.87	4.13	*	0.00
2009	3.46	1.51	2.86	*	0.00
2010	2.70	1.29	2.09	*	0.04
2011	1.89	0.97	1.24		0.22
Month fixed effects (base = January)					
February	1.36	0.34	1.23		0.22
March	1.49	0.40	1.46		0.14
April	1.81	0.62	1.72		0.09
May	0.78	0.34	−0.57		0.57
June	0.26	0.14	−2.59	*	0.01
July	0.34	0.20	−1.84		0.07
August	0.21	0.12	−2.74	*	0.01
September	0.16	0.08	−3.75	*	0.00
October	0.47	0.18	−1.97	*	0.05
November	0.68	0.21	−1.27		0.20
December	0.65	0.18	−1.59		0.11
Tribal unit fixed effects (base = AZSCA)					
IDNPT	0.33	0.13	−2.79	*	0.01
KSHOA	0.25	0.11	−3.11	*	0.00
MNMNA	66.52	49.32	5.66	*	0.00
MNRLA	12.71	4.82	6.70	*	0.00
MTFHA	0.19	0.07	−4.29	*	0.00
NDTMA	1.53	0.55	1.18		0.24
OKANA	0.83	0.32	−0.48		0.63
OKCHA	0.53	0.18	−1.90		0.06
OKOSA	2.20	0.91	1.91		0.06
OKTLA	4.51	1.47	4.60	*	0.00
OKWEA	0.26	0.11	−3.14	*	0.00
ORWSA	0.23	0.07	−4.66	*	0.00
SDPRA	0.43	0.14	−2.51	*	0.01
WACOA	0.54	0.23	−1.43		0.15
WASPA	0.24	0.08	−4.19	*	0.00
WAYAA	0.12	0.05	−5.47	*	0.00

(*Continued*)

Table 8. (Continued)

As expected, higher temperatures and lower relative humidity and precipitation were negatively correlated with incendiary wildfires, as was KBDI. Three out of five of the lagged areas burned are negative and significant. Some of the fixed effects were significant (7 years; 4 months; 11 tribal units).

Equipment-caused wildfire model (Table 9)

Equipment-caused wildfires are the only cause-type in our study that responded to both prevention and law enforcement – with the length of the program and higher numbers of officers correlated with fewer equipment-caused wildfires. Contrary to expectations, however, the pre-2004 WAYAA dummy variable was positive and significant. As in all of the models, higher temperatures and lower precipitation and relative humidity correlated with more ignitions. As in the incendiary model, KBDI was a good predictor of equipment-caused wildfires. In contrast to incendiary wildfires, however, lagged area burned was positively correlated with equipment-caused wildfires (two out of five were significant). Some of the fixed effects were significant (9 years; 1 month; 15 units).

Discussion

The weather variables were generally significant, had the expected signs and were consistent with results from previous studies cited in the introduction. Increases in average temperature and decreases in average relative humidity were correlated with increases in wildfires of all causes. An increase in the number of days of precipitation led to a reduction in wildfires in all of the models. The remaining weather variables were significant in fewer models, but generally with the expected sign. The results for FWI and campfire-caused wildfires (positive effects of more days at high and extreme FWI, but negative effects of average monthly FWI) are inconsistent.

Fixed effects were significant in all of the cause models, indicating that there is information that has been omitted from the estimation. We used fixed effects because we hypothesised that there are effects of seasons, time and location that we could not otherwise capture in the data. We do not expect that any of these fixed effects are correlated with the interventions, and thus will not influence the interventions. The significance of these fixed effects confirms our model choice.

Table 9. Count model of equipment-caused wildfires

*indicates significance at the 5% level. KBDI, Keetch–Byram drought index; FWI, Fire Weather index

Variable	Incidence rate ratio	s.e.	Z		$P > \|z\|$
Intercept	0.40	0.28	−1.30		0.20
Prevention duration in months	0.99	0.00	−2.60	*	0.01
Full-time sworn law enforcement officers	0.97	0.00	−5.69	*	0.00
Average monthly temperature (°C)	1.04	0.02	2.34	*	0.02
Days with wind >24 km h^{-1}	0.99	0.02	−0.58		0.56
Percentage relative humidity	0.95	0.01	−6.88	*	0.00
Average monthly KBDI	1.00	0.00	3.06	*	0.00
Average monthly FWI	0.97	0.04	−0.83		0.41
Days with precipitation	0.94	0.01	−4.31	*	0.00
Days with FWI high	1.03	0.02	1.63		0.10
Days with FWI extreme	1.05	0.04	1.20		0.23
Area burned (10^3 ha)					
Previous 1–12 months	1.02	0.01	2.61	*	0.01
Previous 13–24 months	1.01	0.01	1.23		0.22
Previous 25–36 months	1.03	0.01	4.10	*	0.00
Previous 37–48 months	1.01	0.01	1.71		0.09
Previous 49–60 months	1.01	0.01	1.14		0.25
Pre-2004 WAYAA	2.17	0.67	2.50	*	0.01
Year fixed effects (base = 1996)					
1997	0.85	0.22	−0.63		0.53
1998	1.05	0.26	0.18		0.85
1999	1.19	0.28	0.74		0.46
2000	0.98	0.25	−0.07		0.95
2001	1.13	0.28	0.48		0.63
2002	1.37	0.33	1.32		0.19
2003	1.63	0.39	2.06	*	0.04
2004	2.16	0.53	3.13	*	0.00
2005	2.21	0.55	3.18	*	0.00
2006	4.40	1.13	5.77	*	0.00
2007	3.41	0.97	4.31	*	0.00
2008	7.11	2.09	6.69	*	0.00
2009	5.63	1.83	5.31	*	0.00
2010	5.00	1.79	4.49	*	0.00
2011	6.49	2.53	4.80	*	0.00
Month fixed effects (base = January)					
February	1.08	0.21	0.41		0.68
March	0.88	0.20	−0.57		0.57
April	0.71	0.21	−1.17		0.24
May	0.57	0.21	−1.54		0.13
June	0.79	0.33	−0.55		0.58
July	0.76	0.37	−0.56		0.58
August	0.82	0.39	−0.43		0.67
September	0.45	0.18	−2.00	*	0.05
October	0.60	0.18	−1.68		0.09
November	0.85	0.20	−0.68		0.50
December	0.93	0.20	−0.33		0.75
Tribal unit fixed effects (base = AZSCA)					0.00
IDNPT	6.31	2.04	5.69	*	0.01
KSHOA	3.07	1.31	2.62	*	0.00
MNMNA	25.71	13.15	6.35	*	0.63
MNRLA	1.34	0.80	0.49		0.00
MTFHA	3.69	1.19	4.05	*	0.00
NDTMA	3.41	1.25	3.35	*	0.00
OKANA	9.15	2.83	7.16	*	0.00
OKCHA	6.56	1.94	6.37	*	0.01
OKOSA	9.23	3.07	6.69	*	0.00
OKTLA	2.35	0.76	2.62	*	0.02
OKWEA	3.68	1.27	3.76	*	0.00
ORWSA	1.95	0.58	2.25	*	0.00
SDPRA	50.62	14.82	13.41	*	0.04
WACOA	11.09	3.50	7.63	*	0.01
WASPA	1.99	0.65	2.10	*	0.04
WAYAA	2.39	0.81	2.58	*	0.01

Table 10. Marginal percentage reduction in the rate of wildfires, by ignition cause, per month of a wildfire prevention program and per sworn law enforcement officer

* denotes statistical significance at less than or equal to the 5% level

Ignition cause	Per month of prevention (%)		Per sworn law enforcement officer (%)	
Campfires	0.94	*	1.00	
Smoking	0.99		1.87	
Fire-use	1.98	*	0.40	
Juveniles	1.00	*	1.00	
Incendiary	0.43		3.13	*
Equipment	0.85	*	2.80	*

The variables describing previous wildfire activity – lagged areas burned – were originally included in the model as a proxy for the availability of fuels, with an *a priori* hypothesis that an increase in lagged fire would correspond to a decrease in current ignitions (negative coefficient on lagged area burned). Land that burned in the previous 5 years was expected to reduce the number of wildfires of all causes because the previous fire acts as a fuel treatment, reducing available fuels. This is reflected in the negative and significant coefficients on lagged area burned in the incendiary-caused models and is generally consistent with previous studies relating areas burned to previous areas burned (e.g. Mercer *et al.* 2007).

However, we also find positive and significant coefficients on lagged area burned in the campfire-, fire-use-, equipment- and smoking-caused wildfire models, which is contrary to our initial hypothesis. In these cases, previous wildfires could be indicators of persistent risk factors related to human activities that tend to favour wildfire starts that we did not capture with other included variables.

The marginal effects of prevention programs and law enforcement on the various wildfire causes are shown in Table 10. An additional month of prevention reduced escaped campfire ignitions by 0.94%, fire-use-caused wildfires by 1.98%, wildfires caused by juveniles by 1.0% and those ignited by equipment by 0.85%. An additional full-time law enforcement officer reduced incendiary wildfires by 3.13% and equipment-caused wildfires by 2.80%. Only equipment-caused

Table 11. Observed and estimated avoided number of wildfires, by ignition cause, in total and per tribal unit month from prevention and law enforcement

* denotes statistical significance at less than or equal to the 5% level

Ignition cause	Observed[A]	Observed per tribal month	Avoided by prevention[A,B]	Avoided by law enforcement	Avoided by prevention per tribal month	Avoided by law enforcement per tribal unit month
Campfire	925	0.3	488*		0.3	
Smoking	434	0.1				
Fire-use	6442	2.2	6588*		4.2	
Juveniles	6134	2.1	2925*		1.8	
Incendiary	7337	2.5	232*	249*		0.2
Equipment	1858	0.6	762*	32*	0.5	<0.01
Total	23 130	8.0	10 995	281	6.9	

[A]Computed for observations with a prevention program ($n = 1587$).
[B]Statistical significance was determined via bootstrapping.

wildfires respond to both prevention and law enforcement effort; all other causes respond to either prevention or law enforcement.

The current model specification uses a negative binomial count model, which implicitly assumes non-linear effects over time by assuming a positive second-order effect (regardless of the sign of the first-order effect) – which in our model implies that the effects of prevention duration on ignitions is negative (prevention duration leads to reduced ignitions) at a negative rate (this effect is decreasing over time). The other potential count model that we could have used, the Poisson, also makes this same assumption. The decreasing effect over time is consistent with our *a priori* assumptions. This is a limitation of imposing the negative binomial structure on our data; however, the existence of a diminishing return to a prevention program over time seems more likely than the increasing or constant linear effects. Further improvements in theoretical count model development would be necessary to allow estimation of fixed-effect count models that allow alternative second-order effects assumptions. These conditions are consistent with our *a priori* expectation that the effects of a prevention program in one period will have diminishing marginal returns over time and is consistent with previous studies (Butry *et al.* 2010; Prestemon *et al.* 2010). Table 11 shows the observed number of wildfires by cause, and the estimated counterfactual avoided wildfires as a result of the duration of the prevention program and from an additional month of law enforcement. This table provides the absolute effect of the prevention programs. Each unit began a prevention program at specified dates (see Table 1). Thus, all of the months before the program began represent the no-program counterfactual.

These estimates hold all other values constant. No smoking- and incendiary-caused wildfires are avoided owing to prevention, as the prevention duration variable was not significant in reducing the numbers of these wildfires. Similarly, there are no law enforcement effects on campfire-, juvenile- or fire-use-caused wildfires.

Overall, prevention program duration and law enforcement were estimated to have reduced expected ignitions by 32% (Table 11) on BIA units, with most of these reductions attributable to prevention. Fire-use-caused wildfires were reduced by 51% owing to prevention programs, whereas campfire-, juvenile- and equipment-caused wildfires were reduced by ~30% by prevention. Law enforcement effects, which were modelled as the avoided fires only from one additional officer, were much smaller, less than a 3% reduction, for the marginal ('last one hired') law enforcement officer, for smoking-, equipment- and incendiary-caused wildfires.

The finding that the duration of prevention programs matters is consistent with results in Butry *et al.* (2010) and Prestemon *et al.* (2010) for Florida. These analyses included specific lagged prevention program activities and found that activities had effects that lasted for several months beyond the months they were conducted. These analyses in Florida, however, also showed a positive influence of the number of law enforcement officers on the number of accidental wildfires. However, our findings show that law enforcement led to fewer wildfires only from incendiary and equipment causes. Donoghue and Main (1985) also found that law enforcement negatively affected incendiary wildfires in the US North-east.

We obtained data on the expenditures made for the prevention programs for the 17 tribal units, as well as the suppression expenditures for all BIA units by BIA region, and developed a partial benefit–cost ratio for these prevention programs. The expenditure data were provided by BIA fire specialists by year by BIA region, but data were not available by fire or by tribal unit, which limits the conclusions we can make using these data.[4] We are not able to attribute benefits to the tribal units, or to fire size classes, or to fire causes due to the aggregate nature of these data. This ratio is considered partial because we do not try to measure (1) damage avoidance from wildfire (a benefit in this situation), (2) costs of other types of fuel treatments and preparedness, or (3) changes in suppression expenditures that might have been caused by the feedback effect (in other words, when a wildfire is prevented today, it reduces the effective 'fuel treatment', which could then result in more wildfire in the future) that results. The benefit is measured as the number of avoided

[4]Data are available from Samuel Scranton, BIA (samuel.scranton@bia.gov).

Table 12. Estimated partial benefit–cost ratios by region for prevention programs on 17 Bureau of Indian Affairs (BIA) tribal units using regional average expenditures per fire

Region	Average annual prevention expenditures (2004–09)	Average suppression expenditures per fire[A] (2002–11)	Average annual suppression savings from prevention	Partial benefit–cost ratio
	2004 US dollars			
Eastern Oklahoma	51 326	3068	231 993	4.5
Great Plains	46 870	3093	233 870	5.0
Midwest	40 355	3683	278 547	6.9
North-west	47 111	23 949	1 811 063	38.4
Rocky Mountain	52 680	10 581	800 180	15.2
Western	43 609	17 416	1 317 047	30.2
Southern Plains	54 284	7549	570 837	10.5

[A]Data were unavailable for expenditures by fire cause or fire size, and thus this value represents the average cost per fire for all fire sizes and causes. To the extent that suppression expenditures differ by prevented cause, and by fire size, the benefit–cost ratio may over- or underestimate the true ratio.

wildfires (resulting from an additional year of prevention) times the average suppression expenditure per fire (derived by calculating the average real suppression expenditures per fire for each BIA region). Our data are insufficient to estimate these ratios by fire size, tribal unit or fire cause; however, the structure of the negative binomial model suggests that tribal units with above (below) average wildfire ignition rates should expect larger (smaller) ratios than average, owing to the larger (smaller) estimated marginal effectiveness of prevention, in absolute terms. (The estimated marginal effect of prevention equals the estimated prevention coefficient multiplied by the expected wildfire ignition rate, and is thus proportional to the underlying ignition rate.) This positive relationship between the ignition rate and the marginal effect of prevention also implies that the returns to prevention would be greater (lesser) during times of elevated (below average) wildfire ignition risk and in tribal units with higher (lower) average ignition levels before implementation of a prevention program.

Table 12 shows these partial benefit–cost ratios by BIA region. All are greater than 4.5, indicating that, at least for this simple, narrowly defined ratio for the 17 tribal units studied, the benefits of a continuing wildfire prevention program, as measured by the reduction in suppression expenditures, outweigh the costs of the wildfire prevention program. In a simple analysis using assumed average expenditures on large fires as compared with small fires, we did not find large differences in benefit–cost ratios from those presented in Table 12. However, small changes in the assumptions regarding the sizes of fires avoided by prevention or the expenditures made on fires of different sizes would change these results. A shift of a few fires from ‘avoided large’ to ‘avoided small’ would reduce the benefit–cost ratio substantially, whereas a shift in the other direction would increase the ratio only slightly. These ratios should be used with caution until additional research is conducted to more fully evaluate the effects of prevention on fires of different sizes and causes and data on suppression expenditures by specific units for specific fire sizes and causes are available. However, these ratios exclude the benefits that would be derived from a reduction in fire damages, for which we did not have any estimates, and so are expected to be lower than a fully specified benefit–cost ratio.

Conclusions

This analysis evaluated the effects of both the duration of prevention programs and the number of law enforcement officers for a small selection of tribal units. A recent program to develop prevention activities at the ground level was found to significantly reduce wildfire ignitions from campfire-, juvenile-, fire-use- and equipment-caused wildfires. Of the accidental wildfire causes examined, only smoking-caused wildfires did not respond to prevention program duration. The number of law enforcement officers was found to reduce not only incendiary wildfires, but also accidental wildfires caused by equipment.

Furthermore, we found that most wildfire causes responded as expected to weather and socioeconomic factors, consistent with other studies. The weather variables were month- and tribal unit-specific, and they show consistent and expected correlations with the number of wildfires, indicating that weather contributes to both the opportunity for wildfire ignition and the probability that an ignition will become established and be reported. Differences exist across tribal units and over time, as represented by the month and year fixed effects.

The lagged area burned variables were positively correlated with some wildfire causes, negatively correlated with other causes, and not significant in many cases. There are many potential explanations, but perhaps these correlations most likely reflect the weakness of our assumed relationship between landscape-level fuels and fire start locations and their probabilities. Fuel levels are not the only determinants of successful ignition – although they are determinants of fire extent – and our study shows that their inclusion in a predictive model yields results that are difficult to interpret and may be capturing factors that we did not otherwise include in the models.

We encountered some limitations in our analysis and believe that additional research could overcome these limitations if additional data (number of units) and improved quality of data (i.e. long and consistent series on prescribed fire) can be obtained. Calculation of the tribal unit-level effects for each program component and fire cause, as well as fire-level suppression expenditure data would allow development of tribal unit and fire cause- and fire size-specific benefit–cost ratios, although the random nature of fire ignitions may preclude evaluation of effects at very short (monthly) and small geographic (tribal unit) levels. Information on fire damages by tribal unit would be needed to extend the partial benefit–cost ratio to a more valid estimate of the total effects of a prevention program.

This research evaluated only a few of the BIA tribal units with active prevention programs, and did not include tribal units without currently active programs. Although this study alone does not provide specific effectiveness of prevention programs on units not evaluated, this work, combined with previous studies, continues to strengthen the conclusion that, in general, the benefits of active prevention programs can exceed the costs of such programs. Longer and broader analyses including other land ownerships, different prevention programs and areas lacking in prevention programs would be needed to conclude that prevention benefits always exceed prevention costs.

In summary, our statistical assessment of net benefits of wildfire prevention programs managed by a subset of tribes in the United States, using regional average prevention program costs and measuring benefits as regional average costs of the program, indicate that such programs render benefits exceeding the suppression expenditures averted. Still unanswered, however, are questions regarding the effects of particular prevention activities in preventing wildfires. Further research, with more data covering a longer time span, is needed on these wildfire programs, as budgets are increasingly constrained and total areas burned continue to rise.

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