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The net benefits of human-ignited wildfire forecasting: the case of tribal land units in the United States

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Abstract. Research shows that some categories of human-ignited wildfires may be forecastable, owing to their temporal clustering, with the possibility that resources could be predeployed to help reduce the incidence of such wildfires. We estimated several kinds of incendiary and other human-ignited wildfire forecast models at the weekly time step for tribal land units in the United States, evaluating their forecast skill out of sample. Analyses show that an autoregressive conditional Poisson model of both incendiary and non-incendiary human-ignited wildfires is more accurate out of sample compared with alternatives, and the simplest of the autoregressive conditional Poisson models performed the best. Additionally, an ensemble of these and simpler, less analytically intensive approaches performed even better. Wildfire hotspot forecast models using all model types were evaluated in a simulation mode to assess the net benefits of forecasts in the context of law-enforcement resource reallocations. Our analyses show that such hotspot tools could yield large positive net benefits for the tribes in terms of suppression expenditures averted for incendiary wildfires but that the hotspot tools were less likely to be beneficial for addressing outbreaks of non-incendiary human-ignited wildfires.

Additional keywords: arson, autoregressive, human-caused, incendiary, law enforcement, wildfire hotspotting.

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Introduction

Wildland fire managers often have an objective to reduce the number of unwanted human-ignited wildfires. Such wildfires tend to be more damaging than other kinds of wildfires because, on average, they are ignited closer to values at risk than naturally ignited wildfires (e.g. Butry *et al.* 2002). People in their day-to-day activities in wildland areas, including recreating and operating heavy equipment, accidentally ignite wildfires when fuel conditions are amenable. Arsonists, in turn, ignite wildfires to create damages to property and resources. Research has shown that arson wildfires are clustered in space and time (Butry and Prestemon 2005; Prestemon and Butry 2005; Prestemon and Butry 2008). The tendency of certain kinds of crimes (e.g. burglary) to cluster in space and time has been known for perhaps centuries and was documented in the literature at least eight decades ago (e.g. Lottier 1938). Clusters of wildfires have also been well known but less well documented until recent decades. Butry and Prestemon (2005) and Prestemon and Butry (2005) were the first, as far as we are aware, to quantify the tendencies of arson wildfires to cluster at the daily time scale. Clusters were found to persist for up to 10 days following the initiation of an outbreak in Florida, and clusters were found to extend many kilometres in space. In a similar study of national forests in California (Prestemon and Butry 2008), wildfires were shown to be clustered on national forests at the daily time scale. Prestemon *et al.* (2012) documented the clustering of intentionally ignited wildfires in Galicia, Spain, also at the daily time scale. Prestemon *et al.* (2013*a*) showed how urban arson fires are also clustered in time (days) and space. All of the above studies of intentional firesetting documented temporal clustering at the daily time scale separately from regular temporal patterns in the numbers of wildfires associated with seasons (i.e. seasonality, although some of these studies also quantified weekend day and holiday effects). Although clustering at the daily time scale implies possible clustering at larger temporal aggregates such as weeks (again, separately from seasonality), research of which we are aware has not documented this. And although all of these studies examined intentional firesetting, no study of which we are aware has examined this kind of clustering for other human-ignited wildfires.

Clustering of wildfires can result from a variety of factors. First, and true of all wildfire causes, fuel and weather conditions may favour the successful ignition, spread, and then reporting of a wildfire. Second, wildfire clusters may result from serial or copycat firesetting behaviour (Prestemon and Butry 2005; Prestemon *et al.* 2012). Further, clusters can arise from particular events that happen regularly or irregularly, such as in the days around Halloween (e.g. Thomas *et al.* 2011) or during public disturbances, or in particular locations, such as 'no man's lands', where the threat of discovery is low. Average levels of human-ignited fires, however, are a function of slower-changing bio-physical factors such as climate and land cover as well as socioeconomic variables that contribute to tendencies to intentionally or accidentally ignite fires (e.g. population density, economic conditions; see Thomas *et al.* (2012)). Rates can also be modified by human efforts to limit their occurrence, such as through wildfire prevention education efforts and law enforcement (Prestemon *et al.* 2010; Abt *et al.* 2015) or fuels management (e.g. Butry *et al.* 2010).

Clustering of crimes in space–time has motivated the creation of operational predictive crime models, generally referred to in the criminology and policing literature as hotspot tools (e.g. Johnson and Bowers 2004). And as documented by Prestemon *et al.* (2012, 2013*b*), because temporal and spatiotemporal clustering is evident in intentional wildfires, it is possible to design an arson prospective hotspot tool that could be used by resource managers, firefighting organisations or law enforcement. Such a tool for arson wildfires would utilise statistical information about the manner of spatiotemporal clustering of wildfires across a landscape or the temporal clustering of such fires within a spatial unit to develop a forecast of future wildfire activity.[1] The predictability of firesetting processes implied by the statistical model suggests that managers could respond to cluster events or to conditions indicating imminent cluster events early in the clustering temporal window. This response may reduce either the size of the cluster (in space dimension, time dimension, or space and time dimensions) or the damages that occur from wildfires in the cluster. Reductions in the number of wildfires within a cluster could avert the suppression expenditures and the damages that would have occurred had the numbers not been reduced. Predictability can also allow opportunistic suppression resource pre-placement, which could enable shorter response times and the application of greater suppression resources on fires that occur, reducing the average size or per-unit damages of wildfires that occur, either of which could potentially reduce overall suppression expenditures and damages.

Success in either reducing cluster size or decreasing wildfire damages from fires that occur in the cluster requires that managers (i) understand the clustering process, and (ii) can predict its pattern with forecast skill. Success in economic terms, however, requires also that (iii) predictions and responses to them are less costly than the value of the losses averted. The objectives of the present research are to (1) evaluate the predictive abilities (forecast skills) of alternative forecast models for incendiary[2] and other human-ignited[3] wildfires, based on the level of technical sophistication and associated data requirements, and (2) quantify, using a prototype economic model based on the alternative forecasts and parameters from recently published research on fire prevention (Abt *et al.* 2015), the net benefits of deploying a prospective hotspot tool that incorporates our forecast models. The spatial units of inference are 23 US Bureau of Indian Affairs (BIA) tribal land units in the United States (see Fig. 1). Models are based on weekly counts[4] of historical data on incendiary and other human-ignited wildfires in the tribal land units, from as early as the first week of January 1996 through the first week of October 2008. To gauge forecast skills of these alternative models, they are each then used to forecast wildfires from that point until the last week of December of 2011, the end of our dataset. October generally represents a low point in annual wildfire activity across the tribal units studied. October 2008 also marks the end of ~80% of our data, allowing a forecast evaluation over the remaining 20% of the data. The scientific advances we document include that: (1) both incendiary and other human-ignited wildfires on tribal lands in the United States demonstrate significant temporal autocorrelation at the weekly time scale; (2) the simplest forecast models tend to demonstrate the highest forecast skills; (3) because incendiary wildfires respond more strongly to increased law-enforcement whereas other human-ignited wildfires respond weakly, a prospective hotspot tool for incendiary wildfires is more likely to yield positive net benefits and a high return on its creation and deployment than is a prospective hotspot tool for other human-ignited wildfires on tribal lands; (4) prospective hotspot tools are more likely to yield positive net benefits in places with larger wildfire clusters; and (5) the selection of a forecast modelling form, from an economic perspective, should consider the underlying wildfire risk – e.g. sophisticated models are more appropriate for high-risk, wildfire-prone jurisdictions.

The remainder of this article begins with a description of five alternative forecast approaches used to predict both incendiary and other human-ignited wildfires, followed by a description of the spatial and temporal domains of inference. Then, we describe the hotspot tools and how net benefits are calculated for an out-of-sample deployment in each tribal land unit. Following this description, we report the net benefits of the prospective hotspot tool and discuss the factors that help explain the conditions under which such a tool is most likely to be beneficial from an economic perspective.

Methods

Three forecasting approaches are considered based on the assumed process generating the count of wildfire ignitions: (1) a

[1]In our analysis, we use the term 'hotspot' or 'hotspot tool' to be consistent with its usage in the fields of criminology and policing. Strictly speaking, our spatial unit (defined in the next section) is the tribal land unit, so that the hotspot tool utilises information about temporal clustering (only) within the space defined by the unit. Viewed across all units studied, spatiotemporal clusters – or hotspots – would be visible in space–time.

[2]The US Bureau of Indian Affairs identifies wildfires started intentionally by adults as 'incendiary'. We use 'arson' when referring to the general concept of intentionally setting a wildfire but use 'incendiary' when referring to the wildfire cause as classified in our dataset.

[3]The US Bureau of Indian Affairs identifies the following other human-ignited wildfire causes that we model in our study: campfire, smoking, fire use, equipment, railroad, juveniles, and miscellaneous.

[4]The weekly time step was chosen because we assume that weekly model forecasts are more in line with the operational demands of land management, firefighting and police organisations. These organisations may not have the staff available to daily enter wildfire occurrence data and generate model reports for ensuing days but may have the resources to do this on a weekly basis.

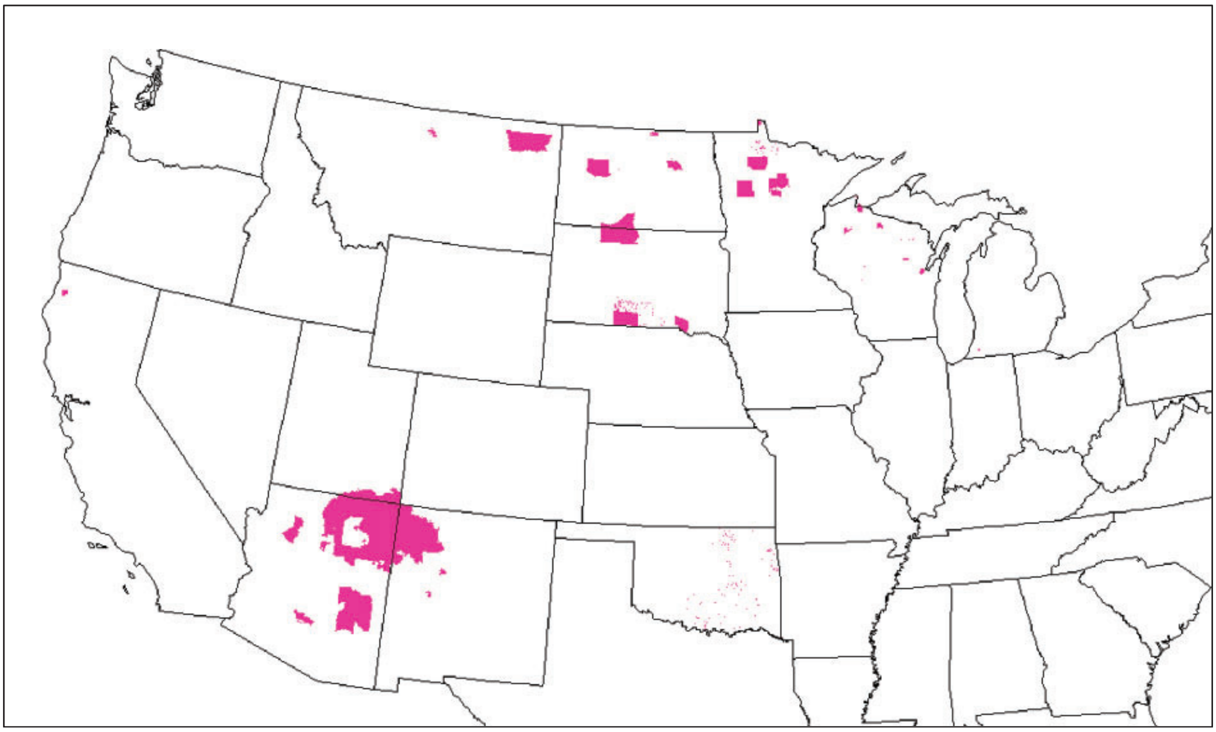

Fig. 1. Locations of tribal land units in the United States modelled in this study.

random-walk process; (2) an annualised moving-average process; and (3) an autoregressive Poisson process. The associated forecasting approaches vary in their level of technical sophistication and data requirements.

The least sophisticated model, with little information needs and hence simple to implement, is the random walk:

$$E[Y(t)] = Y_{t-1} \quad (1)$$

where t indexes time, $E[Y(t)]$ is the expected count and Y_{t-1} is the count of wildfires from the previous period. It is obvious that such a model would not be good at tracking, say, the rise and fall of an outbreak and would also yield an incorrect prediction at the beginning and the period after the end of the outbreak. However, this model would be particularly good at predicting zero fires in long periods of wildfire inactivity.

A second method to predict the count would mimic the 'CompStat' approach first outlined and implemented in New York City (e.g. Kelling and Bratton 1998) as a way of allocating law-enforcement resources to address crime hotspots. CompStat, at its core, is backward-looking, using information on recent crime occurrences to generate a crime probability map for the coming operational period for each spatial unit under consideration. It could be considered a random walk or, when coupled with multiple periods of historical data, a moving-average prediction of crime likelihoods for a given spatial unit. For wildfire count prediction, we implement what we label the 'CompStat53' predictor, a 1-year lag of a 5-week moving average of the observed count. The '53' recognises that 1 year is slightly more than 52 weeks and that we intend to forecast the week's count of wildfires that is approximately centred 365 days previous to the current year:

$$E[Y(t)] = (Y_{t-55} + Y_{t-54} + Y_{t-53} + Y_{t-52} + Y_{t-51})/5 \quad (2)$$

Finally, the autoregressive conditional Poisson (ACP) (Heinen and Rengifo 2003) is a time-series count model that relates the count (of incendiary or other human-ignited wildfires in our case) as a function of observed wildfire counts from previous recent periods, exogenous predictors (such as temperature, a fire index, an indicator variable, which may be from current or previous periods), and lagged predictions of the number of wildfires. Specifically, the ACP model parameterises a vector autoregressive moving-average process that relates the conditional mean in period t, $E[Y(t)|\mathcal{F}(t)] = \mu_t$, to variables in the information set, $\mathcal{F}(t)$, containing a set of exogenous predictors (excluding a constant), $\mathbf{x}(t)$, p lagged observed counts, $\mathbf{Y}_{t-p}$, and q lagged conditional means, $\boldsymbol{\mu}_{t-q}$:

$$\mu_t = \exp[\mathbf{x}(t)'\mathbf{b}]\left[\Omega + \sum_{i=1}^{p} A_i Y_{t-i} + \sum_{i=1}^{q} B_i \mu_{t-i}\right] \quad (3)$$

where exp is the exponential operator; $\mathbf{b}$, $\boldsymbol{\Omega}$, the A_is and the B_is are parameters to be estimated; and i indexes the autoregressive moving-average process. In our modelling, we describe three subtypes, which vary in their data requirements, of the ACP model that is estimated to predict the counts of incendiary and other human-ignited wildfires. First is a 'pure' ACP, i.e. excluding exogenous regressors, implying that $\exp[\mathbf{x}(t)'\mathbf{b}] = \exp[0] = 1$ and up to five lags of observed counts, i.e. $\mathbf{Y}(t) = (Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-4}, Y_{t-5})'$. The second subtype populates the $\mathbf{x}(t)$ vector with a set of 1-week lags of weather variables. The third subtype replaces the weather variables in $\mathbf{x}(t)$ with month indicator variables, intended to capture regular seasonal variations in the occurrences of incendiary and other human-ignited wildfires.

The likelihood function, calculated over all $t = 1,\ldots,T$ observations, associated with Eqn 3 is:

$$\ln L = \sum_{t=1}^{T} \{ Y_t \ln[\exp[\mathbf{x}(t)'\mathbf{b}][\Omega + \mathbf{A}'\mathbf{Y}(t) + \mathbf{B}'\boldsymbol{\mu}_{t-k}]] - \exp[\mathbf{x}(t)'\mathbf{b}][\Omega + \mathbf{A}'\mathbf{Y}(t) + \mathbf{B}'\boldsymbol{\mu}_{t-k}] - \ln(Y_t!)\} \tag{4}$$

In total, there are three ACP models, a random-walk model, a CompStat53 model and an ensemble model, which are described in detail below, resulting in a total of six models being examined. Model parameters are separately estimated for each of the 23 tribal areas.

The ability of a predictive model of wildfires to yield benefits depends in part on its predictive skill, that is, its capacity to accurately forecast the number of wildfires occurring in a future period given information available in the current period. For the present study, we also define a successful prediction as one in which a forecast model correctly predicts whether there will be an outbreak. Given the low counts of wildfires occurring in many of the tribal units we are evaluating, we define an outbreak as a week with at least one wildfire reported for the cause we are interested in (incendiary, other human-ignited). Similarly, we define a forecast outbreak as a forecast count >0.50.[5]

One way to evaluate forecast performance is to estimate the parameters of a predictive model using a training sample and then use the estimated model to predict wildfires over a hold-out sample. Forecast skill, then, can be evaluated by comparing an estimated model with a 'null' model, which could be something simpler. In this study, we offer several measures of comparison, all calculated on the outcomes of forecasts made in the hold-out sample. These include the root-mean-squared error (RMSE), bias (defined here as the average of the actual value minus the predicted or forecast value), the mean absolute error, and the proportion of weeks correctly predicted to have at least one wildfire. A final measure we employ, which is critical to hotspot tool success, is the rate of successful outbreak forecast.

The value of a prospective hotspot model is a function of the underlying statistical model's predictive ability (whether an outbreak is successfully predicted), the costs of hotspot tool development and maintenance, the cost of redeploying resources to respond to a prospective outbreak, and the management costs and losses averted by deploying the hotspot tool, including suppression expenditures averted and the wildfire damage losses averted. We call this value the 'net benefits' of a prospective hotspot tool implementation:

$$\begin{aligned} NB_0 &= R_0 - C_0 \\ R_0 &= -\sum_{t=0}^{T} e^{-rt}[dY_t(A_t - dA_t)(S+D)] + [dA_t(Y_t)(S+D)] \\ C_0 &= I_0 + \sum_{t=1}^{T} e^{-rt}(M_t + P_t) \end{aligned} \tag{5}$$

where NB_0 is the discounted net benefit (e.g. in dollars), R_0 is the discounted benefit from averting wildfire damages due to deployment of the tool, C_0 is the discounted cost of using and reallocating resources (police or firefighting resource prepositioning) in response to the tool, r is the discount rate (fractional interest rate per unit of time), T is the number of periods over which costs and benefits are evaluated, dY_t is the change in the number of wildfires that occur in year t, A_t is the (average) area of a wildfire averted in period t, dA_t is the change in area from average due to improved wildfire response (such as through more effective resource deployment), S is the suppression expenditure per unit area of wildfire, D is the damage from wildfire per unit area of wildfire, I_0 is the initial cost of tool development, M_t is the maintenance cost of the tool, which could include gathering of data on recent wildfire occurrences and the re-estimation of predictive model parameters, and P_t is the additional cost of prevention and deterrence from use of the tool. Another way to evaluate net benefits of a tool would be to relate long-run benefits to long-run costs as a ratio, the benefit–cost ratio W_0:

$$W_0 = R_0 / C_0 \tag{6}$$

As shown in Eqn 5, benefits of a hotspot tool can derive from two possible mechanisms: a reduction in the expected number of wildfires, dY_t, which could happen owing to successful deterrence, arrest or pushing an arsonist to a less fuel-rich location; a reduction in the area burned by the typical wildfire, dA_t; and through changes in those variables, a reduction in damages (D). In the analyses reported in this study, we lacked information on how effective a prospective hotspot tool would be at reducing area burned by wildfires and therefore assumed that $dA_t = 0$, which implies $P_t = 0$, and that $A_t = \mathrm{A}$, a constant; hence, the last square-bracketed term in the second line of Eqn 5 is zero. Furthermore, in our base analyses for the purposes of this article, we also ignore wildfire damages, that is, we set $D = 0$ (although we conduct a sensitivity analysis that describes the potential impacts of accounting for damages when calculating net benefits, reported at the end of the *Results* section). Our analyses therefore only account for the effect of a change in the number of wildfires as a result of a prediction of wildfires in the coming week and, through suppression (S), quantify this in terms of the

[5]Because autoregressive models rely on using observations that immediately precede the time period being forecast, they often struggle to forecast an incident accurately when there is a preponderance of observations with a value of zero preceding that incident. For example, it is difficult for an autoregressive model to predict a wildfire outbreak when there have been long preceding periods without a wildfire. In the data being analysed, many weeks can go by without a wildfire in the spatial unit. For this reason, a single wildfire is considered an outbreak.

suppression expenditures averted. So the change is not only a function of how wildfires respond to a change in a response variable but also the success of the model in predicting that wildfires would occur: $dY_t = f(dZ, \textit{predictive success})$, where dZ is the change in the response variable and *predictive success* is the rate of correct prediction of incendiary or other human-ignited wildfires.

To model the effect of a change in wildfires, we used information on the effect of one response variable, law enforcement, whose measure of effect was obtained from Abt *et al.* (2015). In Abt *et al.* (2015), the effect of an additional full-time equivalent sworn law-enforcement officer was to reduce the occurrence of incendiary by 3.13%, which was statistically significant at the 0.05 level. The average level of these officers among the tribal land units studied was 27.9 from December 2008 through end December 2011. Hence, a one-person increase represented a 3.58% increase in the number of full-time equivalent sworn law-enforcement officers. The elasticity of the count of arson wildfires was therefore $-3.13/3.58 = -0.87$. For other human-ignited wildfires, law enforcement was statistically significant at the 0.05 level only for equipment-ignited wildfires, and its elasticity was -2.80. Equipment-ignited fires represent only ~15% of wildfires on the tribal lands, so the average share-weighted elasticity was set at -0.12. But this elasticity was allowed to vary across land units according to the share of equipment-ignited wildfires among all other human-ignited wildfires besides incendiary. The effective elasticity for other human-ignited wildfires therefore varied from 0 to -0.59.

The predictive success of a model, and the value generated by employment of that model in a forecasting context, can be improved by combining several, alternatively structured forecast models into an ensemble (Levins 1966; Armstrong 2001; Graefe *et al.* 2014). A central finding from the most recent forecasting literature (e.g. Armstrong 2001; Graefe *et al.* 2014) is that uncertainty about the data-generating process of the forecast variable is alleviated by combining multiple models. Armstrong (2001), in a study of 30 different published empirical forecasts, found that an ensemble created by equally weighting all component models generally outperforms individual component models and alternative combinations that apply unequal weights. The exception to the equal-weighting rule is when there is strong evidence to suggest that one model should perform better than others, in which case the former is given greater weight. In our study, we equally weight three alternative forecast models of the number of incendiary and other human-ignited wildfires from the various models: the ACP model without any additional covariates, the random walk and CompStat53. The simple ACP (purely autoregressive) model was chosen in part because it had lower average out-of-sample forecast RMSEs (see Tables S10 and S14 in the supplementary material, available online), compared with the weather- and the seasonality-augmented versions of the ACP. This ensemble is also evaluated in terms of its net benefits, along with those of the individual component models.

Finally, we emphasise that the models used are intended to be simple – with few data requirements – and are designed to forecast. They are not intended to make inferences about the underlying causes of incendiary or other human-ignited wildfires. Those interested in these underlying causes should examine published articles such as Abt *et al.* (2015), Prestemon and Butry (2005, 2008), Prestemon *et al.* (2010, 2012, 2013*b*) and Thomas *et al.* (2011). But it bears mentioning that the week-to-week dynamics, which are one focus of the present analysis, are not likely to be explained by information on the weekly dynamics of most socioeconomic drivers, not least because these drivers are unlikely to vary appreciably at this time scale, but also because data on the drivers identified by those other studies are not reported on a weekly basis and therefore not available to the authors of the current study. Serial and copycat firesetting, which is one social phenomenon identified by these studies, however, is captured in our statistical modelling – the autoregressive nature of fire occurrences, at least for incendiary wildfires.

Data

Data on incendiary and non-incendiary accidentally ignited (other human-ignited) wildfires were obtained from the National Wildfire Coordinating Group (2012), assigning fires according to the ignition start location and cause for each of the 23 tribal land units in the current study (Table 1). We note significant variability in the rate of incendiary and other human-ignited wildfires and substantial variability in the average costs of suppressing an average wildfire across regions. Weather and fire-weather data used in the weather data-augmented version of the ACP model were obtained for the Remote Automated Weather Stations (RAWS) recorded and made available on the National Fire and Aviation Management Web Applications website (FAMWEB) of the National Wildfire Coordinating Group (2012). These weather data were processed through software that uses all available RAWS weather station data to create an area-specific set of monthly weather and fire-weather index averages for each of the tribal units. Although many possible weather variables and fire-weather indices could be used in the analysis, we settled on four: the weekly average of the daily maximum temperature (in degrees Fahrenheit), the weekly average of the maximum daily relative humidity (in percentage humidity), the weekly maximum modified fire weather index (MFWI) (Goodrick 2002) (on a 0 to 100 scale), and the weekly maximum Keetch–Byram Drought Index (KBDI, Keetch and Byram 1968) (on a 0 to 800 scale). In all model estimates, these variables were included as 1-week lags.

Results

Statistical model estimates

A total of six models were examined, with parameters being estimated for 23 tribal areas. We estimated models that omitted the moving-average portion (i.e. all elements of $\mathbf{B}$ were assumed to be zero) of the models shown in Eqn 3 and instead estimated only autoregressive models (i.e. $\mathbf{A} \geq 0$).[6] ACP model estimates without any additional variables beyond the autoregressive terms were made by starting with up to six lags. Invariably, the

[6]Visual inspection of the correlograms of the incendiary and other human-ignited wildfire time series indicated that the autocorrelations declined in geometric progression whereas the partial autocorrelations dropped off abruptly after a two to four lags and tended to be shorter than the autocorrelations across time lags.

Table 1. Tribal units analysed and average weekly fire counts, January 1996 through April 2012

Fire data identifier	Fire data name	States included in unit	Average incendiary fires per week	Average other human fires per week	Suppression expenditures (US$ per fire)
AZFTA	Arizona Fort Apache Agency	Arizona	0.26	0.81	10 581
AZNAA	Arizona Navajo Regional Office	Arizona, New Mexico, Utah	0.42	1.17	10 581
AZPMA	Arizona Pima Agency	Arizona	2.20	1.64	10 581
AZSCA	Arizona San Carlos Agency	Arizona	2.77	3.01	10 581
CAHIA	California Hoopa Valley Tribe	California	0.28	0.41	17 416
CARVA	California Round Valley Tribe	California	0.76	0.25	17 416
CATIA	California Tule River Indian Reservation	California	0.81	0.08	17 416
MNMNA	Minnesota, Minnesota Agency	Minnesota	1.56	1.30	3683
MNRLA	Minnesota Red Lake Agency	Minnesota	0.35	5.89	3683
MTCRA	Montana Crow Agency	Montana	0.36	1.71	10 581
MTFPA	Montana Fort Peck Agency	Montana	0.35	1.77	10 581
MTRBA	Montana Rocky Boy's Agency	Montana	5.34	0.64	10 581
NDFTA	North Dakota Fort Totten Agency	North Dakota	0.62	0.22	3093
NDSRA	North Dakota Standing Rock Agency	North Dakota	0.79	2.06	3093
NDTMA	North Dakota Turtle Mountain Agency	North Dakota, Montana	0.52	2.49	3093
OKANA	Oklahoma Anadarko Agency	Oklahoma	0.27	0.71	3068
OKCHA	Oklahoma Chickasaw Agency	Oklahoma, Texas	1.61	0.75	3068
OKCNA	Oklahoma Cherokee Nation Tribe	Oklahoma	0.58	0.46	3068
OKOMA	Oklahoma Okmulgee Field Office	Oklahoma	0.69	0.41	3068
OKOSA	Oklahoma Osage Agency	Oklahoma	1.05	0.81	3068
OKTLA	Oklahoma Talihina Agency	Oklahoma, Texas	0.34	0.29	3068
SDRBA	South Dakota Rosebud Agency	South Dakota, Nebraska	0.47	3.13	3093
WIGLA	Wisconsin Great Lakes Agency	Wisconsin, Minnesota	0.00	0.66	3683

estimated models' lag structures had to be shortened to permit convergence in maximum-likelihood estimation. Progressively shorter autoregressive specifications were attempted until convergence was achieved. In nearly every case, when convergence was achieved, all included coefficients of autoregressive terms were significantly different from 1 (autoregressive terms were estimated as exponentials) at stronger than 10% significance and usually stronger than 1%. Convergence was not achieved in one tribal unit for other human-ignited wildfires: for MNRLA. In that case, counts ranged from 0 to 267 during the model estimation period (data for this unit were available from the last week in April 1996 to the end of the estimation period, the first week of October 2008). In the tables of ACP model results (available in Tables S1 through S6), the autoregressive terms are estimated as exponentials, which constrains their sign to be positive (tests of the joint significance of the autoregressive terms being zero are available in Table S7); in other words, no negative autoregressive behaviour is permitted in the data-generation process modelled with Eqn 3. The column headers call these terms $A_1, A_2, \ldots$, referring to the elements of $\mathbf{A}$ identified in Eqn 3 and indicating the parameters estimated for autoregression of first order, second order, etc. For the purely autoregressive versions of the ACP model for incendiary (Table S1) and other human-ignited wildfires (Table S2), between two and five autoregressive terms were found. The weather-augmented versions found (Tables S3 and S4) usually included the 1-week lag of maximum temperature, relative humidity and the MFWI, with the 1-week lag of KBDI less often statistically significant. Seasonal subtypes of (1) (Tables S5 and S6), which did not include the weather and fire weather indices but did include month indicator variables to account for the seasonally episodic nature of wildfires in each land unit, had month indicator variables that were highly statistically significantly different from the expected ignition rate in December (the base year). For most tribal land units, only a few month indicator variables remained in the model, corresponding typically with the fire season in the land unit. In the results in Tables S5 and S6, where no value is shown, the month indicator variable could not be estimated owing to failure of log-likelihood convergence. For the weather- and seasonally-augmented versions of the ACP models, often fewer autoregressive terms were sometimes required to achieve convergence in maximum-likelihood estimation. This lower autoregressive order implied that the weather or month indicator variables accounted for some of the autoregressivity evident in the incendiary or other human-ignited wildfire process. We contend that this result indicates that one source of autocorrelation was explained by the biophysical conditions (weather, fuels) that are likely to be similarly temporally autocorrelated.

Model fit statistics for the hold-out sample (from the second week of October 2008 to the end of December 2011) for all models evaluated in this study reveal that the ACP types typically were better at forecasting out-of-sample than the random walk or CompStat53 approaches (Tables S8 through S15). However, the ensemble of the simple ACP, the random walk and CompStat53 usually had the best fit, when considered across all fit measures. For example, the RMSE was lowest for the incendiary wildfire forecast ensemble model in 14 out of 23 cases and the second-lowest in 3 more cases. In terms of the mean absolute error, it was the lowest in only two cases (tying in

Table 2. Assumptions of the baseline net benefits calculations with prototype hotspot models
Note: the ranges shown reflect the variation across tribal units

	Incendiary assumptions	Other human fire assumptions
Elasticity of wildfire count with respect to police patrol density	−0.87	(0, −0.59)
Cost of hotspot tool development		
Initial development (US$)	50 000	50 000
Maintenance (US$ per week)	75	75
Use (US$ per week)	75	75
Time horizon of evaluation (years)	5	5
Discount rate (%)	3	3
Number of hotspots per week [min., max.]	[0.05, 0.61]	[0.03, 0.58]
Number of pre-intervention wildfires per week [min., max.]	[1.08, 8.69]	[0.75, 11.26]
Suppression expenditure (US$ per wildfire) [min., max.]	[3068, 17 416]	[3068, 17 416]
Base response rate in law-enforcement patrol density (% increase in density)	25	25
Predictive success (rate of correct non-zero wildfires forecast)	[0, 1]	[0, 1]

two others). Its success in predicting a week with at least one incendiary wildfire was intermediate in success compared with the performance with respect to the RMSE. The ability of the other human-ignited wildfire forecast models to forecast out-of-sample was not as good as for the comparable incendiary wildfire models. But typically the ensemble model had fitness statistics that were among the best or second best, comparing across models.

Net benefits estimates

Net benefits and the benefit-to-cost ratio were estimated for incendiary and other human-ignited wildfires. Estimates were made for each of the 23 tribal areas, using each of the six models. Key assumptions of the net benefits calculations (Eqns 5 and 6) are documented in Table 2. We assumed a plausible initial cost for tool development for each tribal land unit, tending towards high initial cost, at US$50 000 per model per tribal land unit.[7] In principle, all such tribal land unit models could be estimated simultaneously for the wildfire, firefighting and law-enforcement organisations concerned with such fires, which would reduce the per-land unit cost significantly. For example, dividing the cost equally among the 23 land units in our study would bring the initial cost to just over US$2000. Weekly maintenance and use costs of the models were each set at US$75 per week for both incendiary and other human-ignited wildfires, as the cost of maintaining and using such models is likely to be modest: entry of the most recent week's wildfire counts and the development of the coming week's forecast report. The time horizon for assessing the tool is set at 5 years, which is conservative; such a tool could be deployed for much longer. The discount rate, used to sum up both the future costs of model maintenance and use and the suppression expenditures avoided through deployment of law-enforcement resources, was set at 3%. (A sensitivity analysis showed that application of discount rates from 1 to 7% did not affect the benefit-to-cost ratio appreciably, because both benefits and costs would be affected by the discounting by a similar percentage, although a higher discount rate would tend to reduce the long-run net benefits in cases in which these net benefits are positive.) The number of hotspots per week (actually the number of weeks for which either incendiary wildfires or other human-ignited wildfires were non-zero) varied from 0.05 to 0.61 for incendiary and 0.03 to 0.58 for other human-ignited wildfires in the forecast period (the second week of October 2008 through to the last week of December 2011). The average count of such wildfires in weeks in which incendiary or other human-ignited wildfires were non-zero ranged from 1.08 to 8.69 for incendiary and 0.75 to 11.26 for other human-ignited wildfires in the forecast period. Suppression expenditure estimates were obtained from Abt *et al.* (2015, their table 12), and these also varied by location but not by wildfire cause: from US $3068 per wildfire for eastern Oklahoma (all tribal land units from Oklahoma in our study are assumed to be 'eastern Oklahoma' in the net benefits calculations) to $17 416 for the tribal land units in California (Table 1). The share of wildfire weeks correctly predicted out of sample for both models ranged widely, from a low of zero predicted to a high of all predicted successfully (see Table S11 for incendiary and S15 for other human-ignited wildfires). Predictive success is a key determinant of hotspot model net benefits. Across all tribal units and model types, the average rate of prediction success for incendiary wildfires was highest for the ensemble model, at 0.65, compared with the random-walk and CompStat53 approach averages of 0.54 and 0.57 respectively, with intermediate rates for the variants of the ACP models averaging ~0.58. For other human-ignited wildfires, the ensemble was similarly better, with an average rate of 0.65, whereas the random walk was 0.55, Compstat53 was 0.56, and the ACP model variants were ~0.62.

When modelling the effect of a change in law enforcement, our base assumption was that law-enforcement spatial density during the period of incendiary or non-incendiary human-ignited wildfire outbreak would be increased by 25% from base levels. The cost of this shift is not accounted for in the calculations but it is presumed to be essentially costless to the extent that during non-incendiary periods of the year, law-enforcement

[7]We do not imply here that the tribal unit would be the organisation financing the development of the hotspot tool; the tool could be financed through the Bureau of Indian Affairs or another organisation. The net benefits analysis, however, does recognise the cost of its development as being borne by the same body (e.g. the federal government) also shouldering the cost of wildfire suppression in our analysis.

Table 3. Net benefits of a prototype incendiary wildfire hotspot tool for selected Bureau of Indian Affairs tracked tribal land units in the United States
ACP, autoregressive conditional Poisson

Tribal land unit	Net benefits (US$), multi-year discounted						Average ignitions per week
	Simple ACP	Weather-augmented ACP	Seasonal-augmented ACP	Random walk	CompStat53	Ensemble	
AZFTA	−51 098	−41 206	−51 098	−33 786	−48 625	−18 948	0.17
AZNAA	−41 762	−52 394	−56 501	−25 516	−17 990	−7316	0.71
AZPMA	168 543	−35 866	98 745	303 154	243 327	333 068	0.72
AZSCA	175 586	175 586	182 119	276 843	325 838	325 838	0.78
CAHIA	1 457 404	1 457 404	1 476 455	2 114 661	2 200 390	2 286 119	1.98
CARVA	−4628	−4628	−4628	18 542	−68 344	1165	0.27
CATIA	63 587	63 587	96 767	100 914	212 895	188 011	0.28
MNMNA	−29 722	−35 322	−12 922	−10 122	23 477	23 477	0.50
MNRLA	243 584	243 584	214 527	379 180	408 236	495 405	2.51
MTCRA	−65 609	−65 609	−65 609	−55 553	−10 300	−40 469	0.14
MTFPA	−76 872	−68 022	−76 872	−72 447	−79 084	−72 447	0.07
MTRBA	87 459	87 459	77 272	158 769	296 294	235 172	0.56
NDFTA	329 834	325 593	321 353	429 482	467 645	505 809	2.63
NDSRA	−36 515	−72 302	−43 225	−25 332	−58 882	−21 977	0.51
NDTMA	17 240	10 139	6589	47 418	79 372	74 046	0.99
OKANA	62 073	67 831	63 992	138 849	150 366	176 278	1.35
OKCHA	−79 525	−79 525	−79 525	−77 976	−85 722	−77 976	0.12
OKCNA	359 201	348 215	342 722	499 269	474 551	614 619	3.43
OKOMA	675	−4561	−20 270	36 019	32 092	63 509	0.89
OKOSA	90 668	86 749	82 829	161 224	220 021	208 262	1.78
OKTLA	−15 362	−17 495	−19 627	628	−2570	29 412	0.69
SDRBA	−68 053	−69 820	−71 587	−64 519	−64 519	−48 617	0.34
WIGLA	−37 632	−35 227	−40 036	−20 801	−20 801	−13 587	0.38
Average	110 829	99 312	105 281	186 039	203 377	228 646	0.95

density could be reduced below base levels. In our simulations, we vary this assumption to examine its impacts on net benefits.

Net benefits of hotspot tool development and deployment for incendiary and other human-ignited wildfires are reported in both dollar terms and as benefit-to-cost ratios in Tables 3–6. For incendiary wildfires, net benefits are shown in Table 3 and benefit-to-cost ratios in Table 4; for other human-ignited wildfires, net benefits are reported in Table 5 and benefit-to-cost ratios in Table 6. In our case, the benefits are only suppression expenditures averted because of fewer wildfires for which suppression is applied. Clearly, there could be other benefits to averting incendiary and other human-ignited wildfires, including reduced rates of property and resource damages as well as lowered rates of losses associated with human morbidity and mortality and lost economic activity (in the case of large wildfires) – see e.g. Butry *et al.* (2001). The cost is the discounted sum of the initial tool development and the cost of annual maintenance and use. For incendiary, net benefits under the given assumptions ranged from 5-year net losses of several tens of thousands of dollars (e.g. OKCHA tribal land unit) to gains of over US$2.2 million (e.g. CAHIA). The largest gains, we note, derive from the ensemble approach to forecasting, in which forecasts of incendiary wildfire activity in the coming week were made by averaging the forecasts of the simple ACP model (no covariates besides the constant and an autoregressive term), the random walk and CompStat53. Larger gains are also evident for tribal land units with higher average rates of incendiary wildfires; in these cases, by reducing the count of incendiary wildfires through increased law enforcement, the suppression expenditures averted are larger. For incendiary wildfires, using the ensemble forecasting approach, 8 out of the 23 tribal units would experience negative net benefits from deploying an incendiary wildfire hotspot tool. A simple average across tribal units reveals the most preferred incendiary forecasting approaches. The net benefits were lowest when a weather-augmented ACP was used (US$99 312) and highest when the ensemble was used (US$228 646). These results are in line with the benefit-to-cost ratios (Table 4), in which 15 units had ratios greater than 1, while CAHIA could demonstrate a ratio of 27.67. On average across all land units, the lowest benefit–cost ratio expected was the weather-augmented ACP model (2.16) and the highest derived from the ensemble forecast model (3.67). One finding that emerges from our results on incendiary wildfire hotspot tool net benefits is that such benefits are positively related to predictive success (from Table S11). Locations with higher model predictive success tend to be those with the highest net benefits. A similar finding emerges when examining the net benefits for non-incendiary accidentally ignited wildfires.

A sensitivity analysis (results not shown) of the effect of joint model estimation for all units, which lowered the initial model development cost from US $50 000 to US$2174, resulted in 20 out of 23 tribal units having benefit-to-cost ratios exceeding 1 using the ensemble model. A sensitivity analysis that increased

Table 4. Benefit-to-cost ratio of a prototype incendiary wildfire hotspot tool for selected Bureau of Indian Affairs tracked tribal land units in the United States
ACP, autoregressive conditional Poisson

Tribal land unit	Net benefits (US$), multi-year discounted						Average ignitions per week
	Simple ACP	Weather-augmented ACP	Seasonal-augmented ACP	Random walk	CompStat53	Ensemble	
AZFTA	0.40	0.52	0.40	0.61	0.43	0.78	0.17
AZNAA	0.51	0.39	0.34	0.70	0.79	0.91	0.71
AZPMA	2.97	0.58	2.15	4.54	3.84	4.89	0.72
AZSCA	3.05	3.05	3.12	4.23	4.80	4.80	0.78
CAHIA	18.00	18.00	18.22	25.67	26.67	27.67	1.98
CARVA	0.95	0.95	0.95	1.22	0.20	1.01	0.27
CATIA	1.74	1.74	2.13	2.18	3.48	3.19	0.28
MNMNA	0.65	0.59	0.85	0.88	1.27	1.27	0.50
MNRLA	3.84	3.84	3.50	5.42	5.76	6.78	2.51
MTCRA	0.23	0.23	0.23	0.35	0.88	0.53	0.14
MTFPA	0.10	0.21	0.10	0.15	0.08	0.15	0.07
MTRBA	2.02	2.02	1.90	2.85	4.46	3.74	0.56
NDFTA	4.85	4.80	4.75	6.01	6.46	6.90	2.63
NDSRA	0.57	0.16	0.50	0.70	0.31	0.74	0.51
NDTMA	1.20	1.12	1.08	1.55	1.93	1.86	0.99
OKANA	1.72	1.79	1.75	2.62	2.75	3.06	1.35
OKCHA	0.07	0.07	0.07	0.09	0.00	0.09	0.12
OKCNA	5.19	5.06	5.00	6.82	6.54	8.17	3.43
OKOMA	1.01	0.95	0.76	1.42	1.37	1.74	0.89
OKOSA	2.06	2.01	1.97	2.88	3.57	3.43	1.78
OKTLA	0.82	0.80	0.77	1.01	0.97	1.34	0.69
SDRBA	0.21	0.19	0.16	0.25	0.25	0.43	0.34
WIGLA	0.56	0.59	0.53	0.76	0.76	0.84	0.38
Average	2.29	2.16	2.23	3.17	3.37	3.67	0.95

the change in law enforcement presence by 50% rather than 25% had the same effect using the ensemble model, increasing the number of tribal units to 20 with a benefit-to-cost ratio exceeding 1. In effect, lower costs of model development or maintenance would tend to increase net benefits. We note that, in actual cases of development and field deployment, development and deployment costs will likely differ significantly from the base assumptions of our analysis.

For other human-ignited wildfires, net benefits (Table 5) are much more modest and typically negative, and the benefit-to-cost ratios (Table 6) are accordingly smaller. Because law enforcement would be expected to have only a small effect on the number of other human-ignited wildfires, the number of other human-ignited wildfires averted would be lower and hence the suppression expenditures averted would also be lower. For these other human-ignited wildfires, 5-year discounted net benefits ranged from a loss of nearly US$86 000 (e.g. MTRBA and CATIA) to a gain of US$18 515 (OKOSA) using the ensemble model. As in the case of an incendiary wildfire hotspot tool, tribal units for which tool development and deployment would generate the highest net benefits were typically those which had higher average rates of such other human-ignited wildfires, but also those with higher proportions of equipment-ignited wildfires (assumed to be the only cause of wildfire that responds to law enforcement, as based on Abt *et al.* (2015)). Averaged across tribal land units, the ensemble model generated the highest net benefits, at −US$55 062, whereas the lowest emerged from the random-walk wildfire forecast model, −US $61 458. Benefit-to-cost ratios were generally less than 1 for other human-ignited wildfires. The highest value shown was for OKOSA (1.22 using the ensemble forecasting approach). Averaged across tribal land units, the benefit-to-cost ratio was lowest for the random walk and highest for the ensemble. Only one or two land units (depending on the forecast model) were found to have net benefits exceeding zero and benefit-to-cost ratios exceeding 1. Sensitivity analyses that, like in the case of incendiary wildfires, decreased the model development costs to US$2174 or increased the law enforcement presence to 50% had similar effects: the number of tribal units with positive net benefits and benefit-to-cost ratios exceeding 1 increased to four, five or six (depending on the forecast model) under both sensitivity analyses.

Clear from the above discussion is that the cost of model development is a primary factor working against economic arguments for tool deployment. Lower model development costs tend to improve the net benefits. As a sensitivity analysis on this assumption, we evaluated what would be the maximum cost of tool initial development needed to just achieve net benefits that are positive. Tables 7 and 8 describe those amounts for incendiary and other human-ignited wildfires respectively. Amounts that are negative reveal cases in which the hotspot tool could never yield positive net benefits, under base assumptions for other key variables (Table 2). For incendiary wildfires, the hotspot tool would be deployed with positive net benefits in all

Table 5. Net benefits of a prototype other human-ignited wildfire hotspot tool for selected Bureau of Indian Affairs tracked tribal land units in the United States

Note: 'na' indicates a model that that could not be estimated or a time series of weekly ignitions out-of-sample that contained no weeks with non-zero other human-ignited wildfires; ACP, autoregressive conditional Poisson

Tribal land unit	Net benefits (US$), multi-year discounted						Average ignitions per week
	Simple ACP	Weather-augmented ACP	Seasonal-augmented ACP	Random walk	CompStat53	Ensemble	
AZFTA	−46 567	−49 177	−51 787	−51 787	−67 449	−49 177	0.38
AZNAA	−71 828	−72 218	−75 260	−74 323	−73 734	−72 667	0.98
AZPMA	−17 309	−4826	−15 434	−29 990	−18 637	−17 309	0.98
AZSCA	−66 688	−65 174	−68 777	−67 338	−69 999	−65 760	1.61
CAHIA	−72 834	−56 391	−59 946	−65 776	−57 798	−63 628	0.19
CARVA	−81 105	−81 105	−81 105	−81 105	−84 798	−79 259	0.17
CATIA	−85 722	−85 722	−85 722	−83 636	−83 636	−83 636	0.11
MNMNA	−82 178	−81 882	−80 701	−82 178	−80 996	−80 996	1.50
MNRLA	na	na	na	−84 750	−84 804	na	3.58
MTCRA	−4789	−2178	−6015	−23 449	−1394	−8467	1.33
MTFPA	−58 327	−52 687	−56 715	−63 161	−63 967	−55 910	0.92
MTRBA	−85 722	−85 722	−85 722	−85 722	−85 722	−85 722	0.03
NDFTA	na	na	na	na	na	na	0.00
NDSRA	−42 183	−45 912	−41 095	−50 975	−46 921	−44 360	1.28
NDTMA	−78 212	−80 745	−79 031	−81 100	−80 378	−79 987	0.91
OKANA	235	12 542	8831	−9879	704	15 707	0.87
OKCHA	−61 134	−60 897	−61 857	−65 771	−68 727	−58 964	0.62
OKCNA	−65 958	−72 799	−74 700	−69 379	−68 619	−65 958	0.79
OKOMA	−64 995	−64 917	−64 995	−64 509	−68 648	−63 514	1.06
OKOSA	12 558	2034	−843	5912	7492	18 515	1.78
OKTLA	−79 745	−80 953	−79 745	−78 051	−75 312	−76 756	0.30
SDRBA	−58 330	−52 632	−58 330	−65 721	−59 598	−59 061	1.05
WIGLA	−78 765	−76 867	−77 500	−79 397	−85 089	−79 397	0.27
Average	−56 647	−56 543	−58 281	−61 458	−59 911	−55 062	0.90

cases except two (MTFPA and OKCHA) if the initial cost of tool development were no higher than US$1383 (the maximum allowed for SDRBA) using the ensemble model approach. If tool development were no higher than US$9531, then only SDRBA would drop below positive net benefits under the ensemble approach. For other human-ignited wildfires, as long as the initial cost of tool development were no more than US $823 (for AZFTA), then six tribal units would be able to deploy the hotspot tool with positive net benefits. Raising that cost to US$5640 would allow five units to still have positive net benefits. The implication of these results is that mechanisms for lowering the cost of tool development would allow wider and more beneficial deployment. This lower cost could be achieved by allowing a team of analysts to develop the models for all units simultaneously, and it could also be enabled by developing both incendiary and other human-ignited wildfire hotspot models simultaneously.

We mentioned in discussing the net benefits that the net benefits would be higher if the losses experienced by tribes that occur from wildfire damages (e.g. lost timber and structures) were included in the net benefits calculations. In our final sensitivity analysis, we modelled the effect of setting damages at US$1000 per acre ($2471 per hectare) (across all land units). Although arbitrary, this value is sufficient to describe the order of magnitude of the effect of including losses from wildfire damages. For the incendiary fires with the ensemble model, including damages at US$1000 per acre increases the average benefit-to-cost ratio from 3.67 to 6.88 and the number of units with benefit-to-cost ratios greater than 1 from 15 to 20. For non-incendiary human-ignited wildfires, the effect of including wildfire damages in the net benefits calculations is to increase the average (across all units modelled) ratios from 0.36 to 0.76 for the ensemble model. The number of units with ratios greater than 1 increased from two (OKANA and OKOSA) to five (adding AZPMA, MTCRA, NDSRA).

Conclusions

Wildland managers and law enforcement can benefit from the deployment of forecasting tools that can predict with some accuracy the number of wildfires expected in the coming planning period. In this study, we analysed several kinds of forecasting approaches that could be embedded in hotspot forecast models for incendiary and for other human-ignited wildfires. Models evaluated ranged from exceedingly simple (a random walk) to somewhat more complex (involving autoregressive terms based on historical data). We found that both incendiary and other human-ignited wildfires demonstrate temporal autocorrelation (clustering) on a weekly basis that can be used to improve forecasts over the simpler models. In a test of the benefits of ensemble forecasting, applying plausible assumptions on the costs of tool development and the effects of resource

Table 6. Benefit-to-cost ratio of a prototype other human-ignited wildfire hotspot tool for selected Bureau of Indian Affairs tracked tribal land units in the United States

Note: 'na' indicates a model that that could not be estimated or a time series of weekly ignitions out-of-sample that contained no weeks with non-zero other human-ignited wildfires; ACP, autoregressive conditional Poisson

Tribal land unit	Net benefits (US$), multi-year discounted						Average ignitions per week
	Simple ACP	Weather-augmented ACP	Seasonal-augmented ACP	Random walk	CompStat53	Ensemble	
AZFTA	0.46	0.43	0.40	0.40	0.21	0.43	0.38
AZNAA	0.16	0.16	0.12	0.13	0.14	0.15	0.98
AZPMA	0.80	0.94	0.82	0.65	0.78	0.80	0.98
AZSCA	0.22	0.24	0.20	0.21	0.18	0.23	1.61
CAHIA	0.15	0.34	0.30	0.23	0.33	0.26	0.19
CARVA	0.05	0.05	0.05	0.05	0.01	0.08	0.17
CATIA	0.00	0.00	0.00	0.02	0.02	0.02	0.11
MNMNA	0.04	0.04	0.06	0.04	0.06	0.06	1.50
MNRLA	na	na	na	0.01	0.01	na	3.58
MTCRA	0.94	0.97	0.93	0.73	0.98	0.90	1.33
MTFPA	0.32	0.39	0.34	0.26	0.25	0.35	0.92
MTRBA	0.00	0.00	0.00	0.00	0.00	0.00	0.03
NDFTA	na	na	na	na	na	na	0.00
NDSRA	0.51	0.46	0.52	0.41	0.45	0.48	1.28
NDTMA	0.09	0.06	0.08	0.05	0.06	0.07	0.91
OKANA	1.00	1.15	1.10	0.88	1.01	1.18	0.87
OKCHA	0.29	0.29	0.28	0.23	0.20	0.31	0.62
OKCNA	0.23	0.15	0.13	0.19	0.20	0.23	0.79
OKOMA	0.24	0.24	0.24	0.25	0.20	0.26	1.06
OKOSA	1.15	1.02	0.99	1.07	1.09	1.22	1.78
OKTLA	0.07	0.06	0.07	0.09	0.12	0.10	0.30
SDRBA	0.32	0.39	0.32	0.23	0.30	0.31	1.05
WIGLA	0.08	0.10	0.10	0.07	0.01	0.07	0.27
Average	0.34	0.34	0.32	0.28	0.30	0.36	0.90

Table 7. Prototype incendiary wildfire hotspot tool maximum development costs needed to ensure that net benefits are non-negative, for selected Bureau of Indian Affairs tracked tribal land units in the United States

ACP, autoregressive conditional Poisson

Tribal land unit	US$					
	Simple ACP	Weather augmented ACP	Seasonal augmented ACP	Random walk	CompStat53	Ensemble
AZFTA	−1098	8794	−1098	16 214	1375	31 052
AZNAA	838	−2394	−6501	24 484	32 010	42 684
AZPMA	218 543	14 134	148 745	353 154	293 327	383 068
AZSCA	225 586	225 586	232 119	326 843	375 838	375 838
CAHIA	1 507 404	1 507 404	1 526 455	2 164 661	2 250 390	2 336 119
CARVA	45 372	45 372	45 372	68 542	−18 344	51 165
CATIA	113 587	113 587	146 767	150 914	262 895	238 011
MNMNA	20 278	14 678	37 078	39 878	73 477	73 477
MNRLA	293 584	293 584	264 527	429 180	458 236	545 405
MTCRA	−15 609	−15 609	−15 609	−5553	39 700	9531
MTFPA	−26 872	−18 022	−26 872	−22 447	−29 084	−22 447
MTRBA	137 459	137 459	127 272	208 769	346 294	285 172
NDFTA	379 834	375 593	371 353	479 482	517 645	555 809
NDSRA	13 485	−22 302	6775	24 668	−8882	28 023
NDTMA	67 240	60 139	56 589	97 418	129 372	124 046
OKANA	112 073	117 831	113 992	188 849	200 366	226 278
OKCHA	−29 525	−29 525	−29 525	−27 976	−35 722	−27 976
OKCNA	409 201	398 215	392 722	549 269	524 551	664 619
OKOMA	50 675	45 439	29 730	86 019	82 092	113 509
OKOSA	140 668	136 749	132 829	211 224	270 021	258 262
OKTLA	34 638	32 505	30 373	50 628	47 430	79 412
SDRBA	−18 053	−19 820	−21 587	−14 519	−14 519	1383
WIGLA	12 368	14 773	9964	29 199	29 199	36 413

Table 8. Prototype other human-ignited wildfire hotspot tool maximum development costs needed to ensure that net benefits are non-negative, for selected Bureau of Indian Affairs tracked tribal land units in the United States

Tribal land unit	US$					
	Simple ACP	Weather augmented ACP	Seasonal augmented ACP	Random walk	CompStat53	Ensemble
AZFTA	3433	823	−1787	−1787	−17449	823
AZNAA	−21 828	−22 218	−25 260	−24 323	−23 734	−22 667
AZPMA	32 691	45 174	34 566	20 010	31 363	32 691
AZSCA	−16 688	−15 174	−18 777	−17 338	−19 999	−15 760
CAHIA	−22 834	−6391	−9946	−15 776	−7798	−13 628
CARVA	−31 105	−3 1105	−31 105	−31 105	−34 798	−29 259
CATIA	na	na	na	−33 636	−33 636	−33 636
MNMNA	−32 178	−31 882	−30 701	−32 178	−30 996	−30 996
MNRLA	na	na	na	−34 750	−34 804	na
MTCRA	45 211	47 822	43 985	26 551	48 606	41 533
MTFPA	−8 327	−2 687	−6 715	−13 161	−13 967	−5 910
MTRBA	na	na	−35 722	na	−35 722	na
NDFTA	na	na	na	na	na	na
NDSRA	7 817	4 088	8 905	−975	30 79	5 640
NDTMA	−28 212	−30 745	−29 031	−31 100	−30 378	−29 987
OKANA	50 235	62 542	58 831	40 121	50 704	65 707
OKCHA	−11 134	−10 897	−11 857	−15 771	−18 727	−8 964
OKCNA	−15 958	−22 799	−24 700	−19 379	−18 619	−15 958
OKOMA	−14 995	−14 917	−14 995	−14 509	−18 648	−13 514
OKOSA	62 558	52 034	49 157	55 912	57 492	68 515
OKTLA	−29 745	−30 953	−29 745	−28 051	−25 312	−26 756
SDRBA	−8 330	−2 632	−8 330	−15 721	−9 598	−9 061
WIGLA	−28 765	−26 867	−27 500	−29 397	−35 089	−29 397

reallocations motivated by tool deployment, we also showed that such an ensemble model can outperform the individual models that form the ensemble in the context of hotspot tool net benefits. Although gains of the ensemble compared with individual models were, on average, modest, there were in our study tribal land units for which the gains were calculated to be substantial, particularly for incendiary wildfires. Moreover, simply deploying a hotspot forecasting model based on any of the individual or ensemble forecasting models would generate positive net benefits in terms of suppression expenditures averted. In some cases, the discounted benefits under this narrow category of concern over a 5-year time horizon were calculated to be nearly 28 times their discounted assumed tool deployment costs. But overall, we find, under our base assumptions for costs and the effects of law enforcement, that a hotspot tool designed to motivate reallocation of law enforcement resources is unlikely to yield positive net benefits for non-incendiary human-ignited wildfires, primarily because of the weak response of such wildfires to law enforcement. Responses of these wildfire types, however, have been shown to be more significant when it comes to other forms of wildfire prevention (e.g. Abt *et al.* 2015), and use of such a forecasting tool to respond in short order to non-incendiary human wildfire outbreaks with greater prevention education efforts might yield more cases of positive net benefits.

As well, our analysis of incendiary and other human-ignited wildfire hotspot forecast models would have found higher net benefits had we assumed that such tools were jointly developed, reducing their initial cost, and had we included the damages caused by incendiary and other human-ignited wildfires. Sensitivity analyses on such costs and inclusion of damage losses indicated that such accounting could be important for judging their economic net benefits. Although it is apparent that agency administrators, working with nearly fixed budgets, care most about averting expenditures on suppression, policy-makers often care about more than agency costs – including the rare occurrence of large and damaging wildfires that require evacuations and extended efforts to extinguish. As Butry *et al.* (2001) found, the majority of the sum of suppression expenditures and economic losses from such wildfires is in the economic loss category.

Similarly, the net benefits of a tool could be higher if one effect of the tool were to reduce the area burned by the wildfires that occur, if fire suppression resources were to be deployed such that response times were shorter. Butry (2009) demonstrated the effectiveness of shrinking response times at reducing the area burned – and possibly also therefore suppression expenditures as well as wildfire damages.

Significant questions remain, however, about the value of such tools for incendiary wildfire and other human-ignited wildfire forecasting and response. For example, we assumed in this study that the number of wildfires expected each year is not affected by past success by law enforcement to reduce wildfire occurrence. If part of the success in reducing wildfire occurrences through increased law enforcement effort is achieved through arrests and convictions of firesetters, for example, and these firesetters before arrest demonstrate serial or copycat behaviours, then removing them from the landscape should result in lower numbers of future incendiary wildfires (e.g. Prestemon *et al.* 2012). Furthermore, if stepped-up law enforcement is part of a broader effort to prevent other human-ignited wildfires through educational efforts (e.g. Abt *et al.* 2015; Prestemon *et al.* 2010), then also the number of future wildfires would be lower. These lower numbers of wildfires would tend to reduce the net benefits of tool deployment.

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