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Near-term probabilistic forecast of significant wildfire events for the Western United States

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Abstract. Fire danger and potential for large fires in the United States (US) is currently indicated via several forecasted qualitative indices. However, landscape-level quantitative forecasts of the probability of a large fire are currently lacking. In this study, we present a framework for forecasting large fire occurrence – an extreme value event – and evaluating measures of uncertainties that do not rely on distributional assumptions. The statistical model presented here incorporates qualitative fire danger indices along with other location and seasonal specific explanatory variables to produce maps of forecasted probability of an ignition becoming a large fire, as well as numbers of large fires with measures of uncertainties. As an example, 6 years of fire occurrence data from the Western US were used to study the utility of two fire danger indices: the 7-Day Significant Fire Potential Outlook issued by Predictive Services in the US and the National Fire Danger Rating's Energy Release Component. This exercise highlights the potential utility of the quantitative risk index as a real-time decision support tool that can enhance managers' abilities to discriminate among planning areas in terms of the likelihood and range of expected significant fire events. The approach is applicable wherever there are archived historical data from both observed fires and fire danger indices.

Additional keywords: 7-Day Significant Fire Potential Outlook, Energy Release Component, extreme value, fire probability, forecasting significant fires, Predictive Services.

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Introduction

Wildland fire activity varies significantly across geographic space and time (Littell *et al.* 2009). This is true even at the scale of the western contiguous United States (US), where the majority of the country's wildfire and related suppression activity occurs. Wildfire activity in the Western US has a pre-monsoon-related early season signature in the South-west (April–June), followed by a less defined season of fire activity in the summer and autumn (broadly, July–October, although this varies by location) in most other western areas, coincident with hot and dry weather, cured fuels and, potentially, electrical storms (Malamud *et al.* 2005). Regions such as Southern California may experience wildfires in any month of the year. With this geographic variability in a typical year comes extensive variability between years, which can be aggravated by regional weather phenomena such as the El Niño Southern Oscillation (Barbero *et al.* 2015; Swetnam and Betancourt 1990). This stochastic nature of wildfire occurrence challenges fire managers' efforts to efficiently pre-position and allocate suppression resources ahead of anticipated significant fires.

In the US, an additional management consideration is the need for beneficial fire in the landscape. A full suppression response is dictated in many fire situations due to the proximity of fire to values and human populations. Successful fire containment resulting from effective initial attack ultimately minimises losses in the near term. Long-term effects, however, include the increased potential for extreme fire behaviour and a simultaneous reduction in the suppression effectiveness for future wildfires, particularly in forested ecosystems common in the Western US (Arno and Brown 1991; Stephens and Ruth 2005). This wildfire paradox, described first by Arno and Brown (1991) and discussed most recently by Calkin *et al.* (2015), complicates efficient resource allocation and pre-positioning decisions under an already variable system of suppression demand. Under the current system, the interagency wildfire community in the US relies in large part on fire potential forecasts to allocate suppression resources across the country, including directing resources where they are needed most during periods of concurrent demand and anticipating future needs resulting from emerging and predicted wildfire activity.

In 2015, US federal agencies spent US$2.13 billion on wildfire suppression (https://www.nifc.gov/fireInfo/fireInfo_documents/SuppCosts.pdf). Despite this level of investment, the system that currently guides decisions about countrywide resource allocations to new or existing fires relies largely on managerial experience using mental heuristics and a range of potentially disparate forecasts and information systems. Given the scale of wildland fire consequences and the level of interagency wildland fire activity, there is interest in exploring more formal decision support mechanisms that may improve the efficiency of these resource allocation activities.

Currently, the movement of suppression resources to support existing and predicted wildland fire in the US is coordinated, in part, through interagency efforts organised among 10 distributed Geographic Coordinating Areas, typically referred to as GACCs (Geographic Area Coordination Center) (Fig. S1, available as online supplementary material). Further up the chain of command, the National Interagency Coordination Center (NICC) located in Boise, Idaho, oversees national resource allocation and directs movement of resources between GACCs. Following the 2000 fire season when concurrent and persistent fire activity led to significant resource scarcity (NICC 2001), the Predictive Services program was formed. This program was developed specifically to enhance decision making capabilities related to the allocation of fire suppression resources by successfully forecasting anticipated critical fire events through the integration of climate, weather, fuels, fire danger, situation and resource availability information (Predictive Services 2009). Each GACC employs meteorologists with skills related to fire weather forecasting. GACCs are subdivided into Predictive Services Areas (PSAs), which vary widely in size, ranging from thousands to hundreds of thousands of square kilometres (Fig. S1). PSAs represent geographic areas of similar climate based on statistical correlation of observed weather and fuel moisture data, and some PSA boundaries also reflect political or land ownership considerations.

With the variability in fire occurrence comes great spatial variability in demographic and environmental characteristics between PSAs (Table 1). Some of the largest PSAs include remote areas characterised by fuel types more conducive to lower-intensity fires and with lower relative values at risk from fire effects. Wildfires in these PSAs may burn an extensive land area in a short amount of time, but containment may involve fewer local resources using existing fuel breaks, particularly given relatively accessible terrain. In contrast, a vastly smaller PSA with different characteristics affecting suppression capabilities may in turn see more wildfires that escape containment efforts, potentially requiring mobilisation of additional resources from outside the PSA or even the GACC. For example, consider two adjacent PSAs in the North-west: NW05 and NW10 (Fig. S1). NW05 is much smaller and is characterised by extensive federal wild lands, widespread timber fuels, and generally highly variable and inaccessible terrain. In contrast, NW10 is significantly larger, yet has little federal wild lands, is predominately grass and non-burnable fuels, and is generally more accessible in terms of both terrain and road access.

Table 1. List of the explanatory variables included in the final models
All variables are at the Predictive Services Area (PSA) level

Variable	Unit	Acronym	Source	Description
Area	m^2	psaarea	Predictive Services	Area of a PSA, based on annual PSA boundaries
Population count	No. of people m^{-2}	ppop	LandScan™ (Bright and Coleman *et al.* 2012)	Mean ambient population count summed by PSA
Wildland–urban interface/intermix (WUI) area	m^2		SILVIS (SILVIS Laboratory 2012)	Total land area designated as WUI
Federal land area	m^2		WFDSS (Noonan-Wright *et al.* 2011)	Total federal land area
Protected land area	m^2		WFDSS (Noonan-Wright *et al.* 2011)	Total area designated as Federal Wilderness, Inventoried Roadless, or Wild and Scenic
Terrain slope variability	mean percentage slope		USGS National Elevation Dataset 1/3 arc second digital elevation model (Gesch *et al.* 2002; Gesch 2007)	Mean relief of slope, described by using a large moving window to calculate $slope_{max} - slope_{min}$ (Ruszkiczay-Rüdiger *et al.* 2009)
Evacuation travel time	mean h	evtime	WFDSS (Fisher and Kirsch)	Mean ground transport time from a point on the landscape to a hospital
Fuel type	m^2		LANDFIRE 2010 (US Geological Survey 2013)	Area by majority fuel type (grass/shrub/timber/slash) based on Anderson's (1982) fire behaviour fuel models
Fire regime	m^2	fr1, …, fr5	LANDFIRE 2010 (US Geological Survey 2013)	Area in each fire regime condition class by PSA
Energy Release Component	percentile mean	ERC	Matt Jolly, US Forest Service	Daily mean ERC percentile
Predictive services risk category		fcast1, fcast2 …, fcast7	Brad Quayle, US Forest Service	Daily forecast values 1–5, described in Fig. 1, plus a sixth category (NA) for missing values, for the next 7 days

Both PSAs may have fires that warrant consideration for suppression actions; however, fires in NW05 may be inherently more difficult to suppress due to inaccessibility and the fuels involved. Therefore, pre-positioning efforts will benefit most from accurate forecasts for PSAs that tend to predict challenging fires and also potentially warrant extra protection from unwanted damages from fire based on the values threatened.

One of the most important and relevant data sources for the existing resource distribution process is a Predictive Services forecast product called the 7-Day Significant Fire Potential Outlook (SFPO). Predictive Services issues the 7-Day SFPO on weekdays during the core fire season for individual PSAs within each GACC across the nation (Predictive Services 2009). Predictive Services defines 'significant fire potential' as 'the likelihood that a wildland fire event will require mobilisation of additional resources from outside the area in which the fire situation originates' (NICC 2015). The 'area' in this definition is purposefully vague, and can refer to either the individual PSA or the entire GACC, depending on the level of resource allocation intelligence needed (C. Maxwell, pers. comm., 13 May 2016). Each GACC issues 7-Day SFPO forecasts for its own PSAs and has reliably done so since 2007. The meteorologists in each GACC have the latitude to develop and implement variations on the forecast methods to incorporate regional differences in weather and fire regime. In some GACCs, the forecast methods have changed over time, reflecting attempts to improve forecast performance. Because of these regional variations inherent in calculation of the 7-Day SFPO, it is not a homogenous product for the continental US.

The SFPO widely affects decisions concerning allocation and pre-positioning of firefighting resources at both regional (GACC) and national levels. At the GACC level, Predictive Services forecasts may prompt fire managers to move firefighting resources within the GACC ahead of anticipated fire activity. Pre-positioning resources can be costly, so this tends to occur only when the forecast calls for high likelihood of a significant fire event (Terry Marsha, pers. comm., 5 May 2014). The 7-Day SFPO is used to help inform resource allocation decisions across GACC boundaries during times of elevated national preparedness due to high fire activity and associated resource scarcity; however, the current approach is fairly subjective: although it balances existing fire activity and risks, socio-political considerations and forecasted weather, it does not provide forecasts of the expected number of significant events.

It is generally accepted that fires are most easily contained if suppression resources are used at the very earliest stages following ignition, and most models of initial attack are based on this premise (e.g. Fried and Fried 1996; Fried *et al.* 2006). In the US, ~97% of federal fires are contained within the first operational period (Tidwell 2012; US Department of Interior Wildland Fire Management 2012), yet the 3% of fires that escape containment efforts account for the majority of federal suppression expenditures. Given growing fire expenditure in the US (https://www.nifc.gov/fireInfo/fireInfo_documents/SuppCosts.pdf, accessed 8 September 2016), there is great value in accurate fire activity forecasts that enable effective resource pre-positioning. Further, accurate forecasts should enhance managers' abilities to utilise beneficial fire in their management decisions because they may facilitate effective management of longer-duration events by providing greater foresight into anticipated levels of future fire activity and potentially competing resource demands.

This study presents a statistical framework that can be used to assess the utility of fire danger indices and to produce landscape-level quantitative forecasts for expected number of significant fire events with corresponding uncertainties. As an example, data from the Western US were used to develop the models. The fire danger indices studied here are the qualitative 7-Day SFPO and the gridded Energy Release Component for fuel model G (ERC). The specific concerns of this study are to (1) assess the skill of SFPO values in estimating probability and expected number of significant fire events; (2) assess the utility of gridded ERC in estimating probability and expected number of significant fire events when used alone or in combination with 7-Day SFPO forecasts; (3) produce a risk index for significant fire events based on a probability model that includes ERC, seasonal fire occurrence patterns and PSA characteristics (e.g. topography, demography, fuel regime); (4) quantify observed variabilities around the probabilistic risk index; and (5) estimate the efficacy of near-term SFPO forecasts (upcoming week) in predicting expected distributions of the number of significant fire events. The ultimate aim of the study is to demonstrate how to develop and estimate a statistical model for forecasting an extreme value event – in this case the expected number of significant fires – and to evaluate measures of uncertainties that do not rely on distributional assumptions. This enhancement of the decision support tool for wildland fire managers can be developed wherever there is archived historical data on both observed fires and fire danger indices.

Methods

We restricted our study area to the GACCs in the Western US, where large wildfires are most common. These GACCs include the North-west, Northern Rockies, California North Ops, California South Ops, Western Great Basin, Eastern Great Basin, South-west and Rocky Mountain (Fig. S1). Our study period was constrained to 2007–2012 by data availability of the SFPO. Reliable 7-Day SFPO were first issued in 2007 and at the time of this study, the Fire Occurrence Database (FOD; Short 2014) was available through 2012. Data used in the statistical models were not restricted to the fire season; instead, seasonal patterns in fire occurrence were incorporated and estimated explicitly, as will be seen below. All reported fires in the FOD were included in the study. Fires of all sizes are included in the FOD.

Data

To assess the date and location of historical fires, we utilised the national all-lands FOD, which provided ignition location, ignition cause (natural *v* human-caused) and final fire size for wildfire ignitions in the US (Short 2014). Fire ignition locations were intersected with annual PSA boundaries in ArcGIS 10.1 to obtain total number of fires by ignition cause on a given day within each PSA. This approach accounted for any annual changes in PSA boundaries. We summarised the ignitions by wildfire cause to categorise lightning-caused fires separately from those fires ignited by campfires, children and fireworks, which were flagged as recreation-caused events. A third category of fires encompassed those caused by equipment use and of unknown cause; these were classified as human-caused (not related to recreation). The final fire size was used to assess whether a fire reached the size designated as 'significant' for each PSA. 'Significant fires' are defined by Predictive Services as those larger than a threshold size, which varies both geographically – based on historical fire sizes – and by potential effects on highly valued resources (Tim Mathewson, pers. comm.) (Fig. S2).

To explore the use of demographic and environmental characteristics as potential explanatory variables in our model, we summarised geospatial data from several demographic and environmental factors by PSA; specifically, human populations, wildland–urban interface or intermix (WUI) area, federal land area, protected land area, terrain slope variability, fuel type and fire regime (Table 1). Human population data were obtained from LandScan^{TM} (Bright *et al.* 2012). Ambient population count data were summed by PSA, then divided by total land area to provide a general, relative metric of human population density between PSAs. Total land area classified as WUI (SILVIS Laboratory 2012) and as federal land (geospatial data obtained via WFDSS, Noonan-Wright *et al.* 2011) were each divided by total PSA area to provide relative densities, each of which may require a higher level of federal resource response to control new ignitions.

Landscape accessibility affects the ability of ground resources to respond quickly to new ignitions, and the Western US has extensive, inaccessible land areas free from roads and human developments. Wildfires in these areas may dictate a different level of response than new ignitions in less-remote areas (e.g. those threatening WUI areas). As a potential metric for remoteness and inaccessibility, we summarised percentage of land area classified as Federal Wilderness, Inventoried Roadless, and Wild and Scenic Areas within each PSA. Next we calculated a landscape texture metric that provides a measure of terrain slope variability, derived from $\text{slope}_{max} - \text{slope}_{min}$, calculated for a moving window that is 6 grid cells high and 6 grid cells wide, using a 1/3-arc-second digital elevation model (Ruszkiczay-Rüdiger *et al.* 2009) and then summarised by the mean value by PSA. We also quantified remoteness by summarising a hospital evacuation travel time geospatial product that estimates ground transport time according to walking speeds when travelling off-road and driving speeds on roads based on posted speed limits, from every point in the continental US to a hospital (http://wfdss.usgs.gov/wfdss_help/WFDSSHelp_Est_Grd_Medevac_Time.html, accessed 7 September 2016). Finally, because fuel characteristics influence fire behaviour, we summarised total PSA area by LANDFIRE fuel type (grass, shrub, timber, slash and non-burnable) and fire regime category (US Geological Survey 2013). We obtained geospatial information for each PSA described in Table 1; however, because the borders of some of the PSA regions changed over the course of the study, the quantities for predictors listed in Table 1 sometimes changed for a given PSA over the years included in the study.

In addition, we obtained archived daily forecasted SFPO values for the upcoming week (fcast1, …, fcast7) from Predictive Services for each PSA and day. The 7-Day SFPO forecast may take on any one of nine categorical values, which we grouped into five categories (Fig. 1) for reasons explained below. Of the nine forecast levels, levels 1, 2, and 3 are based on fuel dryness alone, and are usually estimated by a combination of indices including ERC, 10- or 100-h time lag fuel moisture or Burning Index, depending on the GACC and PSA. The rest of the forecast values (4–9) are related to conditions with increased likelihood of natural fire ignitions (lightning) and human-caused ignitions (high recreation – i.e. increased levels of outdoor recreation) or a more favourable burn environment (windy, unstable, hot and dry, or dry). These forecasts represent a 'high risk' alert, and are issued only when the meteorologist assesses the outright probability of a new large fire as ≥20% (NICC 2015). These values appear much more rarely, and are triggered by the weather forecast information and thresholds that are unique to each GACC. For example, the North-west GACC currently uses empirical regression equations between the predicted amount of lightning, fuel dryness and the predicted number of fire starts, to decide when to issue an SFPO forecast of 4 (lightning ignition trigger). They rarely use the other high risk forecast values because the required '20 percent probability of a

	Forecast value	Forecast description	Fire environment
Increasing fuel dryness	1	Moist fuel conditions	Little or no risk of large fire
	2	Dry fuel conditions	Low risk of large fire
	3	Very dry fuel conditions	Low–moderate risk of large fire
High risk	4 (8)	Lightning (High recreation)	Ignition trigger
	5 6 7 9	Windy Unstable Hot and dry Dry	Critical burn environment factor

Fig. 1. US Predictive Services' Significant Fire Potential Outlook (SFPO) forecast categories grouped into five major levels of risk. SFPO level 8 had only eight cases in our study; therefore, it was not used in our analysis.

large fire' threshold is virtually never attained for any event other than a lightning event. Other GACCs issue burn environment and ignition trigger forecast values based on the expert opinion of the meteorologist, and in some cases, the meteorologist will factor in the scarcity of available firefighting resources. Aside from the fuel dryness measures (values 1–3), the forecast values are not ordinal; for example, a value of '9' does not indicate higher significant fire potential than an '8'.

In a preliminary analysis, we used the nine categories separately (Fig. 1). However, we found that not all categories were significantly different from each other. Further, some of the forecast categories included very few cases (e.g. category 8 [recreation ignitions] had only eight observed cases); therefore, our final models use the five groups shown by the blocked colours in Fig. 1, plus an additional category (NA) for days with no forecast issued. The three dryness levels remained as separate categories (1, 2 and 3). We also combined the four forecast levels associated with critical burn environment (5, 6, 7 and 9).

Further, we used a gridded surface weather climatology of temperature, relative humidity and precipitation that was derived by downscaling a combination of the North American Land Data Assimilation System (NLDAS-2) and monthly gridded precipitation from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Abatzoglou 2013). This dataset provides daily measures of 2-m maximum and minimum temperature, 2-m maximum and minimum relative humidity, total daily surface precipitation and 10-m wind speed at 4-km resolution across the continental US from 1979 to 2012. These gridded daily weather values are then combined to calculate the ERC of the US National Fire Danger Rating System (Bradshaw *et al.* 1983). To ensure that ERC values are comparable between locations, we constrained calculations to a single fuel model (model G) that has been demonstrated to have a strong relationship with the occurrence of large fires (Andrews *et al.* 2003; Riley *et al.* 2013; Freeborn *et al.* 2015). ERC is a metric of the potential energy released at the head of a spreading fire (National Wildfire Coordination Group Fire Danger Working Team 2002) and it is used throughout the US as a seasonal indicator of dryness that can be a strong indicator of fire potential (Andrews *et al.* 2003; Jolly *et al.* 2015).

The location and discovery date of each fire in the FOD was used to look up the corresponding ERC value in the gridded dataset described above. The ERC value was then converted to a percentile for that pixel using all days during the study period (e.g., if 105 was the highest value recorded at that pixel, the percentile value would be 100). ERC percentile is more strongly related to large fire occurrence than is the raw ERC value (Riley *et al.* 2013).

Statistical methods

Estimation

Our concern is the estimation of the expected number of significant fire events, π, in a given voxel, where the voxel unit is per PSA, per day. The number of significant fires is a rare stochastic event, and its distribution is highly skewed with most of the values equal to zero (Fig. 2). To account for the latter we used a two-step estimation procedure. In the first step we estimated the probability, P, of the binary variables indicating the occurrence of at least one ignition in a given voxel. Next we estimated the expected number of significant fires, π_c, conditional on the outcome that at least one ignition has occurred. Finally, the expected number of significant fires is evaluated as

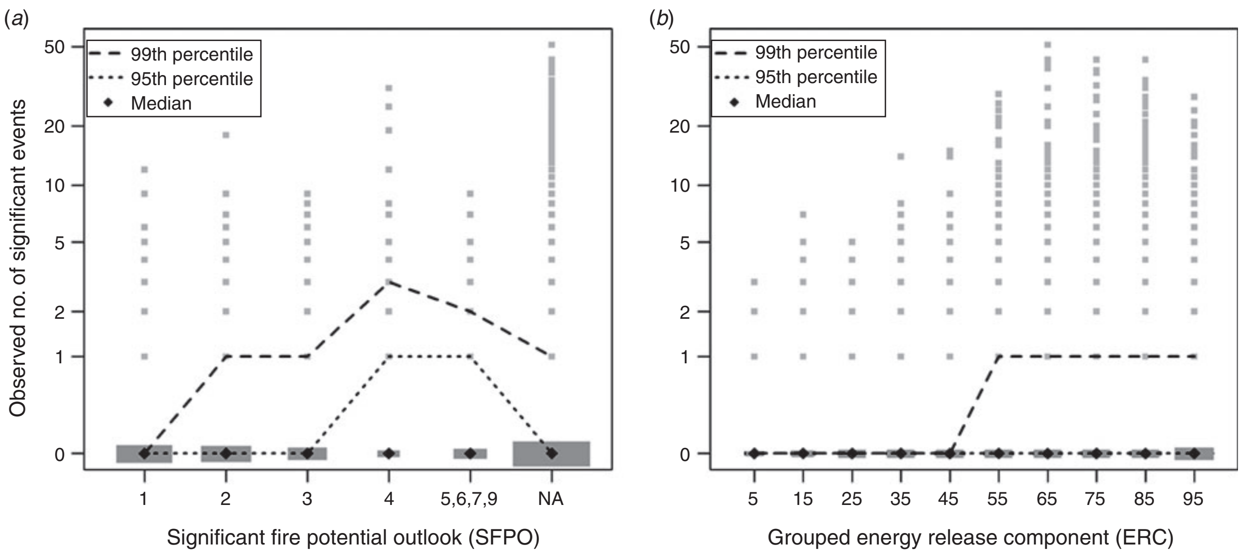

Fig. 2. Boxplots of observed number of significant events per Predictive Services Area (PSA) per day (*a*) for each of the Predictive Services' Significant Fire Potential Outlook (SFPO) groups in Fig. 1 and (*b*) for Energy Release Component (ERC) percentile levels (0–100) grouped into 10 cells of size (or width) 10% each. The sizes of the boxes at zero on the *y*-axis are proportional to the number of observations in each group. The NA category of SFPO (*a*) corresponds to days with no recorded SFPO forecast. The distribution of number of significant events at each group level is highly skewed (median in each case is zero), with the majority of the observations (>95% in most groups) equal to zero. Outliers are represented by grey dots.

the product $P \times \pi_c$. The probability of at least one significant event was evaluated as follows. Let:

p_i = probability of at least one lightning-caused fire in a given voxel

p_r = probability of at least one recreation-caused fire in a given voxel

p_h = probability of at least one human-caused fire, other than recreation, in a given voxel

π_c = expected number of significant fire events in a voxel given at least one ignition. This is the conditional expectation.

Then:

$$1 - P = \Pr[\textit{no ignition in a PSA on a given date}]$$
$$= (1 - p_i)(1 - p_r)(1 - p_h)$$

Finally the unconditional expected number of significant events, π, is evaluated by:

$$\pi = P \times \pi_c$$

We also estimate the conditional probability, p_c, of a significant fire event given ignition.

The probabilities p_i, p_r, p_h and p_c listed above were modelled as a function of the explanatory variables using a logistic regression with the logit line (log-odds) given by:

$$\log\left\{\frac{p}{1-p}\right\} = \mu_o + \sum_{J=1}^{J} s(X_j) + s_g(day) + \mu_k + s(erc) \quad (1)$$

where, p is one of the four probabilities p_i, p_r, p_h or p_c and the term $p/(1\text{-}p)$ is the odds of the corresponding significant event.

The conditional expectation for number of significant fire events was modelled using Poisson regression with the linear predictor:

$$\log(\pi_c) = \mu_o + \sum_{j=1}^{J} s(X_j) + s_g(day) + \mu_k + s(erc) \quad (2)$$

Data from all PSAs and all days were used to estimate the ignition probabilities using Eqn 1. Data from all days and PSAs with at least one ignition were used to estimate the Poisson regression in Eqn 2. Differences in PSA size and other characteristics were handled by including these variables as explanatories, as described below.

In both Eqns 1 and 2, the term μ_0 is the overall intercept of the linear predictor and $s()$ are smooth functions to be estimated from the data. The variables X_j, $j = 1, \ldots$, J are the 10 explanatory variables accounting for the characteristics of a given PSA (Table 1). Note the fire-regime-model variable consists of five variables. The variable *day* is day-in-year. The term $s_g(day)$ was included in the model to account for potentially different seasonal variations in each GACC not accounted for by ERC; examples of this may include lightning frequency patterns, regional nature of wildfire activity and resource demands. The subscript g indicates that a different smooth function will be estimated for each of the eight GACCs in our study area. The categorical variable, μ_k, $k = 1, \ldots, 6$, represents the change in the overall intercept for each of the five SFPO categories in Fig. 1. A sixth category was included for days with missing SFPO forecasts (NA). Finally, $s(erc)$ is the change in the log-odds (for Eqn 1) and, for Eqn 2, the change in the logarithm of expected number of significant events, with increasing values of ERC. The first three terms on the right-hand side of Eqn 1 or 2 give an estimate of the norm for a given voxel (year-invariant), and the last two terms are the expected changes in the 'norm' for a particular PSA $\times$ date with its corresponding SFPO forecast level and ERC value respectively (dynamic).

The utility of each variable in the regression equations, including the SFPO forecasts and ERC, was assessed by studying the significance and level of the contribution each variable makes to the corresponding linear predictor.

Probability-based risk index

We created an index of risk by grouping the predicted number of significant fire events in the upcoming week. For this part of our study we did not include the SFPO forecasts in Eqns 1 and 2 for reasons described below. We used the observed ERC for day 1 to evaluate the regression equation for 2–7 days ahead. In other words, we assumed persistence of the day-1 ERC value for days 2–7. Because we are using ERC for fuel model G, this will be a reasonable assumption most of the time, as there is a strong lag in fuel moisture based on previous days.

Next, we summed the expected number of events, π, for the 7 days in the upcoming week to arrive at $S = \sum_{i=1}^{7} \pi_i$. The sum, S, was then grouped into six categories of increasing S values to arrive at the following six risk levels, [0–0.1), [0.1–0.5), [0.5–1), [1–3), [3 –10), $\geq$ 10. Parallel boxplots of the historic observed number of significant events in the upcoming week provide estimates of the median, range and other percentiles of expected values at each of the six risk levels. These are the empirical percentiles from the data. In addition to providing the range of expected values, the boxplots demonstrate the skill of the overall model in predicting fire risk. The empirical distribution as a non-parametric estimate of the distribution of the extreme value random variable – number of significant events – may be improved with the addition of more years of fire occurrence data.

Model goodness of fit

We produced a reliability diagram (predicted *v* observed probability of significant event given ignition) to evaluate the overall goodness of fit of the conditional probability, given ignition. Estimates of the conditional probabilities were evaluated using Eqn 1 without the categorical variable, μ_k, that is, without the SFPO values. The reliability diagram was produced by grouping the estimated probability values into seven levels, then producing parallel boxplots of the observed fraction of cases, per GACC, per year, for each of the probability groups. By presenting the empirical distributions (boxplots), rather than the observed means for each probability group (i.e., commonly used reliability diagrams), we are able to provide the expected variability in addition to the median at each predicted group level. We produced a similar graph for the overall goodness of fit of the forecasted number of significant events in the upcoming

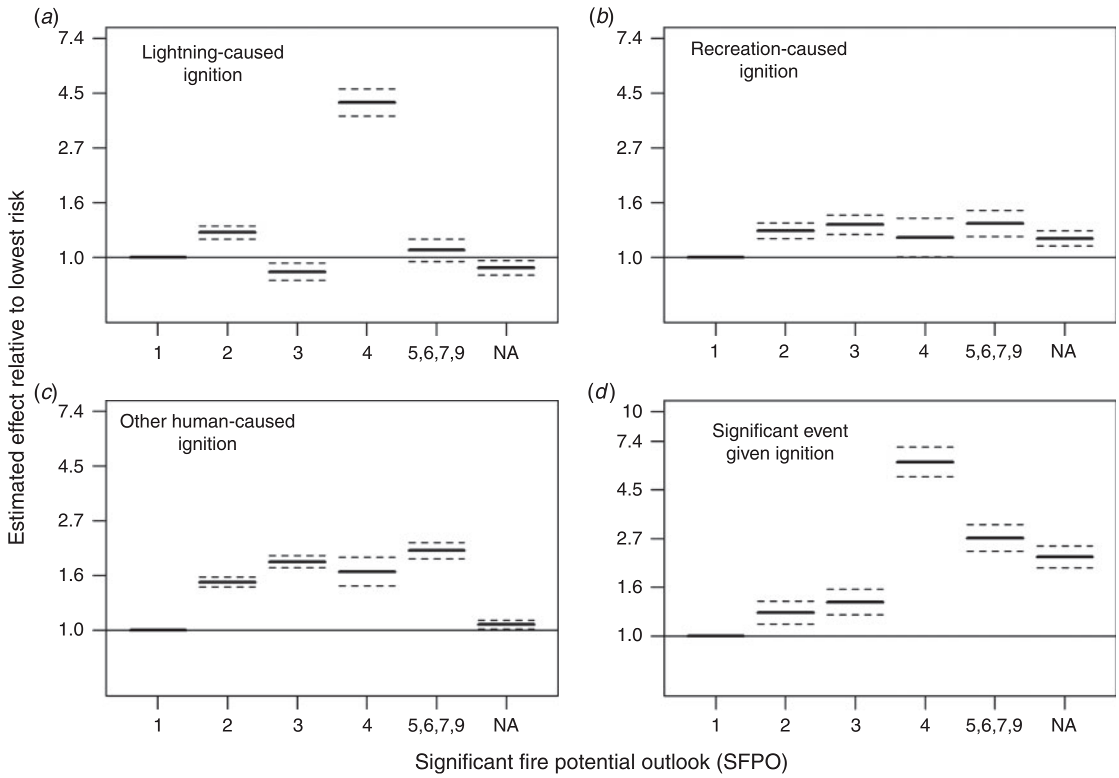

Fig. 3. Odds of a (*a*) lightning-caused ignition; (*b*) human recreation-caused ignition; (*c*) other human-caused ignition, relative to odds at lowest risk (odds ratio), estimated by the logistic regression in Eqn 1. For example, the odds of a lightning-caused ignition is ~4.1 times larger on days with forecast level {4} (lightning) relative to days with forecast level {1} (moist fuel conditions). (*d*) Ratio of number of significant events, given ignition, relative to number at lowest risk, estimated by the log-linear regression in Eqn 2. Dashed lines are the approximate 95% confidence limits for the estimated effects. 'NA' – not available.

week by grouping the forecasted values into the six risk groups listed above, and then producing parallel boxplots of the observed number of significant events for each of the predicted groups (risk levels).

Forecast maps

The above framework allows the production of daily maps of risk for significant events and present the amount of variability to be expected at each of the risk levels. Additionally, maps based on the conditional probability of a significant event, p_c, provide estimates of the risk of an ignition becoming a significant fire, which might also be of interest.

Results

Skill of individual explanatory variables

The skill of the SFPO index issued on the morning of the forecast (fcast1) in predicting occurrence of a fire and of the number of significant fires is demonstrated (Fig. 3) by the increase in the odds of a significant fire relative to the odds on days with low risk (fcast1 = {1}, corresponding to 'moist fuel conditions'). By using the odds generated by the logistic regression model in Eqn 1, we were able to study the skill of the fcast1 variable after controlling for spatial and seasonal differences between PSAs. For example, on days with fcast1 = {4} ('lightning ignition trigger'), the odds of a lightning-caused fire were 4.1 times larger (95% CL, 3.6–4.6) than the odds when fcast1 = {1}. However, as expected, on days with fcast1 other than {4} the odds of a lightning fire were similar to those for low risk days (fcast1 = {1}). For human-caused ignitions (other than recreation), the odds were highest when the fcast1 category was {5,6,7,9}, indicating a critical burn environment, with an estimated odds twice that for days with no risk. Finally, given at least one ignition in a voxel, the expected number of significant fires was ~6.0 times higher (95% CL, 5.0–7.0) for fcast1 categories {4} than for days with low risk. The results for the SFPO forecast given 7 days in advance (fcast7) are similar to those for fcast1 but with larger uncertainty levels (Fig. S3).

The gridded daily ERC values used in our study also had a significant effect on the probability and number of significant fires (Fig. 4). ERC levels seemed to have the largest effect on human-caused ignitions, with the odds of an ignition increasing ~1.5-fold for every 20-point increase in the ERC percentiles (Fig. 4*b*, 4*c*). The effect of ERC on the expected number of significant fire events was also significant with an estimated 1.5-fold increase in the number of significant fires for every 20-point increase for values of ERC <70 and a marginally smaller effect (estimated 1.2-fold increase) for ERC values >70.

The estimated odds of a significant event for some of the other explanatory variables, in particular those pertaining to the static characteristics of a given PSA, describe the effect of each variable after controlling for all other explanatories in the model

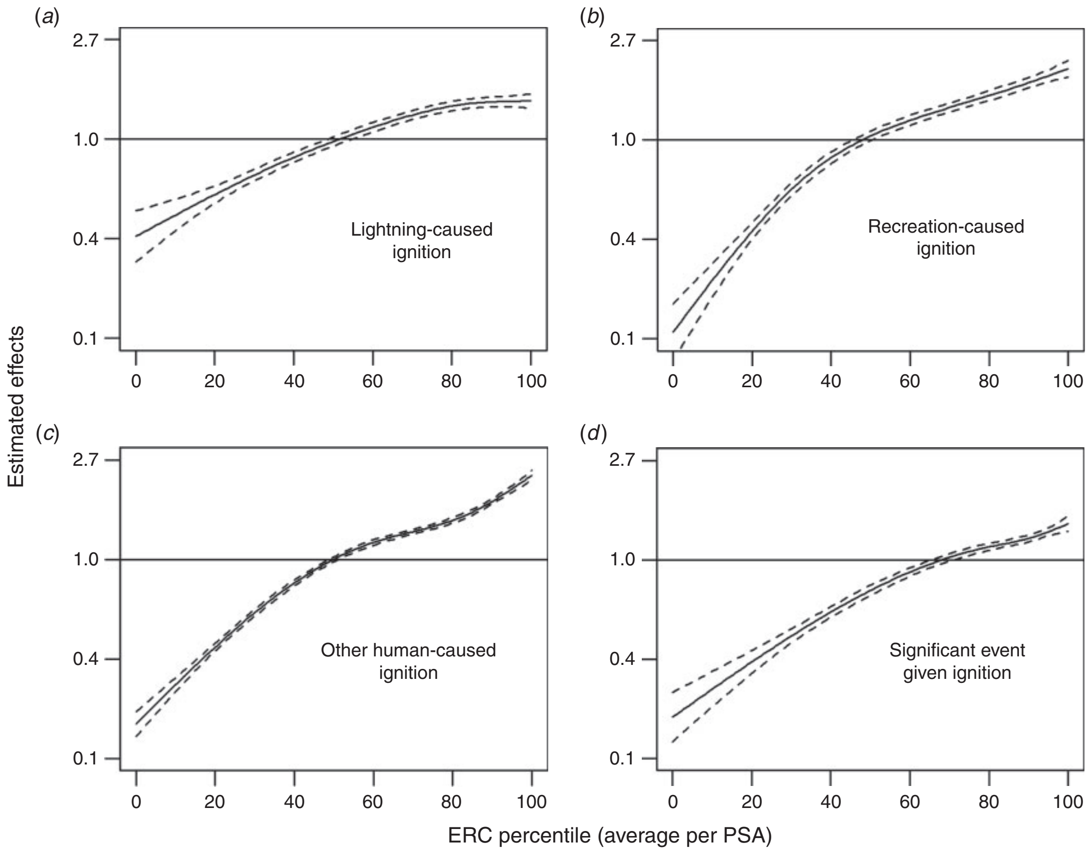

Fig. 4. Odds of a (*a*) lightning-caused ignition; (*b*) human recreation-caused ignition; (*c*) other human-caused ignition, relative to odds at average Energy Release Component (ERC) percentile (58%) over all voxels, estimated by the logistic regression in Eqn 1. (*d*) Estimated ratio of number of significant events, given ignition, relative to number at average ERC percentile (73%) over all voxels with at least one ignition. Dashed lines are the approximate point-wise 95% confidence bounds of the estimated effect.

(Fig. S4–S6). Note, for example, the evacuation time metric had no significant effect on the probability of lightning-caused ignitions (Fig. S4), as would be expected. It also had no significant effect on human recreation-caused fires (probably due to the very small sample size). However, we see a significant decrease in the number of human-caused ignitions with increasing evacuation time, which is probably an indication that remote areas are less likely to have many human visitors. The effect of the evacuation time metric is highly significant for the expected number of significant fires given at least one ignition. This is probably due to the fact that the evacuation time spatial data accurately depict areas in the landscape that are difficult to quickly access; this would likely correlate with a delayed discovery of and initial response to new ignitions, thereby increasing the likelihood that the fire will escape initial containment efforts and become a significant event, requiring mobilisation of additional suppression forces. Estimated effects of day-in-year (Figs S5 and S6) for each GACC demonstrate differences in the seasonal patterns of human-caused and lightning-caused ignitions that are not explained by the time-varying fire danger indices already in the model (i.e., ERC and fcast). The focus of the present study was developing a statistical framework for forecasting fire risk. Therefore, although further discussion of the skills of each of the explanatory variables in our model is of interest, we leave this to future work.

Model uncertainties and goodness of fit

The reliability diagram for the conditional probability of a significant fire, given ignition, demonstrated the skill of the model and the expected variability in each of the predicted groups (Fig. 5*a*). The variability is seen to increase with increasing levels of risk. One reason for the increase in variability is that the number of cases in the larger risk groups is smaller; however, the increase in variability manly indicates a decrease in model skill at the higher risk levels. Similarly, the variability in the observed number of significant events at each risk level was larger at the higher predicted risk levels (Fig. 5*b*). Here we note that, historically, more than 20% of cases in the four highest risk levels had at least one significant fire event in the upcoming week. In the fifth risk category [3–10), 50% of the cases were observed to have at least one significant fire and 20% had more than three.

Analysis of outliers

Another way to assess model fit is to study the residuals. However, given the skewed nature of our random variable, with the majority of values equal to zero, only the positive residuals are of interest, except possibly for the highest risk level (Fig. 5*b*). Consequently, as a further indicator of the skill of the models, we conducted a study of the outliers (i.e., large positive residuals) in

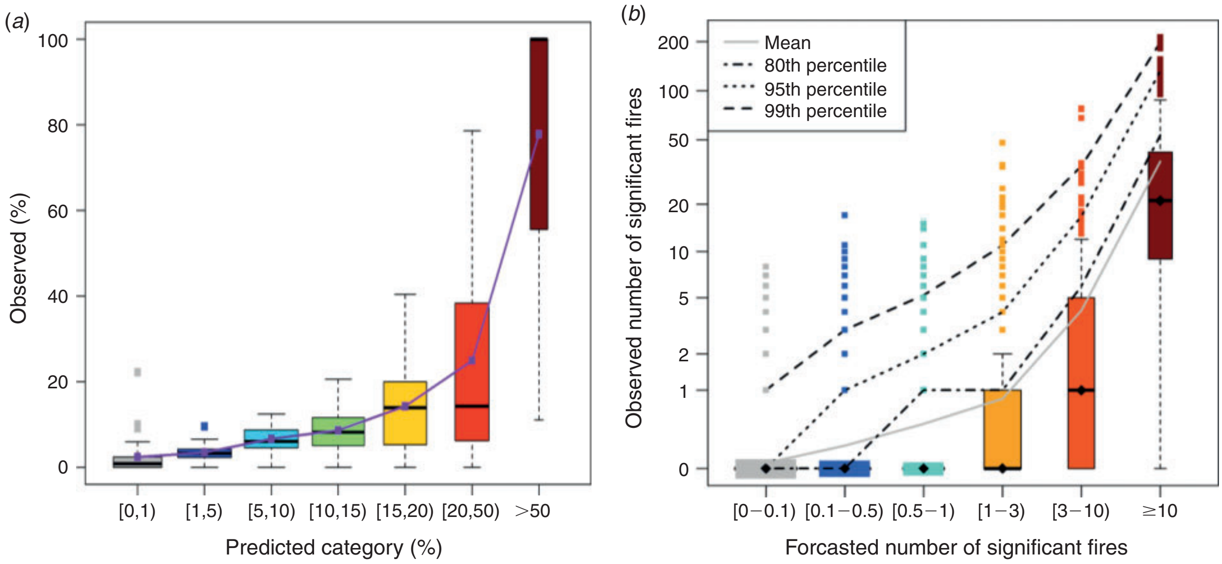

Fig. 5. (*a*) Reliability diagram for conditional probability of at least one significant fire in a given Predictive Services Area (PSA) × day, superimposed with parallel boxplots of the distribution of observed fraction of cases at each risk level. (*b*) Observed *v* predicted number of significant fires in the upcoming week superimposed with parallel boxplots of the empirical distributions (boxplots) and select percentiles of the distributions for each risk level.

Table 2. Number and percentage of outliers (larger than expected number of significant events) in each of the probabilistic risk categories for predicting number of significant events in upcoming week (Fig. 5*b*)

Probabilistic risk category	[0–0.1)	[0.1–0.5)	[0.5–1)	[1–3)	[3–10)	≥10
Number of outliers	1660	1971	651	187	72	69
Total number cases	54382	16040	3081	1315	385	283
Probability of outlier	0.031	0.123	0.211	0.142	0.187	0.244

the predictions of number of significant events. Here outliers are defined as any case with an observed number larger than that predicted by 1.5 times the interquartile range. The outliers were between 3 and 24% of the cases in each of the risk groups (Table 2). Outliers as large as 5–10 significant events are observed in the lowest risk level where the median prediction is zero fires (Fig. 5*b*). These are particularly troublesome because on those days managers will be expecting low or no fire activity, as the forecast predicts a <1% chance of one significant event. A map of the frequency of outliers per PSA (Fig. S7) demonstrates the spatial variability in the skill of the forecasts. Although the probability of an outlier was larger in some PSAs than others, there was no apparent spatial pattern. Almost 60% of the variation in the frequency of outliers between PSAs seem to be 'explained' by lightning-caused fires. However, overall, the number of outliers attributed to lightning fires was only marginally larger (57%) than those attributed to non-lightning fires (43%). Therefore, although most of the spatial differences in model skill may be due to the occurrence of lightning episodes, there remain a large number of outliers (43%) that cannot be explained by lightning phenomena. The exception was the California North Ops GACC, where all the outliers occurred in 2008, coincident with an anomalous dry lightning event in late June that resulted in over 1500 new ignitions (Wallmann *et al.* 2010).

Table 3. Probability of an outlier (1.5 times larger than expected interquartile range for the number of significant events) at the various levels of the Significant Fire Potential Outlook (SFPO) forecast

The overall probability of an outlier was 0.06. The SFPO levels in this table are the maximum forecasted level in the upcoming week, where level {4} is assumed to be larger than level {5,6,7,9}

SFPO level[A]	{1}	{2}	{3}	{4}	{5,6,7,9}
Probability of outlier	0.03	0.09	0.17	0.28	0.16

[A]See Table 1 for definitions of SFPO levels.

Finally, we analysed the outliers as a function of the SFPO forecasts. Note that SFPO was not included in the models that produced the probabilistic risk levels in Fig. 5. Overall, outliers comprised 6% of the total cases, as estimated by the statistical model not including SFPO values. However, when outliers where grouped according to SFPO values, we note that during weeks with an SFPO forecast of level {4}, the probability of an outlier (i.e., a larger than expected number of significant events using our model) was 28% (Table 3) with corresponding values of 17% and 16% for SFPO levels of {3} and {5,6,7,9}.

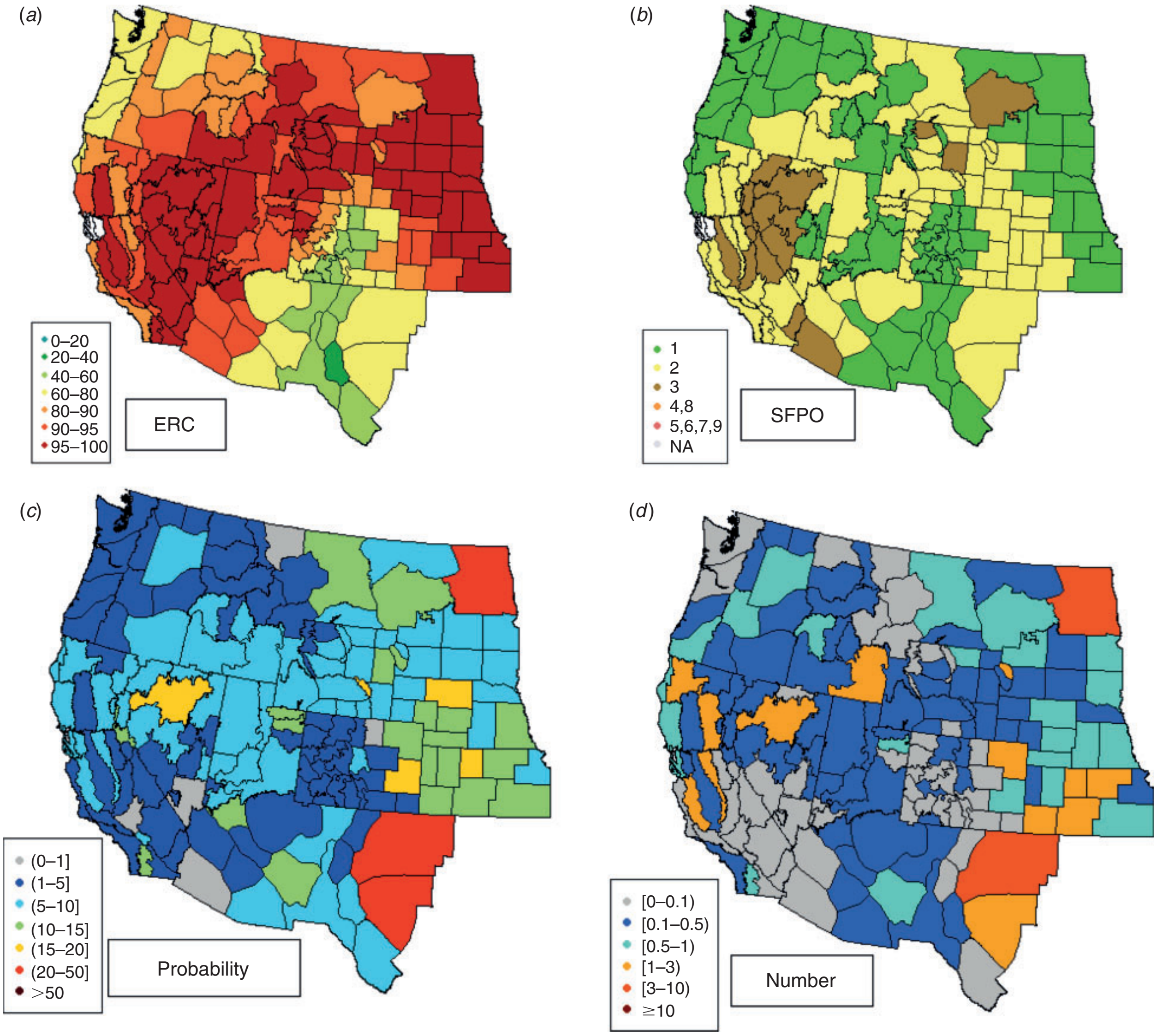

Fig. 6. Maps of average Energy Release Component (ERC) value (*a*) and Predictive Services Significant Fire Potential Outlook (SFPO) (*b*) issued on the morning of 18 July 2012. Maps of conditional probability of a significant fire given ignition for 18 July 2012 (*c*) and the expected number of significant fires per Predictive Services Area (PSA) for the week starting 18 July 2012 (*d*). The maps in (*c*) and (*d*) should be used in conjunction with the boxplots in Fig. 5. For example, PSAs with an orange forecast for expected number of significant fires ([1–5)) are estimated to have a >20% chance of having at least one significant fire in the current week. (For colour figure, see online version available at http://www.publish.csiro.au/nid/17.htm.)

Maps of probabilistic risk forecasts

The models described above may be used to produce daily maps of probability of a significant fire event and maps of expected number of significant events in the upcoming week. As an example, we produced maps for 18 July 2012 (Fig. 6). The parallel boxplots in Fig. 5 give the empirical distributions at each of the risk levels. Matching the colours in the map with the corresponding boxplots gives the expected level of uncertainty for each of the forecast levels. For example, the observed conditional probability of an ignition becoming a significant event was ~14% on average in the [15, 20) (orange) category and the variability around this average over various years and GACCs ranged between 0 and 40%, with an interquartile range of 6–20% (Fig. 5 left panel). For the expected number of significant events for 18 July 2012, we note that PSAs with a red forecast should expect a >50% chance of having at least one significant fire and a 20% chance of at least five significant fires, based on the historic empirical distribution of events (Fig. 5 right-hand panel).

Conclusions

Predictive Services meteorologists are leaders in providing innovative fire weather and wildfire potential forecasts. In the US, fire managers and suppression personnel at all levels utilise their products. At the individual firefighter level, knowledge of anticipated weather events related to fire behaviour increases personal situational awareness and enhances decision making abilities and safety. At the managerial level, this same information can minimise losses from unwanted fires by facilitating effective pre-positioning of suppression forces in areas where significant fires – those that exceed the response capacity of local resources – are most likely to occur. Managers may also use forecast information to aid in informed decision making related to opportunities to utilise beneficial fire to achieve land management objectives. Despite the wide use of the Predictive Services 7-Day SFPO in the US, our work represents the first significant effort to correlate forecast levels from all PSAs in the Western US with historical fire occurrence. In this study, we quantified the utility of the 7-Day SFPO for predicting wildland fires by estimating the change in odds of a significant fire for each of the Predictive Services forecast levels, after accounting for spatial and temporal differences between PSAs. We found the odds of a lightning-caused fire were about four times larger than normal on days when the SFPO indicated an ‘ignition trigger’ (forecast level {4}). Also, the number of ignitions resulting in a significant event was 2.7 and 6.0 times higher than normal on days when the SFPO forecast was one of the ‘high risk’ categories (forecast level {5, 6, 7, 9} and {4} respectively). The ERC fire danger index also was shown to have a significant effect on probabilities of ignition, with the odds of an ignition increasing ~1.5-fold for every 20-point increase in ERC. The expected number of ignitions becoming a significant fire event also increased by ~1.5 for every 20-point increase in ERC for ERC values less than the average, and by a marginally smaller amount (~1.2-fold) for ERC values greater than the average.

Although the 7-Day SFPO forecasts were shown to have utility with respect to predicting ignitions and significant fires, the probability-based risk index developed in this paper may enhance the value of fire forecasts by providing a risk index that combines many of the fire drivers, including time of year, size of PSA, and other spatial and temporal characteristics. Additionally, the probability-based index can be used to produce daily large fire risk maps for the upcoming week that include ranges of the expected values (Figs 5 and 6). Such maps are useful for managers charged with making resource allocation decisions at the PSA, GACC or west-wide scales, particularly during times of resource scarcity. The expectation and uncertainty associated with the number of ignitions and significant fire events provides considerably more information than the current categorical output from the 7-Day SFPO. The probabilistic risk index presented here can provide additional information needed to discriminate among PSAs in terms of the likelihood and range of expected significant fire events, enhancing pre-positioning decisions. Timely initial response to new ignitions that prevent future significant fires may then free up resources to manage long-duration events where beneficial fire to meet land management objectives is encouraged.

Future work includes updating and possibly improving the probability-based indices presented here as more years of forecast and fire occurrence data become available. Additionally, incorporation of other common gridded fire danger indices, such as Burning Index, could be assessed to determine whether these additions improve model performance. Finally, future work will aim to tie these probability-based indices into current efforts to model suppression resource movement and mobility across the US, with the ultimate goal of working towards improved efficiency in fire management.

Developing improved decision support systems to inform the distribution of suppression resources across the US will require a firm understanding of the information needs and the environment in which decisions are made. Further, research to align Predictive Services products with improved decision support systems could have significant payoffs in terms of improved suppression resource distribution reducing potential wildfire losses by directing resources to where they are needed most, simultaneously reducing management costs by improving the efficiency of resource movement.

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