Continental-scale simulation of burn probabilities, flame lengths, and fire size distribution for the United States

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Abstract

Components of a quantitative risk assessment were produced by simulation of burn probabilities and fire behavior variation for 134 fire planning units (FPUs) across the continental U.S. The system uses fire growth simulation of ignitions modeled from relationships between large fire occurrence and the fire danger index Energy Release Component (ERC). Simulations of 10,000-50,000 years were performed using artificial weather sequences generated by time-series analysis of recorded ERC values at local weather stations. Also needed were monthly distributions of wind speed and direction, as well as spatial data on fuel and topography. Fire suppression was represented by a model of the probability of fire containment by suppression forces, based on fire growth rates, days since ignition, and fuel type. Simulated values of burn probability generally fell within a factor of three of observed values. At the pixel level, burn probabilities vary markedly based on differences in fuels, weather, and topography. The slope of the frequency-magnitude distribution of simulated fire sizes was compared to historic records in each region, demonstrating that the model produced fire size distributions similar to historic patterns. Because model parameters included only a limited suite of weather, fuel, and suppression variables, this result is interpreted to mean that observed fire size distributions are a function of the joint distributions of spatial opportunities for fires to grow to different sizes (dependent on fuels and ignition location) and temporal variability in the length of weather sequences conducive to fire growth. A contribution of this research is the practical aspect of performing fire simulations at national scales for operational planning and ecological research.

Keywords: fire simulation, fire risk assessment

1. Introduction

A national assessment of wildfire risk provides a consistent method for understanding and comparing threats to highly valued resources and for planning management activities that mitigate those risks. In this article we present a system that

employs fire growth simulation for estimating the probability of wildfire for the entire continental U.S. on a 270m grid and evaluate its performance compared to historical records.

The simulation system focuses on large fires since they are responsible for the majority of area burned, and thus heavily influence burn probabilities (Podur, Martell *et al.* 2009; Strauss, Bednar *et al.* 1989). We use the term "large" in a general way to refer to fires that escape initial attack. The probability of an area burning depends on its proximity to ignitions as well as the spatial and temporal processes that promote and restrict fire spread across a landscape. Among these processes are suppression efforts, which presumably have reduced burn probabilities during the past century (Littell, McKenzie *et al.* 2009) compared to previous centuries (Stephens, Martin *et al.* 2007). Burn probabilities vary across several orders of magnitude in the continental U.S. due to variation in vegetation, climate, and human activities (Parisien and Moritz 2009; Schmidt, Menakis *et al.* 2002; Schroeder and Buck 1970). This variability in fuels, weather, and topography, as well as different suppression responses and the rarity of large fire events, contributes to difficulty in risk modeling. The large-fire simulation system presented here accounts for spatial and temporal variation in weather and fuel moisture, and is capable of running tens of thousands of years of simulations in order to capture rare fire events.

2. Methods

The modules of the large-fire simulator, called FSim, are described in this section. The modules include weather generation, fire ignitions, fire suppression, and fire growth.

Weather Generation. Due to the paucity of large fires in our short modern record and the brief length of weather records which typically extend over only 10-50 years for most weather stations, a practical method was needed for generating artificial weather sequences with the same statistical properties as current weather records. This simulated weather stream enables generation of thousands of years of daily weather scenarios in order to produce moderately stable and repeatable estimates of burn probability. Weather data were obtained from National Fire Danger Rating System (NFDRS) Remote Automated Weather Stations (RAWS) located throughout the U.S. (Zachariasson, Zeller *et al.* 2003) (www.fs.fed.us/raws).

The continental U.S. is divided into 134 Fire Planning Units (FPUs), and a single weather station which represented local conditions was chosen for each unit. The environmental and weather variables required for fire behaviour calculations (Rothermel 1972) consist of wind speed, wind direction, and fuel moistures by percentage of dry weight for six fuel categories. Live fuels consist of two components, woody and herbaceous, while dead fuels are divided by size into four time-lag classes: 1 hr, 10 hr, 100 hr, and 1000 hr, with these numbers signifying the amount of time it takes for fuels in these classes to asymptotically approach equilibrium in fuel moisture under steady conditions (Fosberg and Deeming 1971). Fuel moisture for these six categories is calculated from daily weather records: temperature, humidity, solar radiation, and precipitation (Andrews 1986; Deeming, Burgan *et al.* 1977; Fosberg and Deeming 1971). We used the fire danger rating index the Energy Release Component (ERC) of the U.S. National Fire Danger Rating System

(NFDRS) as a proxy for the influence of fuel moisture on fire behaviour, as it reflects daily, seasonal, and regional variability for different fire climates of the U.S. (Andrews, Loftsgaarden *et al.* 2003) (Figure 1).

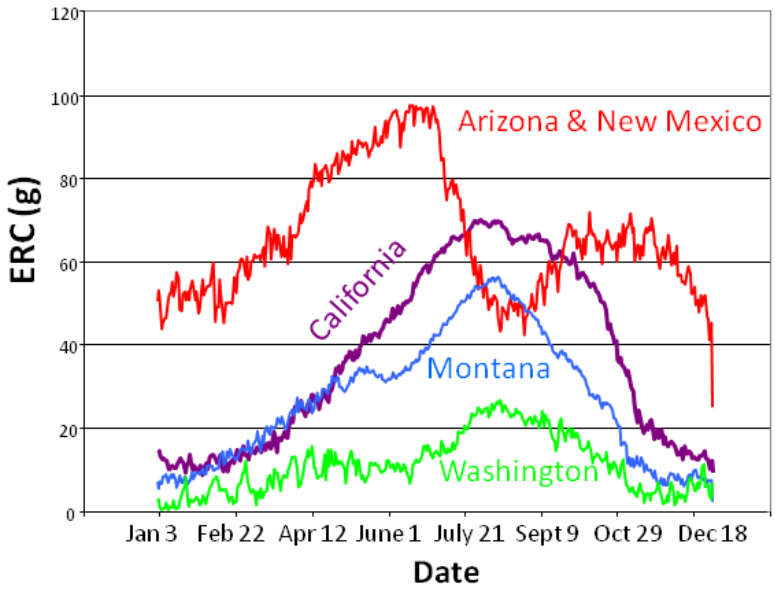

Figure 1. The average daily value of the Energy Release Component (ERC) for four weather stations in different climate regions of the western United States, demonstrating how ERC captures trends in timing, duration, and amplitude of seasonal moisture trends. Higher ERCs correspond to lower fuel moistures.

Time series analysis was used to model seasonal and annual variability in fuel moisture using ERC as a proxy. The weather generation module captures: 1) the historic trend in ERC throughout the year, using a polynomial fitted to daily values over the period of record, 2) daily standard deviations in ERC, and 3) the mean temporal autocorrelation in ERC values, which captures how an ERC value is dependent on the values of the preceding days. ERC exhibits strong autocorrelation due to the time lag of larger woody fuels such as the 100-hr and 1000-hr categories, which take 4-40 days to equilibrate (Fosberg and Deeming 1971). Using the three time-series components above, thousands of years of artificial ERC sequences were generated as inputs to fire ignition and fire growth modelling. Statistical methods are detailed in Finney *et al.* (In review).

Fuel moistures were then derived from ERC values using look-up tables created for each of the 134 weather stations using the average historic fuel moisture content for each ERC percentile range. Because FSim was designed to simulate only large fires, which typically burn under extreme weather conditions, ERC categories were set at the 80th, 90th, and 97th percentiles.

Variability in winds was characterized by joint probability distributions of speed and direction during the afternoon active burning hours for each month of the year. LFSim randomly sampled these monthly distributions to create the daily wind speed and direction used for fire behaviour simulation. This method assumes wind probabilities are uncorrelated with fuel moistures and random from day to day.

Included in each artificial “year” of weather data, therefore, were 365 daily ERC values based on historic trend and variability, wind speed, wind direction, and the fuel moisture values based on the simulated ERC trend. In order to estimate burn probabilities in

areas with infrequent fire, which can have fire recurrences of more than 500 years, the simulation used 10,000-50,000 years of simulated weather streams.

Large fire ignitions. The relationship of historic large fire ignitions with ERC was characterized by logistic regression for each FPU (Andrews, Loftsgaarden *et al.* 2003; Martell, Otukul *et al.* 1987; Preisler, Brillinger *et al.* 2004) (Figure 2a). This logistic regression models the probability of at least one large fire starting on a particular day, given the ERC. The threshold for determining what is a large fire is somewhat subjective, and was assigned to each FPU based on historic fire sizes, vegetation, and topography. Based on the simulated ERC for each day, FSim makes a random draw from the probability distribution determined by the logistic regression, and if there is at least one large fire start, a second draw is made from the empirical distribution of the number of historic large fire starts per day for each FPU. Figure 2b shows the empirical distribution of fire starts for a sample FPU. It is most common to have only one large fire start on a given day, but in the case of large lightning storms, 20 or more large fires may start in an FPU on one day. The location of fire ignitions was determined randomly. However, future versions of FSim will have spatially driven ignitions weighted toward locations with higher historic large fire occurrence.

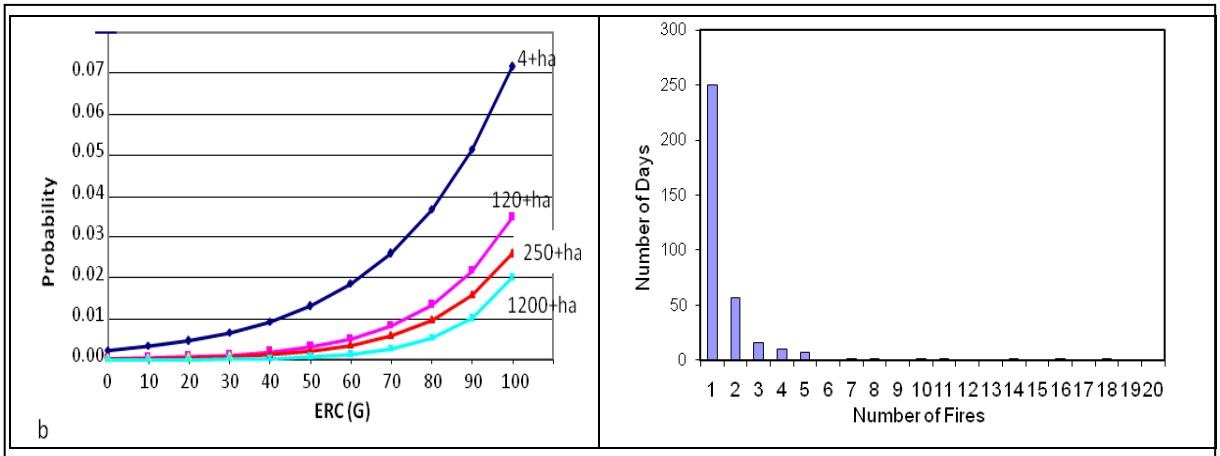

Figure 2. Examples of (a) logistic regression predicting the probability of at least one large fire starting on a given day as a function of ERC, with functions plotted for four different minimum fire sizes (fires greater than 4 ha, >120 ha, >250 ha, and >1200 ha), and (b) an empirical distribution function derived from observed fire starts. The x-axis indicates the number of large fires starting on a given day, and the y-axis indicates the number of times this occurred in the historic record.

Fire suppression. The effect of fire suppression efforts on large fire size is not well understood, but was represented in this system by a statistical model of containment based on large fire records from 2000-2005 (Finney, Grenfell *et al.* 2009). Probability of containment is higher: 1) in non-forested fuels, 2) during periods of slow growth, and 3) with increasing fire duration. Fires are terminated stochastically based on these containment probabilities.

Fire growth and behavior. FSim starts at the beginning of the calendar year, and determines on each day whether there are any new fire starts. Each fire grows from its ignition point using as inputs the sequence of daily values of ERC, wind direction, and wind speed generated by the simulated weather stream. Fire growth is performed by a minimum travel time (MTT) algorithm, which finds the shortest travel times along nodes of a regular lattice (in this case, the corner of each 270m cell) overlain across a landscape (Finney 2002). The MTT algorithm was enhanced to permit variations in burning conditions and include spotting from torching trees (Albini 1979). A series of fire behavior calculations (Finney 1998; Finney 2006) yield the spread and intensity of surface fire (Rothermel 1972) and crown fire (Rothermel 1991; Van Wagner 1977). Fireline intensity in units of kW/m is calculated at each node; intensity is later used to estimate flame lengths and thus fire effects (Byram 1959).

On days when ERC dropped below the 80^{th} percentile, fire spread was not simulated. Daily fire spread calculations also required determining the length of the afternoon "burning period" when fuel moistures are lowest and fires are most active. The burning period increases as fuels become drier. The lengths of these periods is uncertain, but for FSim they were fixed at 1 hours, 3 hours, and 5 hours for the 80^{th}, 90^{th}, and 97^{th} percentile ERC conditions, respectively.

Fires are "extinguished" by the model by one of two methods: 1) ERC drops below a threshold value, indicating the end of the fire season, or 2) the suppression model determines the fire is contained.

Model Validation. Output variables from each FSim run include: 1) the burn probability for each 270m cell, determined by counting the number of times each cell burned and dividing by the number of years in the simulation, 2) the distribution of fire areas, by FPU, and 3) the conditional probability distribution of flame length for each 270m cell. These outputs were compared with historic fire records for the purposes of model validation. The discussion below focuses on validation of burn probabilities; future work will focus on validation of flame length outputs.

Historic fire records were obtained from federal, state, and county agencies from circa 1970-2008, although these dates vary somewhat by FPU. Fortuitously, this time span corresponds well with that of the weather station data used in the fire simulations. Fire records suffer from some inconsistencies in reporting between jurisdictions as well as errors of omission. Records were screened for obvious errors, with duplicate entries removed and some location information corrected. Sources of uncertainty remain, especially errors of omission, with the net effect being underestimation of the number of large fires and area burned. These errors are more likely in the case of small fires, which are not included in this simulation.

Two metrics for comparing simulated and observed fire patterns were: 1) mean burn probability for each FPU, and 2) the fire size distributions for each of eight Geographic Areas (a regional collection of FPUs delineated for the purposes of fire suppression activities). The first metric, mean burn probability, was calculated for each FPU by summing the area burned by all fires, and dividing by the total area in each FPU and the number of years in the record.

Fire size distributions compiled from the simulation data were plotted on logarithmic axes for each FPU along with the historic distribution of fires for the

corresponding Geographic Area (GA). Historic fires are grouped by GA since too few large fires exist in the record to plot them by FPU, because the historic records cover a much shorter span of time than the simulation data which extends over thousands of years. The slope parameter of each log-transformed fire size distribution was calculated by means of robust regression using Kendall's Tau statistic (Sen 1968) which does not assume normality of the residuals. The slope parameter of the fire size distributions is the parameter of interest since it characterizes the relative frequency of smaller versus larger fire events, while the intercept parameter changes with respect to the total number of fires. We utilized the median frequency in each size category as the dependent variable instead of the actual frequencies which are sparse for the larger fire sizes. In order to compare the slope parameters, the 95% confidence intervals for each slope coefficient were calculated.

3. Results

Mean annual burn probabilities for each FPU were mapped for the historic (Figure 4a) and simulated data (Figure 4b), with burn probabilities varying across four orders of magnitude ($1x10^{-5}$ to $1x10^{-2}$). The observed and simulated burn probabilities correspond reasonably well with each other, as evidenced by visual inspection of these maps and a scatterplot (Figure 4c), with burn probabilities generally higher in the west than in the east. This pattern results primarily from lower fuel moisture values in the west, as well as vast expanses of unroaded wildlands. Burn probabilities mapped at the pixel level reveal more complex fine-scale patterns driven by local vegetation and topography (Figure 4d).

The slopes of simulated fire size distributions were all reasonably linear and negative when plotted in log-log space, characteristic of power-law distributions (Figure 5b). The slopes of simulated fire sizes by FPU were generally similar to those of historic fire sizes by GA (Figures 5b and 5c), although some variability is expected since FPUs within a GA vary in terms of fuels and weather. Figures 5a-c show results for the California GA. Results for the seven other GAs are given in Finney *et al*., In review. The slope of the historic fire size distributions fell between approximately -1.4 and -1.6 for all GAs, considering the 95% confidence interval. In the California GA, Great Basin GA, Northwest GA, and Rocky Mountain GA, the majority of confidence intervals of the slope parameters of the FPUs overlapped with the value calculated for the GA. In the Eastern Area GA, Northern Rockies GA, Southern GA, and Southwest GA, the slope values of the majority of FPUs were different from that of the GA as a whole. Because the total number of fires in the 20-30 year historic record is almost always lower than that of the 10,000-50,000 year simulations, the historic data curve plots below that of the FPUs. The largest simulated fires were larger than those in the historic record, and were likely driven by rare extreme sequences of fire weather.

Where an FPU's mean annual burn probability was more than an order of magnitude or 1%/year different from historic values, one of the following adjustments was made to the model parameters: 1) the weather station was switched to a station with ERCs, wind speeds and directions more typical of the region, 2) the minimum large fire size was altered to better convey the size of fires relative to neighboring FPUs, or 3) the rate of spread was adjusted in one or more fuel models (this occurred most commonly in grass and shrub models with extremely high rates of spread, which may have over-estimated the true rate of

spread given fuel conditions on the ground). Adjustments were made to approximately one-third of the FPUs.

Simulations were also run without the fire suppression algorithm which, as predicted, caused most fires to grow to larger sizes and flattened the fire size distribution.

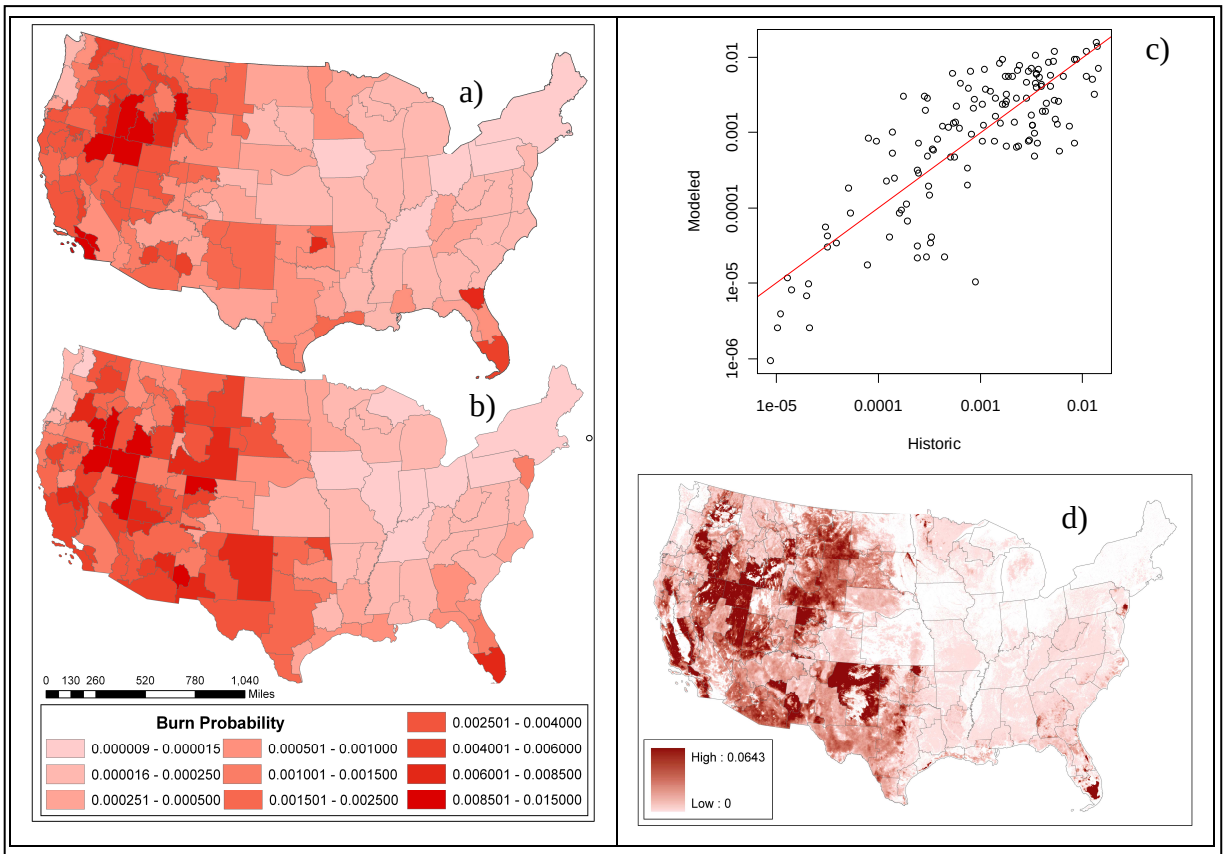

Figure 3. Comparison of burn probabilities for the continental U.S.: a) annual historic burn probabilities by FPU, b) annual simulated burn probabilities by FPU, c) modeled vs. historic burn probabilities for all 134 FPUs, d) map of burn probability outputs at 270m resolution.

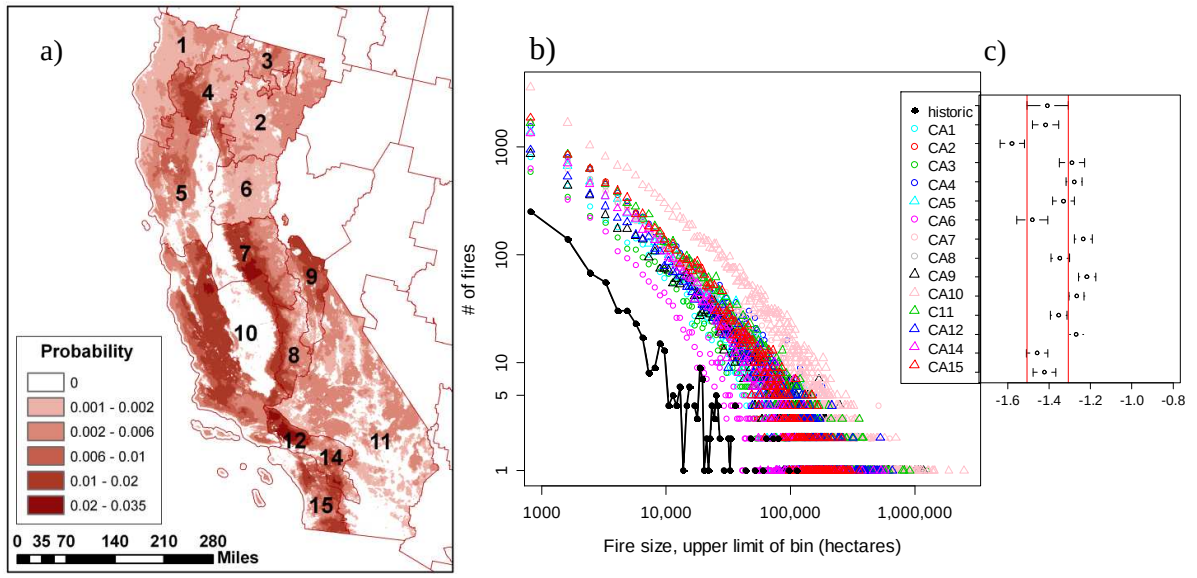

Figure 4. Comparison of burn probabilities for California GA. a) Burn probabilities from each FPU at 270m output resolution. b) Fire size distributions, simulated data for each FPU and historic data for the California GA. c) Slope and 95% confidence interval for each FPU in comparison to the 95% CI for the historical distribution for the GA (red lines).

4. Discussion

This project demonstrates that continental-scale spatial simulation of wildfire burn probabilities, a task not previously attempted, is becoming practical in terms of data availability, computing requirements, and modelling components. While this project was motivated by a need for risk assessment, the results present the opportunity for research on fire patterns and their causes over eco-region scales. Following adjustments in model parameters in approximately one-third of the FPUs, FSim captured the historic trends in burn probability and fire size distributions, at least to the standards of precision of historic fire records. The consistency, reliability, and time-span of fire records currently limit the accuracy of modelling for areas as large and heterogeneous as the continental U.S.

The most common adjustment to model parameters was reduction in the rate of spread for two grass and shrub fuel types mapped by LANDFIRE, which were found to produce excessive fire sizes and spread rates. The limited need for such adjustments in a minority of FPUs suggests that the root issues are fuel-specific or region-specific; otherwise adjustments would be necessary for most FPUs. The aggregated spatial resolution (LANDFIRE data was resampled from 30m to 270m cells in order to achieve practical simulation times) or temporal resolution (only one wind direction and speed was assigned for each day) could have produced over-prediction in these fuel types. Conversely, variation in fuels at the sub-270m scale, such as streams and roads, can impede fire growth but is not represented in the model (Reed and McKelvey 2002; Ricotta, Avena *et al.* 1999; Yang, He

et al. 2008). In addition, the use of weather data from a single station per FPU may have contributed to disparities between observed and predicted burn probabilities.

Close correspondence between simulated and observed fire size distributions suggests that LFSim captures the spatial and temporal factors that both contribute to and limit fire growth. Specifically, these results imply that the observed power-law distribution of fire sizes is governed by the joint distribution of spatial and temporal opportunities for fire growth and extinguishment (Malamud, Morein *et al.* 1998). In the simulations, extinguishment and growth opportunities resulted from the combination of: 1) ignition location relative to spatial patterns in fuels and topography, 2) fire weather sequences subsequent to the ignitions, and 3) the statistical probability of containment dependent on weather. Reed and McKelvey (2002) proposed the same general argument: that competing probabilities of growth and extinguishment could drive the distribution of fire sizes, but not the observed power-law behavior. We found power-law fire size distributions in both historical and simulated data over a wide range of fire sizes across the U.S. The fuel layers are not updated yearly to reflect burning, and our simulation does not allow for spatial interference from burned patches as proposed by self-organized criticality (Bak, Chen *et al.* 1990; Bak, Tang *et al.* 1988; Malamud, Morein *et al.* 1998; Moritz, Morais *et al.* 2005). Thus, our findings suggest there are probably a number of explanations for power-law distributions of fire sizes.

5. Conclusions

Continental-scale assessment of wildland fire risk by repeated fire simulations was shown to be practical. Simulated burn probabilities and fire size distributions showed reasonable correspondence to historical values and patterns, as well as the results of previous studies (Littell, McKenzie *et al.* 2009; Malamud, Millington *et al.* 2005; Martell and Sun 2008; Moritz, Morais *et al.* 2005). LFSim provides for the first time a methodology for evaluating: 1) fire management options, through use of alternative suppression algorithms or no suppression, and 2) land management options, by analysis of alternative landscape inputs including stands with fuel treatment such as prescribed fire. Properly implemented fuel treatments can achieve the goal of ecosystem restoration, while also reducing flame lengths and slowing rates of spread, which in turn may reduce burn probabilities of the adjacent landscape (Ager, Finney *et al.* 2007). Risk mitigation to highly valued resources could be achieved by carefully designed fuel treatments (Calkin, Ager *et al.* 2010). Much work remains to be done by natural resource specialists and economists concerning the responses of highly valued resources to fires of various severities.

6. Acknowledgements

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