Wildfire Prediction to Inform Fire Management: Statistical Science Challenges

S. W. Taylor, Douglas G. Woolford, C. B. Dean and David L. Martell

Abstract. Wildfire is an important system process of the earth that occurs across a wide range of spatial and temporal scales. A variety of methods have been used to predict wildfire phenomena during the past century to better our understanding of fire processes and to inform fire and land management decision-making. Statistical methods have an important role in wildfire prediction due to the inherent stochastic nature of fire phenomena at all scales.

Predictive models have exploited several sources of data describing fire phenomena. Experimental data are scarce; observational data are dominated by statistics compiled by government fire management agencies, primarily for administrative purposes and increasingly from remote sensing observations. Fires are rare events at many scales. The data describing fire phenomena can be zero-heavy and nonstationary over both space and time. Users of fire modeling methodologies are mainly fire management agencies often working under great time constraints, thus, complex models have to be efficiently estimated.

We focus on providing an understanding of some of the information needed for fire management decision-making and of the challenges involved in predicting fire occurrence, growth and frequency at regional, national and global scales.

Key words and phrases: Environmetrics, forest fire, prediction, review, wildland fire.

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1. INTRODUCTION

"Predicting the behavior of wildland fires—among nature's most potent forces—can save lives, money, and natural resources."

Frank Albini (1984)

Wildfires have likely occurred on the earth since the appearance of terrestrial vegetation in the Silurian era, 420 million years B.P. (Bowman et al., 2009), and are an important ecosystem process on all continents except Antarctica, influencing the composition and structure of plant and animal communities, as well as carbon and other biogeochemical cycles. Emissions of CO_2, other trace gasses and particulates from biomass burning contribute to annual and inter-annual variation in atmospheric chemistry (Andreae and Merlet, 2001), including the formation of cloud condensation nuclei that influence global radiation and precipitation budgets, and in the case

of black carbon, accelerate the melting of ice and snow (Bond et al., 2013). Wildfires also have significant social and economic impacts, sometimes resulting in the evacuation of communities, fatalities, smoke impacts on human health (Finlay et al., 2012), property loss and the destruction of forest resources.

Instrumental records suggest that the average global temperature increased 0.8°C in the last century (Hansen et al., 2006). However, because global annual burned area data have only been available for about the past 15 years from satellite observations,[1] it has only been possible to examine the effects of changes in climate during the past century on fire activity in a few regions with long-term administrative records. For example, area burned increased significantly in Canada as a whole, the province of Ontario, Canada, and in northwestern Ontario in the latter compared to the earlier half of the period 1918–2000 (Podur, Martell and Knight, 2002); and, the fire season has been lengthening in the provinces of Alberta and Ontario, Canada (Albert-Green et al., 2013). Increases in the area burned in the western US during the 1970–2005 period were associated with earlier spring snowmelt (Westerling et al., 2006). However, at a regional scale, decreases in area burned in many ecological zones in the province of British Columbia, Canada, were associated with increases in precipitation during 1920–2000 (Meyn et al., 2010). Climate warming scenarios of 2.5–3.5°C over the next century are expected to result in increases in global wildfire activity (Flannigan et al., 2009), but such changes are expected to vary by region due to projected changes in the amount and distribution of precipitation (Krawchuk et al., 2009).

Since wildfire management is likely to become increasingly challenging under a changing climate, better predictive tools will be needed. We believe that statistical science can make important contributions to improving wildfire prediction at local to global scales.

1.1 Prediction in Wildfire Management

Most wildfire management organizations in North America and elsewhere have developed the capacity to respond rapidly to wildfires that threaten communities and other values with highly-mobile fire management resources (fire fighters, equipment and aircraft) in order to contain and extinguish fires while they are small. Minimizing the time intervals between when a fire is ignited, detected and actioned is key to successful initial attack. While this approach is effective for most fires, a small number (typically less than 5% in Canada) escape initial attack and continue to spread, requiring additional resources as fire size and complexity increase.[2]

The number, severity and sizes of fires vary substantially within and between regions, as well as within and between years, due in part to variation in weather, climate, other environmental conditions and demographic and human behavioral factors. Much early fire research in North America focused on the development of fire danger rating systems that were designed to capture the cumulative effects of weather in numerical measures of daily fire potential (Taylor and Alexander (2006); Hardy and Hardy (2007)). The fire danger systems developed and used in Australia, Canada and the United States, for example, are based primarily on empirical models of weather effects on the moisture content and flammability of various organic layers (e.g., the moss layers and dead pine needles on the forest floor) (Fujioka et al., 2008). Fire danger measures are connected to fire activity in many environments (Viegas et al., 1999). Thus, when fire occurrence and fire behavior models were later developed, they often included fire danger measures as covariates (Wotton, 2009). Computer-based fire management information systems have subsequently been developed to collect, process, interpolate and distribute weather, fire danger measures and model predictions throughout fire organizations, many in almost real-time (Doan and Martell (1974); Lee et al. (2002)).

One important feature of many fire regimes is the sharp peaks in fire activity that are often associated with high pressure systems, lightning storms

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[1]Using MODIS satellite data, Giglio et al. (2009) estimated that the global annual burned area was between 3.31 and 4.31 million km^2 during 1997–2008 (Figure A.3).

[2]The Incident Command System (ICS) is used by many wildfire management organizations. It provides a flexible organizational structure that can be expanded depending on the complexity of the incident (Bigley and Roberts, 2001). The five incident complexity classes (Type 5–1) recognized in ICS are associated with an increasing need for resources for longer periods of time. For example, a Type 5 wildfire that is less than a few hectares in size may be controlled by 3–5 fire fighters, which may be supported by helicopters or airtankers for up to one or two days, while a larger Type 1 incident of thousands of hectares in size that threatens a community will require a much more significant response, including a specialized incident management team (IMT) and hundreds, perhaps even thousands of firefighters and other resources that can be sustained for many days to weeks.

or other severe synoptic-scale weather events. Although fire management organizations collaborate and often share resources on regional, national and even continental scales, they are not always able to respond fully to some peaks in fire activity, which subsequently place significant stress on the system and increase the likelihood of elevated costs and losses. In addition to limits on resources, fire suppression effectiveness varies with fire size and intensity—direct fire suppression methods cannot be used when the fire intensity exceeds safe working conditions for ground crews, or when high winds or smoke ground aircraft or render their drops ineffective. Thus, there is increasing interest in mitigating the risk of extreme fire behavior by manipulating fuel conditions (vegetation), in reducing the vulnerability of communities, and in choosing to monitor rather than fully suppress some fires that pose little or no threat to public safety, property or forest resources.

Fire activity varies substantially, and often rapidly, from local to national scales; spatio-temporal variability is one of the main challenges in wildfire management. Because resources are limited, both for mitigating and responding to wildfire risks, predictive models are needed to support planning and decision-making (Andrews, Finney and Fischetti (2007); Preisler and Ager (2013)). Martell (1982) described many of the strategic, tactical and operational decision-making problems faced by fire managers, and of early efforts to bring operations research methods to bear on them. These include:

1. Strategic decisions about the long-term requirements for resources (e.g., number and type of airtankers) in large regions, such as states or provinces, and where they should be home-based, depending on the expected number, variation and distribution of incidents.

2. At the tactical level, the number and size of fires that are expected to be ignited, detected and reported over shorter periods of days to weeks influences decisions concerning the state of preparedness or organizational readiness, the allocation of resources within a region, and the acquisition (or release) of additional resources from outside the region through mutual aid resource sharing agreements. The expected daily fire occurrence is important for prepositioning fire crews and routing aircraft for fire detection. The expected growth of individual fires over days or weeks informs decisions concerning the
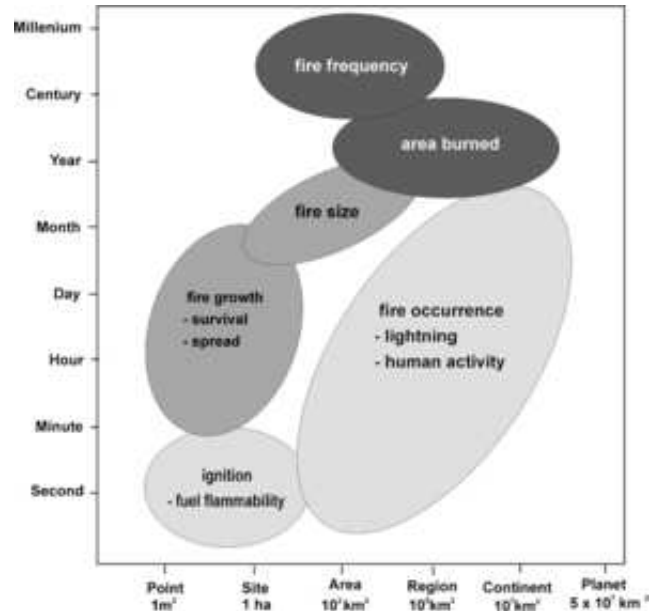

Fig. 1. *Wildland fire risk elements are compounded over a range of spatial and temporal scales. Reinterpreted from Simard (1991).*

evacuation of communities in the path of a fire or whether some fires burning in remote areas can be simply monitored and allowed to burn relatively freely without threatening public safety, resources or infrastructure.

3. Because conditions can change rapidly, operational decisions are typically made over minutes and hours during a day. Airtankers and other resources may be re-deployed and dispatched to fires as each day progresses. The expected behavior and growth of an individual fire over the daily burning period is important for planning the dispatch and safe deployment of firefighters and other resources on fires.

In this paper we review some of the models that have been developed to predict fire occurrence, growth and frequency, and how they are linked across multiple scales (Figure 1). While there have been important contributions from many regions, we have focused on the North American fire literature because that is the region in which we have carried out most of our fire-related research. Section 2 discusses tools for ignition and fire occurrence prediction, with connections to point processes and case–control methods. Section 3 discusses fire spread/growth and fire size models. Section 4 reviews models for estimating burned area and fire frequency. The Appendix provides an overview of the sources—and limitations—of various types of wildfire data that have been used in predictive models.
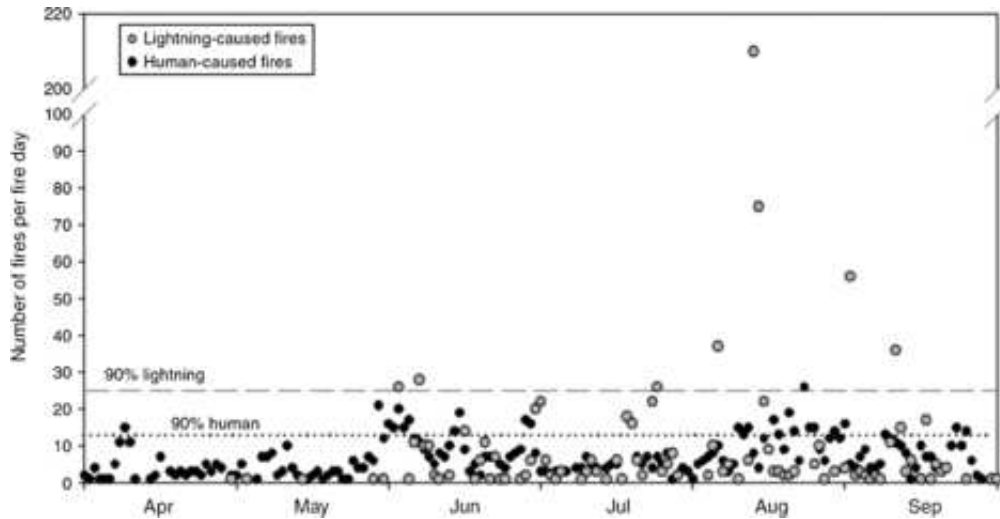
FIG. 2.   *The raw daily number of human- and lightning-caused fires in British Columbia, Canada, during the 1986 fire season observed on fire days, defined as a day during which at least one fire is observed. The 20-year 90th percentile thresholds are indicated (Magnussen and Taylor, 2012b). Days with >90th percentile number of lightning fire starts are difficult to predict but severely challenge the ability of fire management agencies to respond quickly to all fires.*

Interspersed throughout this paper, and especially in the closing section, are discussions of open challenging wildfire management questions that we hope will be of interest, stimulating the development of new tools for this critical area of science. We note that, personally, our collaborative work with teams of statisticians, fire scientists and fire managers has proven to be a rich and rewarding platform for interdisciplinary research and training.

2. FIRE OCCURRENCE

Wildland fires are ignited by both people and natural processes. Natural fires are caused mainly[3] by cloud-to-ground lightning strokes (Anderson, 2002) that ignite trees or organic matter at the base of the tree they strike, while people-caused fires occur when needle, leaf or grass litter is ignited. Anthropogenic sources of ignition include machinery (sparks, friction and hot surfaces), arcing from electrical transmission lines, sparks or firebrands from escaped campfires, prescribed fires, agricultural and land clearing fires, and arson. An ignition that leads to sustained fire spread may be reported and recorded by a fire management agency or, in some cases (e.g., in more northern regions of Canada), it is

detected by satellite-borne sensors. The locations, times and number of forest fire ignitions appearing in historical fire records are inherently random. In many cases such records contain truncated or censored data: only fires that are reported to a fire management agency appear in the records and in many cases the time of ignition is estimated.[4] Fire ignition rates vary drastically over both time and space and their relative frequency of occurrence depends on locally observed covariates, including the intensity of the ignition process. There is often greater variability in the daily number of lightning than anthropogenic ignitions (Figure 2). This is because, when lightning storms occur, they can produce thousands of lighting strikes and tens–hundreds of fire starts in a few hours.

2.1 Probability of Ignition

Regardless of the initial source of ignition, if sufficient heat is produced from combustion, adjacent particles (e.g., needle, leaf, grass and twig litter, or other organic material) will also be heated to their ignition temperature, resulting in sustained fire spread. The probability of ignition is related mainly

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[3]A small number of wildfires have also been ascribed to volcanic activity (Ainsworth and Kauffman, 2009) and meteorites [e.g., the 1908 Tunguska event in Siberia (Svetsov, 2002)].

[4]Most fire managers and researchers use the term "occurrence" to refer to fires that are detected and reported, although the queueing theory term "arrivals" is also sometimes used to distinguish detected and reported from nondetected fires.

to the physical properties of dead organic matter and its moisture content, which varies by day and across all spatial scales. Regression methods have been employed to quantify the probability of sustained ignition under varying conditions. In some studies, samples of litter or sub-litter fuels taken in the field are subjected to ignition experiments in the laboratory (Frandsen (1997); Plucinski and Anderson (2008)). In other cases, ignition experiments are conducted directly in the field. In their logistic regression based reanalysis of experimental test fires in Canada, Beverly and Wotton (2007) concluded that the primary driver of sustained flaming ignition from firebrands is the moisture content of fine fuels. The moisture in more heavily compacted organic matter below these fine fuels along with relative humidity also impacted the probability of sustained ignition for some fuel types. Similar results have been observed in other regions of the world. An analysis of experimental fires in Tasmanian grasslands, for example, revealed that sustained ignition was strongly driven by the moisture content of the dead fuel as well as the amount of dead fuel available for combustion (Leonard, 2009). Earlier analyses, using logistic regression and classification trees, for data on Tasmanian grassland fires also revealed and quantified the interaction between wind speed and dead fuel moisture: wetter fuels require a higher wind speed to sustain ignition, otherwise they are more likely to self-extinguish (Marsden-Smedley, Catchpole and Pyrke, 2001).

2.2 Fire Occurrence Prediction

Early fire occurrence prediction related the number of fires per day to fire danger indices, usually for a single spatial unit or administrative region. Many models have subsequently been developed using a variety of modeling approaches and covariates and for a variety of spatial and temporal scales. Fire occurrence models typically include variables believed to influence ignition potential (fuels, fuel moisture, ignition source) in a particular environment, tempered with practical considerations regarding data availability. In addition to weather, fuel moisture and fire danger indices, other explanatory variables have included historic spatial and seasonal trends, vegetation type, the number and attributes of lightning strikes, population and road density.

Fire occurrence models for large areas need to accommodate variation in topographic, fuel, weather and fuel moisture conditions. Advances in computing, communication and data collection from weather station networks in near-real time (Lee et al., 2002) have permitted the implementation of sophisticated grid-based fire occurrence models for larger and more variable geographic areas. In these models, the weather and fire danger index variables derived from multiple weather stations are interpolated across the grid units based on distance and elevation (Kourtz and Todd (1991); Todd and Kourtz (1991)). The advent of lightning location systems (Krider et al., 1980) also facilitated lightning-caused fire prediction (Kourtz and Todd, 1991). Models of lightning fire occurrence should have greater temporal and spatial specificity (correct prediction) than human-caused fires because the ignition process can be observed.

It is important to note that the probability of ignition differs from the probability of fire occurrence in the sense that not all fires that achieve sustained ignition may be detected: fire occurrence data is left censored. However, fire occurrence prediction models are much more common than models for the probability of ignition. Woolford et al. (2011) provided a brief review of fire occurrence prediction, which focused on the use of logistic generalized additive models to approximate the covariate-dependent, inhomogeneous intensity function of a point process model. There, they also discussed how the response-based sampling used in some of these models is related to case–control studies. We paraphrase and expand upon that discourse in what follows; we also summarize a newly developed methodology for monitoring for temporal trends in historical records on fire occurrence, motivated by climate change concerns. For a recent and concise review of fire risk and other forest fire models, see Preisler and Ager (2013).

Given the stochastic nature of fire ignitions, a point-process with a conditional intensity function is a natural modeling framework. The first stochastic model for predicting the occurrence of fires appears to have been developed by Bruce (1960), who utilized a negative binomial model that related counts to a fire danger rating index. Subsequently, Cunningham and Martell (1973) developed a Poisson model for counts of fires whose nonspatial conditional intensity function depended on fuel moisture, as measured by the Canadian Fine Fuel Moisture Code (FFMC) (Van Wagner, 1987). The FFMC represents the moisture content of litter fuels on the forest floor—for example, the higher the FFMC, the

drier the needle litter on the forest floor. Data from a weather station near the center of a fire management unit in northwestern Ontario were used to predict daily counts of fires within that region.

In Ontario, Bernoulli processes have been used to model the risk of forest fire occurrence since the late 1980s. For example, Martell, Otukol and Stocks (1987) constructed a set of logistic models for the daily risk of people-caused fires in northern Ontario. These were marginal models, without spatial or temporal components, fit to individual "subseasons" that partitioned the fire season. Seasonal trends were subsequently incorporated by Martell, Bevilacqua and Stocks (1989) through periodic functions. The seasonality of fire occurrence is of interest to fire management for planning purposes, although the strong seasonal variation in Ontario's boreal is not universally observed in other regions. Moreover, such seasonal trends are not spatially homogeneous, as illustrated in the site-specific fire risk curves presented by Woolford et al. (2009) who also explored for spatial patterns using a singular-value decomposition approach, somewhat analogous to regression on principal component scores.

Some modeling efforts have quantified ignition and occurrence risk, such as the site-specific models for fire ignition and occurrence of Wotton and Martell (2005). Logistic methods have the advantage that locally observed covariates can be related to each individual fire, while Poisson-based models connect counts to averages of such covariates over a larger region. Moreover, overdispersion is of concern when Poisson-based methods are used to model counts. Overdispersion is of less concern when logistic models are fit to binary data; however, this is not true when temporal and/or spatial correlation needs to be incorporated.

Relatively little work has been done to explore the use of point-process methods for analyzing the occurrences of forest fires in space–time. However, some recent advances in point-pattern software hold promise in this regard [see Turner (2009) for an example]. Nonparametric tests for investigating the separability of a spatio-temporal marked point process are described and compared in Schoenberg (2004), where a Cramer–von Mises-type test is demonstrated to be powerful at detecting gradual departures from separability, while a residual test based on randomly rescaling the process is powerful at detecting nonseparable clustering or inhibition of the

marks. An application to Los Angeles County wildfire data shows that the separability hypotheses are invalidated largely due to clustering of fires of similar sizes within periods of up to about 4 years. In more recent work, Xu and Schoenberg (2011) showed that the Burning Index, produced by the US Fire Danger Rating System, and commonly used in forecasting the hazard of wildfire activity, is less effective at predicting wildfires in Los Angeles County than simple point process models incorporating raw meteorological information. Their point process models incorporate seasonal wildfire trends, daily and lagged weather variables, and historical spatial burn patterns. Nichols et al. (2011) developed a method for summarizing repeated realizations of a space–time marked point process, called prototyping, and applied this technique to databases of wildfires in California to produce more precise summaries of patterns in the spatio-temporal distribution of wildfires within each wildfire season.

The importance of Poisson processes in modeling the risk of wildfire occurrence was described by Brillinger, Preisler and Benoit (2003), who focused on the underlying spatio-temporal conditional intensity function and described methods for approximating the corresponding likelihood. They advocated partitioning the space–time domain into a set of space–time voxels $(x, x + dx] \times (y, y + dy] \times (t, t + dt]$, where (x, y) are spatial location covariates and t indexes time. The spatio-temporal point process of interest, $N(x, y, t)$, counts the number of fires in a voxel and has conditional intensity function

$$\lambda(x, y, t) = \frac{\Pr\{dN(x, y, t) = 1 | H_t\}}{dx \, dy \, dt},$$

where the σ-algebra H_t denotes the history of $N(x, y, t)$ over $(0, t]$, which consists of the set of observed points in space–time up to time t.

If the underlying intensity function depends on a parameter $\theta = \theta(\mathbf{x})$, where $\mathbf{x}$ denotes a vector of locally observed covariates, the log-likelihood of the process is

$$L(\theta) = \int_0^T \int_x \int_y \log[\lambda(x, y, t | \theta)] \, dN(x, y, t) \\ - \int_0^T \int_x \int_y \log[\lambda(x, y, t | \theta)] \, dx \, dy \, dt.$$

Brillinger, Preisler and Benoit (2003) listed three practical approaches to approximation of this log-likelihood that could be used for model fitting. (Note

that although both terms in the above equation cover large regions of both space and time, it is the second term which is challenging to evaluate.) Their first approach outlined a method for approximating the expected value of the log-likelihood. However, that does not appear to be widely employed in forestry applications. Instead, their two other approaches, related to binomial approximations to the Poisson, are more commonly used. In such approximations, the number of binomial trials may be very large especially if a set of voxels on a very fine spatio-temporal scale, such as $1 \text{ km}^2 \times$ daily cells, is used. On this scale fires are very rare events and only presence/absence is recorded. Then the underlying rate $\lambda_{x,y,t} = \lambda(x, y, t|\theta)$ is approximately the Bernoulli probability of observing a fire in that given space–time region, leading to the Bernoulli approximation to the log-likelihood:

$$\sum_{x,y,t} N_{x,y,t} \log(\lambda_{x,y,t})$$
$$+ \sum_{x,y,t} (1 - N_{x,y,t}) \log(1 - \lambda_{x,y,t}).$$

Therefore, a generalized linear model with the linear predictor $\text{logit}\{\lambda[x, y, t|\theta(\mathbf{x})]\} = \mathbf{x}\boldsymbol{\beta}$, where $\mathbf{x}$ denotes a vector of covariates and $\boldsymbol{\beta}$ denotes the corresponding vector of parameters, can be used to approximate the underlying process and, more importantly, quantify the probability of fire occurrence as a function of locally observed covariates. Generalized additive models (GAMs) have been employed to incorporate potential nonlinear relationships for the explanatory variables (Preisler et al. (2004); Preisler and Westerling (2007); Vilar et al. (2010); Woolford et al. (2011)). For example, periodic seasonal effects may be incorporated into the linear predictor using locally weighted regression or penalized spline smoothers (Wood, 2006). Thin plate splines have also been used to add a spatial term as a surrogate for unobservable human land use patterns or unobserved vegetation patterns.

The Bernoulli approximation of the likelihood function induces computational difficulties since for any practical study, the cardinality of the set of voxels explodes to such a large size that model fitting is not computationally convenient/feasible. Response-based stratified sampling schemes are employed to deal with this issue: data from voxels where a fire is present are kept, but only a random sample of the zero-fire voxels are retained for the analysis.

The response-based sampling of the voxel data is analogous to study designs from logistic retrospective case–control studies. This induces a deterministic offset of $\log(1/\pi_{st})$ in the logistic GAM, where π_{st} denotes the inclusion probability for the observation at site s at time t. Note that the use of an offset in the linear predictor to account for the response-based sampling only works when modeling on the logit scale and not when other link functions, such as the probit or the complementary log–log, are employed in a binomial GAM. Garcia et al. (1995) appear to be the first to use response-based sampling in a logistic model for fire occurrence. More recently, it has been employed in logistic GAMs which incorporate temporal and spatial effects (e.g., Brillinger, Preisler and Benoit, 2003, 2006; Preisler et al. (2004); Vilar et al. (2010); Woolford et al. (2011)).

Let Y denote the fire occurrence indicator, $P(Y = 1|\mathbf{x}) = p_{\mathbf{x}}$, and assume $\text{logit}(p_{\mathbf{x}}) = \alpha + \mathbf{x}\boldsymbol{\beta}$, where $\mathbf{x}$ is a row vector of covariates and $\boldsymbol{\beta}$ is a column vector of parameters. This logistic framework implies that the relative risk corresponding to two voxels with corresponding explanatory variables $\mathbf{x}_1$ and $\mathbf{x}_2$ is $\exp\{(\mathbf{x}_1 - \mathbf{x}_2)\boldsymbol{\beta}\}$. Similar formulations hold for a logistic GAM because the nonlinear relationships on the link scale are modeled as a linear combination of basis functions. In that context, $\exp\{f_m(x_{m1}) - f_m(x_{m2})\}$ is the associated change in risk when the covariate in the mth additive nonlinear partial effect f_m in a GAM changes from x_{m1} to x_{m2}. This framework is the same as a prospective analysis in medical studies when whether or not an individual will develop a disease is not known in advance. In contrast, with a case–control study, subjects are selected based on their disease status (here, fire or nonfire voxel is the analogy) and their exposure or treatment (here, covariate vector) is determined retrospectively. In this context, the covariate values are viewed as random. However, it has been shown that inferences surrounding relative risk can be obtained using the same logistic model as in the prospective study (Breslow and Powers, 1978). Letting δ denote an indicator for whether or not an individual is sampled, the corresponding inclusion probabilities can be stratified by response: $\pi_1 = \Pr\{\delta = 1|Y = 1\}$ and $\pi_0 = \Pr\{\delta = 1|Y = 0\}$. Usually a case $(Y = 1)$ is a rare event, relative to the population size. In the fire study analogy, all cases are included $(\pi_1$ is 1) and π_0 is usually fairly small. Through a Bayes argument,

it is straightforward to show that such response-dependent sampling induces a deterministic offset into the model. Specifically, the intercept changes by an additive factor of $\log(\pi_1/\pi_0)$. Since the sampling probabilities depend only on the observed disease (fire) status and not on covariates, the covariate effects are identical to those from a prospective analysis. The analyses of the fire occurrence data where all fire events are retained for the analysis and only a sample of the nonfire events are included is identical to the above case–control formulation.

Over the past decade, there have been multiple studies using response-specific sampling in logistic GAMs for fire occurrence. Brillinger, Preisler and Benoit (2003) quantified "baseline" spatial and temporal effects for wildfire occurrence in federal lands in Oregon, U.S.A. Preisler et al. (2004) extended that work, incorporating partial effects of other locally observed fire-weather covariates, and proposed modeling the risk of a large fire event conditional on a fire occurrence being present [Figure 3(a)]. Similar models for California were presented by Brillinger, Preisler and Benoit (2006), who also assessed whether random effects should be included. Other related work includes Vilar et al. (2010) and Woolford et al. (2011), who modeled people-caused wildfire risk in Madrid, Spain and a region of boreal forest in northeastern Ontario, Canada, respectively. Both of those studies explored how locally observed anthropogenic variables (e.g., density of roads in the cell, distance to the nearest railroad line, population density, etc.) impacted the probability of fire occurrence. These types of models have been extended to produce one month ahead forecasts for the probability of large fires (Preisler and Westerling (2007); Preisler et al. (2008)) and have been used to quantify spatially explicit risk forecasts for large fires and to estimate suppression costs (Preisler et al., 2011). We elaborate on these latter developments when we discuss burn probability models.

Recently, Magnussen and Taylor (2012a) developed a set of six models to predict daily lightning and person-caused fire occurrence for the province of British Columbia, Canada, at 20-km (400 km^2) resolution [Figure 3(b)]. Their methodology employs an ensemble of annual logistic models for predicting the risk of fires being present in a given cell. Piecewise linear predictors were incorporated to handle nonlinear relationships on the logit scale and separate annual models were fit. Those models connected linear segments together at sets of knots which form a partition over the range of the predictor to produce
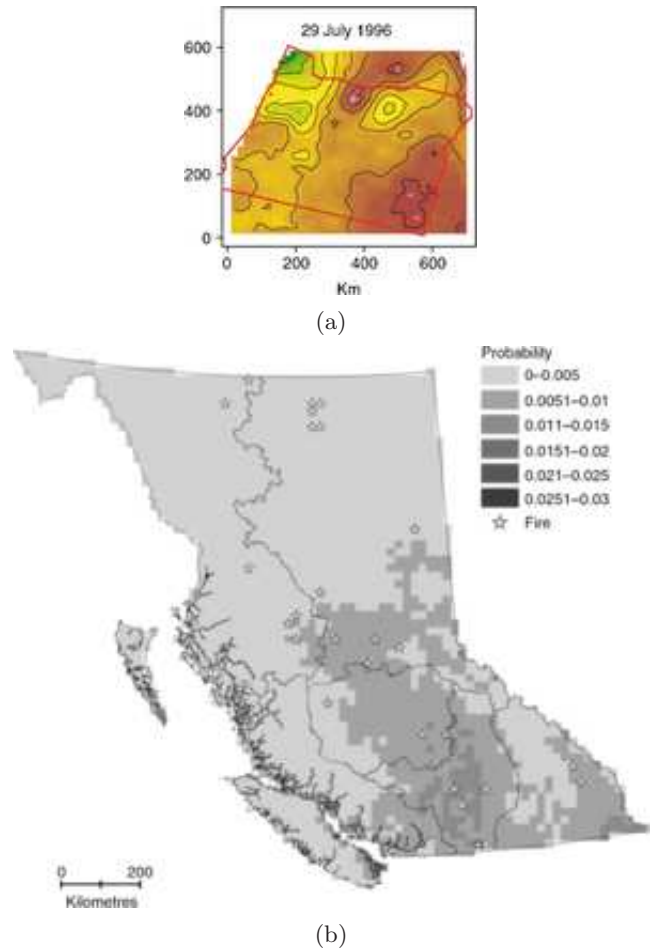

(a)

(b)

FIG. 3. (a) *The probability of a large fire given ignition in 1 km cells in Oregon on 29 July 1996 (Preisler et al., 2004).* (b) *The probability of more than person-caused fire occurring in $\sim$9000 400 km^2 cells and observed fires on 21 May 1985 in British Columbia, Canada (Magnussen and Taylor, 2012a).*

a piecewise linear function. This piecewise linear framework had the advantage that the placement of knots could be done using domain knowledge, rather than the penalized spline approach where many knots are employed and the likelihood is penalized to prevent overfitting of the data. Separate annual models were fit because of known variability in parameter effects from year to year. This permitted (1) leave-one-out cross-validation assessment of predictive ability (e.g., Wood (2006)) and (2) the quantification of unbiased estimators of the regression parameters, and corresponding standard errors, without explicitly stating the structure of year-to-year random effects. This allowed for the joint fitting of a province-wide model, rather than separate marginal models over a partition of a province, such as Wotton and Martell's (2005) lightning occurrence models for the province of Ontario, Canada. Magnussen and

Taylor (2012a) coupled the results from their logistic models to zero-truncated Poisson models in order to model the daily number of fires, conditional on fires being present in a given cell. They also developed models for predicting medium-term (i.e., 2–14 days ahead) lightning fire occurrence using an atmospheric stability index (determined from the mesoscale ensemble weather model output) as a proxy for future lightning activity. While this model is less accurate than those including observed lighting strikes, forecasts over this time period are important for fire management planning.

It is desirable to model fire occurrence risk on a fine scale, so the probability that a fire will occur can be related to locally observed conditions, rather than some average value. Then, fitted values can be aggregated to "scale up" to a coarser resolution. However, not all such logistic GAMs use a fine scale. Large scale models must often be at coarser resolution because of data availability and computational limitations. Krawchuk et al. (2009) investigated spatio-temporal patterns in fire activity in a global sense, by modeling on a coarser 100-km (10,000 km^2) × decadal scale. Climate scenarios were then used to forecast future changes in fire activity. Their work found increases in future fire activity in certain regions and decreases in other regions.

Recently, researchers have been exploring methods for monitoring long-term trends in forest fire occurrence through analyses driven by historical fire records, focusing on natural, lightning-caused forest fires (e.g., Albert-Green et al. (2013); Woolford et al., 2010, 2013). Woolford et al. (2010) looked for changes to inter and intra-annual trends in lightning-caused fire occurrences in a region of Boreal forest in Ontario, Canada. They compared a set of nested logistic generalized additive mixed models that had fixed effects for seasonality components, annual trends and their interactions, along with annual random effects to account for year-to-year variability, and an autoregressive component to account for daily serial correlation. Their final model employed a bivariate smoother of the ordered pair (day of year, year) and suggested that the probability of fires being present in this region was increasing over time and that the effective length of the fire season appeared to be lengthening.

One feature of the Woolford et al. (2010) model was that the local seasonal behavior within a given year could be impacted by neighboring years due to the functional form of the specified signal component. In arid regions, a wet growing season may result in higher grass biomass and more fire activity in a subsequent dry year (Greenville et al., 2009). However, except in cases of extreme drought at the end of a fire season and low winter precipitation, there is usually enough wintertime precipitation in temperate and boreal forests to saturate surface organic fuels (Lawson and Armitage, 2008) such that fire seasons are essentially independent. Albert-Green et al. (2013) addressed this concern in the boreal forest by estimating the historical seasonal trends in fire occurrence risk as a single risk curve (i.e., a univariate smoother of time over the entire study period). When annual slices of those curves were explored, it appeared that the fire season's length was changing by starting earlier and/or ending later each year. A second stage to their analysis tested for trends in the lengthening of the fire season. The fire season was defined as the time between the first upcrossing and last downcrossing of a pre-specified fire risk threshold each year. Confidence bands associated with the estimate smoother were used to find a range of dates that were plausible for each given crossing that defined the start and end of each year's fire season, so uncertainty in these estimates was incorporated in testing for trends. They found that the lightning-caused fire season appeared to be both starting earlier and ending later in Alberta, Canada, and ending later in Ontario.

A difficulty with historical analyses such as in Woolford et al. (2010) or Albert-Green et al. (2013) is the potential confounding effects of changes in fire detection system effectiveness. For example, Woolford et al. (2010) noted that the median size at detection of lightning-caused fires decreased during 1963–2004. Lightning fires occurring in remote areas may take longer to detect (and so grow in size) than person-caused fires, which tend to be concentrated near populated places. Smaller lightning fire sizes at detection suggested that detection may have become more effective, which is a potential confounder with any changes due to a warming climate.

These and further complications to the analysis of data from such historical records have led to more complicated approaches, such as the use of mixture models for analyzing trends in historical fire risk. Three dominant characteristics are observed in records of lightning-caused fire occurrence in Ontario: regular seasonal patterns and large departures above or below this pattern, where many more fires are observed than normal, or so-called zero-heavy behavior when no fires are present on the landscape.

Letting X_t denote the number of fire days during time period t, and letting 0, R and E denote the zero-heavy, regular and extreme behavior components, Woolford et al. (2013) proposed the use of a mixture of logistic GAMs to model weekly counts of fire days:

$$X_t \sim \pi_0(y)\bin(7, p_0(w) = 0) + \pi_R(y)\operatorname{Bin}(7, p_R(w))$$
$$+ \pi_E(y)\operatorname{Bin}(7, p_E(w)),$$

where w and y index the week and year, respectively. The binomial probabilities for the nondegenerate component are modeled using penalized spline smoothers (e.g., Wood (2006)) and the mixing probabilities are parameterized to test for shifts away from zero-heavy behavior toward regular or extreme behavior by the multinomial regression of the log-odds against year (y):

$$\operatorname{logit}\left(\frac{\pi_j(y)}{\pi_0(y)}\right) = \alpha_j + \beta_j y, \quad j = R, E.$$

When used to analyze lightning-caused forest fire occurrences in a region of northwestern Ontario, Woolford et al. (2013) found a dramatic decline in the probability of zero-heavy behavior, which was offset by shifts toward increased chances membership in the regular seasonal or extreme behavior components. Their model corroborated that the probability of fire occurrence, especially the length of elevated risk, has been increasing over time in that region. Moreover, through a second-stage analysis they found a significant association with temperature anomalies and fire-weather indices, which suggests that the increased likelihood of seeing more fire on the landscape than during "regular" years was related to a warming climate. Their work also quantified the power of three hypothesis tests (Wald, score and permutation) for testing for trends, as well as the length of historical record which would be required for achieving high power when testing for trends. They found that the permutation test had the highest power and that the power of such tests would dramatically increase as the sample size (i.e., length of the study period) increased beyond 40 years of data for this region. Investigating the length of historical records required to test for trends with a specified power has been overlooked in these sorts of analyses.

3. FIRE GROWTH

After a fire has been ignited, it will continue to spread as long as sufficient heat is produced by the fire front to ignite adjacent dead or live organic mat-ter, if available. The rate of fire spread (ROS) is determined by the rate at which heat is transferred from burning to unburned fuel, which is captured in the fundamental equation of spread (Weber, 2001):

$$\text{Rate of spread} = \frac{\text{Heat flux from active combustion}}{\text{Heat required for fuel ignition}}$$
$$= \frac{q}{\rho Q_{\text{ig}}},$$

where q is the heat flux from active combustion, ρ is the fuel density, and Q_{ig} is the enthalpy per unit mass required for ignition. ROS is influenced by many environmental factors (e.g., moisture content of fine fuels, air temperature and wind speed) and characteristics of the fuel complex (surface area/volume, void space, depth, temperature).

Fires spread horizontally in surface fuels in two dimensions—with and parallel to the wind direction at the head of the fire, but also, at a decreasing rate, laterally and against the wind direction around the flanks and back of the fire (Figure 4). However, in coniferous forests and shrub vegetation, fires can also spread from the ground surface to and in the vegetation canopy if sufficient heat is produced by the surface fire to heat the crown foliage to ignition temperature (Van Wagner, 1977). When a fire "crowns," ROS increases substantially as the flame zone becomes exposed to the ambient wind above the vegetation canopy. As a fire continues to grow in size, firebrands may be lofted ahead and start new fires; as the smoke plume extends to greater heights in the atmosphere, it may develop a three-dimensional circulation with stronger upper level winds.

ROS and fireline intensity (energy release per unit timer per unit of fire front length) have a diurnal cycle associated with daily variation in temperature, relative humidity and wind speed—typically following a sine-wave pattern with a pre-dawn minimum and late afternoon peak (Beck et al., 2002) which is compounded by stochastic variation in wind speed over seconds–minutes. Thus, ROS can vary over more than 2 orders of magnitude from less than 1 m min^{-1} to 100–200+ m min^{-1} within and between days during a single fire event, as well as between fires due to variation in the environment.[5]

[5]Sustained ROS of 110+ m min^{-1} has been observed in crown fires in conifer forests in North America, while ROS of 250+ m min^{-1} has been documented in grass fires in Australia (Cheney, Gould and Catchpole, 1998).

FIG. 4.   *The Cobbler Road Fire near Yass, New South Wales, Australia, on 2 January 2013 (Photo: Chris Hadfield/NASA). At the time the photograph was taken, the fire was approximately 18 km long and was spreading through fully-cured grass and open woodland under the influence of an ∼50 km/h wind (Cruz and Alexander, 2013). The maximum flame zone depth and intensity occurs at the head of the fire in the lower right, and decreases around the perimeter toward the origin in the upper left.*

Fire duration (the time from ignition to extinguishment) varies from shorter than 1 day to many weeks or even months. Within this period a fire may only exhibit significant spread for a period of minutes to hours within a single day or during a number of burning periods on multiple days. Variation in wind direction also influences fire growth. In the extreme case, an abrupt 90° shift in the surface wind direction (which commonly precedes a cold front) can turn a long fire flank (e.g., Figure 4) into the head, greatly increasing fire growth. Thus, variation in the number, magnitude and direction of spread events results in fire sizes[6]from 10^{-3}–10^4 km^2.

The simplicity of the fundamental equation of fire spread belies the significant challenge of developing models that provide useful estimates of wildfire spread and growth over a range of weather conditions, vegetation types and time periods. Show (1919) carried out the first known field research on wildland fire spread, summarizing fire perimeter growth in relation to fuel moisture content and wind speed, while Fons (1946) proposed the first physical model of wildfire spread. Subsequently, spread modeling has followed these two divergent approaches, which are commonly classified as (a) empirical or (b) physical and quasi-physical (Sullivan, 2009a, 2009b). Empirical models are based on statistical relationships between environmental factors and ROS, while physical models are based on physical and chemical principles; quasi-physical conserve energy, but do not differentiate between modes of heat transfer. At least 30 empirical and 40 physical/quasi-physical models of fire spread have been developed [see reviews by Weber (1991); Pastor et al. (2003); Sullivan, 2009a, 2009b, and Alexander and Cruz (2013)].

3.1 Spread Rate Models

ROS models express fire growth as the simple one-dimensional linear progression of the head, back or flank of the fire at 0, 180 and 90° to the wind direction, respectively (e.g., in units of m·min^{-1} or km·hr^{-1}).

Empirical approaches have used regression methods to predict ROS as function of wind speed, fuel

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[6]The size of the largest recorded individual fire is an unsettled question. Among the largest documented is the Great Black Dragon fire, which coalesced from several fires to ultimately burn 1.3×10^5 km^2 in northern China during May 1987 (Cahoon et al., 1994).

moisture content, fuel weight and ground slope. Models are typically developed for different vegetation conditions such as conifer and hardwood forests, grassland, shrub and heathland fuels, and logging slash based on field and laboratory experiments (e.g., Figure A.2), administrative fire reports and observations of wildfires.

The Canadian Forest Fire Behavior Prediction (FBP) System (Forestry Canada Fire Danger Group, 1992) is an example of a well-developed empirical fire behavior system, where likelihood approaches were used to estimate the parameters a and b in the Chapman–Richards equation:

$$\text{ROS} = a \times [1 - e^{(-b \times ISI)}]^c.$$

The parameter c represents the asymptote and was set for each fuel type as the maximum fire spread rates observed in coniferous forests and grasslands (see footnote 5). The Initial Spread Index (ISI) is an index that is based on wind speed and fine fuel moisture content. FBP model calibration was based on observations of ROS in experimental fires and wildfires in 17 forest and grass fuel types. The transition from surface to crown fire is implicit in the sigmoidal curves relating initial spread index to ROS (Figure 5), except in one vegetation type where it is based on physical considerations (Van Wagner, 1977). In reanalyses of the FBP System data, Cruz, Alexander and Wakimoto (2003) estimated the probability of crown fire using a logistic model, and developed a model of crown fire ROS as a function of crown bulk density, wind speed and moisture content in coniferous forests (Cruz, Alexander and Wakimoto, 2005).

An important milestone in translating physical principles to practical application was Rothermel's (1972) semi-physical implementation of the fundamental equation of spread as

$$\text{ROS} = \frac{(I_p)_o(1 + \phi_w + \phi_s)}{\rho \varepsilon Q_{\text{ig}}},$$

where the propagating heating flux for a zero wind/ slope situation $(I_p)_o$, the wind and slope correction factors ϕ_w and ϕ_s, and the effective heating number ε were parameterized for surface fires in laboratory experiments. The fuel density ρ can be estimated for various fuel types by field sampling. This equation was incorporated in the BEHAVE model (Andrews, 1986), which is widely used to predict surface fire spread in the United States and elsewhere.
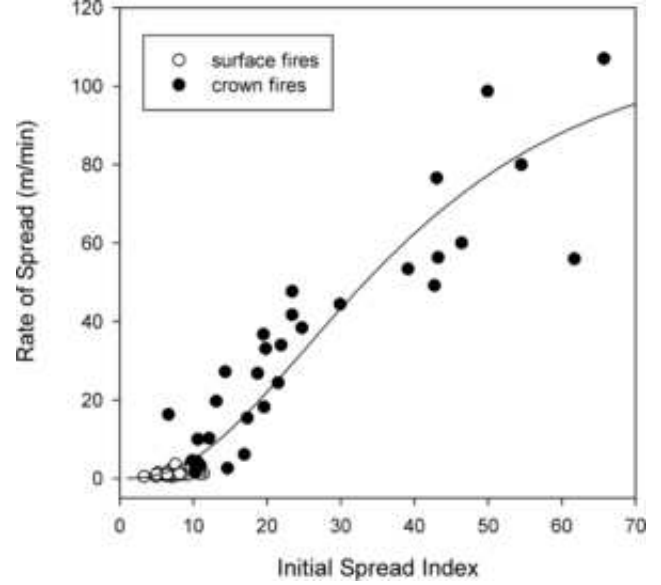

FIG. 5. *Observed (points) and predicted (line) rate of fire spread in lodgepole and jack pine forests in relation to the Initial Spread Index of the FWI System (redrawn from Forestry Canada Fire Danger Group, 1992). The predicted curve is derived from MLE of parameters of the Chapman–Richards equation. The surface fire observations are from experimental fires, while a number of the crown fires include wildfire observations.*

Sources of error in wildfire spread prediction include lack of model suitability and accuracy, as well as measurement or sampling errors in data used as input (Albini (1976); Alexander and Cruz (2013)). It may be difficult to decompose prediction error into these sources when evaluating the accuracy of a particular spread model against wildfire observations. A major challenge in this regard is that model inputs such as wind speed vary over both space and time. For example, because air flow over and within forest canopies is turbulent (and also may be affected by the fire dynamics), wind speed varies at a scale of seconds over distances of 10 s metres, making accurate estimates at the fire front difficult (Sullivan and Knight, 2001). In a review of the accuracy of ten empirical and semi-empirical models of fire spread (Cruz and Alexander, 2013), six of the models had mean absolute prediction errors (MAPE) of 20–40% with respect to their source data sets. MAPE was defined as

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|\hat{y}_i - y_i|}{y_i}\right)100,$$

where y_i was the observed rate of spread, $\hat{y}_i$ was its corresponding predicted value, and i indexed the sample of size n.

Those identical ten spread models have been applied in at least forty-eight independent studies with more than five observations arising from experimental, prescribed fires and wildfires. Seven studies comprising mostly experimental fires (which presumably had the most accurate inputs and spread documentation) had a MAPE of 20–30%. A further nine, twenty-six, and seven studies with MAPE of 31–50%, 51–75%, and >75%, respectively, are a mix of wild, experimental, and prescribed fires. The Rothermel (1972) spread model was the most widely applied—its median MAPE in twenty-eight studies was 57% (range 20–310%). Because there have been few model comparison studies (e.g., Sauvagnargues-Lesage et al. (2001)) or systematic model evaluation programs (Cruz and Alexander, 2013), validation data have only accumulated slowly over time. The accuracy of some models and/or the accuracy of predictions in some vegetation types is, unfortunately, not well described.

3.2 Fire Growth Models

Because fire spread rate in empirical and semiphysical models such as BEHAVE and the FBP System is one dimensional, geometric models have been developed to project fire growth over time in two dimensions. Van Wagner (1969) proposed the use of an elliptical fire growth model with fire size A and perimeter length P:

$$A = \frac{\pi}{2}(v + w) \times u \times t^2;$$

$$P \approx \pi(a + b)\left(1 + \frac{M^2}{4}\right),$$

where u, v and w are the flank, head and back fire ROS, respectively, t is the elapsed time since ignition, and a and b are the long and short semi-axes of the ellipse, respectively [which are related to ROS as $a = (v + w)t/2$ and $b = ut$], and $M = (a - b)/(a + b)$. The equation for P is an approximation for the circumference of an ellipse, truncating an infinite Gauss–Kummer series at the second term. Other models that extend the idea of an elliptical-based model have also been proposed (Anderson, 1983). Although critical examination shows that fire growth, even in uniform conditions, is ellipse-like at best, the use of a model based on an ellipse nonetheless provides robust estimates of area and perimeter in the early stages of fire growth [Figure 6(a)].[7] The
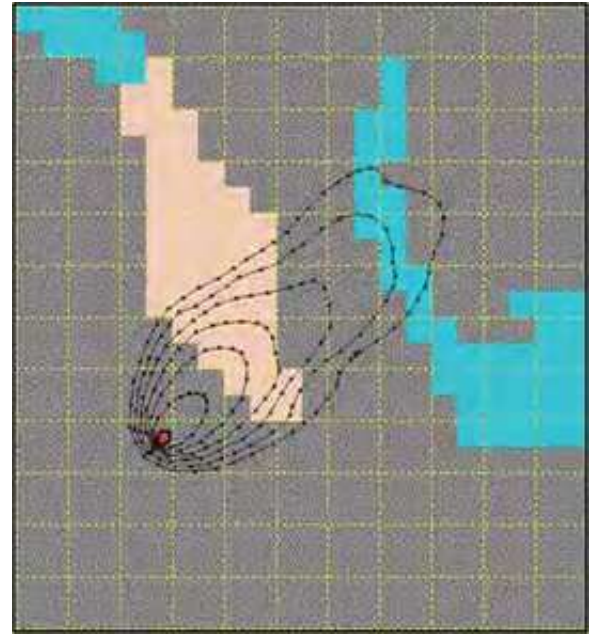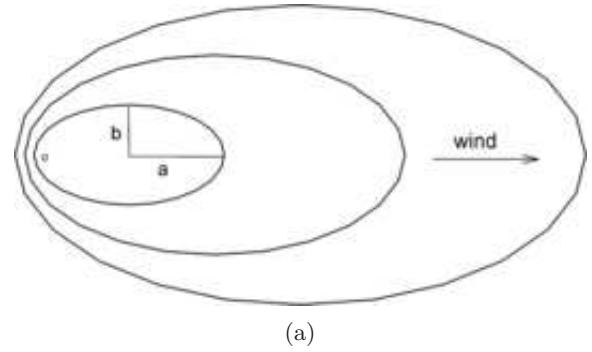

(a)

(b)

Fig. 6. (a) *The elliptical fire growth model is robust in early stages of fire growth. The area and perimeter can be calculated from the long and short semi-axes, a and b, respectively, which in turn can be calculated from the head, back and flank fire spread rates and the elapsed time from the fire origin, denoted by an "o" in the plot (redrawn from Van Wagner, 1969).* (b) *Thirty-five-minute simulation of fire perimeter growth in heterogenous fuels at 25 m resolution at 5 minute intervals following the wavelet propagation approach in Prometheus (Tymstra et al., 2010). The colors represent different fuel types (gray is boreal spruce, beige is grass, and blue is spruce lichen woodland). The red circle represents the ignition point, and the black dots are the individual vertices along the fire perimeters.*

elliptical model has two useful properties when ROS is constant: (1) the area burned by the fire at any time is proportional to the square of the time since

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[7]It is worth noting that only a thin zone around the fire perimeter from tens of centimetres–metres in depth is actively

flaming at any time [Figure 5(a)]; this is because the duration of flaming at any point is in the order of several seconds–minutes, and flame zone depth = ROS× flaming duration.

ignition (growth in area follows a power function), and (2) the rate of fire perimeter increase with time is constant (Van Wagner, 1969).

However, where fires spread for periods of hours to days, ROS and spread direction are influenced by variation in wind speed and direction, as well as by variation in fuel properties and topographic conditions. Fire growth simulation models have been developed to project fire growth in heterogeneous conditions in two dimensions using one-dimensional ROS equations, often at hourly or sub-hourly intervals, for periods of hours to days. At least 20 fire growth simulation models and 22 mathematical analogue models have been developed (Pastor et al. (2003); Sullivan (2009c)); the latter implement a variety of methods including Markov chains, interacting particle systems, percolation, cellular automata and differential equations.

Kourtz, Nozaki and O'Regan (1977) developed one of the first "contagion" models of fire growth, implemented in a lattice (grid) structure, where the spread distance from cell to cell was based on ROS from the FBP System and wind direction. However, lattice models constrain the potential spread direction and distance in each time period. Richards (1990, 1995) developed an algorithm to project the increase in fire perimeter based on Huygens' principle of wave propagation that overcomes this constraint. The fire perimeter is discretized into a polygon of vertices joined by line segments. Fire spread from each vertex is then projected as an elliptical wavelet of dimensions calculated from ROS equations, and the new perimeter is formed as the outer hull of the projected points (removing interior knots, overlaps and crossovers that may evolve) [Figure 6(b)]. This method was implemented in the fire growth simulators FARSITE (Finney, 1998) and Prometheus (Tymstra et al., 2010); the spread distance of wavelets in each iteration is calculated using BEHAVE and the FBP System in the former and latter models, respectively. Minimum travel time methods have subsequently been implemented in FARSITE (Finney, 2002).

Hybrid empirical–physical approaches have also been used, coupling empirical surface fire growth with atmospheric fluid dynamics models in order to represent the complex interactions between large fires and the atmosphere (Clark et al. (1997); Clark, Coen and Latham (2004)).

More recently, physical models have been developed which allow for fine scale representations of fuel structures and fire growth in a three-dimensional lattice. Examples of these are FIRETEC (Linn et al., 2002) and the Fire Dynamics Simulator (Mell et al., 2007). FIRETEC has also been linked to a fluid dynamics model in order to represent interactions with the atmosphere. Fire growth is implicit in these physical models, although it is limited to relatively short time periods and small areas for computational reasons, while head, back or flank fire spread rates are derived quantities. Furthermore, replicating the behavior of full scale fires with physical models remains very challenging (Mell et al. (2007); Linn et al. (2012)).

Fire growth prediction errors may also arise due to a lack of model suitability, accuracy limitations of the given model (e.g., due to the scale on which predictions are made) and noisy input data. Model performance has been assessed using various measures that compare observed and predicted results, including the difference in the radial distance from the fire origin to points around the perimeter (Fujioka, 2002); difference in fire spread distance (Duff, Chong and Tolhurst, 2013); association between predicted and observed burn perimeters [using Cohen's Kappa coefficient, Sorensen's coefficient Arca et al. (2007) and a Shape Deviation Index (Cui and Perera, 2010)]; and agreement in final fire size distributions [using the Kullback–Leibler divergence (Couce et al., 2010)] without regard to spatial association. However, a major challenge is that validation data from wildfires are often of poor quality and/or at a coarser spatio-temporal resolution than model simulations. Weather data inputs may be obtained from a single station many kilometres distant from the fire location or interpolated from a number of distant stations, or estimated from a numerical weather prediction model (Jones et al., 2003). Furthermore, fire perimeters are not usually mapped more frequently than daily in fire operations. It then becomes problematic when the interval between observations is several times the model time step because of error accumulation, particularly in fire spread direction and head fire location. Importantly, note that after analysis of twenty-five fires, Finney (2000) concluded that it was not possible to determine growth model performance or error without controlling or quantifying uncertainty in the input data. On the other hand, analysis of a large number of fire growth predictions should reveal model biases if data input errors are unbiased.

The accuracy of both empirical and physical fire spread models, as well as of fire growth simulation

models, is limited by imperfect understanding of and ability to represent the physical processes over appropriate scales, variation in atmospheric conditions such as wind speed and direction that affect spread but which cannot be precisely known or forecasted, and variation in vegetation and topographic conditions that is imperfectly represented in models.

However, uncertainty in data inputs has only be incorporated into fire growth models in a few cases. Wiitala and Carlton (1994) estimated the probability of a free-burning fire in wilderness areas spreading over a period of weeks from the probability of a "spread event day" with strong winds and the probability of significant precipitation determined from climatological records. Anderson (2010) extended these concepts spatially, combining estimates of the spatial probability of daily spread and extinguishment in a probabilistic model of the fire growth over weekly to monthly periods. Anderson, Flannigan and Reuter (2005) also demonstrated the use of ensemble methods from meteorology to represent the effect of varying weather conditions by introducing random and systematic perturbations to weather forecast inputs to a fire growth model. Finney et al. (2011a) also applied ensemble methods to implement FARSITE in a fire probability simulator by randomly and systematically perturbing the weather input data. Additional links could be made to probabilistic methods utilized in meteorology and climatology. Indeed, medium term ensemble numerical weather model output, such as from the North American Ensemble Forecast System (Toth et al., 2005), are believed to be well suited to making probabilistic fire projections over 3–10 day time periods, while climatological methods may be more suited to longer time periods (Anderson, 2002).

Boychuk et al. (2009) developed a stochastic fire growth model using a continuous time Markov chain on a lattice, which also incorporates a stochastic spotting mechanism. They remarked that while it is well known that embers can be produced from intense fires, lofted in the smoke plume and deposited ahead of the fire, where they may start new fires, these processes are difficult to observe and measure.

3.3 Fire Size

Wiitala and Carlton (1994) observed that the spread of a free-burning wildfire over a long period is made up of normal spread days, punctuated by rare spread events, where major growth occurs—this is particularly true for crown fire regimes, where there

can be almost an order of magnitude increase between surface and crown fire ROS. They considered that the probability of fire movement at any time was related to the probability of spread and to the probability of extinguishment, both of which were calculated from waiting time distributions for major wind events and fire-ending rainfall.

A number of studies have suggested that fire size distributions follow an exponential (Baker (1989)), power law (Malamud, Morein and Turcotte (1998); Jiang et al. (2009)) or a truncated Pareto distribution (Cumming (2001); Schoenberg, Peng and Woods (2003); Cui and Perera (2008); Holmes, Hugget and Westerling (2008)). Power-law behavior has been argued based on self-organized criticality (Malamud, Morein and Turcotte, 1998) or highly optimized tolerance (Moritz et al., 2005) arising in dynamical systems.

Reed and McKelvey (2002) provided an important review of parametric models for fire size distributions. They examined power-law behavior through the lens of goodness of fit in analyses of several data sets (Figure 7) and demonstrated that such behavior is only approximated over limited ranges of fire
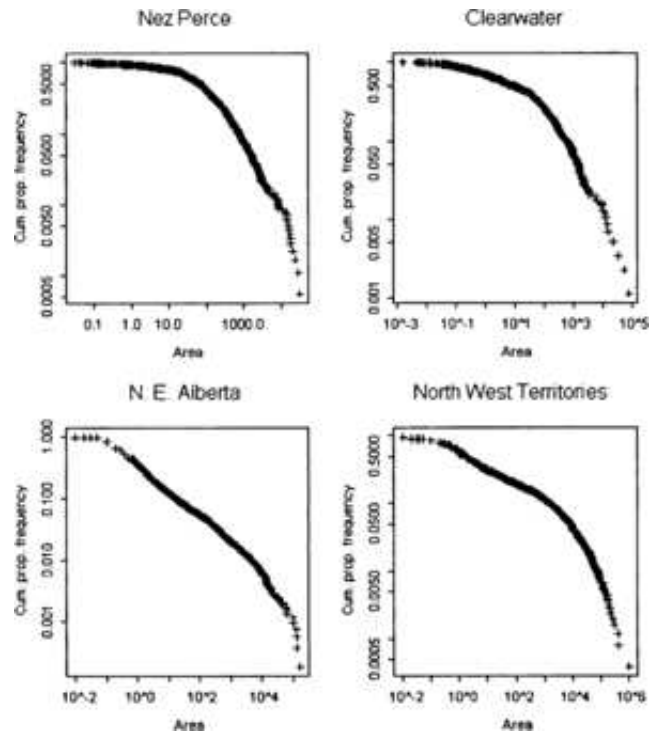

FIG. 7. *Fire size distributions in the Nez Pierce and Clearwater National Forests, Idaho, USA, and in northern Alberta, and the Northwest Territories, Canada (Reed and McKelvey, 2002). Note the increasing maximum fire sizes in the latter two, larger and less managed, northern regions.*

sizes. More importantly, a model is developed which blends both stochastic processes for growth and extinguishment of fires and is used to develop an essential model feature, termed the extinguishment growth-rate ratio (EGRR) from which conditions for power-law behavior are examined in depth. The growth in area burned is assumed to depend on the current size of the fire (ignoring spatial aspects, such as the fire's shape), modeled as a pure birth process whose discrete states represent regularly spaced, increasing "markers" of fire sizes. The extinguishment of a fire is modeled through a stochastic "killing rate" function, where the probability of extinguishment also depends on the current size (i.e., state) of the fire. The EGRR is analyzed to determine general conditions for when a given fire size distribution follows power-law behavior. For example, power-law behavior over a given interval of fire sizes would be characterized by a constant EGRR over that interval; deviations from a constant EGRR suggest departures from a power-law behavior. Thus, a single power-law distribution for the size distribution of a given set of fires would be exhibited by a single, constant EGRR—a rather restrictive condition—while power-law behavior in the upper tail of a fire size distribution would be exhibited by an EGRR converging to a positive limit. Special cases are also considered, for example, when the fire front moves at a fixed velocity or when the shape of the fire is not regular but fractal, with area related to length by a power-law relationship and with the fire front moving at a fixed velocity. None of the special cases were generally deemed appropriate in practice; most seemed highly restrictive. Several models are also proposed for fire size, including a 3-parameter Weibull and a competing hazards model which allows for competing causes of extinguishment. These are also used to illustrate that no single model seems superior for the several data sets examined. Although the power law continues to be used in the literature (Malamud, Millington and Perry (2005); Holmes, Hugget and Westerling (2008)), Zinck and Grimm (2009) emphasized that it is better to refer to power law-like behavior and to use caution when making interpretations based on model assumptions.

There are several aspects of fire size modeling which are not well incorporated into current approaches for analysis. For example, the amount of effort applied to extinguishing fires varies with a number of factors, including proximity to settlements,

commercial value of timber and current fire load. Furthermore, fire size is limited by factors such as fuel continuity, topography and the change of seasons (especially in regions where snow accompanies the arrival of winter); the effect of fuel continuity on extinction varies with fire size, while seasonality effects vary with ignition date.

4. BURNED AREA AND FIRE FREQUENCY

The annual area burned (BA) in a region is one of the most common statistics recorded by fire management agencies. It is often used as a measure of fire season severity, as the risk to timber, air quality and other values is more closely related to the area burned than the number of wildfires (Wiitala, 1999). Annual BA often varies by a factor of 10 or more, in a region, with variation in annual weather and fire danger, and longer term climate cycles (Meyn et al., 2009). A number of different methods have been used to model the relationship between BA and climate and fire danger variables, including so-called multivariate adaptive regression splines (Balshi et al., 2008) and general additive models (Krawchuk et al., 2009). A surrogate measure of suppression effectiveness was included in Martell and Sun (2008) along with fuel and a climatic measure of fire weather in their analysis of BA in the province of Ontario. Both increases (Westerling et al., 2006) and decreases (Meyn et al., 2010) in BA have been reported in different regions in the past decades, suggesting that BA is nonstationary in some regions.

Assessing correlation in the number of fires and BA between regions is important for estimating the collective demand for fire management resources in larger mutual aid schemes, such as the national resource sharing systems used in Canada and the United States. Magnussen and Taylor (2012b) modeled correlations between regions and employed Monte Carlo sampling to estimate the likelihood of peaks in BA between two or more regions occurring within a 14 day period.

Wiitala (1999) combined a model for fire size variability with a Poisson process for fire arrivals to yield the compound Poisson probability model of BA. However, because of the difficulties in parameterizing fire size distributions, the risk of BA exceeding particular values was estimated by discretizing fire sizes into classes, estimating parameters within classes and calculating joint probabilities of the number of fires in each class exceeding the threshold.
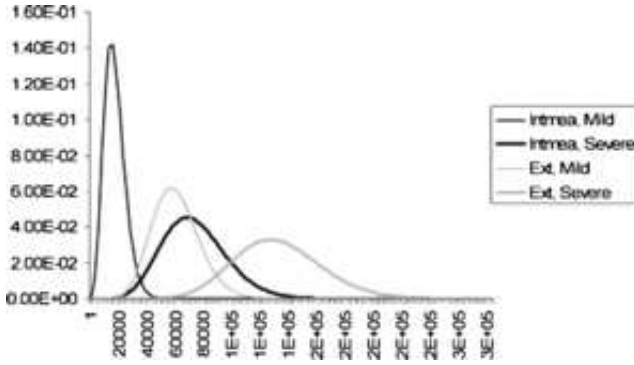
Fig. 8. *Compound Poisson distributions fitted to annual area burned for four scenarios: mild and severe years in intensively (Intmea.) and extensively (Ext.) protected forests in Ontario, Canada (Podur, Martell and Stanford, 2010). Categorization into mild or severe years was based on a Seasonal Severity Rating, namely, an average of the Canadian Forest Fire Weather Index System's Daily Severity Rating.*

Drawing on models of aggregate claims in insurance, Podur, Martell and Stanford (2010) demonstrated that the annual BA could be estimated as a compound Poisson distribution of the large fire occurrence rate and expected large fire size. If fire sizes are exponentially distributed, the total BA is Poisson-exponential and is distributed as

$$Fs(s) = e^{-(\lambda + sX)}(2\sqrt{\lambda X/s})I_1(\sqrt{\lambda sX}), \quad s > 0,$$

where s is the annual area burned, λ is the annual occurrence rate of large fires, X the expected fire size, and I_1 the modified Bessel function (Figure 8). If fire sizes are Weibull-distributed, BA is Poisson–Weibull and fire size distribution quantities can be calculated using the lognormal or Pareto approximations.

The annual or average percentage BA has been used as a measure of fire control success for many years (Show et al. (1941); Beall (1949)). Heinselman (1973) introduced the term Natural Fire Rotation (NFR) in an ecological context, defined as the time required to burn an area equal in size to the study area,

$$\text{NFR} = \frac{A}{A_f}N_y,$$

where A is the total area of the land, A_f is the total area burned by all fires (re-burned areas included), and N_y is the period of observation in years. However, NFR is simply the inverse of the average annual percent BA, which in turn is equal to the average probability of a point in the landscape burning (Fall and Lertzman, 1999), assuming fires occur as a Poisson process in space and time. Both percent BA

and NFR are calculated using annual BA, compiled from administrative records (e.g., Figure A.1) or by reconstructing fire boundaries from stand age maps. Thus, both the size of the sampling area and the length of observation influence NFR, in as much as they influence the likelihood of including rare large fire events. Although informal, NFR remains a popular concept because it is easy to calculate and to communicate.

However, a complete history of burned areas is often not available. In unmanaged forests of fire origin, the so-called age distribution depends principally on fire frequency. The age-distribution represents the distribution of time-since-fire over every point on the landscape. Conceptually, the statistical problem can be understood as dividing the study area into a large number of small subunits over a grid and viewing the resulting survival analysis as a context where time moves backward, with subunits surviving until they fail through the most recent past fire occurrence. What is typically available for analysis is the proportion of the study area that falls within various time-since-fire classes. Classes are usually determined from forest stand age maps in decades; where long term maps are available, annual classes may be used.

Typically, the negative exponential survivorship model is fitted to the cumulative time since fire data:

$$A(t) = e^{\lambda t},$$

where $A(t)$ is the proportion of the landscape surviving to time t, and λ is the hazard rate or proportion of area burned, assuming that fire occurrence in space and time is a Poisson process (Van Wagner (1969); Johnson and Gutsell (1994)). Sampling areas should be homogeneous with a uniform hazard rate and larger than the largest fire. The inverse of λ has been called the fire cycle, which is the average stand age of a forest whose age distribution fits the exponential or Weibull distribution. When age class data are used, bias may be introduced by the "missing tail" (Finney, 1995), where very old stands are censored by other competing hazards (insects, wind, old age).

The key element is the identification of changepoints in fire hazard rates as well as comparisons of epochs and their hazards over large scale landscapes globally. Up until the early 1990s, estimation of such changepoints in the forestry literature was based on identifying changes through visual inspection of related empirical plots (Reed, 1994). In the late 1990s,

likelihood inference emerged in the forestry litera-
ture for estimation of parameters of survivor func-
tions arising from step-function hazard forms, where
changepoints were specified (Reed et al., 1998). Reed
et al. (1998) developed a test for homogeneous haz-
ard against an alternative of their being a single
changepoint.

A substantial shift to more rigorous approaches
was initiated by Reed (2000, 2001), where quasi-
likelihood methodology was employed to obtain es-
timates of hazards, given k changepoints, while the
number of changepoints was determined through the
Bayes Information Criterion. Using the conceptual
framework described earlier where the study area is
divided into N subunits over a grid, the number of
units falling in each time-since-fire class is assumed
to follow an overdispersed multinomial distribution;
overdispersion is incorporated to accommodate spa-
tial correlation in a simple way. The quasi-log like-
lihood is

$$Q = \frac{1}{\sigma^2} \sum_{j=1}^{m} y_j \log(\theta_j)$$

$$= \frac{1}{\sigma^2} \sum_{j=1}^{m-1} [s_j \log\{q^{(j)}\} + y_j \log\{1 - q^{(j)}\}],$$

where

$$s_j = \sum_{i=j+1}^{m} y_i$$

and

$$q^{(j)} = e^{-\lambda_j T}.$$

In the above, θ_j is the probability that a particu-
lar subunit belongs to time-since-fire class j; classes
here are $((j-1)T, jT] (j = 1, \ldots, m-1)$, while pe-
riod m is defined as more than $(m-1)T$ years ago.
As mentioned previously, T is typically 10 years.
Models with k changepoints at prespecified times
$p_1 T < \cdots < p_k T$ have hazard rates λ_i between $p_{i-1}T$
and $p_i T$. Estimation of λ_i and the overdispersion pa-
rameter σ^2 is trivially accomplished through quasi-
likelihood estimation. By assigning prior probabili-
ties to models M_k with k changepoints, the Bayes
Information Criterion for M_k as well as posterior
probabilities for M_k can be used to guide plausi-
ble choices for k. By contrasting changepoint values
for a sequence of models $M_0, M_1, M_2, \ldots$, and using
a sensitivity analysis of priors, assessments can be
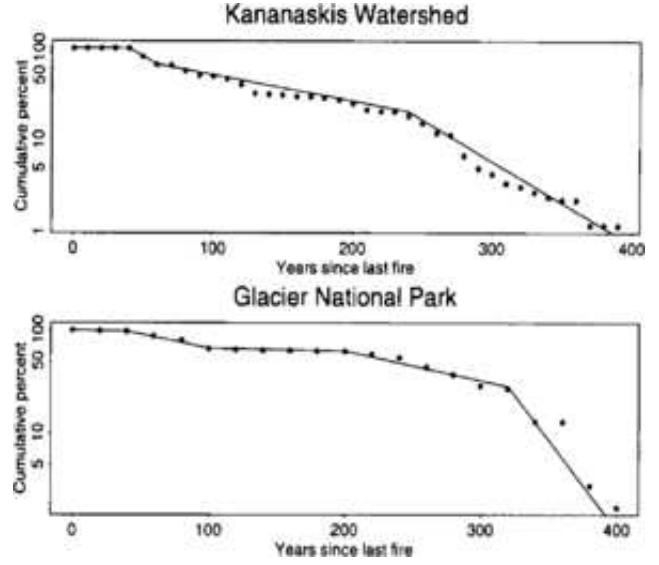made on the consistency of changepoints to evaluate
model choice.

Fig. 9. *Cumulative time-since-fire distributions derived
from forest stand ages in the Kananaskis watershed, Al-
berta, Canada, and Glacier National Park, British Columbia,
Canada. The line segments extend over epochs defined by the
most plausible change points; epochs are assumed to have a
constant hazard (Reed, 2000).*

Reed (2000) applied this methodology to contrast
fire epochs over two major regions, identifying im-
portant scientific hypotheses related to fire regime in
these regions (Figure 9). Two major advancements
in this methodology would result from further treat-
ment of spatial correlation using more modern tools
available, as well as incorporation of uncertainty in
estimates arising from the model selection process.

4.1 Point Frequency

The interval between fire arrivals at a point in a
landscape, as recorded on fire scars on trees (e.g.,
Figure A.4) or as charcoal intensity in sediments, is
well modeled by a Poisson process. The challenging
problem of estimating fire frequency from fire-scar
data requires essential design and analysis consid-
erations which take into account that (i) all possi-
ble fire-event chronologies have an equal chance of
being chosen, (ii) not all trees are scarred in a par-
ticular fire, (iii) methods based on an independent
normal assumption are likely untenable, (iv) fire fre-
quency intervals change over large epochs of time.
Johnson and Gutsell (1994) discuss design consider-
ations related to (i) above, including the impact of
choosing trees for fire-scar studies which are easily
accessible or which have the most scars. While this
approach can extend estimates of fire frequency to
hundreds and thousands of years (in the case of fire

scars and sediments, resp.), neither trees nor sediments are perfect recording instruments; some fires may be missed or erased by other processes.

For many years the traditional approach considered the observed intervals between scars on all trees in the sample and computed estimates of the mean time between fires—the mean fire interval (Arno, Sneck and Forest (1977); Kilgore and Taylor (1979); Agee (1996)) where the confidence intervals come from the t-distribution, assuming that all sites have equal probability of burning (data are normally distributed and independent). Exploiting larger numbers of samples, Grissino-Mayer (1999) fit two- and three-parameter Weibull distributions to long fire interval data sets in Arizona. Reed and Johnson (2004) advanced approaches substantively by developing methods which account for the potential that fires may not leave scars and, as well, that the independence assumption is invalid as fires spread spatially. The approach uses first principles to develop a model whereby a constant hazard rate for fire occurrence within epochs is combined with an overdispersed binomial to handle the contagious effect of fire spread; as well, the probability that a scar-registering fire leaves a scar is assumed constant for all objects sampled. By partitioning the probability of the observed data into a sequence of conditional probabilities, an overall log likelihood function is constructed. Estimation, however, proceeds via estimating equations which are a combination of the maximum likelihood equations for parameters in the mean and a moment estimator for the dispersion parameter.

4.2 Burn Probability

Because data from unmanaged crown-fire dominated forests and fire scarred trees are restricted to certain environments (and in some cases are becoming rare within these environments), other methods are needed to estimate fire frequency at local and landscape scales, the probability that fires may threaten settlements, infrastructure, timber and other values at risk, and the influence of climate changes on fire frequency. In the last decade both simulation and regression-like approaches have been developed.

Monte Carlo approaches implicitly or explicitly combine distributions of ignitions and spread event days with deterministic fire growth models to estimate fire sizes, annual area burned and burn probability or local hazard of burning in a landscape. For example, the Prometheus fire growth model was implemented in software called BurnP3, to simulate fire spread in landscapes defined by vegetation (fuel type) and topography grids (slope, aspect), over time periods defined by a series of daily weather conditions (Parisien et al., 2005). The fire footprints resulting from many thousands of simulations are "added up" to determine the burn probability or local hazard of burning in a grid cell. Either random or spatially-explicit ignition probabilities may be used (Braun et al., 2010). A similar scheme was used to estimate burn probability in the contiguous United States of America (i.e., excluding the noncontiguous states of Alaska and Hawaii) [Figure 10(a)] by implementing the FARSITE growth modeling in FSIM software (Finney et al., 2011b).

In a two-stage approach, Preisler et al. (2011) used a linear model to estimate mean suppression cost as a function of covariates (including fire size) and parametric models were developed for the distribution of fire sizes. Then, a Monte Carlo approach was employed: spatially explicit probabilities of large fire occurrence were forecast and then were stochastically mapped to presence/absence of ignition in a cell. Conditional on large fire ignition being present, a fire size is simulated and then the projected mean suppression cost is obtained from the related linear model. This procedure was repeated a large number of times to produce spatial maps of expected suppression costs over an upcoming fire season.

Parisien and Moritz (2009) applied two tree-based machine learning algorithms (e.g., Hastie, Tibshirani and Friedman (2009)), MaxEnt (maximum entropy) and boosted regression trees (BRT), to predict the environmental space where wildfire can occur in California and in the contiguous United States of America. The models were fitted to fire map and large fire occurrence data, including a large suite of environmental variables such as climate normals, as well as vegetation and topography covariates, in order to evaluate the contribution of the individual variables to the susceptibility to fire in a landscape. Parisien et al. (2011) also used boosted regression trees to evaluate environmental controls on area burned in the boreal forest of Canada. MaxEnt methods were used to evaluate a broader set of environmental variables, including lightning and road density on wildfire probability in the western United States (Parisien et al., 2012) [Figure 10(b)].

5. DISCUSSION AND CONCLUSIONS

All events in a wildfire—ignition, growth and extinguishment—are governed by physical principles of
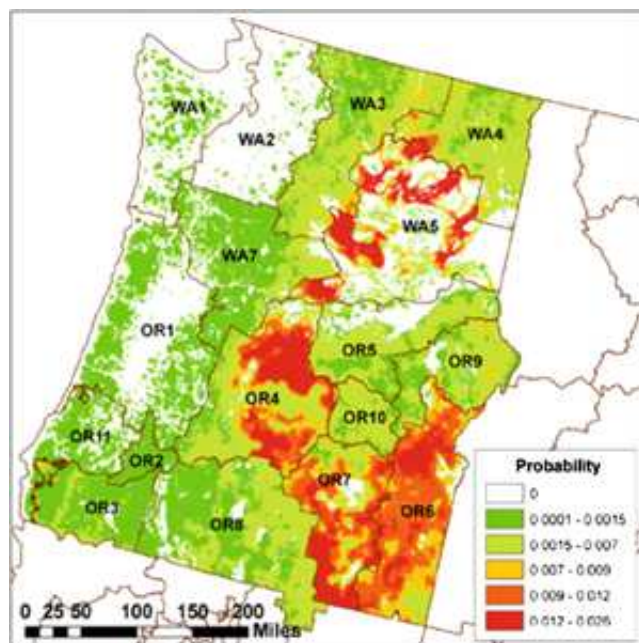
(a)
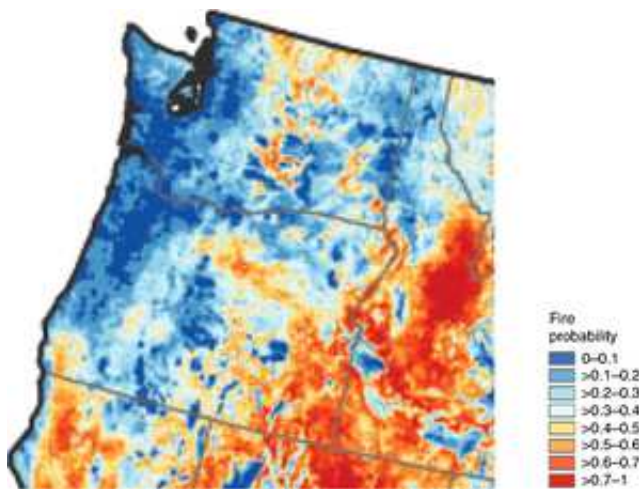
(b)

FIG. 10. (a) *Annual probability of a 270 ha cell burning on federal lands in Washington and Oregon, USA, estimated from simulation modeling of potential fire ignitions and spread (Finney et al., 2011b).* (b) *Relative probability of burning in the western United States estimated from MaxEnt methods (Parisien et al., 2012).*

conservation of energy, mass, chemical species and angular momentum (Saito, 2001). While a number of deterministic physical and empirical models of fire spread have been developed, wildfire prediction is essentially probabilistic. This is because, even if we had perfect knowledge of the physical processes, (1) human and lightning ignition sources are random, (2) the flammability of dead organic fuels and

fire spread rates are influenced by the state of the atmosphere, and this cannot be precisely known over any period,[8] (3) vegetation characteristics important to fire behavior vary across the landscape and cannot be precisely represented in models. While physical models may contribute further understanding, statistical models and approaches are needed to quantify uncertainties which are crucial for making decisions with specified precision. Data are available from a number of sources to support modeling of fire risk elements over different time periods; these include administrative and historical records, case studies, laboratory and field experiments, vegetation proxies (tree rings, stand age, charcoal), remote sensing and numerical models, as summarized in our article's Appendix. Each data source has its own strengths and weaknesses. Administrative records of fire management organizations have been a primary source for fire occurrence and size data. However, such records are commonly only available for decades to a century at most, and in a limited number of regions. Data quality is variable, and there are few opportunities for verification of historical records. Furthermore, records collected for administrative purposes may be at a different resolution or have missing information that would be important for modeling. For example, while it is common to record the day a fire starts and its final size, the dates of control and extinguishment may be missing, and information on daily fire growth progression is rare and comes mostly from case studies and historical records. Remote sensing data on fires are available for the last few decades but at different temporal and usually coarse spatial scales. Fire frequency can be inferred from proxy vegetation data over periods of hundreds to thousands of years but with declining temporal resolution. Censoring is common in all of these data types. Small fires may be missing (left censored) from administrative data, vegetation proxy data (tree-rings, age class, charcoal) and remote sensing data due to incomplete detection; furthermore, detection effectiveness may vary over time in administrative data. Right-censoring is common in tree ring and stand age data because trees can die from other causes. Over long time series, fire

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[8]Similar considerations apply to statistical uncertainty in meteorology (Palmer et al., 2005) and climatology (Von Storch and Zwiers, 2002.)

frequency records are nonstationary, due to variation in climate, fire management strategies and efficiency, patterns of development and land use practices. Many studies combine more precise, extensive, physical data on weather or climate covariates with less accurate, consistent and rigorous fire data (or vice versa) without accounting for differences in the precision of various data elements. Different study designs, some perhaps encompassing clustering, repeated measures, stratification and multi-stage sampling, could be considered. Hence, substantial data cleaning, in collaboration with forestry managers and scientists, is required as a first step to any analysis.

The theoretical framework (Poisson process theory) for fire occurrence modeling is well developed. Further improvements in prediction may come from both improved data, for model assessment and refinement, and improved modeling frameworks. Although lightning fire prediction has been greatly aided by lightning detection system data, strikes are missed in a nonrandom manner–detection efficiency and spatial accuracy is related to the proximity to a sensor. If detection system effectiveness could be quantified (in particular, how the probability of a fire not being reported has changed over time/space), it could be incorporated into a logistic model using inclusion probabilities analogous to the case–control literature. One crucial aspect deserving of further study is the prediction of sharp peaks where a large number of lightning fires occur in a very short time period, which can be a significant fire management problem. A major challenge is the difficulty in assessing (or predicting) whether lighting storms are followed by precipitation (which can quench lightning ignitions). This is because convective precipitation often has a local distribution that is not measured accurately by sparse weather station networks. Assimilation schemes that combine data from surface weather stations, remote sensing, precipitation radar and numerical weather models (e.g., Mahfouf, Brasnett and Gagnon (2007)) may improve the accuracy of future lightning fire prediction models by providing a better representation of the spatial distribution of precipitation.

Despite many decades of research and development, fire spread modeling remains a challenge in some vegetation types. Although more than 70 fire spread models have been developed, only a small number (perhaps not more than half a dozen) of empirical and quasi-physical fire spread models are used in fire management; physical models have limited ability to replicate the full range of ROS observed in nature. Fire growth models often have a temporal resolution of seconds–minutes to match the temporal variability in wind speed. However, most wildfire data have been obtained by fire management agencies and are often not recorded more than daily. Detailed data sets on fire spread and growth at spatio-temporal scales that more closely match model resolution are needed to facilitate validation and inter-comparison studies in different vegetation types. However, obtaining good weather data observations near and during wildfires is difficult, and opportunities to carry out large free burning experimental fires (where weather can be closely monitored) are very limited. It may be necessary to monitor fire growth expressly for validation purposes (Finney, 2000), such as with airborne infrared imagers (e.g., Jones et al. (2003)).

Although it is likely that empirical models will continue to be used for practical applications for many years, it is well recognized that they have limited flexibility to account for variability in fuel characteristics and do not explicitly account for interactions with the mid-atmosphere that may occur in large fires. Representing different components of fire spread (surface spread, crown fire initiation, crown fire spread, spotting) in a system of equations may provide a means for increasing flexibility of empirical models (Cruz, Alexander and Fernandes, 2008).

Although extinguishment ultimately limits fire growth, it is not well studied empirically and only rarely included in fire growth models. Almost all of the physical and empirical fire spread models that have been developed are deterministic. Methods to represent uncertainty in fire spread and growth models deserve more attention, as this is important to decision-making.

Parametric modeling of fire sizes and area burned is difficult due to a myriad of causes, including spatial heterogeneity and the variable effects/effectiveness of fire suppression over the range of fire sizes. As well, fires that occur late in the year are not as likely to survive long due to changing weather, while earlier fires have the potential to last much longer—and hence, grow bigger; seasonality is not accounted for in current models. Monte Carlo simulation of fire growth can provide an approximation of fire sizes and area burned; however, it depends critically on models of fire spread and growth which are imperfect and often do not account for fire management influences. In future work, simulation and regression-like approaches might be used in a com-

plementary manner, where the latter, for example, may provide validation of simulation models.

In a warming climate, it will be imperative to improve fire risk assessment and prediction. This is both a scientific and management challenge. Systems are needed to predict fire occurrence and frequency at national and larger scales, including correlation in fire occurrence between regions. Methods are needed to accommodate nonstationarity. Model development is constrained in some regions by a lack of long term fire records. Satellite observations can be used at a coarse scale, such as for large fire prediction, and will likely become increasingly important as resolution increases. At present, few fire prediction models are used by fire managers at national, let alone global scales.

Finally, when the aim of statistical model development is to enhance fire management decision support systems used by fire managers to improve their decision-making, it is crucial to consider how such models can be integrated in management decision support tools while they are being developed. Complex models need to be implemented in computer-based fire management information systems in a manner that provides information (including uncertainty) at the appropriate scale for the decision problem. It can often take up to 10 years or more from the development and validation of new models to full implementation in operational systems and practices. Experience suggests that work is more likely to influence fire or land management if it involves collaboration between statisticians with an understanding of the strengths and limitations of statistical methods as applied for fire science, and scientists or practitioners with knowledge of the management questions, the knowledge of limitations of the data, and sometimes the means to implement new models in practice (e.g., Reed et al. (1998); Preisler et al. (2004); Wotton and Martell (2005)). Statistical science has an important role in bringing rigour to fire prediction and risk assessment in both fire management and fire ecology, and so providing a link between these two sometimes disparate disciplines.

APPENDIX: AN OVERVIEW OF WILDFIRE DATA SOURCES AND LIMITATIONS

The types of statistical models that can be developed and analyses that can be conducted are influenced by the type, resolution and availability of data. This appendix outlines eight major sources of quantitative and qualitative data which have been used to inform wildfire occurrence, growth, size and frequency models.

1. *Administrative records*: As systematic management principles began to be applied to wildfire suppression across much of North America in the early 1900s, foresters in some regions realized that detailed records would be needed to assess the effectiveness of fire management efforts—reports of individual fires have been kept in all national forests in the United States since 1922 (Show et al., 1941). Thus, individual fire reports, maps of perimeters of significant fires and annual summaries have been compiled for about 100 years in parts of the United States and Canada, and more recently in other regions (Figure A.1). Researchers soon realized that administrative records were a rich data source. For example, Show and Kotok (1923) used administrative records to examine annual fire frequency in California, while Abell (1940) made inferences about fire spread rates from individual fire reports. Some common limitations of administrative records include: (1) limited accuracy of spatial locations in older records—fire perimeters, for example, are often from sketched maps; (2) data are often left censored, as not all small fires may be detected; (3) the observational period may be relatively short in relation to the return period of extreme events in some regions; (4) data collected for administrative purposes may be missing some information that may be needed to address research questions; (5) the fire management agency passes over jurisdiction of some fires to other agencies (e.g., in the province of Ontario, Canada, the Ontario Ministry of Natural Resources transfers some fires over to municipalities). Nevertheless, administrative records continue to be a primary source of information on fire occurrence, fire size and area burned in managed forests and other regions where organized fire management is carried out. It is important to note, however, this is only a portion of the earth's fire environment.

2. *Historical records*: Though anecdotal, records of historical wildfires (Plummer, 1912) may provide important information on the occurrence of rare, extreme events. For example, Haines and Kuehnast (1970) reanalyzed the meteorological conditions of America's deadliest wildfire, the 1871 Peshtigo fire disaster, which killed at least 1500 people in Wisconsin. That fire had been investigated by Robinson (1872), who reported that embers from the fire landed 7 miles away on the decks of vessels in Lake Michigan.
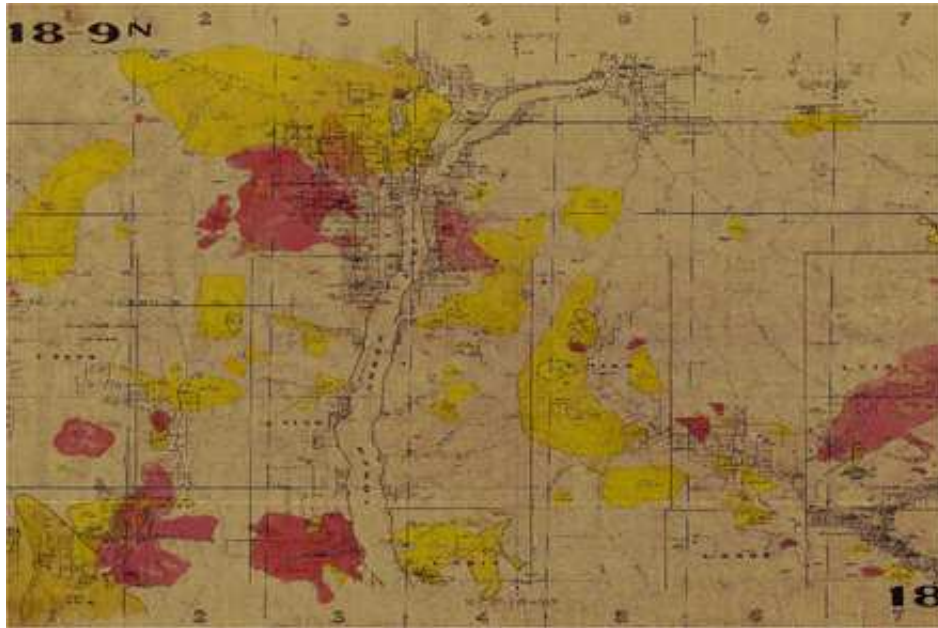
Fig. A.1. *Maps and other administrative records are important sources of data on fire locations, sizes and area burned. Lightning- (yellow) and person-caused (red) fires along the Columbia River in southern British Columbia, Canada, during 1920–1945 as recorded on a historical watercolor-on-linen map.*

3. *Outdoor experiments*: Fires that were lit under controlled conditions have provided among the most reliable data on fire ignition probability and fire behavior under measured environmental conditions for over half a century (Curry and Fons, 1938). Because such experiments are logistically difficult to carry out under severe burning conditions (Stocks, Alexander and Lanoville, 2004) (Figure A.2), they have been limited to fires smaller than 10 hectares in size. However, some phenomena associated with large fires cannot be readily reproduced in small experimental fires. These include long-range spotting ahead of the fire front and the development of smoke plumes reaching and interacting with winds in the lower and mid-troposphere.

4. *Case studies*: Detailed analyses of significant wildfires by expert observers (Gisborne (1927); Olsen (2003)) can provide important insights into extreme or unusual events (Alexander and Taylor, 2010). For example, the report by Kiil and Grigel (1969) remains the most complete documentation of one of the fastest spreading fires observed in the northern Hemisphere—a single fire spread event which extended 60 km in 10 hours; an average sustained rate of spread of $110+$ m min^{-1}.

5. *Laboratory experiments*: The effect of individual environmental factors, such as fuel moisture (Fons, 1946) or wind speed (Rothermel, Anderson and Forest, 1966), on fire ignition and spread has been examined under controlled laboratory conditions, which often employ wind tunnels. Such experiments have been important to parameterize physical and semi-physical models, but are limited to fires in the order of a metre in size. Fire spread in complex vegetation structures and phenomena related to vertical development, such as crown fire initiation, cannot be readily reproduced in the laboratory.

6. *Numerical and simulation modeling*: Mathematical models of fire initiation and spread have been implemented in computer simulations since the 1970s (Kourtz and O'Regan, 1971), allowing for experiments in the computer that are not possible in the laboratory or in nature. Physical models can be computationally intensive, so simulations of individual fires have typically been of limited size (several hectares) and duration (minutes). Monte Carlo-like methods have been used to simulate the growth of many thousands of fires (using empirical and quasi-physical spread models) on a regional scale to estimate fire size distributions and burn area probability or fire frequency (Parisien et al. (2005); Finney et al. (2011b)). There are still practical limits on the size of region that can be modeled at high resolution, which can result in edge matching issues between regions.

Fig. A.2. *Experimental fires allow for detailed observations of fire behavior. Crown fire in a 3 hectare jackpine stand carried out in the International Crown Fire Modeling Experiment, Northwest Territories, Canada (Stocks, Alexander and Lanoville, 2004).*

7. *Infra-red imaging and other remote sensing*: Infra-red imaging systems have been used to detect and map forest fires from aircraft since the late 1960s (Bjornsen, 1968), allowing accurate repeated measurements of forest fire perimeters and growth of large fires over periods of hours or days. Satellite imagery on the earth's land surface became available in the 1970s, and this has provided increasingly refined estimates of global burned area. LANDSAT imagery has been used to map burned areas, particularly in remote regions, since the late 1970s at 30 m resolution, but with only monthly sampling frequency. Radiometers such as the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) deployed on the NOAA and the NASA Aqua and Terra satellites, respectively, have been used to detect and map forest fires since the 1980s and 2000s (Flannigan and Haar (1986); Justice et al. (2002)). AVHRR and MODIS sensors detect fire activity at 1000 and 500 m resolution, respectively, several times a day at a global scale. Global burned area estimates, derived primarily from MODIS data, are shown in Figure A.3. Since 2002, the European MeteoSat geostationary satellites have detected fires over Europe and Africa every 15 minutes at 3000 m resolution (Roberts, Wooster and Lagoudakis, 2009). Remote sensing observations may provide an important source of data for fire occurrence modeling in regions where administrative records are incomplete.

8. *Vegetation and charcoal proxies*: Surface fires often cause nonlethal injuries in tolerant trees that result in "fire scars" observable in the live wood (Figure A.4). Dating fire scars using tree rings provides a point sample of time since fire. The frequency of such fires, typically in the order about 10–40 years, was first examined by Clements (1910), Howe (1915) and other pioneering researchers (McBride, 1983). However, the sampling period for fire scar records is limited by the lifespan of the tree species—up to several hundred years for long-lived species such as Ponderosa pine. Thus, the number of records in a region tends to decrease over time (right censored) as trees are cut or die from various other causes. Similar methods have been used to date anomalies in ring growth in eucalypts (Burrows, Ward and Robinson, 1995) and Australian grasstrees (*Xanthorrhoea*) that can survive high intensity fires.
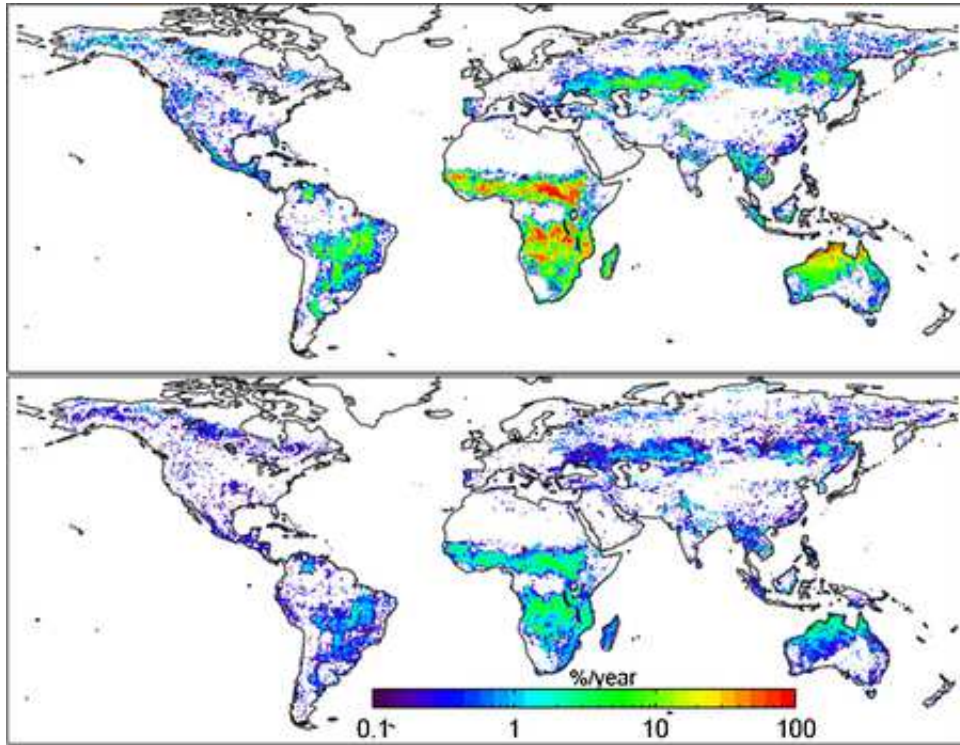
FIG. A.3. *Satellite imagery has been used to map fires since the 1970s. Mean annual global burned area (top) and associated one-sigma uncertainties (bottom) expressed as a fraction of each grid cell that burns each year derived from 1997–2008 (Giglio et al., 2009).*

Charcoal resulting from burning of woody vegetation is incorporated into the soil, while small fragments may be transported and deposited in lake sediments. Counts of charcoal fragments in soil or lake sediment cores represent point samples. Combined with carbon dating, fire frequency has been determined from the time between charcoal pulses in sediment cores (Swain, 1973). Although temporal
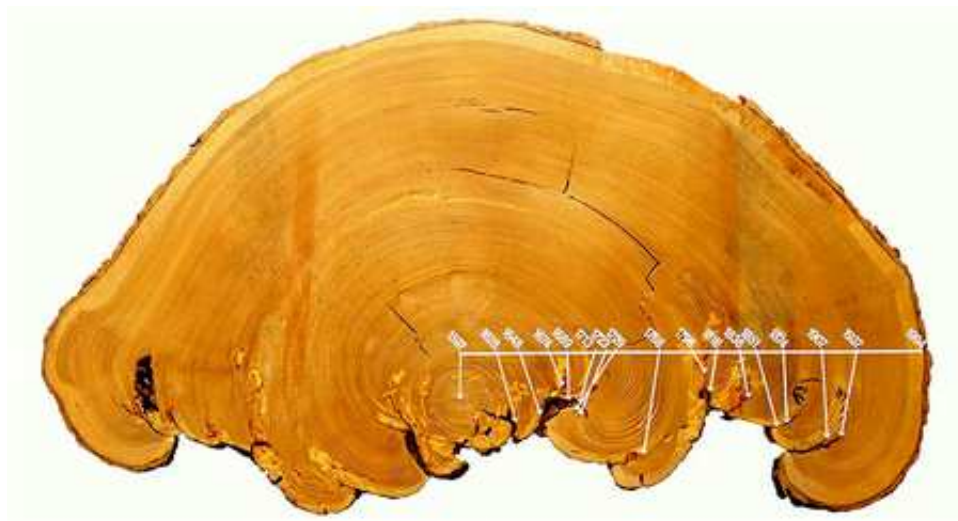

FIG. A.4. *Low intensity fires scar living trees, creating a record of the time between fires at a point over long time periods. Cross section of a western larch (90 cm diam.) from southern British Columbia with approximately 10 fire scars over 400 years (NRCan photo).*

resolution is coarser than annual tree rings, sampling periods can extend from centuries to millennia, depending on the geological history of the sampling area. Laboratory analysis of sediment cores is time consuming, which limits the sampling intensity. In a review of data analysis methods, Higuera et al. (2011) note that fire frequency over long time periods is usually nonstationary. Indeed, the association between climate variation and fire risk is often the motivation for paleo-ecological studies.

Northern temperate and boreal coniferous forests with crown fire regimes are made up of cohorts of approximately even-aged stands, whose ages can be used to date the fire initiating events. The age distribution of stands in a region can be used to estimate the fire frequency (typically 50 years to several centuries) assuming a frequency distribution such as the negative exponential (Heinselman (1973); Van Wagner (1978)) or the Weibull. However, the frequency of extreme events may be underestimated because it is difficult and time consuming to classify the age of all forest stands except in relatively small areas and such sampling areas are often small relative to the size of extreme events. As with tree ring data, older stands may be missed in sampling or lost due to mortality from other causes (right censored).

ACKNOWLEDGMENTS

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