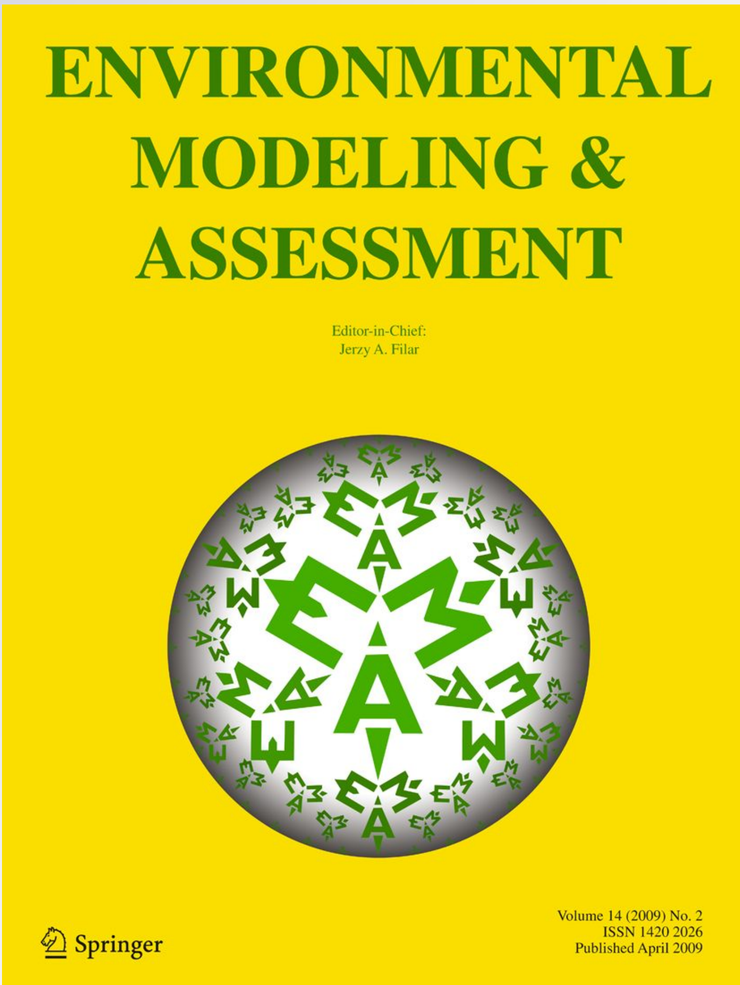
Modeling Large Fire Frequency and Burned Area in Canadian Terrestrial Ecosystems with Poisson Models

Yueyang Jiang, Qianlai Zhuang & Daniel Mandallaz

Environmental Modeling & Assessment

ISSN 1420-2026

Environ Model Assess
DOI 10.1007/s10666-012-9307-5



Springer

Environ Model Assess
DOI 10.1007/s10666-012-9307-5

Modeling Large Fire Frequency and Burned Area in Canadian Terrestrial Ecosystems with Poisson Models

Yueyang Jiang · Qianlai Zhuang · Daniel Mandallaz

Received: 31 January 2011 / Accepted: 16 January 2012

Abstract Large wildland fires are major disturbances that strongly influence the carbon cycling and vegetation dynamics of Canadian boreal ecosystems. Although large wildland fires have recently received much scrutiny in scientific study, it is still a challenge for researchers to predict large fire frequency and burned area. Here, we use monthly climate and elevation data to quantify the frequency of large fires using a Poisson model, and we calculate the probability of burned area exceeding a certain size using a compound Poisson process. We find that the Poisson model simulates large fire occurrence well during the fire season (May through August) using monthly climate, and the threshold probability calculated by the compound Poisson model agrees well with historical records. Threshold probabilities are significantly different among different Canadian ecozones, with the Boreal Shield ecozone always showing the highest probability. The fire prediction model described in this study and the derived information will facilitate future quantification of fire risks and help improve fire management in the region.

Keywords Large fires · Poisson model · Compound Poisson model · Ecozone · Large fire occurrence · Threshold probability

Y. Jiang (✉) · Q. Zhuang
Department of Earth and Atmospheric Sciences, Purdue University,
West Lafayette, IN, USA
e-mail: jiang5@purdue.edu

Q. Zhuang
Department of Agronomy, Purdue University,
West Lafayette, IN, USA

D. Mandallaz
Department of Environmental Sciences, ETH Zurich,
CHN K74.1,
CH 8092 Zurich, Switzerland

1 Introduction

Large fires (fire size ≥2 km^2) are a dominant disturbance in boreal ecosystems and exert significant effects on carbon cycling [1–3], vegetation dynamics [4], and the climate system [5]. Despite their small percentage (3%) of the total fire count, large fires accounted for approximately 97% of the total burned area during the period 1959–1999 [6]. As shown in Stocks et al. [6], the annual variability in fire occurrences is considerably high, both in terms of large fire frequencies and their burned areas. This substantial variability is caused by a complex variety of environmental factors, such as climate [7, 8], human influence [9, 10], and insect outbreaks [11]. In addition, the accuracy of reporting could vary in different periods and among the different regions. A number of studies have found a significant increase in Canadian burned area during the last four decades of the twentieth century [12, 13]. An investigation of the factors that could be responsible for this increasing trend would provide useful information to forest managers for predicting wildfire risk in a given region.

Previous studies have shown that climate and topography are very important factors in determining the occurrences and spread of large fires in boreal forests [14–16]. Although these studies have strived to link fire activity to climate and topography, the relationship between fire regime and these factors is not well quantified in terms of fire frequency and spread. In this study, we make a step forward in quantifying fire frequency considering the effects of climate and elevation.

Similar to Mandallaz and Ye [17], we use an exponential function of fire frequency versus climate to estimate the mean frequency, or count, of large fires in Canadian forest ecosystems. The estimated frequency is defined as the expectation of a Poisson distribution, which has been proven and widely used as an ideal approach to model a discrete rare event [18], such as fire occurrence [19, 20]. Because

Published online: 08 February 2012

large fires with different sizes could respond distinctly to climate and elevation, we modeled large fire frequencies in different classes according to their size. Since large fire activity shows obvious regional characteristics due to distinct regional climate patterns, topography, and human activities [21, 22], a regional characterization of fire regimes is very necessary. In this study, along with the national-level analysis, we also model the large fire frequency at the ecozone level and focus on presenting the results for the Boreal Shield ecozone.

In addition to fire frequency, burned area is also an important element in characterizing the fire regime [19]. However, because the fire spread is controlled by a complex variety of factors, it is still a big challenge to model the burned area of an individual large fire. In this study, we construct a probability function of a compound Poisson process to estimate the risk that the total burned area exceeds a certain size (hereafter referred to as the "threshold probability"). The derived fire risk map for different Canadian ecozones provides useful information for regional analyses of large fire regimes.

2 Method

2.1 Overview

To conduct the analysis, we first divide the fire data (1959–1999) into five classes according to their size and optimize the parameterization in the frequency prediction model for each class. We use the first 31 years data (1959–1989) for model calibration and the remaining years (1990–1999) for validation. Finally, we construct a probability function for a compound Poisson process to calculate the threshold probability for all of Canada and for each Canadian ecozone. It should be noted that we perform this analysis for all Canadian ecozones but focus primarily on the Boreal Shield ecozone. All calculations are conducted at a 0.5° spatial resolution and at a monthly temporal step.

2.2 Data Description and Study Area

This study relies on the Canadian Large Fire Database (LFDB, 1959–1999) from the Canadian Forest Service [6]. The LFDB is constructed based on provincial and territorial fire reports and includes digitized and georeferenced maps of fire perimeters. The database represents a compilation of all fires greater than 2 km^2 that occurred in Canada from 1959 to 1999 and contains information on fire location, start date, final size, and cause. In total, there are 11,453 fire events that occurred during the fire season (May through August). A limitation of the LFDB is that fire records are organized by various provinces, territories, and parks, which all have different methods for estimating and reporting fire sizes. Furthermore, some fires which occurred in the remote northern regions of some jurisdictions during 1959 and the mid-1970s are missing [6]. During the 1970s, only fires larger than 10 km^2 were recorded in Saskatchewan. In addition, Stocks et al. [6] indicated that more recent fire size estimates tend to be more accurate.

Two sets of historical climate data (0.5°, 1959–1999) are used to drive the model. The first dataset is the National Centers for Environmental Prediction (NCEP) Reanalysis-derived data provided by NOAA/OAR/ESRL PSD, Boulder, CO, USA [23]. The second dataset is obtained from the Climate Research Unit (CRU) of the University of East Anglia [24]. The CRU dataset is derived from first-order weather station observations [25], and the NCEP dataset is produced by a statistical reanalysis of historical climate observations based on a static data assimilation scheme [23]. For the period 1959–1999, the two climate datasets produce significant spatial and temporal differences for the study region. As mentioned in Rupp et al. [8], the NCEP dataset has substantially wetter and colder conditions compared with the CRU data values. In addition, previous studies (e.g., [26]) have shown a severe overestimation of summer precipitation in the NCEP data. Besides the climate data, a spatially explicit elevation dataset (gridded at 0.5°) outlined in an earlier study by Zhuang et al. [27] is used in this study.

Our study area includes 12 out of the 15 total Canadian ecozones. "Ecozone" here refers to the classification system developed by the Ecological Stratification Working Group [28]. The reason for conducting the analysis at the ecozone level, rather than at the provincial level, is that ecozones incorporate distinctive regional ecological factors (e.g., climate and vegetation) to some degree, and regions are much larger than the burned area of any individual fire. Ecozone distinctions transcend provincial boundaries and better reflect the continuity of the landscape [1, 6]. Here, we do not consider the three northernmost ecozones (Arctic Cordillera, High Arctic, and Low Arctic), since they experience very few large fire events historically, and the forest area in these three ecozones is very small. Based on ecozone boundary and polygon data from the Ecological Stratification Working Group [28], we attribute an ecozone to each of the 0.5° cells. If a cell overlaps two or more ecozones, we divide the cell and assign the corresponding part to the ecozone to which it belongs.

2.3 Characterization of Fire Occurrence

According to Mandallaz and Ye [17], the large fire number ($y_{l,t}$) in the (l,t) statistical unit is assumed to follow a Poisson distribution with expected value $\lambda(x_{l,t})$:

$$f(y_{l,t}|x_{l,t}) = \exp(-\lambda(x_{l,t}))\frac{\lambda(x_{l,t})^{y_{l,t}}}{y_{l,t}!} \tag{1}$$

where the subscript l refers to a geographic area and t to time (year).

The expected value is estimated by an exponential function with climate variables serving as explanatory variables:

$$\lambda(x_{l,t}) = s_l \cdot h_l \cdot e^{x_{l,t} \cdot \beta} \tag{2}$$

Here, s_l is the forest area in the lth spatial unit and h_l the elevation-specific parameter of the lth grid. We assume that the mean burned area is proportional to the total forest area, which is also an upper limit for the burned area. The vector $x_{l,t}$ contains the explanatory variables (i.e., averaged fire season air temperature and precipitation) in the lth grid. Vector β is the parameter vector for the explanatory variables.

Because no direct function is found between elevation and the large fire frequency, here, we categorize the elevation data into five groups which have similar areas. For each group, we quantify a scalar for the calculation of the mean large fire frequency. The number of groups is determined by the trade-off between the accuracy of the estimation and the computational feasibility. On the one hand, we try to make more groups to increase the accuracy of estimations; on the other hand, we need to limit the number of groups since a large number of groups could lead to significant computational challenges.

To estimate the large fire number $y_{l,t}$, following Mandallaz and Ye [17], we partition the whole region into a large number ($[s_l]$) of spatial units with equal areas, in which at most only one fire can occur during a given period. It should be noted that the spatial unit here is not the same as the 0.5° unit used for climate input. To obtain an accurate estimate, we guarantee that $y_{l,t}/[s_l] < 10^{-3}$ holds. This approach is based on the fact that the Poisson distribution is the limit of an independent binomial distribution with a very small probability. Therefore, the Poisson random variable $y_{l,t}$ can be approximated:

$$y_{l,t} \approx \mathrm{Bin}([s_l],\ h_l \cdot \exp(x_{l,t} \cdot \beta)) \tag{3}$$

Then, the Poisson expected value is determined as:

$$\lambda(x_{l,t}) = [s_l] \cdot h_l \cdot \exp(x_{l,t} \cdot \beta) \tag{4}$$

Expanding β, we obtain:

$$\lambda(x_{l,t}) = [s_l] \cdot h_l \cdot e^{p_1 + p_2 \cdot T_{l,t} + p_3 \cdot P_{l,t}} \tag{5}$$

where $T_{l,t}$ and $P_{l,t}$ are the averaged fire season air temperature (degrees centigrade) and precipitation (millimeters), and p_1, p_2, p_3 are the parameters which need to be optimized. It should be noted that a second-order polynomial function for air temperature and precipitation does not significantly improve the model performance. Here, we use a linear function for air temperature and precipitation, due to its simplicity. Using Eq. 5, we estimate the annual fire number in each statistical unit. The number of units $[s_l]$ in a gird cell is determined by its forest cover ratio. Finally, the sum of the annual results for all grid cells produces the total large fire numbers for a specific year.

Parameters are optimized by minimizing the sum of squared error between modeled annual values and observed counts. Since the regional fire regime analysis is of great importance [22], we perform a separate analysis for the Boreal Shield ecozone. This ecozone is selected because it experienced the highest number of large fires (38% total large fire occurrences) and the largest burned area (34% total burned area) during the fire seasons within the 41-year period, compared with the other 14 ecozones in Canada.

We calculate the Partial Rank Correlation Coefficient (PRCC) [29, 30] to identify the relative importance of the contribution of uncertain values for air temperature and precipitation on the modeled fire frequencies in each statistical unit using the 41-year calibrated results. To examine the model performance, we organize the climate data for 1990–1999 and use the developed parameterization to predict the number of annual large fires from 1990 to 1999 and compare the modeled results with the observed counts.

2.4 Calculation of the Threshold Probability

To calculate the probability that total burned area exceeds a certain size, we estimate individual and joint event probabilities and then aggregate the results. Because the probability of a fire with an exact size is almost zero, instead, we calculate the probability of a fire with size in a specific range. This strategy is inspired by Wiitala [20], which claimed that any continuous distribution used to represent the variability in wildfire size can be approximated by a discrete distribution with a suitable size and number of classes. Following Pitman [31] and Ross [32], we customarily partition the fire size distribution into five classes (Table 1). The 41-year observed fire events are apportioned into each class, and the annual large fire count in each class is used as the reference data.

For the ith class, the number of spatial units $[s_l]$ which are used to calculate the large fire frequency is determined as the quotient of regional forest area divided by the upper bound of the fire size range (i.e., the upper bound for the first class is 10 km^2) to ensure that each unit can accommodate the largest fire size in the ith class. For the last (fifth) class, we customarily determine 2,000 km^2 as the upper bound to get the $[s_l]$ value.

Referring to the example described in Wiitala [20], fires are assumed to occur in three size classes with frequencies of 6, 2, and 0.5 per year, with mean fire sizes of 10, 250, and 1,000 ha, respectively. Here, we assume that large fire occurrences are independent events. Therefore, we neglect the correlation between large fires. The probability of a joint

Table 1 Mean fire frequency and mean fire size of five fire classes for Canada and the Boreal Shield ecozone

Fire class index	Range of fire size	Canada				Boreal Shield			
		Mean fire size	EST	CRU	NCEP	Mean fire size	EST	CRU	NCEP
1	2 km^2, 10 km^2	4.6	115.8	112.8	112.8	4.6	44.3	42.8	43.1
2	10 km^2, 30 km^2	17.5	55.2	53.9	53.5	17.7	21.2	20.6	20.6
3	30 km^2, 100 km^2	55.3	43.8	43.6	43.1	55.7	16.6	16.5	16.3
4	100 km^2, 500 km^2	214.0	28.6	29.0	27.5	217.1	11	10.9	10.7
5	500 km^2, +∞	1176.2	6.8	6.9	6.8	1019.7	2.2	2.2	2.2

Mean fire frequencies are estimated based on observed fire data (EST) and CRU and NCEP climate data

occurrence of i, j, and k fires in the respective size classes could be calculated as:

$$p = \frac{e^{-6}(6)^i}{i!} \cdot \frac{e^{-2}(2)^j}{j!} \cdot \frac{e^{-0.5}(0.5)^k}{k!}.$$

Then, the probability of the total burned area not exceeding a threshold can be estimated by enumerating, calculating, and aggregating probabilities for all joint fire occurrence outcomes that do not exceed the threshold. As shown in Wiitala [20], the probability of having a larger than 2,000-ha total burned area in a given year is:

$$1.0 - \sum_{k=0}^{2} \sum_{j=0}^{8-4k} \sum_{i=0}^{200-100k-25j} \frac{e^{-0.5}(0.5)^k}{k!} \cdot \frac{e^{-2}(2)^j}{j!} \cdot \frac{e^{-6}(6)^i}{i!} = 0.134.$$

The upper limits on the summation signs are constructed from the threshold (2,000 ha) and the three different mean fire sizes to guarantee that the final combination of all joint fire events does not result in a combined burned area larger than the threshold. It should be noted here that the largest fire size class must be in the most outer summation because the number of larger fires controls the number of smaller fires to guarantee that all combinations of fire events result in a combined burned area less than or equal to the threshold (2,000 ha). A more detailed method description can be found in Wiitala [20].

In a general form, the probability of a joint occurrence with the combination of large fires in all fire size classes is:

$$p = \prod_{i=1}^{I} \frac{e^{-\lambda_i}(\lambda_i)^{k_i}}{k_i!} \tag{6}$$

where k_i is the number of large fires in the $i$ths class.

To construct a more general probability function with a compound Poisson process, we first construct the upper limit number of fires for the ith class from the threshold A_S and the mean fire sizes of the previous (I-i) classes:

$$U_i = \frac{1}{a_i}\left(A_S - \sum_{j=i+1}^{I} a_j k_j\right) \quad \left(a_i < a_{i+1} \text{ and } A_S - \sum_{j=i+1}^{I} a_j k_j \geq 0\right) \tag{7}$$

where I is the total number of classes (5 in this case), a_i is the mean fire size and k_j is the number of fires in the jth class. Then, based on the estimated mean frequencies and the corresponding mean fire sizes of the five successive classes (Table 1), we calculate the final probability that the total burned area A_T exceeds a specific threshold A_S using the following probability function:

$$P(A_T > A_S) = 1 - P(A_T \leq A_S)$$
$$= 1 - \sum_{n_I}^{U_I} \sum_{n_{I-1}}^{U_{I-1}} \ldots \sum_{n_2}^{U_2} \sum_{n_1}^{U_1} \left(\prod_{i=1}^{I} \frac{e^{-\lambda_i}(\lambda_i)^{k_i}}{k_i!} \right) \tag{8}$$

Three separate sets of calculations are conducted with identical mean fire sizes but different mean fire frequencies derived based on CRU and NCEP climate data and observed fire data. Several studies used the Pareto and Weibull continuous probability distributions [33] or other extreme value distributions [34] to characterize the variability in wildfire sizes. However, as mentioned in Wiitala [20], combining one of these models for modeling fire frequency for various fire sizes with a Poisson process model would require sophisticated statistical techniques to identify and estimate the parameters of a probability model [33]. To avoid this mathematical and computational challenge, we determine the mean fire size as the observed averaged annual burned area based on the historical records from 1959 to 1999. Finally, we calculate the threshold probability for each ecozone and the whole of Canada, respectively.

3 Results

3.1 Parameterization and Goodness of Fit

We perform two separate sets of optimization with identical elevation data but different climatology (CRU and NCEP). Parameters associated with environmental components (air temperature and precipitation) are optimized by minimizing the sum of squared error between modeled annual fire numbers and observed counts in each fire class. Parameters for temperature always have positive values for either the whole

Table 2 Parameters of Eq. 5 for five fire classes in Canada

Parameter	Class 1		Class 2		Class 3		Class 4		Class 5	
	CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP
Intercept	−10.13	−10.62	−10.81	−11.23	−9.87	−10.5	−9.47	−11.96	−12.55	−15.7
Temp.	0.31	0.29	0.33	0.3	0.37	0.3	0.4	0.38	0.54	0.52
Precip.	−0.021	−0.005	−0.015	0.007	−0.021	0.006	−0.023	0.017	−0.011	0.029

Parameters are optimized by minimizing the sum of squared errors between modeled annual values and observed counts

country or the Boreal Shield ecozone (Tables 2 and 3). An increasing trend of parameter values associated with air temperature exists in all five classes for both the whole of Canada and the Boreal Shield ecozone. Generally, precipitation has a negative parameter value, while for the whole of Canada, positive values may also result when the model is driven by the NCEP dataset.

Elevation also contributes substantially to large fire frequency, and the corresponding parameters vary dramatically among the different groups (Tables 4 and 5). For Canada, elevation has a significant effect on the regulation of the mean large fire frequency, except for the second and third elevation group, in which all scalars through the five fire classes are close to 1. For the Boreal Shield ecozone, elevation has a distinct effect in determining the large fire frequency through all five groups. Under different climate datasets, estimates of elevation parameters could also be different.

In comparison with observation-based estimates, fire frequencies are well simulated for the first four classes using either CRU or NCEP data. However, the discrepancies become much more obvious in the fifth class which contains extremely large fires. In normal fire years, the Poisson model performs reasonably in simulating fire frequencies. Although the model always underestimates large fire frequencies in extreme fire years, the output is still somewhat reasonable. A chi-square test is conducted to check the goodness of fit for each class. For both Canada and the Boreal Shield ecozone, estimations using the CRU data are more comparable to observational data than those using the NCEP data (Table 6). It should be noted that the chi-square values are significantly reduced if we remove the outlier in 1989.

3.2 Prediction of Fire Numbers

We compare the predicted large fire numbers with the 10-year observed counts from 1990 to 1999 (Fig. 1). The root mean square errors (RMSEs) are calculated between the predicted numbers (CRU and NCEP) and the observed counts for the period 1990–1999. For Canada, the RMSEs are respectively 61.71 (coefficient of determination, R^2= 0.43) and 52.98 (R^2=0.28). Two substantial underestimates are produced for the years 1995 and 1996 using both the CRU and NCEP data. For the other 8 years, our prediction agrees well with the observed counts. However, the 10-year period used in this study is relatively short; therefore, the uncertainty is considerably large.

A sensitivity analysis shows that, for Canada, large fire frequencies are more sensitive to air temperature (CRU: PRCC=0.75; NCEP: PRCC=0.86) than to precipitation (CRU: PRCC=−0.54; NCEP: PRCC=0.27). For the Boreal Shield ecozone, the CRU air temperature (PRCC=0.61) and precipitation (PRCC=−0.64) contribute similarly to the uncertainty of modeled fire frequencies, while the NCEP air temperatures are much more correlated to large fire frequencies (PRCC=0.79) compared with the NCEP precipitation (PRCC=0.12).

3.3 Threshold Probability

Three separate sets of calculations are performed with identical mean fire sizes but different mean fire frequencies for each fire class. Three different mean fire frequencies are from (1) averaged large fire numbers based on observation, (2) estimated values from the exponential function using the

Table 3 Parameters of Eq. 5 for five fire classes of the Boreal Shield ecozone

Parameter	Class 1		Class 2		Class 3		Class 4		Class 5	
	CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP
Intercept	−10.47	−10.49	−10.13	−10.38	−9.25	−9.33	−9.01	−10.23	−8.75	−9.26
Temp.	0.26	0.25	0.3	0.28	0.33	0.35	0.39	0.37	0.43	0.44
Precip.	−0.016	−0.021	−0.019	−0.011	−0.024	−0.018	−0.023	−0.009	−0.037	−0.024

Parameters are optimized by minimizing the sum of squared errors between modeled annual values and observed counts

Table 4 Parameters associated with elevation in Eq.5 of five fire classes for Canada

		Class 1		Class 2		Class 3		Class 4		Class 5	
Group	Range	CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP
1	$h \leq 210$ m	1.9	0.1	1.8	0.8	1.9	0.1	0.7	1.9	0.5	1.9
2	210 m$<h\leq$320 m	0.9	1.0	1.0	0.9	1.0	1.0	1.1	0.7	0.9	0.9
3	320 m$<h\leq$470 m	0.8	1.5	0.8	0.9	0.9	1.1	0.9	1.0	1.0	0.9
4	470 m$<h\leq$780 m	1.7	0.1	1.9	0.1	1.9	0.9	1.9	1.9	1.9	1.9
5	$h>780$ m	0.1	0.1	1.8	0.1	0.1	0.1	0.1	1.9	1.9	1.9

Parameters are optimized by minimizing the sum of squared errors between modeled annual values and observed counts

CRU climate, and (3) estimated values from the exponential function using the NCEP climate. We find that the three sets of threshold probabilities are similar (Fig. 2). The major reason for this is that, in each class, predictions of the mean fire frequency, either using CRU climate data or NCEP data, are almost identical to the observed mean frequencies. Together with the identical mean fire size in each class, they lead to very similar threshold probabilities.

A threshold probability calculated using the annual total burned area from 1959 to 1999 is defined as the reference to which other values will be compared. Generally, the threshold probability for the whole of Canada is slightly overestimated when the threshold is smaller than 3.7×10^4 km^2 (Fig. 2a); otherwise, the modeled threshold probabilities are always smaller than the observed ones. For the Boreal Shield ecozone, our model overestimates the probability that the annual burned area exceeds a certain threshold (when it is not large) (Fig. 2b). As the threshold becomes larger, the modeled probabilities are more comparable with the observed ones. Among different ecozones, the differences in threshold probability are considerably large, while the Boreal Shield ecozone always shows the highest risk (Fig. 3).

4 Discussion

Consistent with previous analysis (e.g., [16]), our results show that air temperature always exerts a positive effect on large fire frequency across all fire classes (Tables 2 and 3). Based on our results, the effects of air temperature become more substantial as fire size increases. In particular, it has the strongest effect on the fifth class which contains the extremely large fires. A possible reason for this is that higher air temperature always increases evaporation and transpiration and further reduces the fuel moisture. Furthermore, the saturation vapor pressure increases exponentially with air temperature; therefore, a higher air temperature could increase the difference in the water vapor pressure between air and surface layers of the fuel. Consequently, a higher air temperature might contribute to drier fuel conditions and facilitate fire ignition and burning. Consequently, a fire could more easily extend to encompass a large area.

The CRU precipitation always exerts a negative effect on large fire occurrences throughout all five classes for both the whole of Canada and the Boreal Shield ecozone. Although the regional analysis for the Boreal Shield suggests that the NCEP precipitation always has a negative effect on fire occurrences, nationally, it could exert either a negative effect (the first class) or a positive effect (the other four classes) on large fire occurrences. The negative effect is mainly due to the enhanced fuel moisture caused by increased rainfall. The positive effect seems to be counterintuitive; however, it is possible that the precipitation in the “normal year” cases are associated with lightning-bearing summer precipitation, which peaks in the summer. The periods just before the peak and after the peak in precipitation (middle summer)

Table 5 Parameters associated with elevation in Eq.5 of five fire classes for the Boreal Shield ecozone

Group		Class 1		Class 2		Class 3		Class 4		Class 5	
		CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP	CRU	NCEP
1	$h \leq 210$ m	1.9	1.9	1.5	1.7	1.3	0.1	0.1	1.9	1.6	0.1
2	210 m$<h\leq$280 m	0.1	0.1	0.1	1.2	0.1	0.1	0.1	1.9	0.3	0.3
3	280 m$<h\leq$330 m	0.3	1.1	0.2	1.1	0.5	1.1	0.5	1.5	0.1	0.1
4	330 m$<h\leq$450 m	0.2	0.1	0.1	1.5	0.1	0.1	0.1	1.7	0.1	0.5
5	$h>450$ m	1.9	1.9	1.4	1.9	1.9	1.9	1.3	1.9	0.1	1.9

Parameters are optimized by minimizing the sum of squared errors between modeled annual values and observed counts

Table 6 Results of chi-square test for Canada and the Boreal Shield ecozone

Class	Canada		Boreal Shield	
	CRU	NCEP	CRU	NCEP
1	190 (130)	239 (167)	193 (152)	208 (165)
2	182 (132)	229 (178)	172 (134)	198 (161)
3	162 (140)	233 (209)	165 (151)	191 (175)
4	215 (188)	251 (229)	152 (133)	170 (154)
5	141 (127)	131 (122)	48 (44)	53 (48)

All calculations are with 40 degrees of freedom (values in parentheses are calculated with 39 degrees of freedom by removing the outlier in 1989)

are when there are convective storms, but not necessarily heavy rain, and thus are more prone to igniting fires [35]. Furthermore, this highlights the necessity to characterize the effect of precipitation on fire regime among different ecozones.

Our results show that both air temperature and precipitation have significant influence on large fire frequencies at both a national scale and an ecozone scale. Because warmer temperatures potentially increase the duration and intensity of the wildfire season [36, 37], extreme fire seasons may

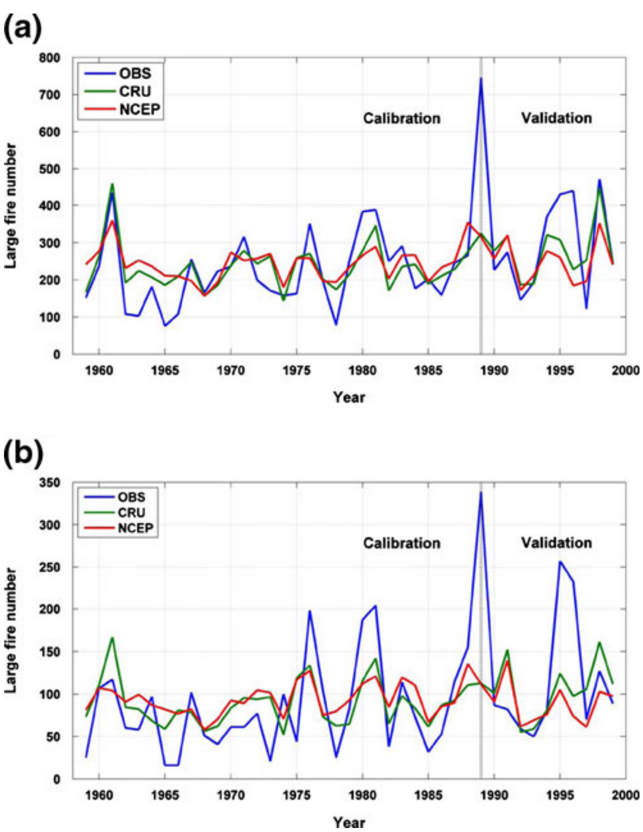


Fig.1 Calibrated (1959–1989) and validated (1990–1999) results of annual large fire numbers for Canada (**a**) and the Boreal Shield ecozone (**b**)

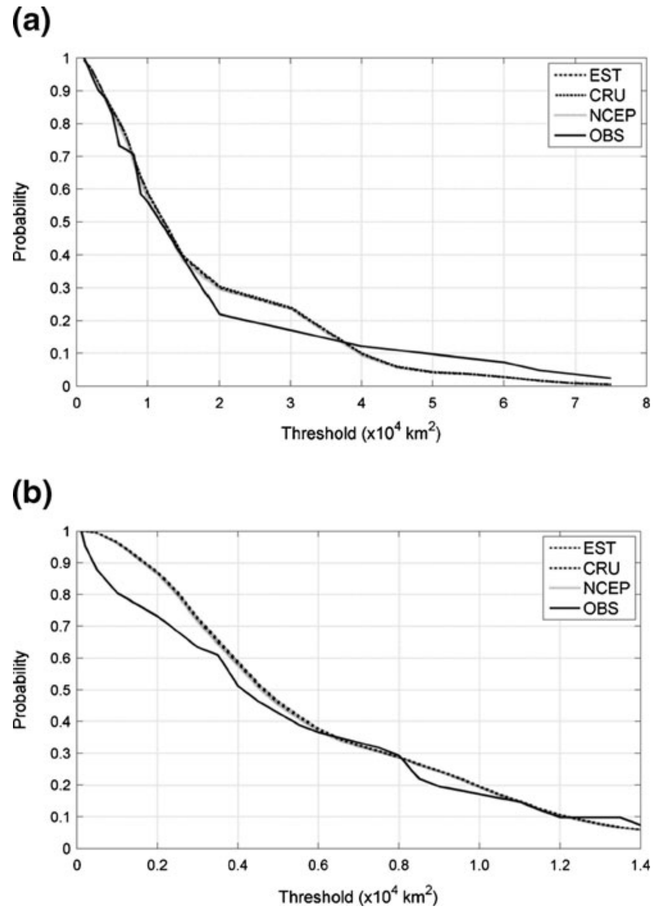


Fig. 2 Threshold probability for Canada (**a**) and the Boreal Shield ecozone (**b**). The threshold probability is calculated using the compound Poisson model (Eq. 8). The observations (*solid line*) in these figures are derived from the observed 41-year large fire counts. *Est* mean frequency derived from the 41-year fire data, *CRU* mean frequency estimated using CRU climate and elevation data, *NCEP* mean frequency derived using NCEP climate and elevation data

increase in their frequency under a warming climate. However, the influence of precipitation still needs to be further investigated. For example, the relative importance of the rainfall duration and total amount of rainfall is still an open problem. Our results imply that the accuracy of projecting future climate could largely influence the prediction of future large fire occurrences.

Although elevation also plays an important role in regulating large fire behavior, it shows no clear relationship with large fire frequency. A possible reason is that it is difficult to separate the effect of elevation from the other factors which influence large fire occurrence. For example, elevation is always related to lightning occurrence, since lightning strikes are more likely in high elevation locations [38, 39], while fires in the lower elevations could be more influenced by human activities [40]. The topographic features at different ranges of elevation could be much different, which could be either facilitating or hindering to the spread of large

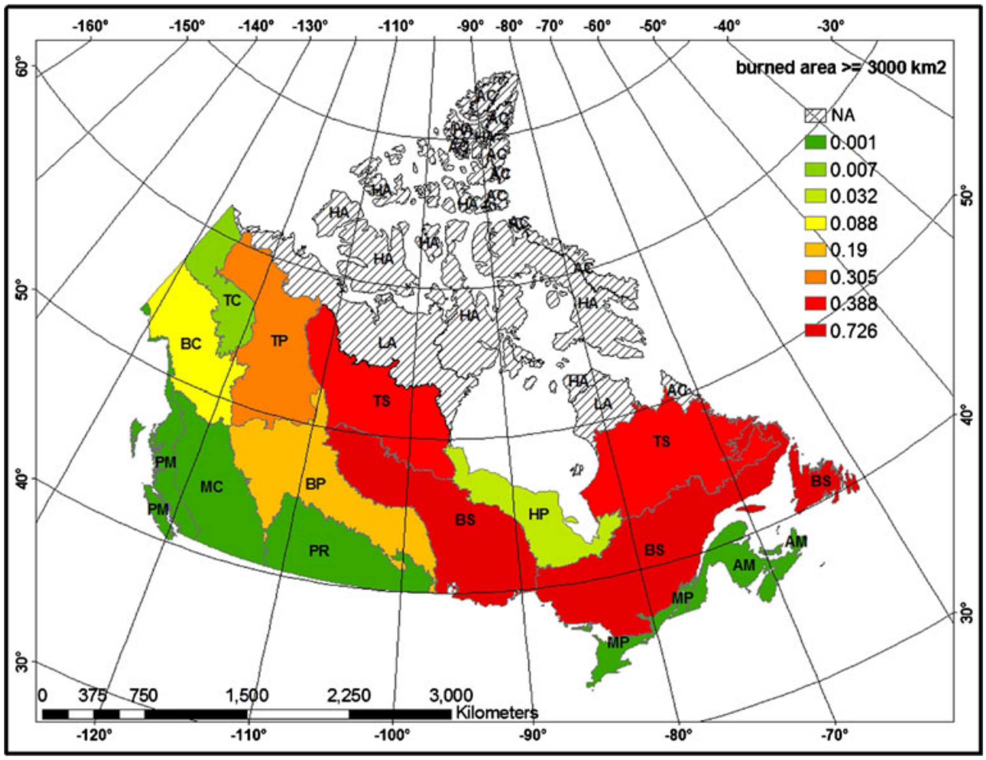


Fig. 3 The probability that the annual burned area is larger than or equal to 3,000 km^2 in each Canadian ecozone. Because the three sets of threshold probabilities (Est, CRU, and NCEP) are similar, here, we only present the results derived from the CRU climate, elevation, and vegetation data. *AC* Arctic Cordillera, *HA* High Arctic, *LA* Low Arctic, *TC* Taiga Cordillera, *BC* Boreal Cordillera, *PM* Pacific Maritime, *MC* Montane Cordillera, *BP* Boreal Plains, *PR* Prairies, *TS* Taiga Shield, *TP* Taiga Plains, *BS* Boreal Shield, *HP* Hudson Plains, *AM* Atlantic Maritime, *MP* Mixedwood Plains, *PM* Pacific Maritime

fires. Furthermore, different ranges of elevation are often associated with distinct levels of fire and fuel management [41], which potentially regulate the large fire regime. In addition, the change of elevation is often followed by a change in plant type that largely influences fire ignition and extension [42]. Therefore, it is still a challenge to quantify the relationship between continuous elevation and the large fire regime.

Using both the CRU and NCEP data, the Poisson model estimated reasonable large fire frequencies in comparison with historical records. However, simulations driven by the CRU data produce more comparable large fire frequencies, relative to the NCEP data. A major possible reason is that the CRU data are obtained from the first-order weather station observations and take into account a direct spatio-temporal linkage to past fire seasons [8]. In addition, the overestimation of summer precipitation in the NCEP data weakens the true relationship between precipitation and large fire frequencies. In this study, hotter and dryer conditions (lower precipitation) are associated with higher large fire frequencies in the study region, which is consistent with previous studies (e.g., [14, 43].

In the recorded extreme fire years, many other factors (e.g., wind speed, frequency of lightning strike, and human behavior), rather than those described in this study, could be responsible for the unusual frequent large fire occurrences. For example, our estimates of large fire numbers in Canada in 1989 (325 using CRU data and 316 using NCEP data) are much lower than the observed count (745), which could be attributed to an unusually high frequency of lightning strikes (663 fires were ignited by lightning strikes).

In model validation (1990–1999), our predicted Canadian large fire counts agree well with the observed numbers through the 10-year period (Fig. 1). The two biggest discrepancies are in 1995 and 1996, in which our model underestimates large fire numbers. We attribute the high value of observed large fire occurrences to factors other than climate, because neither the CRU nor NCEP data show substantially high air temperature or low precipitation during these 2 years. In contrast, we attribute the high large fire number in 1998 to the relatively high air temperature which is evident in the CRU data. Generally, our model produces fewer large fires under the NCEP because of the substantially colder and wetter fire seasons relative to the CRU dataset. Nevertheless, using the NCEP data, we also produce reasonable results. This is different from findings in Rupp et al. [8], which produce almost no annual area burned when driven by the NCEP data.

Many other studies (e.g., [44–47]) used the Pareto distribution to fit fire size, which shows excellent fit to the fire data. Also, the return level derived from this extreme value distribution provides useful information for the forecasting of long-term fire risk, especially for extreme fires [35]. However, the characterization of behaviors of those non-extreme fires for a specific period (year, in this case) is still unclear. In contrast, the Poisson model is able to simulate fire occurrence at different sizes and meanwhile provide a clear physical and probabilistic meaning [17].

The compound Poisson process is a theoretically simple and flexible way to simulate large fire occurrences with described fire sizes. The predicted fire frequency and the threshold probability both have a clear physical and probabilistic meaning. The accuracy of the prediction depends on the selection of classes and the reality of mean fire size and mean frequency in each class. Estimates of threshold probabilities over a range of thresholds provide more information than that of a single probability with a specific threshold, since the probability estimates produce a full view of risks with undesirable large fire outcomes [20]. A threshold probability map of various ecozones would provide useful information for a regional analysis of large fire regimes and could serve as a tool for assessment of fire management.

We acknowledge that several limitations exist in this study. A better classification of elevation is needed in future efforts. Because monthly average climate data are not able to capture weather extremes, which are known to affect the occurrence of extreme fires, climate data and models with finer resolutions should be used to improve the accuracy of predicting extreme fire occurrences. For example, previous studies showed that it is the continuity of a dry spell rather than the total number of dry days within a month affecting the burned area [9]. The potential effect of the timing of precipitation on fire occurrence could also be considerable and thus should be taken into account in future studies [48]. In addition to climate, other factors, such as lightning strike frequency [49], topology [42, 50], human influence [9, 10], land use [51], and fire management [52] are also necessary to consider in future fire frequency modeling efforts. For example, fire suppression efforts would potentially increase with the possible increase of burned area through the twenty-first century. However, the effectiveness of fire suppression remains an important issue for future fire regime predictions [52]. Additionally, it has been suggested that insect outbreak behavior (i.e., large bark beetle outbreak in western Canada) [53] will intensify as the climate warms [54]. Incorporating the response of disease and insect outbreaks to future climate change and the interactions of these phenomena with fire regimes will be also essential in the improvement of fire prediction modeling.

5 Conclusion

We use information on climate and elevation to quantify large fire frequencies for different fire sizes with a Poisson model. We conclude that: (1) the Poisson model performs reasonably well in the simulation of large fire frequency during the fire season (May through August); (2) although monthly climate does not represent the variation in daily weather, it is sufficient for use in the estimation of annual large fire frequencies; (3) the Poisson model produces more reasonable large fire frequencies when driven by the CRU climate data than when it is driven by the NCEP climate data; (4) although elevation plays a significant role in large fire occurrences, further effort is necessary in order to quantify the relationship between elevation and large fire regime; (5) the threshold probability calculated by the compounded Poisson model is comparable with historical records for the last four decades of the twentieth century; and (6) among different ecozones, the threshold probability could be much different, while the Boreal Shield ecozone is always found to have the highest large fire probability. The fire prediction model described in this study and the derived information will facilitate future quantification of fire risks and help improve fire management in the region. Our study highlights the necessity of future efforts to capture other factors (e.g., forest insect outbreaks and diseases) to better forecast large fire occurrences.

Acknowledgments The fire databases are used courtesy of the Canadian provincial, territorial, and federal fire management agencies. This research is supported by NSF Arctic System Science Program (NSF252 0554811) and NSF Carbon and Water in the Earth Program (NSF-0630319). The high-performance computing is supported by the Rosen Center for Advanced Computing (RCAC) at Purdue University.

References

1. Amiro, B. D., Todd, J. B., Wotton, B. M., Logan, K. A., Flannigan, M. D., Stocks, B. J., et al. (2001). Direct carbon emissions from Canadian forest fires, 1959 to 1999. *Canadian Journal of Forest Research, 31*, 512–525.
2. Zhuang, Q., McGuire, A. D., O'Neill, K. P., Harden, J. W., Romanovsky, V. E., & Yarie, J. (2002). Modeling the soil thermal and carbon dynamics of a fire chronosequence in interior Alaska. *Journal of Geophysical Research, 107*, 8147. doi:10.1029/2001JD001244.
3. Balshi, M. S., McGuire, A. D., Zhuang, Q., Melillo, J., Kicklighter, D. W., Kasischke, E., et al. (2007). The role of historical fire disturbance in the carbon dynamics of the pan-boreal region: A process-based analysis. *Journal of Geophysical Research, 112*, G02029. doi:10.1029/2006JG000380.
4. Thonicke, K., Venevsky, S., Sitch, S., & Cramer, W. (2001). The role of fire disturbance for global vegetation dynamics: Coupling fire into a Dynamic Global Vegetation Model. *Global Ecology and Biogeography, 10*, 661–677.
5. Randerson, J. T., Liu, H., Flanner, M. G., Chambers, S. D., Jin, Y., Hess, P. G., et al. (2006). The impact of boreal forest fire on climate warming. *Science, 314*, 1130–1132.
6. Stocks, B. J., Mason, J. A., Todd, J. B., Bosch, E. M., Wotton, B. M., Amiro, B. D., et al. (2002). Large forest fires in Canada, 1959–1997. *Journal of Geophysical Research, 107*, 8149. doi:10.1029/2001JD000484.
7. Gillett, N. P., Weaver, A. J., Zwiers, F. W., & Flannigan, M. D. (2004). Detecting the effect of climate change on Canadian forest fires. *Geophysical Research Letters, 31*, L18211. doi:10.1029/2004GL020876.

8. Rupp, T. S., Chen, X., Oleson, M., & McGuire, A. D. (2007). Sensitivity of simulated boreal fire dynamics to uncertainties in climate drivers. *Earth Interactions, 11*, 1–21.
9. Mollicone, D., Eva, H. D., & Achard, F. (2006). Human role in Russian wild fires. *Nature, 440*, 436–437.
10. Calef, M. P., McGuire, A. D., & Chapin, F. S., III. (2008). Human influences on wildfire in Alaska from 1988 through 2005: An analysis of the spatial patterns of human impacts. *Earth Interactions, 12*, 1–17.
11. Balshi, M. S., McGuire, A. D., Duffy, P. A., Flannigan, M., Kicklighter, D. W., & Melillo, J. M. (2009). The vulnerability of carbon storage in boreal North America during the 21st century to increases in wildfire activity. *Global Change Biology, 15*, 1491–1510.
12. Podur, J., Martell, D. L., & Knight, K. (2002). Statistical quality control analysis of forest fire activity in Canada. *Canadian Journal of Forest Research, 32*, 195–205.
13. Kasischke, E. S., & Turetsky, M. R. (2006). Recent changes in the fire regime across the North American boreal region—Spatial and temporal patterns of burning across Canada and Alaska. *Geophysical Research Letters, 33*, L09703. doi:10.1029/2006GL025677.
14. Flannigan, M. D., Logan, K. A., Amiro, B. D., Skinner, W. R., & Stocks, B. J. (2005). Future area burned in Canada. *Climate Change, 72*, 1–16.
15. Stocks, B. J., Fosberg, M. A., Lynham, T. J., Mearns, L., Wotton, B. M., Yang, Q., et al. (1998). Climate change and forest fire potential in Russian and Canadian boreal forests. *Climatic Change, 38*, 1–13.
16. Xiao, J., & Zhuang, Q. (2007). Drought effects on large fire activity in Canadian and Alaskan forests. *Environment Research Letters, 2*(044003), 6. doi:10.1088/1748-9326/2/4/044003.
17. Mandallaz, D., & Ye, R. (1997). Prediction of forest fires with Poisson models. *Canadian Journal of Forest Research, 27*, 1685–1694.
18. Elsner, J. B., & Schmertmann, C. P. (1993). Improving extended range seasonal predictions of intense Atlantic hurricane activity. *Weather and Forecasting, 8*, 345–351.
19. Alvarado, E., Sandberg, D. V., & Pickford, S. G. (1998). Modeling large forest fires as extreme events. *Northwest Science, 72*(Spec. Issue), 66–75.
20. Wiitala, M. R. (1999). Assessing the risk of cumulative burned acreage using the poisson probability model, USDA Forest Service Gen. Tech. Rep. PSW-GTR-173.
21. Morgan, P., Hardy, C. C., Swetnam, T. W., Rollins, M. G., & Long, D. G. (2001). Mapping fire regimes across time and space: Understanding coarse and fine-scale fire patterns. *International Journal of Wildland Fire, 10*, 329–342.
22. Jiang, Y., Zhuang, Q., Flannigan, M. D., & Little, J. M. (2009). Characterization of wildfire regimes in Canadian boreal terrestrial ecosystems. *International Journal of Wildland Fire, 18*, 992–1002.
23. Kistler, R., Kalnay, E., Collins, W., Saha, S., White, G., Woollen, J., et al. (1999). The NCEP-NCAR 50-year reanalysis: Monthly means CD-ROM and documentation. *Bulletin of the American Meteorological Society, 82*, 247–267.
24. Mitchell, T. D., & Jones, P. D. (2005). An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology, 25*, 693–712.
25. Mitchell, T.D., Carter, T.R., Jones, P.D., Hulme, M., & New, M. (2004). A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: The observed record (1901–2000) and 16 scenarios (2001–2100). Tyndall Centre for Climate Change Research Working Paper 55, University of East Anglia, Norwich, United Kingdom p 25.
26. Serreze, M. C., & Hurst, C. M. (2000). Representation of mean Arctic precipitation from NCEP-NCAR and ERA reanalyses. *Journal of Climate, 13*, 182–201.
27. Zhuang, Q., McGuire, A. D., Melillo, J. M., Clein, J. S., Dargaville, R. J., Kicklighter, D. W., et al. (2003). Carbon cycling in extratropical terrestrial ecosystems of the Northern Hemisphere during the 20th Century: A modeling analysis of the influences of soil thermal dynamics. *Tellus, 55B*, 751–776.
28. Ecological Stratification Working Group (1995). A national ecological framework for Canada. Agriculture and Agri-Food Canada, Environment Canada, Ottawa, ON
29. Saltelli, A. (2002). Making best use of model evaluations to compute sensitivity indices. *Computer Physics Communications, 145*, 280–297.
30. Marino, S., Hogue, I. B., Ray, C. J., & Kirschner, D. E. (2008). A methodology for performing global uncertainty and sensitivity analysis in systems biology. *Journal of Theoretical Biology, 254*, 178–196.
31. Pitman, J. (1993). *Probability* (p. 559). New York: Springer.
32. Ross, S. M. (1989). *Introduction to probability models* (4th ed., p. 544). San Diego: Academic Press, Inc.
33. Alvarado-Celestino, E. (1992). Large forest fires: An analysis using extreme value theory and robust statistics, Ph. D. Dissertation, University of Washington, Seattle, Washington.
34. Jiang, Y., & Zhuang, Q. (2011). Extreme value analysis of wildfires in Canadian boreal forest ecosystems. *Canadian Journal of Forest Research, 41*, 1836–1851.
35. Gisborne, H. T. (1926). Lightning and forest fires in the northern Rocky Mountain Region. *Monthly Weather Review, 54*, 281–286.
36. Running, S. W. (2006). Is global warming causing more, larger wildfires? *Science, 313*, 927–928.
37. Westerling, A. L., Hidalgo, H. G., Cayan, D. R., & Swetnam, T. W. (2006). Warming and earlier spring increase western U.S. forest wildfire activity. *Science, 313*, 940–943.
38. Rorig, M. L., & Ferguson, S. A. (1999). Characteristics of lightning and wildland fire ignition in the Pacific Northwest. *Journal of Applied Meteorology, 38*, 1565–1575.
39. Díaz-Avalos, C., Peterson, D. L., Alvarado, E., Ferguson, S. A., & Besag, J. E. (2001). Space–time modelling of lightning-caused ignitions in the Blue Mountains, Oregon. *Canadian Journal of Forest Research, 31*, 1579–1593.
40. Rieman, B. E., Hessburg, P. F., Lee, D. C., Thurow, R. F., & Sedell, J. R. (2000). Toward an integrated classification of ecosystems: Defining opportunities for managing fish and forest health. *Environmental Management, 25*, 425–444.
41. Veblen, T. T., Kitzberger, T., & Donnegan, J. (2000). Climatic and human influences on fire regimes in ponderosa pine forests in the Colorado Front Range. *Ecological Applications, 10*, 1178–1195.
42. Heyerdahl, E. K., Lertzman, K., & Karpuk, S. (2007). Local-scale controls of a low-severity fire regime (1750–1950), southern British Columbia, Canada. *Ecoscience, 10*, 40–47.
43. Duffy, P. A., Walsh, J. E., Graham, J. M., Mann, D. H., & Rupp, T. S. (2005). Impacts of large-scale atmospheric-ocean variability on Alaskan fire season severity. *Ecological Applications, 15*, 1317–1330.
44. Cumming, S. G. (2001). A parametric model of the fire-size distribution. *Canadian Journal of Forest Research, 31*, 1297–1303.
45. Krawchuk, M., & Cumming, S. (2009). Disturbance history affects lightning fire initiation in the mixedwood boreal forest: Observations and simulations. *Forest Ecology and Management, 257*, 1613–1622.
46. Westerling, A. L., Turner, M. G., Smithwick, E. A. H., Romme, W. H., & Ryan, M. G. (2011). Continued warming could transform Greater Yellowstone fire regimes by mid-21st century. *Proceedings of the National Academy of Sciences USA, 108*, 13165–13170.
47. Preisler, H. K., Westerling, A. L., Gebert, K. M., Munoz-Arriola, F., & Holmes, T. P. (2011). Spatially explicit forecasts of large

wildland fire probability and suppression costs for California. *International Journal of Wildland Fire, 20*, 508–517.
48. Holden, Z. A., Morgan, P., Crimmins, M. A., Steinhorst, R. K., & Smith, A. M. S. (2007). Fire season precipitation variability influences fire extent and severity in a large southwestern wilderness area, United States. *Geophysical Research Letters, 34*, L16708. doi:10.1029/2007GL030804.
49. Kilinc, M., & Beringer, J. (2007). The spatial and temporal distribution of lightning strikes and their relationship with vegetation type, elevation and fire scars. *Journal of Climate, 20*, 1161–1173.
50. Dwire, K. A., & Kauffman, J. B. (2003). Fire and riparian ecosystems in landscapes of the western USA. *Forest Ecology and Management, 178*, 61–74.
51. Bella, C. M. D., Jobbágy, E. G., Paruelo, J. M., & Pinnock, S. (2006). Continental fire density patterns in South America. *Global Ecology and Biogeography, 15*, 192–199.
52. Miyanishi, K., & Johnson, E. A. (2001). Comment—A reexamination of the effects of fire suppression in the boreal forest. *Canadian Journal of Forest Research, 31*, 1462–1466.
53. Bentz, B. J., Regniere, J., Fettig, C. J., Hansen, E. M., Hayes, J. L., Hicke, J. A., et al. (2010). Climate change and bark beetles of the western United States and Canada: Direct and indirect effects. *Bioscience, 60*, 602–613.
54. Logan, J. A., Régnière, J., & Powell, J. A. (2003). Assessing the impacts of global warming on forest pest dynamics. *Frontiers in Ecology and the Environment, 1*, 130–137.