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ORIGINAL PAPER

Considerations for modeling burn probability across landscapes with steep environmental gradients: an example from the Columbia Mountains, Canada

Marc-André Parisien · Gregg R. Walker · John M. Little · Brian N. Simpson · Xianli Wang · Daniel D. B. Perrakis

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Abstract Fire and land management in fire-prone areas can be greatly enhanced by estimating the likelihood of fire at every point on the landscape. In recent years, powerful fire simulation models, combined with an in-depth understanding of an area's fire regime and fire environment, have allowed forest managers to estimate spatial burn probabilities. This study describes a methodology for selecting input data and model parameters when creating burn probability maps in difficult-to-model areas and reports the results of a case study for a large area of the Columbia Mountains, British Columbia, Canada. In addition to having particularly mountainous topography, the study area is covered by vegetation types that are poorly represented in fire behavior systems, even though these vegetation types have experienced considerable (if highly irregular) fire activity in premodern times (before 1920). Parameterization of the fire environment for simulation modeling was accomplished by combining various types of fire information (e.g., fire history studies, reconstructed fire climatologies), new technologies (high-resolution remotely sensed data, wind flow modeling), and—a must in data-limited areas—ample expert advice. In this study, we made extensive use of personal accounts from experienced fire behavior officers for the creation of model inputs. Despite difficulties in validating outputs of burn probability models, the multisource model-building approach described here provides a conservative, yet informative, means of estimating the likelihood of fire. Due to the data-intensive nature of the

M.-A. Parisien (✉) · J. M. Little · B. N. Simpson
Northern Forestry Centre, Canadian Forest Service, Natural Resources Canada, 5320 122nd Street, Edmonton, AB T5H 3S5, Canada
e-mail: Marc-Andre.Parisien@NRCan-RNCan.gc.ca

G. R. Walker
Mount Revelstoke and Glacier National Parks, Parks Canada, PO Box 350, Revelstoke, BC V0E 2S0, Canada

X. Wang
Department of Renewable Resources, University of Alberta, 751 General Service Building, Edmonton, AB T6G 2H1, Canada

D. D. B. Perrakis
Wildfire Management Branch, British Columbia Ministry of Forests, Lands, and Natural Resource Operations, 2957 Jutland Road, Victoria, BC V8T 5J9, Canada

modeling and paucity of input data, an argument is made that modelers must focus on the inputs that are the most influential for their study area.

Keywords Burn probability · Fire · Simulation modeling · Fuels · Ignitions · Weather

1 Introduction

In large fire-prone landscapes, an increasingly popular method of estimating spatial fire likelihood involves simulating the ignition and spread of individual wildfires across a range of environmental conditions (Miller et al. 2008). This fire simulation technique, termed burn probability (BP) modeling, relies heavily on modern fire-growth algorithms (Finney 2002; Richards 1995). These models depict fire shapes realistically and, as a result, yield more accurate spatial BP estimates. In addition, explicitly incorporating spread into the prediction of fire likelihood captures the spatial topology or landscape "context" in which fires burn. For example, a forest stand that is flammable but highly isolated, such as an island in a large lake, will have a low BP, as observed in field studies (Wardle et al. 1997). Similarly, BP models can depict spatial effects such as "fire shadows" (areas of low fire frequency on the lee side of large nonburnable features such as lakes) (Cyr et al. 2005; Heinselman 1973). In short, BP models offer the possibility of depicting the fine-scale patterns of fire likelihood that exist on the landscape and thereby allow for better strategic planning of fire and forest management (Moghaddas et al. 2010; Thompson et al. 2011a; Scott et al. 2012a).

As a result of these characteristics, the BP modeling approach has been applied to a variety of ecological and land management objectives. Because BP maps represent quantitative estimates of fire likelihood, they can be readily incorporated into risk management frameworks by the superimposition of other mapped impacts or values (Calkin et al. 2010; Finney 2005; Miller and Ager 2012). For example, fire likelihood (i.e., BP) has been used to assess likely points of contact with the wildland–urban interface (Braun et al. 2010), to evaluate the potential loss of habitat for endangered wildlife (Ager et al. 2007), and to identify the trade-offs among fuel management strategies for competing values (Ager et al. 2010; Thompson et al. 2011a). BP modeling has recently been applied to the entire conterminous US by collation of 134 landscapes with estimated BP (Finney et al. 2011), the final product of which was used to develop the US Cohesive Wildfire Management Strategy (Calkin et al. 2011). As a complement to fire probability, many of these studies have used simulated fire behavior components (e.g., fire intensity, rate of spread) to integrate measures of fire effects, such as flame length or tree mortality, into their risk analysis. BP models have also been used to enhance our basic understanding of spatial controls on fire likelihood. For example, Bar Massada et al. (2009) showed that the relative severity of fire weather (normal vs extreme) significantly affected not only the magnitude of BP, but also its spatial distribution and patterns. Similarly, by manipulating inputs into the model, Parks et al. (2012) showed that bottom-up controls on BP, ignitions, fuels, and topography varied substantially across the fire-prone landscapes of western North America.

Despite recent technological advances and improvements in the availability of spatial data (e.g., Rollins 2009), BP modeling remains a challenge for some areas. The first potential limitation to creating a BP project is a lack or sparseness of source data for building the inputs (e.g., fine-scale vegetation, reliable fire atlas). For example, in settings where the base data describing vegetation are suboptimal, modelers must often make somewhat arbitrary decisions when translating information about vegetation into fuel models (Ager et al. 2011). An equally important problem stems from the fact that in some areas with potential fire problems (as indicated by their rich history of fire occurrence) area burned has been minimal, because fire has been effectively excluded in modern decades (Collins et al. 2010). As a result, potential locations and effects of large conflagrations are speculative. Another major impediment to BP modeling is that the complexity inherent to a given landscape may compromise the ability to accurately capture all of the key spatio-temporal patterns in fire ignition and spread that modellers are attempting to incorporate into a BP framework. This is often true of mountainous landscapes, where topography affects every aspect of the fire environment: vegetation, fire weather, and ignition patterns (Kellogg et al. 2008; Parks et al. 2012).

In spite of the various issues that can undermine the ability to map fire likelihood with BP models, the usefulness of this technique justifies the effort necessary to overcome challenges to its implementation (Thompson et al. 2011b). It is up to the landscape fire modeling community to uphold the imperative of Ager et al. (2011) that "modeling needs to keep pace with the demand of the planners." The central goal of this study was to demonstrate how BP modeling projects can be created in spite of the aforementioned obstacles. The study area used for this research was the diverse and complex environment of the Columbia Mountains of British Columbia, Canada. The Burn-P3 model (Parisien et al. 2005), a BP model designed for the forested landscapes of Canada, was used for the simulation modeling. A key objective was to illustrate how several disparate sources of data, combined with expert advice, could be used to assemble the necessary inputs for running data-hungry BP models. Therefore, we aimed to develop a "recipe", including all of the necessary ingredients and procedures, for mapping BP in areas that might appear problematic. We also developed a short list of specific recommendations that will assist in implementing future BP projects in similarly challenging landscapes.

2 Methods

2.1 Study area

The study area, located in the Columbia Mountains of southeastern British Columbia (Fig. 1), covers 1,343,921 ha. It encompasses two national parks: Mount Revelstoke and Glacier. The Columbia Mountains form a range with distinct geology, remarkably steep slopes, and highly complex terrain that is naturally fragmented by barren peaks and numerous avalanche paths (Valentine et al. 1978). The climate of the study area is affected by both dry continental air masses and wet air moving inland from the Pacific Ocean, which results in warm summers with moderate precipitation and winters that are cool, snowy, and wet (Chilton 1981). Winter snow packs are among the deepest in North America (Brown et al. 2003). As a result of the prolonged period of snowmelt (longer than 1 month at higher elevations), the onset of vegetation green-up may be considerably later than adjacent areas. By contrast, after the snow has melted gradual drying of the study area leads to likely conditions for fire occurrence from July to September or later.

Although the study area is far inland, its distinctive climate and geology have resulted, at low elevations (400–1,500 m), in an interior rain forest that is unique in North America (Ketcheson et al. 1991): the Interior cedar–hemlock forest (ICH; Meidinger and Pojar 1991). Scattered patches of natural or human-induced meadows are found at these elevations, as are deciduous and mixed forests, but the conditions clearly favor coniferous trees. At mid-to-high elevations (1,500–2,300 m), the forests form a wet and highly

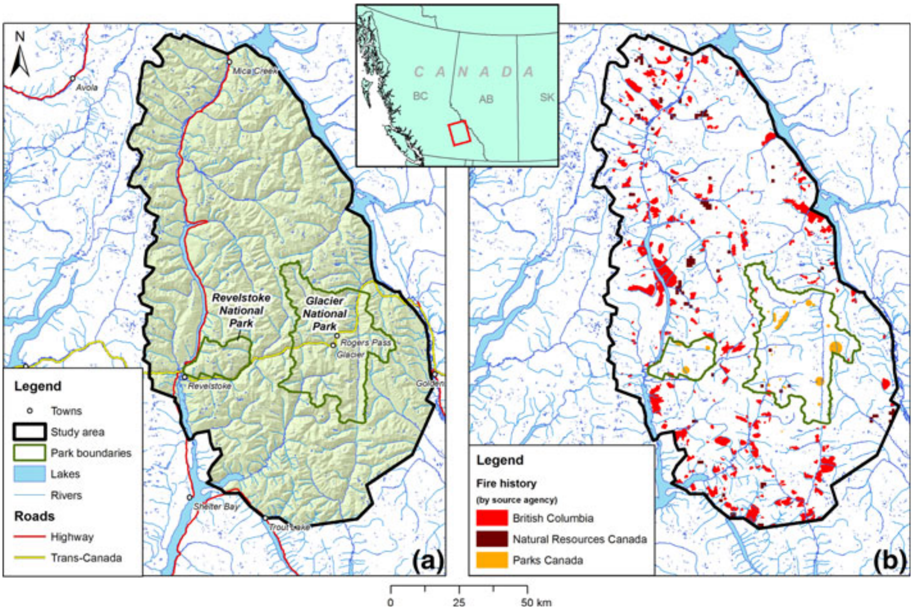

Fig. 1 Boundary of the study area in the Columbia Mountains of British Columbia, Canada (**a**) and fires ≥10 ha for the period 1920–2009 by data source (**b**). Mount Revelstoke National Park and Glacier National Park are outlined in *green*

productive variant of Engelmann spruce-subalpine fir forest (ESSF; Meidinger and Pojar 1991), a forest type found throughout the mountainous areas of western North America (Coupe et al. 1991). Stands of pine (mainly the serotinous *Pinus contorta* Dougl. ex Loud.) are also found at this elevation range, especially where high-intensity fires have occurred in recent decades. At higher elevations, there is a large alpine zone comprising meadows, sparse patches of trees (often with stunted or krummholtz form), and bare rock.

Given this particular ecological setting, the fire regime of the Columbia Mountains is regionally unique (Wong et al. 2004) and poorly studied. First, spring fire activity is rare, largely because of the extended snowmelt period (Fig. 2). Historical records have shown that the fire season generally extends from mid-May to mid-September, but only about 5 % of area burned is accounted for by fires occurring during the spring (May and June), with the majority of area burned (87 %) being accounted for by fires that occur in July and August (Rogeau 2003). In most mountainous areas, fire cycles are believed to be shortest at the valley bottom, increasing with elevation (Schoennagel et al. 2004). However, some estimates suggest that this pattern is reversed in the Columbia Mountains, with shorter fire cycles at higher elevations (in the ESSF forests) than at lower elevation (in the ICH forests). Estimated historical fire-return intervals in the ESSF forests of the study region range from 110 to 300 years; for the ICH forests, historical fire-return intervals are between 150 and 250 years (Parminter 1995; Rogeau 2003). This pattern of relatively high fire occurrence at high elevation may arise from the occurrence of strong mid-slope thermal belts (nocturnal temperature inversions leading to cooler and wetter valley bottoms) (Powell 1970), a concentration of lightning at mid-elevations (Rogeau 2003) and more flammable forest fuels in the ESSF forests. Another difference of the study area is that, unlike adjacent areas where human-caused fires are more frequent, a large proportion (about 80 %) of fires recorded since 1960 were ignited by lightning (Rogeau 2003). The Columbia Mountains lie in a region where lightning-caused fires are relatively frequent and, although lightning strike density is not particularly high, lightning is especially effective at igniting fires (Wierzchowski et al. 2002).

For most of the past century, fire management across British Columbia, including Mount Revelstoke and Glacier national parks, was designed to minimize the impacts of fire on values at risk, including communities and natural resources. The 'Hit hard, hit fast' motto succinctly describes an aggressive initial attack focus that was effective at excluding fire for much of the twentieth century (Pyne 2007). This began to change after a number of severe wildfire seasons with structural losses. In 2010, the province adopted a new provincial wildland fire management strategy that outlines a more ecosystem-based focus for fire management, including increased use of prescribed fire and wildland fire use, in addition to mechanical fuel treatments and other prevention programs. The implementation

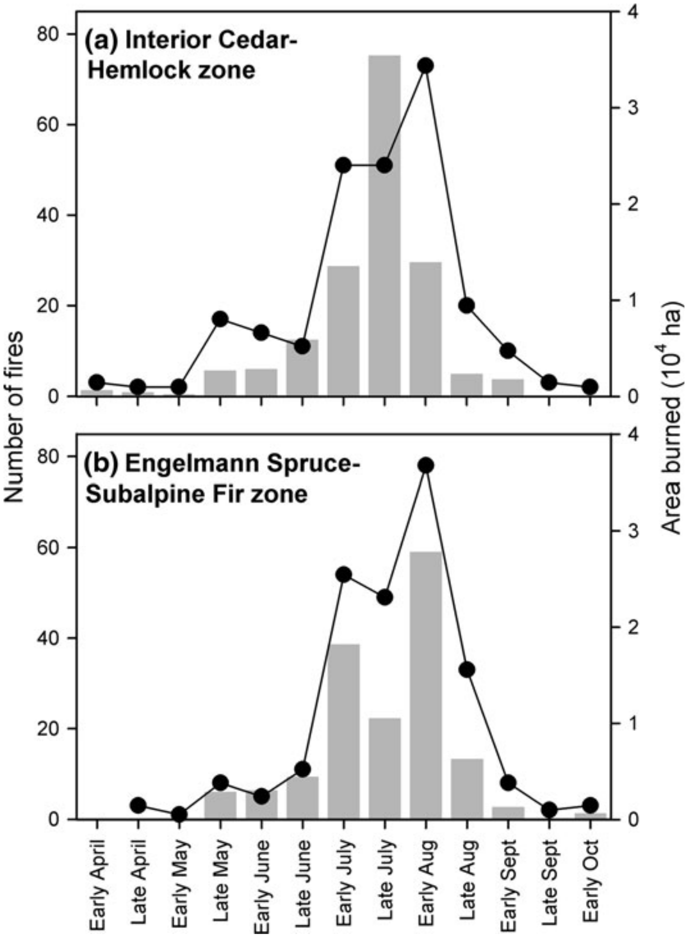

Fig. 2 Mean number of fires (*points*) and area burned (*bars*) for each 2-week period of the fire season for **a** the interior cedar-hemlock and **b** Engelmann spruce-subalpine fir fire zones. Values are based on the atlas of fires ≥10 ha for the period 1920–2009

of the new strategy has just begun, but it will take many years to undo the mark of the twentieth century exclusion.

2.2 The Burn-P3 model

We used the Burn-P3 model (Parisien et al. 2005) to estimate BP in the study area. Burn-P3 is a fire simulation model that uses the Prometheus fire-growth engine (Tymstra et al. 2010) to explicitly simulate the ignition and spread of a very large number of fires (e.g., 10^4–10^6 fires). The Burn-P3 model is conceptually similar to other BP models, such as FSIM (Finney et al. 2011), as well as versions of succession-disturbance models, such as Landis (Yang et al. 2008) and BFOLDS (Perera et al. 2008), that can be adapted to run like a BP model. BP models do not model postfire succession; instead, they focus on properly modeling fine-scaled fire patterns. The main result of a BP model is a surface of fire probabilities for a given year (e.g., the upcoming fire year); however, such models can also generate various other outputs, such as fire intensity, which can be used to infer some measure of fire effects (e.g., biomass consumption, flame length, tree mortality). Burn-P3 simulates the fires burning in a single year, but repeats this year a large number of times (hereafter termed “iterations”) on the basis of the variability that is known to occur on the landscape and in the regional climate. Each iteration is therefore a representation of fires in a specific fire year. For example, a given iteration might model a “mild” fire year, with only a few fires burning under moderate conditions, whereas the following iteration might simulate an “extreme” fire year, during which a large number of fires, some burning under high to extreme weather conditions, happen to occur. A pixel-wise BP estimate consists of the cumulative number of times a pixel burns divided by the total number of iterations, such that a BP of 0.01 represents a 1 % annual likelihood of burning.

The accuracy of BP estimates is strongly dependent on replicating the natural spatio-temporal variability with which fires ignite and spread (Lertzman et al. 1998; Parisien et al. 2010). To avoid straying from the natural variability of the fire regime, all Burn-P3 inputs are based on a modern historical (i.e., observed) data set. As such, Burn-P3 model represents a modern measure of fire risk that is not necessarily representative of historical fire regimes. Burn-P3 is well equipped to model the fluctuations in fire regimes that occur from year-to-year and from fire-to-fire within a given fire season. The general simulation flow for a given iteration comprises the following four steps. First, the number of fires is drawn from a probability distribution, and, for each of the fires, the season and cause are determined from categorical probability distributions. The next step consists of assigning an ignition location to each fire by drawing a coordinate from grids of spatial probabilities of ignitions. In the third step, the duration (in days) is drawn independently for each fire from a historical frequency distribution of spread-event days (subsection 2.4.8). Finally, for each day that a given fire is simulated, Burn-P3 selects daily fire weather as a function of its season and geographic location (hereafter termed “fire zone”). More detailed descriptions of the model are available in previous studies (Beverly et al. 2009; Braun et al. 2010; Parisien et al. 2011).

2.3 Selection of input data and modeling parameters

Building a BP project is typically a time-consuming endeavor. Like other models of its kind, Burn-P3 is a data-hungry model that requires a large number of data inputs. The effort required to prepare the inputs depends on the ability to obtain or develop the following data sets: a detailed fire atlas, mapped fuels, elevation, and daily weather observations. The level of detail required varies tremendously from one study area to another, depending on the complexity of the landscape and its fire regimes. One should always strive to obtain the highest-quality geospatial data for fire simulation modeling. However, given the financial and time investment that is often required in developing some BP inputs, a grasp of the sensitivity of these inputs can help dictate the necessary degree of data refinement (Parks et al. 2012). For example, in much of the boreal forest, the land is flat enough that topography-related inputs have a negligible effect on spatial fire likelihood (Parisien et al. 2011).

A representation of flammable vegetation (i.e., fuels) is a required and crucial input, and every BP project must have the best available gridded fuels map. If there is appreciable topography within the study landscape, the same principle applies to elevation. By contrast, inputs related to spatiotemporal patterns of ignitions and weather can vary greatly in complexity. For example, if the spatial patterns of ignitions vary significantly as a function of cause (human or lightning), season and/or geographic area, the inputs must capture this variability. Such stratification implies substantially more work; therefore, its potential influence on model output should be assessed. In this study, the threshold used to determine if a given input should be stratified was based on an "influence" threshold of 5 %. For instance, although the majority of fires in the study area are ignited by lightning, human ignitions account for 16.7 % of the historical area burned, so ignition locations were stratified by cause.

Because the study area is large and encompasses substantial natural variability in topography, vegetation, and weather (and hence in its fire environment), a multifaceted set of inputs was warranted for BP modeling. To guide our modeling decisions with respect to the more complex input types (specifically, ignitions and weather), we developed a simple flowchart (Fig. 3). In terms of ignitions, it was necessary to model the annual number of fires (those $\geq$10 ha; subsection 2.4.7) as a frequency distribution, because of significant interannual variability in fire occurrence. The total number of fires was apportioned by cause, season, and fire zone, given important spatiotemporal differences in ignition numbers according to these factors. In this study area, ignition locations were stratified by cause and fire zone, but not by season (not shown in the flowchart) because there was a lack of seasonality in the historical fire records. For the purpose of BP modeling, weather is defined both by the duration of fire (analogous to the rain-free interval) and the daily weather conditions under which fires burn. Because the burning time of fires varies significantly, fire duration was sampled from frequency distributions for each fire zone. The daily weather conditions were also stratified by fire zone, as well as by season. In addition, wind speed and wind direction were adjusted for topographic roughness.

2.4 Source data and Burn-P3 inputs

Inputs for the Burn-P3 model include both spatial and nonspatial variables, all of which are described in Table 1. The spatial variables are represented as raster grids to capture environmental factors that vary considerably from one location to another. For this study, five spatial variables were used: topography, fire zones, fuels, ignition probability grids, and wind grids. Nonspatial inputs are those that are not applied to specific locations (i.e., pixels), although they are often stratified geographically (i.e., by fire zone). These variables pertain to temporal aspects, such as the number of fires and seasonality, as well as the weather component. Five nonspatial variables were used: season, number of fires, escaped fire rates, fire duration, and daily fire weather. This section describes the functions of the

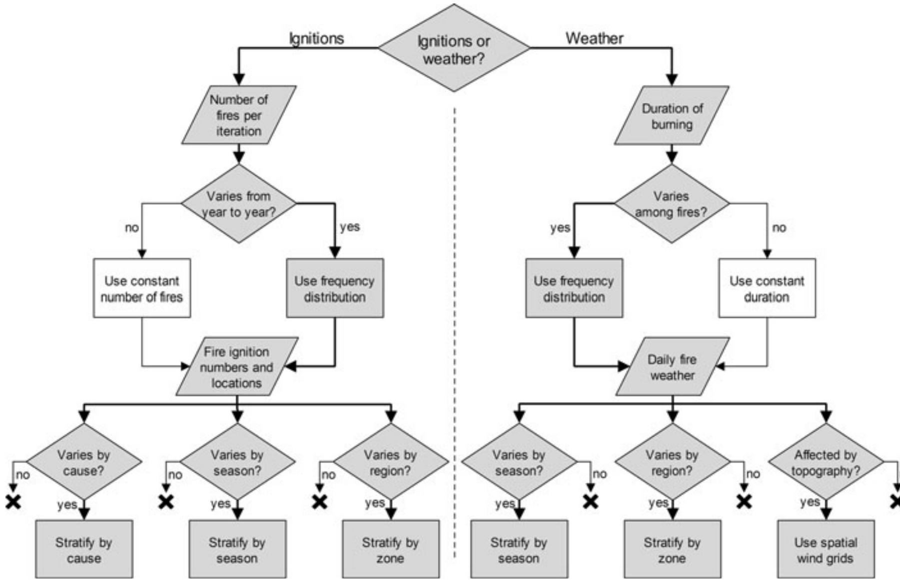

Fig. 3 Decision tree for the process of creating a Burn-P3 project. The user must apply a predetermined threshold (e.g., 5 or 10 %) to determine if a given factor (e.g., ignition locations by cause) is variable enough to warrant the additional input stratification. *Parallelograms* represent data types, *rectangles* represent processes, and *diamonds* represents decisions. *Gray boxes* and *thick arrows* indicate decisions made as part of the project reported here. The Burn-P3 project for this study area required a very high level of input complexity to adequately estimate burn probability

variables used in simulation modeling and the source data from which they were derived for the purposes of this study. All input raster grids in this study had a resolution of 100 m. To account for fires that ignite outside and then spread into the study area, a 10-km buffer was added to the study area for the fire modeling; this buffer was removed for the analysis.

2.4.1 Topography (spatial variable)

The topography variable is based on a digital elevation model (Fig. 4). Burn-P3 uses topography only to calculate the wind-slope vectoring of fire growth. However, topographic effects are considered implicitly in many other variables related to fuels, ignitions, and weather. In addition, topography is used to compute the wind grids using external software (subsection 2.4.5).

2.4.2 Fire zone (spatial variable)

Because the two main vegetation types, ICH and ESSF, support distinct fire regimes, it was deemed necessary to stratify the territory by geographic zone (i.e., fire zone) for the modeling of ignitions and weather in Burn-P3 (Fig. 4). These zones were delineated using the British Columbia Biogeoclimatic Classification System (Meidinger and Pojar 1991). A third fire zone encompassing the alpine areas exists but was not considered in the modeling for this study because very few fires $\geq$10 ha occur in this zone.

Table 1 Burn-P3 state variables used in modeling burn probability in the Columbia Mountains study area

Variable (subsection described)	Data type	Description[a]
Spatial variables		
Topography (Sect. 2.4.1)	Raster grid (numeric)	Elevation (m)
Fire zone (Sect. 2.4.2)	Raster grid (nominal)	Geographic zones with distinct fire regimes and fire weather: Interior cedar–hemlock (ICH) and Engelmann spruce-subalpine fir (ESSF)
Fuels (Sect. 2.4.3)	Raster grid (nominal)	Fuel types and nonfuel features defined by Canadian Forest Fire Behavior Prediction System
Ignition location (Sect. 2.4.4)	Raster grids (2 grids; numeric)	Relative probability of ignition, by season (unitless)
Wind grids (Sect. 2.4.5)	Raster grids (16 grids; numeric)	Influence of topography on wind direction (degrees) and wind speed (km/h) for the eight main cardinal directions
Nonspatial variables		
Season (Sect. 2.4.6)	Setting (nominal)	Start and stop dates of periods for which fire weather, grass curing and green-up change (spring = April 1 to June 15, summer = June 16 to September 31); deciduous trees modeled as "green," except for spring in ESSF; grass curing set at 60 and 75 % in spring and summer, respectively
Number of fires (Sect. 2.4.7)	Frequency distribution (numeric)	Number of fires $\geq$10 ha per iteration; range = 0–38 fires per iteration
Escaped fire rate (Sect. 2.4.7)	Frequency distribution (numeric)	Overall proportion (percent) of fire ignitions by season, cause and fire zone in a Burn-P3 run
Fire duration (Sect. 2.4.8)	Frequency distribution (numeric)	Number of spread-event days per fire (i.e., duration of burning); range = 1–10 for ICH, 1–8 for ESSF
Daily fire weather (Sect. 2.4.9)	List of burning conditions (numeric)	Daily fire weather conditions at noon local standard time and associated Fire Weather Index System components (Van Wagner 1987); list partitioned by season and fire zone

[a] For numeric variables, units are provided in parentheses

2.4.3 Fuels (spatial variable)

In all but the most homogeneous landscapes, fuels is usually the most important variable driving spatial patterns in BP at the spatiotemporal frame of BP studies (Parks et al. 2012). As such, it is a worthy investment of time to obtain the best possible fuel grids. Although readily usable maps of forest fuels have been produced for extensive areas (e.g., Nadeau et al. 2005 for Canada; Rollins 2009 for the conterminous US), the Canada-wide fuels are too coarse and outdated to be used for our study area. Therefore, a vegetation map for the study area was built from a composite of sources using supervised classification and decision rules based on expert advice (Fig. 4). In general, priority was given to the British Columbia Vegetation Resource Inventory, but where data were missing or of doubtful

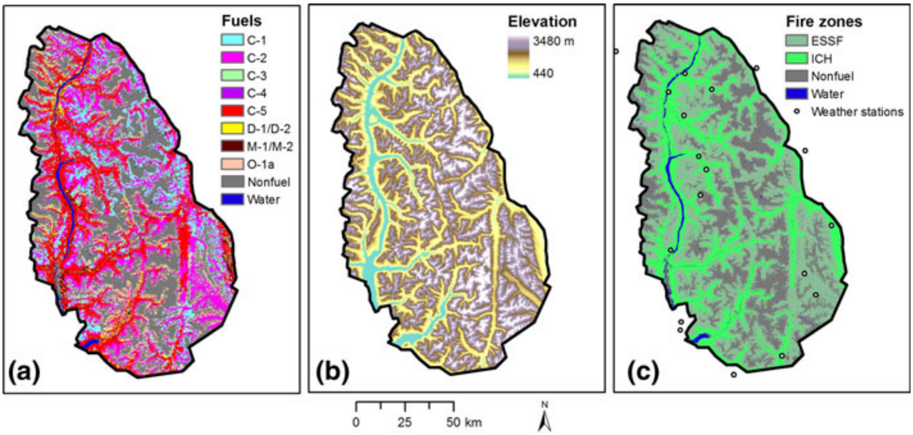

Fig. 4 Spatial inputs to the Burn-P3 fire simulation model: **a** Canadian Fire Behavior Prediction System fuel types (Table 2 for descriptions), **b** elevation and **c** fire zones (*ICH* interior cedar-hemlock, *ESSF* Engelmann spruce-subalpine fir). The weather stations used in the modeling are shown in the fire zones map

quality (e.g., outdated), remote sensing products were used: the Earth Observation for Sustainable Development (Wulder et al. 2003) and the Land Cover Map of Canada 2005 (Canada Centre for Remote Sensing 2008). Finally, where omissions and obvious errors remained, modified zones from the British Columbia biogeoclimatic classification system (Meidinger and Pojar 1991) and elevation were used to infer missing vegetation types.

Vegetation was classified as fuel types according to the Canadian Forest Fire Behavior Prediction (FBP) System (Forestry Canada Fire Danger Group 1992). Substantial expert advice was sought to translate vegetation into FBP System fuel types because some vegetation types are not adequately described by the FBP System. Fire behavior varies by fuel type depending on weather conditions and slope. Fuel types can be broadly categorized as coniferous, deciduous, mixed wood, grasses, and slash. The coniferous fuel types are typically viewed as the most flammable (i.e., most conducive to fire ignition and spread) of forested types; however, flammability varies greatly among fuel types. The deciduous (D-1) and mixed wood (M-1) fuel types (Forestry Canada Fire Danger Group 1992) have greater susceptibility to fire growth in the spring, before leaf flush, than later in the season. The grass fuel type (O-1) is also more flammable in spring than in summer because most of its standing biomass is dead and dry during that season. The proportions of FBP System fuel types by fire zone are presented in Table 2.

2.4.4 Ignition location (spatial variable)

Assessing where fires are most likely to occur is the most challenging aspect of BP modeling. Using past ignitions to model current potential ignitions would not be valid in this study area for a number of reasons. First, past ignitions represent only a finite sample of all of the potential ignitions that might have occurred. Second, some past ignitions are likely to have occurred in areas that are no longer suitable for ignition (e.g., the vegetation has been burned or a major avalanche has occurred). To circumvent these limitations, we used a statistical model to link past fire ignition locations (subsection 2.4.6) to certain environmental factors (compare Bar Massada et al. 2011; Parks et al. 2012, Scott et al. 2012b).

Table 2 Distribution of fire behavior prediction (FBP) system fuel types in the study area and in the two fire zones

FBP System fuel type[a]	Entire study area (%)	Interior cedar-hemlock (%)	Engelmann spruce-subalpine fir (%)
Spruce-Lichen Woodland (C-1)	14.8	8.6	17.2
Boreal Spruce (C-2)	21.5	9.6	26.0
Mature Jack or Lodgepole Pine (C-3)	0.7	1.3	0.4
Immature Jack or Lodgepole Pine (C-4)	0.1	0.3	0.1
Red and White Pine (C-5)	19.9	56.7	5.9
Boreal Mixedwood (M-1 and M-2)	2.5	6.1	1.2
Aspen (D-1 and D-2)	3.5	5.9	2.6
Matted Grass (O-1a)	8.7	4.4	10.3
Nonfuel Features	27.0	3.0	36.0
Water	1.3	4.0	0.3

[a] Fuel codes as described by Forestry Canada Fire Danger Group (1992)

Given the transient nature of vegetation patterns, the environmental factors used as independent variables for the ignition models consisted only of features that that would not be expected to change over the period modeled, such as topography.

We used logistic regression analysis to generate ignition probability grids (Fig. 5). The dependent variable was a binary vector of presumed ignition locations of fires $\geq$10 ha (i.e., fire "presences") and 500 randomly chosen background points that did not overlap with fire-presence pixels (i.e., fire "absences"). When the location of origin of a fire was unknown, the centroid of the fire was used as the ignition location. The statistical model evaluated differences in the environment between the presence and the absence points. Exploratory analyses showed that spatial patterns of ignitions in the study area varied significantly by cause (lightning or human), but not by season. Therefore, ignition models were built only by cause. Three variables were selected for the logistic regression model of lightning-caused fires: elevation; topographic position index, which is an index of concavity (calculated with a 3-km window) (Weiss 2001); and solar radiation, which is computed from aspect and slope (ESRI 2010). For the model of human-caused ignitions, an additional variable, the distance to roads (of any type), was considered as a proxy for human influence.

The ignition models were built in a two-step process. First, a self-fitting model was built using generalized additive models (Hastie 2011; R Development Core Team 2007). This allowed us to determine which predictor variables were significant and whether nonlinear functional forms were warranted for some variables. The next step consisted of building generalized linear models with the significant variables and with the appropriate transformations (e.g., quadratic). In the model for lightning-caused ignitions, all three topographic variables were significant; the topographic position index was linear, but solar radiation and elevation both required a quadratic term. In the model for human-caused ignitions, all of the variables except solar radiation were significant, and distance to road, topographic position index and elevation were all linear. Ignition grids were generated from the logistic models and the mapped predictor variables using the "raster" package in *R* (Hijmans and van Etten 2012).

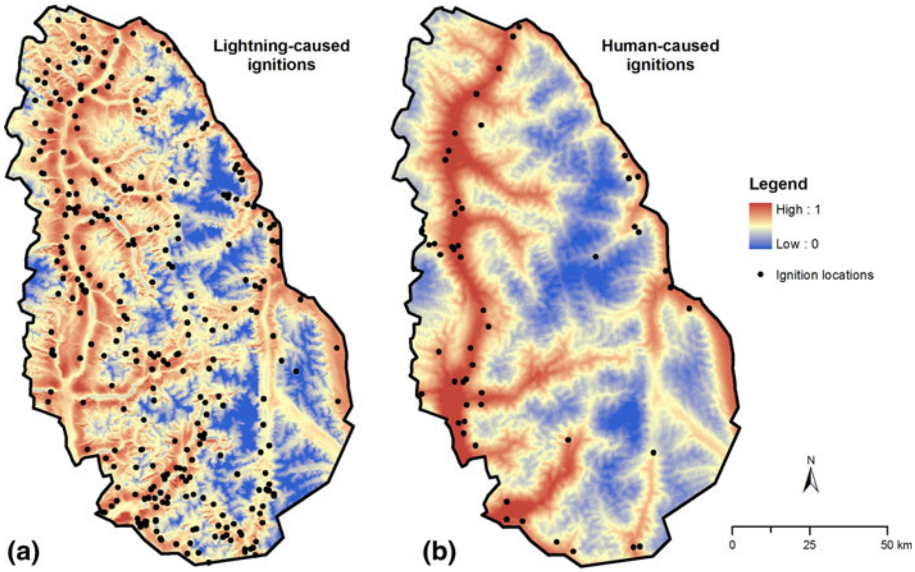

Fig. 5 Ignition grids for **a** lightning-caused and **b** human-caused fires used in Burn-P3 modeling of the study area. These *grids* represent the relative probability of ignition of fires ≥10 ha. Fires used in the statistical modeling of ignitions are shown as *black dots* (see Sect. 2)

2.4.5 Wind grids (spatial variable)

To capture the effect of wind channeling in mountainous areas, grids for wind direction and wind speed were incorporated into the modeling. WindNinja version 2.1.1 (Forthofer and Butler 2007) was used to generate the topography-modified wind direction and wind speed grids for the eight cardinal wind directions (at 45° intervals). These grids modify the winds at every point on the landscape according to the underlying topography. In Burn-P3, specific wind direction and wind speed grids are activated as a function of the wind direction input from the list of daily fire weather conditions, if this direction falls within the range from 22.5° below to 22.5° above a given cardinal point.

2.4.6 Season (nonspatial variable)

The seasonality of fire activity—in conjunction with its spatial variation—is highly important because neither the number of fires nor the areas burned is uniform throughout the fire season (Fig. 2). Fire behavior varies because of seasonal differences in vegetation (e.g., before and after leaf flush) and daily fire weather. The seasons incorporated into the BP model were determined through summary explorations of fire weather, by examining temporal fire activity and—most importantly—through the advice of experienced fire managers.

Using the criteria above, two seasons were deemed adequate for capturing spatiotemporal patterns of ignition and spread in the study area: spring (April 1–June 15) and summer (June 16–September 31). The bulk of fire activity (~90 %, in terms of both fire ignitions and area burned) occurs in the summer. The season start and end dates are fairly comprehensive, in that they correspond to, on average, the earliest and latest dates at which fires $\geq$10 ha occur. The average green-up date in each fire zone was taken into consideration for the classification. Although the timing of phenology has an important effect on fire activity in many northern forests (e.g., the boreal forest), it is hardly a factor in the study area. In the ICH fire zone, leaf flush has usually occurred by the time of the fire season; in the ESSF, green-up is initiated at the start of the summer season, following the extended period of snowmelt. Grass fuel cover (i.e., FBP System fuel type O-1), which is relatively sporadic in the study area, was set at a low level of curing (60 %), except for the ICH zone in summer, where it was increased to 75 %.

2.4.7 Number of fires and escaped fire rates (nonspatial variables)

To better understand fire history and develop certain variables, a reliable fire atlas had to be assembled for the study area. Such an atlas was compiled for fires $\geq$10 ha for the period 1920–2009. To ensure that the atlas would be as comprehensive as possible, data from multiple data sources were collated. The main database used was that of the British Columbia Wildfire Management Branch (for 1920–2009). Some recent fires (occurring in the period 1995–2010) were added from the Natural Resources Canada coarse-resolution burned area maps derived using a multi-technique approach (Fraser et al. 2000). Finally, the Parks Canada fire database (for 1960–2004) was used to fill in gaps in the two national parks in the study area. For some of these fires, the data consisted only of an ignition point and total area burned, so a circular buffer was added to represent their final size. Compiling these multiple sources into an atlas with complete coverage for the study area involved standardizing attributes and selecting the best available data source for each fire event. The resulting fire atlas undoubtedly underestimates the number of fires and area burned, especially in the early decades of the simulation study; however, the database did allow us to adequately characterize the spatioseasonal patterns of fire used to build BP model variables.

In this study, only fires $\geq$10 ha were simulated, and, accordingly, only the fires meeting this size threshold were used to develop the inputs. Smaller fires are usually not comprehensively reported, and they represent only a small fraction (2–3 %) of the total area burned. Importantly, only fires with the potential to become large should be considered for building BP model inputs; for example, very small fires ($\leq$0.1 ha), which are typically disproportionately numerous, usually exhibit spatial and temporal patterns of occurrence that differ from those of larger fires (Sturtevant and Cleland 2007).

At the start of each iteration, Burn-P3 must determine how many fires will be simulated using the number of fires variable (Table 1). This information is drawn from a frequency distribution based on the historical atlas of fires, which is smoothed using a logistic function (as shown in Fig. 6). Once the number of fires for a given iteration has been determined, the fires are assigned to a given combination of season, cause, and fire zone from a categorical probability distribution (the escaped fire rates variable) that is also based on historical fire data (Table 3).

2.4.8 Fire duration (nonspatial variable)

Although wildfires in the study area may burn for periods ranging from days to weeks, the bulk of their progression is usually limited to a few days (Parisien et al. 2005; Podur and Wotton 2011). In Burn-P3, only days on which fires experience substantial spread (hereafter termed "spread-event days") are modeled. Spread-event days were extracted from a database of daily fire progression derived from satellite-detected hot spots for 1994–2010.

Fig. 6 Frequency distribution of the number of large fires per year (modeling parameter applied to each iteration). The *gray bars* are based on observations for the number of large fires, and the *dots* represent logistic smoothing of the distribution used in Burn-P3. These values are based on the atlas of fires ≥10 ha for the period 1920–2009

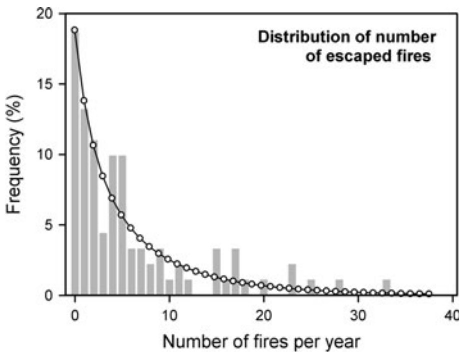

Table 3 Distribution of fire ignitions simulated in Burn-P3 by season, cause, and fire zone (escaped fire rate variable)[a]

Season	Cause	Interior cedar-hemlock (%)	Engelmann spruce-subalpine fir (%)
Spring	Human	4.5	1.7
	Lightning	2.9	1.6
Summer	Human	7.5	3.0
	Lightning	35.6	43.2

[a] Values are based on an atlas of fires ≥10 ha for the period 1920–2009

Fire progression was mapped as follows: (1) a 2,000-m buffer was applied to the accumulated season-to-date Moderate-Resolution Imaging Spectroradiometer (MODIS) hot spots (USDA Forest Service 2008) available for each day throughout the fire season; (2) the overlapping buffered areas were dissolved to create single fire-event clusters; (3) each cluster was then reduced by 1,300 m using an inward buffer, which helped to smooth the perimeter and resulted in an updated estimate of total area burned for that day; and (4) each daily fire perimeter was clipped (i.e., subtracted) where there was overlap with the previous day, and perimeters were then successively combined to produce a fire-progression estimate for each burned area.

To distinguish between spread-event and non-spread-event weather days, a cutoff was applied to the fire-progression data. Here, we attempted to relate fire progression to daily fire weather of the closest weather station, as Podur and Wotton (2011) did for the boreal forest of Ontario, but our attempt was deemed unsuccessful. The sparseness of weather stations and the localized weather patterns due to mountainous topography, compounded by the noise inherent to the daily progressions (e.g., because of cloud cover), blurred the relationship between fire spread and daily weather. We thus opted for another approach, in which days of spread-event weather were identified by means of a fire-growth threshold, specifically by calculating a rate of spread value for each day of each fire, assuming circular growth. We set the minimum threshold for rate of spread as 2 m/min, on the basis of 4 h of burning per day; these values allowed for a reasonable dichotomy of spread and non-spread days. Although it involves simplifications, this method of calculation is preferable to a size-based threshold because it does not depend on the final size of each fire.

A frequency distribution of the number of spread-event days was produced for each fire zone (Fig. 7). The areas burned by individual fires are highly sensitive to this input variable (Parisien et al. 2010). As such, these distributions may require further adjustment to ensure

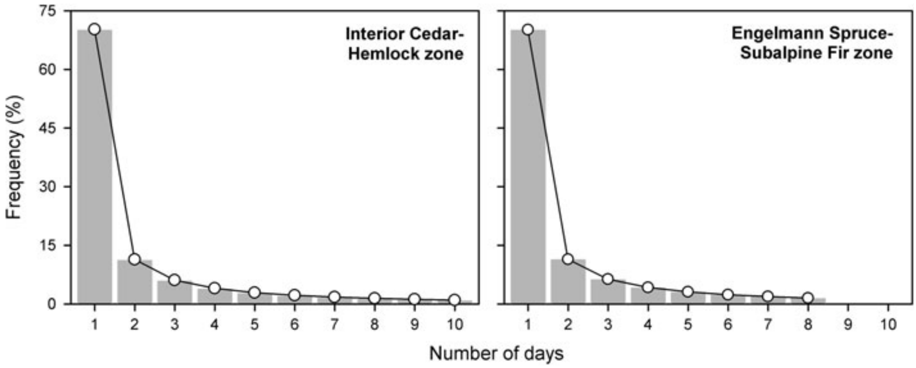

Fig. 7 Frequency distributions of the number of spread-event days per fire (duration of burning variable) for each forest type. The *gray bars* are based on observations for spread-event days, and the *dots* represent logistic smoothing of the distributions used in Burn-P3. These values are based on a database of the daily progression of fires ≥10 ha for the period 2000–2011

that simulated fires approximate the sizes of historical fires. In our study, size discrepancies were indeed observed between the "first-pass" simulated fires and the historical fires. Using trial and error, we decided to make the following adjustments. First, we limited the number of spread-event days to 10 and 8 days in the ICH and ESSF fire zones, respectively. Second, we increased the frequency of 1 day spread events slightly, to 70 %, for both of the fire zones, because too few small fires (i.e., <100 ha) were simulated relative to the fire atlas data. Finally, we adjusted the classes for spread-event days >1 using a multiplier to retain the shape of the distribution.

2.4.9 Daily fire weather (nonspatial variable)

Only days with substantial fire spread are modeled in Burn-P3, so only daily fire weather conditions that are conducive to substantial spread are considered in the model. Fire weather refers to noon weather observations of temperature, relative humidity, wind speed, wind direction, and 24-h precipitation, recorded daily, as well as the associated fuel moisture codes and fire behavior indexes of the Fire Weather Index System (Van Wagner 1987). Using observations from 19 weather stations in and around the study area, we extracted days with fire-conducive conditions according to the threshold established by Podur and Wotton (2011) (i.e., Fire Weather Index ≥19). The list of daily fire weather conditions is stratified by fire zone and by season, and Burn-P3 therefore draws daily fire weather for a given simulation according to the location of ignition and the time of year. Table 4 highlights the mean differences among fire zones and seasons within the days deemed conducive to fire. For example, although fire-conducive days in the spring are, on average, cooler, the cooler temperatures are compensated by drier and windier average conditions.

3 Results

As expected for such a complex region, the modeled annual fire likelihood across the study area was highly heterogeneous (Fig. 8). The mean BP was 0.0024 and the median 0.0011,

Table 4 Selected fire weather components (mean ± standard deviation) for fire-conducive conditions (Fire Weather Index ≥19) by fire zone and season

Fire zone	Season	Temperature (°C)	Relative humidity (%)	Wind speed (km/h)	Fire Weather Index
Interior cedar-hemlock	Spring	22.6 ± 3.9	27.7 ± 9.5	10.0 ± 5.5	24.8 ± 4.9
	Summer	26.0 ± 3.6	31.8 ± 8.4	8.0 ± 5.3	27.5 ± 7.1
Engelmann spruce-subalpine fir	Spring	19.6 ± 3.4	25.4 ± 6.9	13.1 ± 3.4	21.7 ± 2.9
	Summer	23.7 ± 3.5	30.0 ± 8.1	10.3 ± 4.7	27.6 ± 7.4

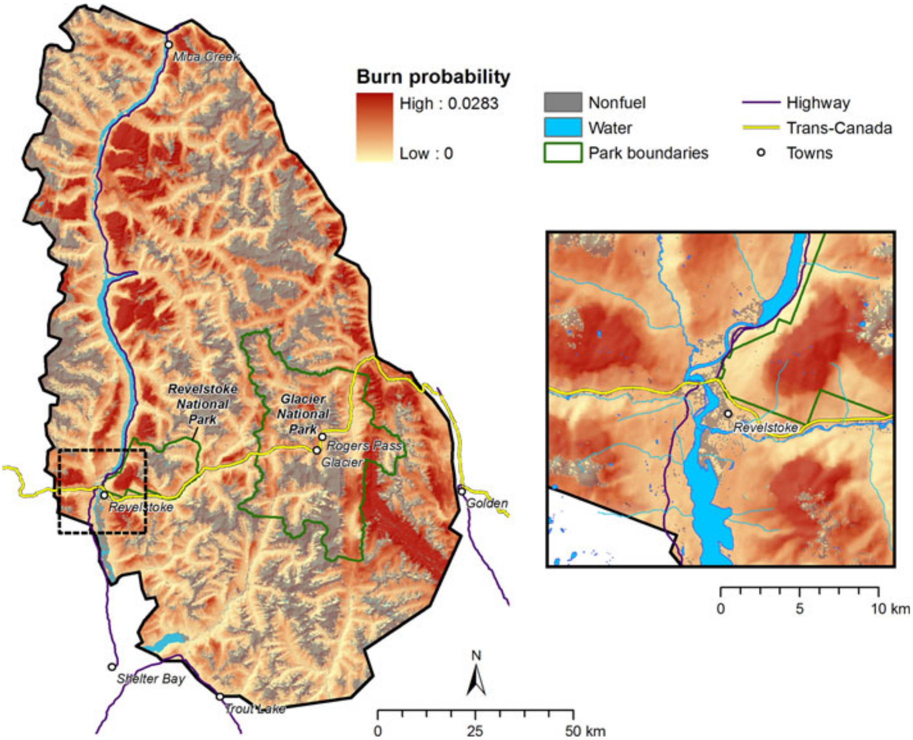

Fig. 8 **a** Burn probability estimates of the entire study area, and **b** magnified portion of the area around the town of Revelstoke, BC

but the range (0–0.0283) was wide and the standard deviation (0.0033) high. Furthermore, the BP varied considerably between the two fire zones, with the ESSF zone predicted to be generally more prone to fire than the ICH zone (mean BPs of 0.0026 and 0.0017, respectively). However, the BP was highly spatially variable within a given zone. When the BP map was compared with the fuels map (Fig. 4a), much of the variation in BP appeared to be explained by the configuration of fuel types. The fuels input tells only part of the story, however, as various other factors (e.g., daily fire weather, patterns of nonfuel features, ignition patterns) interact to produce any given BP value.

The modeled patterns of fire likelihood can be interpreted across two spatial scales: broad patterns at the regional level and fine patterns at the local level. At the regional scale, the highest BP seemed to be concentrated in three areas: along the series of lakes and rivers from Revelstoke to Mica Creek; in the southeast corner of the study area; and to some extent along the eastern edge of the study area, along the Rocky Mountain Trench. As the scale is increased (zooming in), striking fine-scale patterns emerge. For example, the right-hand map in Fig. 8 illustrates the BP patterns at the local scale in the area surrounding Revelstoke.

4 Discussion

4.1 Interpreting the BP map for the Columbia Mountains study area

Our results support the claim that the steep topographic and climatic gradients of the study area, as well as its variable land-use history, contribute to highly localized fire regime patterns (Nesbitt 2010; Wong et al. 2004). The BP patterns also reflect the landscape changes of recent decades—in terms of vegetation succession, human land-use and fire-suppression capabilities—that have altered the potential for fire ignition and spread in some areas. Broad areas of high fire likelihood suggest that some parts of the study area that have not experienced many fires in the past century may be more fire-prone than the recent fire data might indicate. Some areas may have been spared from fire during the period spanned by the fire atlas because of successful fire suppression, because of omissions in the database, or simply because of chance. Ager et al. (2012) have provided compelling evidence that, even if ignition densities are low in a given part of a landscape (or alternatively, initial attack success is high), the BP approach can effectively capture its potential for large fires to burn through.

Localized patterns of modeled fire likelihood, obtained by zooming in on a specific area, are useful to assess the susceptibility of burning around communities and infrastructure (e.g., roads, pipelines). For example, the town of Revelstoke may not be located within the most extensive tracts of high BP, but areas of high fire likelihood only 1–5 km away practically surround the townsite and deserve further scrutiny. Fine-scale patterns of BP are also useful to better understand the underlying controls on fire likelihood, such as the high connectivity of highly flammable fuels, the concentration of ignition probabilities, or topographic (i.e., uphill) effects (Parisien et al. 2011). A more detailed examination of the sensitivity of BP to the environmental factors in a given area is worthwhile, in that it provides some guidance with respect to the potential for reducing BP through management of fuels (e.g., thinning or prescribed burning) or ignitions (i.e., prevention and initial attack) (Ager et al. 2012; Collins et al. 2011; Suffling et al. 2008).

Mapping fire likelihood in this study area highlights the importance of considering the spatial context in highly fragmented areas. In the Columbia Mountains, high BP values are largely confined to large core areas of connected fuels, whereas BP is relatively low in greatly fragmented areas (i.e., where there are numerous high peaks). In other words, large portions of the study area are naturally limiting in terms of fire spread, as suggested by Rogeau (2003). This information has practical implications for fuel treatments, as it helps in determining what proportion of the landscape should be treated to effectively reduce BP (e.g., Finney et al. 2007; Parisien et al. 2007). Conversely, it may also help in identifying areas where fuels treatment would be largely ineffective at reducing fire likelihood around values at risk and where a focus on ignition prevention and initial attack may provide greater benefits in terms of reducing fire likelihood (Cary et al. 2009). That said, we emphasize that a low BP value should never be interpreted as meaning that an area is invulnerable to large, high-intensity fires. For instance, parts of the study area that currently have low fire likelihood have, in the past, had a high frequency of large fires because of high rates of ignition, notably along the railroad, which locally inflated fire probabilities for several decades (Johnson et al. 1990).

4.2 Creating burn probability model inputs: focus on what matters most

BP models are useful, but building their inputs can be onerous. As such, careful planning should be undertaken before the lengthy process of acquiring and manipulating data for BP modeling is initiated. Fortunately, there is a body of the literature on BP modeling from various parts of the world that can help to guide this process (Carmel et al. 2009, Chuvieco et al. 2012, Miller and Ager 2012). For instance, some studies (e.g., Parisien et al. 2010, 2011) have explicitly evaluated the sensitivity of certain inputs on fire likelihood. However, most of the modeling decisions need to be specific to the study area, because every landscape is unique, exhibiting its own fire-environment relationships (Parks et al. 2012). In fact, the sensitivity of certain inputs—or combinations of inputs—makes it risky to extrapolate the results of BP models from one study area to another, even though the areas may be similar in appearance (Bar Massada et al. 2009).

At the spatiotemporal frame of BP modeling, the spatial configuration of fuels strongly influences patterns of fire likelihood in most study areas. Even in flat terrain, it is extremely rare for land cover patterns to be so uniform that they only minimally affect fire likelihood. Although obtaining a reliable fuel grid can be difficult in some areas, a rudimentary map built on experts' rules of thumb will be preferable to a completely uniform fuels map (Nadeau et al. 2005; Thompson et al. 2011b). As a first step, the modeler can focus on nonfuel features of the landscape, which are partially responsible for the spatial variability in BP by impeding fire spread. These features can be derived from an array of remote sensing products (which are available free of charge) and should thus be carefully depicted. Similarly, if high-quality vegetation data are spatially sporadic for fuel typing, as was the case in the study area, it can be useful to fill in the blanks with remote sensing products refined according to expert advice, even if those data are coarse. Detailed vegetation structure and composition data are certainly preferable for accurate fuel typing; however, where this type of information does not exist, a simplistic representation of fuels is more likely to produce realistic BP outputs than is a uniform representation. Nonetheless, the importance of accurately depicting fuels for fire modeling needs to be assessed relative to other inputs to BP modeling (e.g., Salvador et al. 2001) in a variety of landscapes and fire regimes.

Topography exerts a strong indirect influence on fire regimes through its effect on vegetation, ignition patterns, weather, and fire spread (Parks et al. 2011). The effect of wind-slope interactions on fire spread is well established (e.g., Rothermel and Rinehart 1983; Van Wagner 1977), and such interactions are already incorporated in all major fire behavior systems. Digital elevation models are available worldwide and may always be included as a model. However, in study areas that are particularly flat (e.g., Parisien et al. 2011), this input need not be included in a BP model, especially if it further taxes already-high computational demands. A more complex—and less well understood—input to BP models is wind, expressed by speed and direction grids in Burn-P3. Even if an approximation is used, taking wind channeling into account in a study such as ours will likely be beneficial to the fire likelihood predictions. However, the accuracy of this input, and its effect on fire likelihood remain to be fully assessed.

The weakest links with respect to BP modeling inputs are undoubtedly the temporal and—most importantly—spatial patterns of ignitions: It is simply unknown when and where fires are most likely to ignite. When ignitions are highly clustered across a landscape (Krawchuk et al. 2006), BP patterns may be fairly sensitive to modeled ignition locations. However, ignition clustering may not contribute much to the spatial patterns of BP in areas that experience fires large enough to dwarf the effect of ignition clusters (Bar Massada et al. 2011; Parisien et al. 2011). As mentioned, it is inappropriate to model only the ignition locations that have occurred in the past. However, methods have been proposed to capture broad patterns of ignitions without modeling specific ignition locations by means of a smoothing function (e.g., determining kernel density) (Beverly et al. 2009; Braun et al. 2010). In this study, we used statistical techniques to model ignition probability (Bar Massada et al. 2009; Parks et al. 2012; Scott et al. 2012b). The advantage of this method is that areas without recent fires may be modeled as ignition-prone. In addition, the method can be used with sparse or geographically biased data, to a certain extent. As such, we consider this approach superior to others that have been proposed, but we acknowledge that simpler techniques may be equivalent for some landscapes.

An important aspect of modeling fire likelihood is the ability to simulate a distribution of fire sizes similar to that of the historical fires on which the inputs were based. In fact, matching the fire size distribution of simulated fires to that of fires in the fire atlas represents the main calibration in BP models (Parisien et al. 2005; Braun et al. 2010). In this study, the only input that required a post hoc adjustment for calibration purposes was the fire duration (i.e., spread-event days distributions), as the initially derived distributions yielded fires that were generally too large. Because fire weather largely controls the size and shape of fires, this component requires careful attention within the BP modeling framework. Whereas the size of a fire is mainly a function of its duration (analogous to the rain-free period), fire shape is mainly controlled by daily fire weather conditions, in particular wind direction. The relative influence on fire likelihood of these two components of fire weather appears to vary greatly over the landscape. For example, Parisien et al. (2011) found that BP was highly sensitive to fire duration in the western boreal forest of North America, where fires can grow very large. By contrast, such may not be the case in areas where most fires achieve their spread in a single day, that is, where there is little variability in the duration of burning (e.g., Ager et al. 2012; Weise et al. 2010). Although in the past some BP modelers have been constrained to using simplifications (e.g., conditions associated with a single percentile), the manner in which BP models incorporate daily weather is evolving rapidly (Finney et al. 2011).

Evaluating the accuracy of BP estimates is an arduous task, but one that will need to be better addressed in the future. Currently, validation of BP outputs is not routinely performed and leaves us relying heavily on our knowledge of the study area and expert advice. Very few studies have attempted to validate their estimates of fire likelihood. One way this can be achieved is to produce a BP map for a period in the past and assess if the fires of subsequent years have occurred in high probability areas more often than expected (cf. Parisien et al. 2005; Paz et al. 2011). This approach has produced encouraging results but is often difficult to implement because it relies on the availability of data (e.g., fuels data for some period in the past). Another validation method would involve cross-validation using different methods. If the predictive outcome of different techniques is the same (in this case, based on area burned), such a comparison could be informative.

4.3 Limitations of burn probability models

As in any model, the predictive estimates produced in this study are contingent on various assumptions. In particular, caution is required when using simulation models such as Burn-P3 because combining fairly simple inputs can cause behavior that is difficult to predict (Parisien et al. 2010), a phenomenon known as "emergence." Despite substantial effort to capture variability relevant to BP, many inputs inevitably represent simplifications of the real world and may be prone to error. For instance, the fuel grid of the study area, which we consider reasonably good, is limited by the Canadian FBP System, a factor that is beyond our control. Because one of the main fuel types in the study area, the ICH forest, is not yet considered in the FBP System, we opted to use a fuel type based on vegetation that occurs more than 3,000 km to the east of the study area (i.e., Red and White Pine [C-5]). Although this modeling decision translates into some uncertainty in the inputs, according to local fire behavior experts, this uncertainty is far less than the error that would have occurred from simply using the fuel types of the upper slopes (e.g., Boreal Spruce [C-2] and Mature Jack or Lodgepole Pine [C-3]).

Typically, the most important limitation to building a BP modeling project is the lack of data required to properly model spatio-temporal patterns of ignitions. However, using random spatial ignition patterns in BP modeling instead of spatially variable ignition patterns can be quite informative, even if it is not realistic. Using different inputs will result in BP maps that lend themselves to different interpretations. Spatially random ignitions would result in simulations that exclude any effects of ignition location. These simulations would assess the BP potential of the landscape (e.g., fuels and topography) and weather, which might be preferable if processes controlling the likelihood of ignition are unknown, relatively even across the landscape, or highly variable in time (and therefore unknown at any one time) (Ager et al. 2010; Parisien et al. 2007).

Despite efforts to provide the most accurate inputs to a BP model, some limitations associated with the model itself. First, because these models do not explicitly take into account fire-suppression activities, inputs must implicitly factor in their effect on fire ignition and growth. For example, ignition grids are built using fires that are all assumed to have escaped initial attack, which is a reasonable assumption in our study area. Second, burn probability models cannot fully capture the changes in fuel moisture associated with fine-scale variation in aspect and elevation, resulting in a homogenization of BP patterns. Finally, some discrepancies between simulated fire perimeters and those observed on the ground may be due to the mathematical processes driving the spread algorithm. However, the relative degree at which the spread algorithm affects the accuracy of fire spread compared with the model inputs remains to be investigated.

Some instances of data or model process limitations for BP modeling may be insurmountable. In such cases, certain alternative means of mapping fire probability are available. For example, statistical techniques can be used to relate fire occurrences or area burned to environmental factors describing climate, ignitions, and vegetation (or fuels) (Parisien et al. 2012; Syphard et al. 2008). However, because this broad-scale, "top-down" approach does not explicitly simulate fire ignition and spread, it cannot fully capture fine-scale spatial effects such as fire shadows. At this fine spatial scale, BP mapping provides a more spatially detailed estimate of fire likelihood.

5 Conclusions and recommendations

BP modeling is a time-consuming and often onerous means of obtaining spatial fire probability estimates. However, we would argue that to properly model something as complicated and variable as fire ignition and spread, a certain degree of model complexity is necessary and even desirable. Fortunately, the payoffs that can be achieved through careful preparation of inputs and a thoughtfully built BP project are numerous. For instance, the BP map can be refined and updated as the landscape changes or as new data or information becomes available. Once a BP project is in place, it is possible to manipulate the inputs for use in a multiscenario approach that can, for example, measure the potential effectiveness of proposed fuel treatment strategies.

This study illustrates how complementary data types, combined with expert advice, can be used to generate spatial estimates of fire likelihood using BP modeling. Preparing the modeling inputs for this study area was time-consuming, and investing a tremendous amount of time into creating model inputs may not always be feasible. However, this challenge should not dissuade scientists or land managers from using this tool, because sensible shortcuts may be available that will allow BP mapping with only minimal loss in accuracy (Finney 2005). In fact, the following guidelines should ensure that most of the variability in fire likelihood is captured:

1. *Fuels*: Because BP estimates are likely to be strongly sensitive to the fuels input, use the highest-quality fuel grid; if information about fuels is sparse, focus on nonfuel features, and approximate the fuel types on the basis of expert advice.
2. *Fire duration*: Realistic fire sizes lead to more accurate BP patterns; therefore, if daily fire progression data are not available, use trial and error to build a distribution of daily spread-event days that will yield representative fire sizes.
3. *Daily fire weather*: Fire shapes are highly sensitive to changes in weather; if integrating the full level of variability is onerous, produce BP maps for a single set of percentile weather conditions, but for each of the main directions of fire spread. The resulting maps can ultimately be combined.
4. *Ignitions patterns*: Ignitions patterns represent the weakest link of BP models. These patterns should be modeled by season and cause (if warranted), but if ignition patterns are highly uncertain or are unlikely to affect BP patterns (compare Parks et al. 2012), it is preferable to use random ignitions.
5. *Topography*: Free digital elevation models are available for the entire planet. If topography is a factor, it should be incorporated, as well as spatial wind grids, into the model.

In summary, a lack of data for modeling, or quasi-absence of fire in a study area, need not present a roadblock to mapping fire likelihood. These challenges can usually be overcome, by accessing the existing "fire intelligence" for the area of interest, which may come from databases (modern or paleoecological), the published literature or local experts, to provide a basic understanding of how fires ignite and burn across the landscape (Collins et al. 2010). We emphasize that careful a priori planning is crucial to facilitate the project-building phase and perhaps to prevent researchers from spending time on inputs that are unlikely to influence the final BP output. Ultimately, a simple suite of input variables may be sufficient to generate an estimate of fire likelihood that is far better than anything currently available.

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