

Spatial bottom-up controls on fire likelihood vary across western North America

SEAN A. PARKS,^{1,†} MARC-ANDRÉ PARISIEN,² AND CAROL MILLER¹

¹USDA Forest Service, Rocky Mountain Research Station, Aldo Leopold Wilderness Research Institute, Missoula, Montana 59801 USA

²Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta T5H3S5 Canada

Citation: Parks, S. A., M.-A. Parisien, and C. Miller. 2012. Spatial bottom-up controls on fire likelihood vary across western North America. *Ecosphere* 3(1):12. <http://dx.doi.org/10.1890/ES11-00298.1>

Abstract. The unique nature of landscapes has challenged our ability to make generalizations about the effects of bottom-up controls on fire regimes. For four geographically distinct fire-prone landscapes in western North America, we used a consistent simulation approach to quantify the influence of three key bottom-up factors, ignitions, fuels, and topography, on spatial patterns of fire likelihood. We first developed working hypotheses predicting the influence of each factor based on its spatial structure (i.e., autocorrelation) in each of the four study areas. We then used a simulation model parameterized with extensive fire environment data to create high-resolution maps of fire likelihood, or burn probability (BP). To infer the influence of each bottom-up factor within and among study areas, these BP maps were compared to parallel sets of maps in which one of the three bottom-up factors was randomized. Results showed that ignition pattern had a relatively minor influence on the BP across all four study areas, whereas the influence of fuels was large. The influence of topography was the most equivocal among study areas; it had an insignificant influence in one study area and was the dominant control in another. We also found that the relationship between the influence of these factors and their spatial structure appeared nonlinear, which may have important implications for management activities aimed at attenuating the effect of fuels or ignitions on wildfire risk. This comparative study using landscapes with different biophysical and fire regime characteristics demonstrates the importance of employing consistent methodology to pinpoint the influence of bottom-up controls.

Key words: burn probability; fire; fuels; ignitions; simulation modeling; topography.

Received 26 October 2011; revised 15 December 2011; accepted 16 December 2011; final version received 17 January 2012; **published** 30 January 2012. Corresponding Editor: D. P. C. Peters.

Copyright: © 2012 Parks et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits restricted use, distribution, and reproduction in any medium, provided the original author and sources are credited.

† **E-mail:** sean_parks@fs.fed.us

INTRODUCTION

Across most of the globe's landmass, complex environmental gradients induce a spectrum of fire regimes that, in turn, help shape biological communities (Bond and van Wilgen 1996, Krawchuk et al. 2009). Recent frameworks have attempted to characterize fire regimes according to the environmental factors limiting fire activity (Meyn et al. 2007, Krawchuk and Moritz 2011). At one end of the dichotomy are areas where fire

is rare, such as in most rainforests, because of a lack of fire-conducive weather conditions (i.e., it is rarely hot, dry and windy). At the other extreme are areas where fire is rare because of a lack of available biomass or fuel, such as some of the world's deserts. However, these examples represent the most extreme ecological cases; fire activity in most fire-prone ecosystems is limited not only by weather or available biomass, but also by other factors that vary across space and time, such as climate patterns (e.g., ENSO and

PDO), topography, and ignition patterns (Krawchuk et al. 2009, Bradstock et al. 2010).

In recent years, there has been considerable interest in assessing the top-down versus bottom-up controls on fire regimes (Heyerdahl et al. 2001, Mermoz et al. 2005). Weather is considered a ‘top-down’ control because it exerts its influence across large areas, whereas fuel is considered a ‘bottom-up’ control because its effect on fire is spatially more variable (Peters et al. 2004). The influence of top-down controls has been highlighted across relatively broad spatial scales (regional to global) (e.g., Gedalof et al. 2005, Balshi et al. 2009, Littell et al. 2009), but the study of bottom-up influences among a range of fire regimes has been challenging, in part because comparable information (i.e., data) has not been expansive enough to encompass areas of contrasting fire regimes (but see Rollins 2009).

Bottom-up controls on fire regimes can be thought of as a biophysical template upon which fire occurs. Notwithstanding anthropogenic effects, spatial patterns in fire activity are most often linked to three main bottom-up factors: ignitions, fuels and topography (Kennedy and McKenzie 2010, Parisien et al. 2010). Because bottom-up fire controls are intrinsically spatially heterogeneous, their arrangement in space will invariably shape fire patterns across a landscape (Turner 2005a). That is, the spatial configuration of a given bottom-up factor largely determines its relative influence on fire regimes among landscapes, whereby greater spatial variability in a given factor translates into more variable fire patterns. For example, topography will exert a greater influence on fire regimes in landscapes with rugged topography compared to landscapes with gentler relief (McKenzie et al. 2006).

Bottom-up fire controls have been elucidated for only a handful of landscapes (e.g., Rollins et al. 2002, Taylor and Skinner 2003, Gavin et al. 2006, Kellogg et al. 2008). Although these important studies have advanced our understanding of particular fire regimes, generalizing across the ecosystems that were studied is difficult due to different methods and spatial and temporal scales of analysis. A standard approach for comparing diverse ecosystems would enhance our understanding of bottom-up factors on fire regimes. The increasing availability of fire and fire environment data, as

well as recent advances in fire simulation modeling (Miller et al. 2008), makes this comparison possible. Specifically, simulation models that produce spatially continuous estimates of fire likelihood (hereafter, burn probability [BP]) provide a platform for a systematic comparison of the influence of bottom-up controls (i.e., ignitions, fuels, and topography) among landscapes. BP models are parameterized using detailed fire, weather and landscape (fuels and topography) data whose purpose is to produce fire likelihood estimates for the current state of the landscape. These models do not simulate forest succession and therefore cannot be used to recreate past fire regimes; rather, their strength lies in their ability to conduct experiments and explore the sensitivities of different components of the fire environment.

In this study, we used parallel methods and data to investigate the influence of ignitions, fuels, and topography on BP in four fire-prone landscapes of western North America that differ substantially in their biophysical and fire environment. We developed working hypotheses of the influence of each of these factors on BP based on their spatial structures. These hypotheses were tested in a simulation study whereby the influence of each bottom-up factor on BP was evaluated by manipulating its spatial variability (cf. Cary et al. 2006, Parisien et al. 2011). This technique allowed us to directly compare the contribution of each bottom-up factor on BP among very different study areas, as well as assess the relative influence of these factors on BP within each study area.

METHODS

We used a simulation modeling approach to evaluate the relative influence of the spatial configuration of ignitions, fuels, and topography on BP patterns. First, we developed working hypotheses of the relative influence of each of these factors on BP. Next, we produced a BP map parameterized with observed data for each study area (hereafter the ‘control’ BP maps). Then, we created a series of BP maps in which a single bottom-up control was randomized or homogenized (termed ‘treatments’). This approach uses a strategy similar to that of neutral models (Gardner et al. 1987), whereby we created

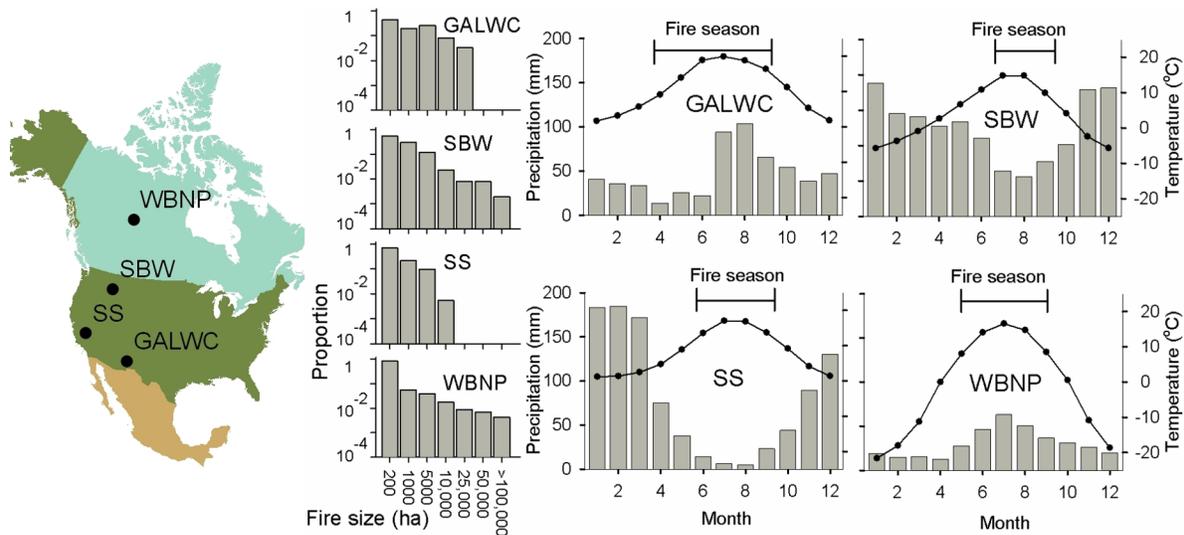


Fig. 1. Locations of the four study areas in North America, as well as their respective observed fire size distributions and climate diagrams. The fire size distributions were computed from about 50 to 100 years of data from fires ≥ 200 ha; the scale of the y-axis is logged. The climate diagrams represent monthly precipitation and temperature (Daly et al. 2002, McKenney et al. 2006).

surfaces that were neutral to one bottom-up factor by removing the spatial structure of the factor while keeping all other factors unchanged. For example, in one treatment, topography was rendered completely flat, whereas all other modeling inputs remained unchanged. This treatment map was neutral to topography and comparing it with the control BP map revealed the influence of topography. Finally, we calculated the influence of each of these bottom-up factors in driving BP spatial variability.

Study areas

We selected four fire-prone landscapes of western North America that are characterized by vastly different climates, topography, dominant vegetation, and fire regimes: Gila/Aldo Leopold Wilderness complex (GALWC), Selway-Bitterroot Wilderness (SBW), southern Sierra (SS), and Wood Buffalo National Park, Canada (WBNP) (Fig. 1). The four landscapes also have several important features in common, which facilitates comparison. All are fairly large and have experienced significant fire activity in the last century that has been well documented. In all the study areas, ‘resource benefit’ fires (i.e., those that are allowed to burn for ecological reasons) are permitted, whereby lightning-caused fires

can burn unencumbered by fire suppression activities. Although the degree to which this occurs varies among study areas, this type of management has contributed to a fairly in-depth understanding of their respective fire regimes and, accordingly, high-quality data.

Gila-Aldo Leopold Wilderness Complex (GALWC).— The GALWC (3190 km²) in New Mexico comprises both the Gila and Aldo Leopold wilderness areas. Elevations range from 1462 to 3314 m; the topography is diverse and includes broad valleys, steep canyons, extensive mesas, and rugged mountains. At the lowest elevations, the vegetation consists of desert scrub and grasslands and, as elevation increases, transitions to piñon-oak-juniper woodland, then to ponderosa pine (*Pinus ponderosa*) woodland and forest. The highest elevations are composed of Douglas fir (*Pseudotsuga menziesii*), white fir (*Abies concolor*), subalpine fir (*A. lasiocarpa*), Englemann spruce (*Picea engelmannii*), southwestern white pine (*P. strobiformis*), and aspen (*Populus tremuloides*). Although the fire season runs from April through September, mid-summer fires are relatively uncommon unless there is a prolonged drought (Rollins et al. 2002). Fires in GALWC are generally low-severity surface fires, but fire severity tends to increase with elevation (Swetnam and Dieterich 1985,

Holden et al. 2009).

Selway-Bitterroot Wilderness (SBW).—The SBW (6550 km²) straddles the border of western Montana and north-central Idaho. The study area encompasses the entire Selway-Bitterroot wilderness and adjacent Forest Service lands that are managed for resource benefit fires. Ranging in elevation from 480 to 3091 m, SBW is rugged and dissected by numerous rivers and streams. Pacific maritime forests, composed of western hemlock (*Tsuga heterophylla*), western red cedar (*Thuja plicata*), western white pine (*P. monticola*) and Douglas-fir (*P. menziesii*) cover the west and northwest portion of the study area up to about 1500 m elevation (Rollins et al. 2002). As elevation increases, Douglas-fir and grand fir (*A. grandis*) are prominent on mesic sites and ponderosa pine (*P. ponderosa*), Douglas-fir, and western larch (*Larix occidentalis*) are common on drier sites. The subalpine forests of the higher elevations (>~2500 m) are composed of a collection of Engelmann spruce (*P. engelmannii*), whitebark pine (*P. albicaulis*), lodgepole pine (*P. contorta*), subalpine fir (*A. lasiocarpa*), and alpine larch (*L. lyallii*). At the highest elevations, alpine environments (i.e., barren or snow/ice) are common. The fire regime is categorized as mixed: lower-severity surface fires are common in the lower elevations and patchy, stand-replacing fires become more common as elevation increases, although during extremely dry years, stand replacing fires can occur throughout the study area (Brown et al. 1994).

Southern Sierra (SS).—The SS study area (5720 km²) is located in the southern Sierra Nevada, California. Elevations extend from 212 to 4297 m; the main mountain range is north-south oriented and is dissected by large, steep canyons, numerous smaller canyons, and, at upper elevations, glacially-carved valleys. The vegetation at the lowest elevations is a mosaic of grassland, oak woodland, and chaparral shrubland. As elevation increases, the vegetation transitions into pure ponderosa pine (*P. ponderosa*) stands, then to mixed conifer forest (*P. ponderosa*, sugar pine [*P. lambertiana*], white fir [*A. concolor*], incense cedar [*Calocedrus decurrens*]), then to red fir (*A. magnifica*) and lodgepole pine (*P. contorta*). At upper elevations, the vegetation consists of open subalpine forests and alpine environments dominated by sparse low vegetation (i.e., alpine

grassland and shrubland, stunted trees). Fires vary in severity throughout the study area depending on the vegetation. Grasslands and woodlands typically experience surface fires, chaparral experiences crown fires, and the conifer belt experiences a mixed-severity fire regime, where many fires are non-lethal surface fires, but under suitable weather and fuel conditions, lethal surface fires and stand-replacing crown fires occur.

Wood Buffalo National Park (WBNP).—WBNP (44,800 km²), a UNESCO world heritage site and Canada's largest national park, straddles the border of northern Alberta and southern Northwest Territories. The park is relatively flat, ranging in elevation from 163-965 m; there are two low-relief mountain ranges, the Birch and Caribou Mountains. The vegetation of WBNP is representative of the mixedwood boreal forest and is a complex and patchy mosaic of wetlands (fens and bogs), forest, and open water (rivers and lakes). The uplands of WBNP are generally occupied by jack pine (*P. banksiana*) and trembling aspen (*P. tremuloides*). Poorly drained lacustrine deposits are dominated by black spruce (*P. mariana*) and tamarack (*L. laricina*), whereas alluvial flats are dominated by white spruce (*P. glauca*) and balsam poplar (*P. balsamifera*) (M. Heathcott, unpublished manuscript). Fires are generally stand-replacing. Although the numerous wetlands sometimes act as barriers to fire spread, they dry out during drought years and become conducive to fire ignition and spread. This ephemeral connectivity, in conjunction with suitable fire weather, results in some of the largest fires in North America.

Working hypotheses

Burn probability (BP) is a function of three main bottom-up controls: ignitions, fuels, and topography. Within a given landscape, the spatial configuration of these controls is a major contributor to spatial variability in fire patterns (Turner 2005a). That is, if every fire regime control—bottom-up or top-down—were uniform, there would be no spatial variability in BP. Therefore, we developed working hypotheses relating to the relative influence of ignitions, fuels, and topography on BP based on the spatial structure of each factor. To quantify spatial structure, we computed the spatial autocorrelation (Moran's *I*) of each factor using

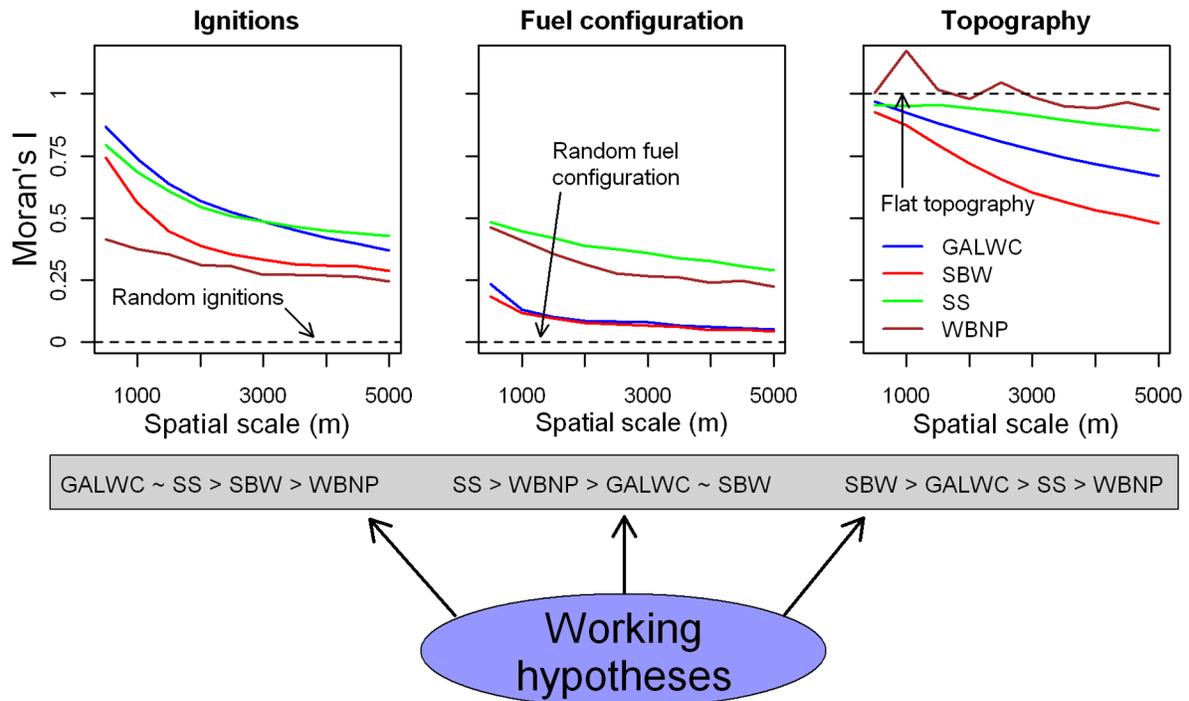


Fig. 2. The working hypotheses with respect to the bottom-up factors controlling fire regimes in the four study areas. The influence ranks of study areas were based on the degree of spatial structure (i.e., the area under the curve compared to the spatial structure of the treatment). Correlograms were built using the Moran's I metric of autocorrelation at multiple spatial scales (500 m increments). We limited this calculation to a maximum radius of 5000 m (corresponding to an area of ~ 8000 ha) because most simulated fires were less than this value.

grids of the probability of ignition, potential spread rate of fuels, and elevation (see *Simulation model: inputs—Spatial inputs* for data descriptions) at multiple spatial scales, from 0 to 5000 m radii at 500 m increments (Fig. 2). We expected that the spatial pattern in BP would be most strongly influenced by the factor that exhibited the strongest spatial structure among study areas. That is, those factors with more area under the correlogram curve in Fig. 2 (compared to the spatial structure of each treatment) are expected to have a higher influence. Our hypotheses are thus presented as 'rank orders' among study areas of the influence of each factor (as shown in Fig. 2). These hypotheses merely serve as a starting point for analyzing and discussing the results.

Ignitions influence the likelihood of fire in that, if all other factors are constant, areas of high ignition density will equate to greater fire likelihood (Sturtevant and Cleland 2007). In this study, the spatial clustering of ignitions is most

pronounced in the GALWC and SS and least pronounced in WBNP. Ignition density generally increases with elevation in the mountainous study areas (GALWC, SBW and SS).

The connectivity of fuels exerts a strong influence on fire spread (Miller and Urban 2000, Duncan and Schmalzer 2004, Viedma et al. 2009) and therefore BP patterns. Fuels that are conducive to fire spread dominate all four study areas, but the spatial arrangement of those fuels differs considerably (Fig. 2). Fuels are most highly autocorrelated in the SS study area, which is characterized by an extremely large, yet gradual, gradient of elevation that drives important changes in vegetation and fuel types (Vankat 1982). The fuels of WBNP are only slightly less autocorrelated than those of SS and the fuels in the GALWC and SBW are considerably less autocorrelated than in the other study areas, although differences in fire patterns among fuel types have been reported for these two study

areas (Rollins et al. 2002).

When all other factors are held constant, topography influences spatial fire likelihood by accelerating the rate at which fire spreads up-hill and decreasing the spread rate down-hill, relative to a flat area. Slope thus affects fire size and shape, especially in areas exhibiting rugged relief (McKenzie et al. 2006, Moritz et al. 2011). As measured by the spatial autocorrelation in elevation, SBW is the most rugged study area, followed by the GALWC (Fig. 2). In both of these study areas, fire patterns have been shown to vary with topography (Rollins et al. 2002). Though elevation has been found to influence BP in SS (Parks et al. 2011), elevation varies more gradually in SS than it does in SBW or GALWC. WBNP has very low topographic variability; in fact, it has been shown using these data that topography has virtually no effect on BP in this area (Parisien et al. 2011).

Simulation model: modeling processes

To estimate BP of each point on a landscape, we used fire models that simulate the ignition and spread of thousands of individual wildfires. Because fire behavior prediction systems of the U.S. and Canada are fundamentally different, notably in how they characterize flammable vegetation (i.e., fuel types), we used two different BP models. For the three U.S. study areas, we used a customized version of the FlamMap model, called Randig (Finney 2006), and for WBNP we used the Burn-P3 model (Parisien et al. 2005). Conceptually, Randig and Burn-P3 are very similar (Miller et al. 2008) although some inputs and internal mechanisms may differ. Detailed descriptions of the modeling processes and inputs can be found in Parks et al. (2011) and Parisien et al. (2011).

In this study, vegetation is static and does not change from year to year. Rather, the BP approach attempts to capture all possible situations in which fires might burn the landscape under current vegetation conditions. It does so by probabilistically drawing from model inputs for each fire and for each day a fire burns. We simulated between 50,000 and 100,000 fires, depending on the size of the study area. The spatial resolution (i.e., pixel size) was 100 m for the three U.S. study areas and, because of its larger size, 200 m for WBNP. To avoid edge

effects, each study area was buffered (10 km for the U.S. study areas and 50 km for WBNP) so that fires igniting outside the study area boundary could potentially burn into the study area and contribute to BP. The buffer was ultimately removed so that analyses were confined to within the study area boundaries.

Fire spread was simulated using the minimum travel time (MTT) algorithm within Randig (Finney 2002) and the Prometheus fire growth model within Burn-P3 (Tymstra et al. 2010). Given identical inputs, Finney (2002) showed that the MTT algorithm produces nearly identical fire perimeters as those produced with the FARSITE fire growth model (Finney 1998), which uses the same spread algorithm as Prometheus. Fire spread in Randig and Burn-P3 is deterministic given a particular set of inputs; however, variability was incorporated through a number of probabilistic inputs. First, the ignition location was drawn from a spatial grid of ignition likelihood (Fig. 3). Next, the length of the burning period for each fire (analogous to the ‘rain-free’ period) was sampled from a probability distribution of number of spread-event days (see *Simulation model inputs—Weather inputs*). Then, fire weather conditions were attached to each spread-event day by sampling from a probability distribution of wind speed coupled with wind direction (U.S. study areas); or from an extensive list of daily fire weather observations (WBNP). Finally, the number of fires occurring at each pixel was counted with the resulting BP value representing the proportion of times a given pixel burned relative to the total number of simulations.

Simulation model: inputs

All inputs for this study were based on relatively recent historical data (i.e., the last few decades) and thus represented the modern conditions under which fires ignite and burn in each study area. Historical fire atlas data were used to build the inputs for ignition locations and weather conditions. We used comprehensive databases of fires ≥ 50 ha for the U.S. study areas and ≥ 200 ha for WBNP (hereafter, ‘large fires’). Small fires were excluded from the parameterization process because, based on detailed fire atlases of each study area, these fires are responsible for only a small fraction of the total

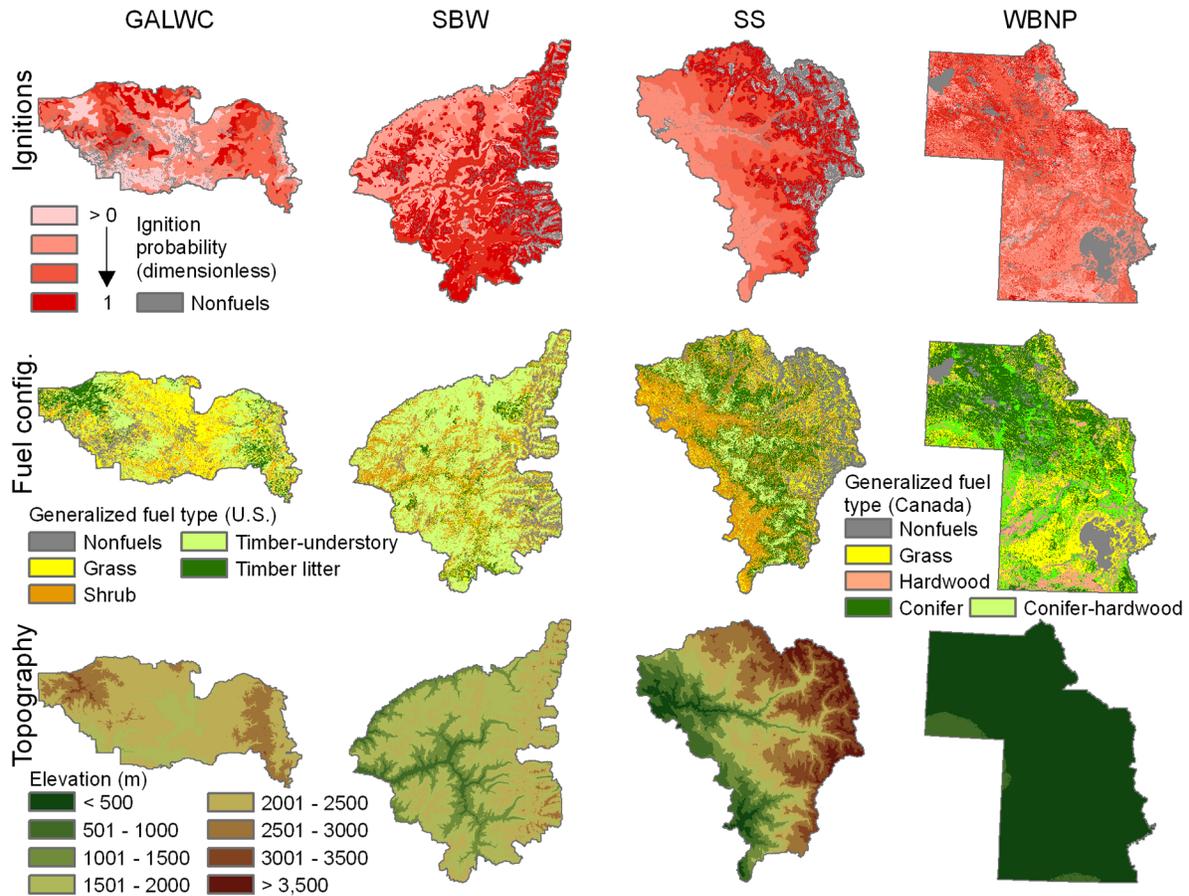


Fig. 3. The bottom-up factors of burn probability by study area. These also act as inputs to the fire simulation models. Note that the fuels have been aggregated into broader classification for visualization purposes.

area burned ($\leq \sim 5\%$).

Spatial inputs.—Ignition probability density grids depict the spatial variability of ignition locations. For the U.S. study areas, these grids were created using a classification and regression tree (CART) approach. The CART model related known ignition locations (Brown et al. 2002) (dependent variable) to elevation and generalized fuel type (Rollins 2009) (Fig. 3). In addition to observed ignition locations, CART also required information with respect to where ignitions did not occur; we therefore used randomly placed points in equal proportions to the number of ignitions (ranging from 76 to 261, depending on study area) to serve as pseudo absences. We used the resulting CART model to generate a generalized and spatially continuous grid of relative ignition probability (Fig. 3). In WBNP,

because the park is relatively flat, we simply used the observed ignition density by fuel type. The resulting grids adequately described recent history and our knowledge of ignition patterns of the study areas (Rollins et al. 2000, Krawchuk et al. 2006, van Wagtenonk and Cayan 2008).

Vegetation was represented as fire behavior fuel types (Fig. 3), which predict quantitative fire behavior for a given set of fire weather and topographic inputs. We used the standard fuel typing for the U.S. (Anderson 1982, Scott and Burgan 2005) and Canada (Forestry Canada Fire Danger Group 1992). Fuels data for the GALWC were developed by Keane et al. (2000), and slightly modified based on local expertise. LANDFIRE (Rollins 2009) fuels data were used for SBW and SS. The fuels data for WBNP was developed by Jensen and Sanchez-Azofeifa

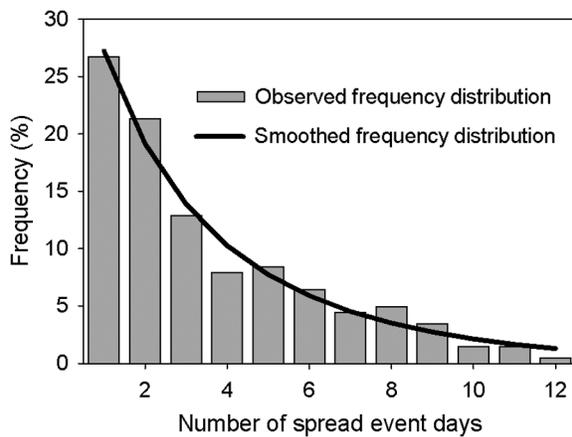


Fig. 4. Observed and smoothed frequency distribution of spread event days for WBNP.

(2006) (see Parisien et al. [2011] for details). Elevation grids (Fig. 3) were obtained from the US Geological Survey and Natural Resources Canada.

Weather inputs.—Weather inputs to the BP models had two components: the duration of each fire, which corresponded to the ‘rain-free’ period, and the daily weather station observations that drive the fire spread. All weather parameters varied daily for fires in WBNP, but only wind speed and wind direction fluctuated daily for fires in the U.S. study areas.

Fires may burn for weeks to months, but only achieve significant spread during a few days of high to extreme fire weather (hereafter ‘spread-event days’) (Podur and Wotton 2011). We identified the dates of significant spread to inform other parameters in the BP models. First, the duration of each fire was drawn from a frequency distribution of the number of spread-event days (Fig. 4). This distribution was created from daily fire progressions of large fires (71 to 202, depending on study area) in or near each study area detected by the MODIS satellite fire data from 2001 to 2008 (USDA Forest Service 2008). We defined a spread-event day according to a minimum daily area burned threshold equivalent to 5 percent of the cumulative area burned to date:

$$\frac{\sqrt{a_i}}{\sum_{i=1}^n \sqrt{a_i}} \geq 0.05 \quad (1)$$

where a_i represented the area burned for a given fire on the i th day and n was the total number of days of burning. The square root transformation of area burned accounts for the nonlinear (power function) expansion of fire size with time. The 5% threshold was selected through trial-and-error and captures the major spread of fires we’ve analyzed. Applying this threshold resulted in a distribution of spread-event days with a decaying form, which we smoothed according to a logistic or linear function, depending on the study area (Fig. 4). This process also identified specific dates that experienced substantial fire growth, which were then used to select fuel moisture values and wind data for the U.S. study areas.

For days identified as spread-events for the U.S. study areas, fuel moisture values were calculated with the FireFamily Plus weather analysis software program (Bradshaw and McCormick 2000) using historical weather data from multiple weather stations in or near the study area. Daily fuel moisture values for spread-event days were then summarized across stations and the median value was used for the simulations. We also created frequency distributions of wind speed and wind direction for the dates identified as spread-event days from which Randig randomly drew values; wind speed and direction were coupled to avoid unrealistic combinations. For this purpose, we used a single weather station most representative of wind conditions in each study area based on input from local experts.

Daily weather conditions were modeled somewhat differently in WBNP. For each day of each simulated fire, weather conditions and their associated fuel moisture indexes were drawn from a large list of fire-conducive weather conditions. As in the U.S. study areas, only days of high to extreme fire weather were considered for the modeling. These days were defined as having an Initial Spread Index (ISI) ≥ 8.6 ; ISI is an index describing ease of spread (Hirsch 1996). This list was built from daily observations from 13 weather stations from 1957 to 2006 (depending on data availability from each station). Daily conditions in this list were sequentially ordered by date and the weather conditions for the first day of fire growth for each fire were selected randomly; weather conditions for subsequent

spread-event days were selected sequentially thereafter for each fire (Parisien et al. 2011).

Experimental treatments

For each experimental treatment, we removed the spatial variability in one of three bottom-up factors: ignitions, fuels and topography. That is, we simulated BP using inputs identical to those of the control except for the factor of interest. The ignitions treatment randomized ignition locations. The fuel configuration treatment removed the patch structure (i.e., clustering) of fuel types by randomizing the pixels in the same proportion as the original fuels grid while retaining existing non-fuel areas. For the fuel configuration treatment, we averaged three BP maps generated from three different randomizations of fuel grids in an effort to avoid any effect of fortuitous spatial arrangements due to a single randomization. The topography treatment rendered each study area completely flat (slope = 0) to evaluate the direct effect of slope on fire spread and BP. This approach allowed us to determine the direct effects of each factor on BP but not the indirect effects. For example, although elevation also affects ignition pattern and fuel configuration, we considered these to be indirect effects of topography on BP and did not attempt to quantify them. This process resulted in four BP maps for each study area representing the control, randomized ignitions, randomized fuels and flat topography.

Data analysis

The BP values generated from our simulations are considered *relative* probabilities that are comparable only within a particular study area. For example, a pixel with a value of 0.02 represents twice the likelihood of burning as another pixel in the same study area with a value of 0.01. Because of the difficulty in comparing BP values *among* study areas, we scaled all BP grids—the treatment BP maps and the control BP maps—by dividing the value of each pixel by the mean value of the control BP map:

$$\text{BP.scaled}_i = \frac{\text{BP}_i}{\overline{\text{BP.control}}} \quad (2)$$

where BP_i represents the BP of the i th pixel in the map being scaled, and $\overline{\text{BP.control}}$ represents the BP of the control averaged across all pixels in the

study area. This equation created a scaled control BP map for each study area with a mean value of 1; that is, the scaled BP of the control averaged across all pixels in each study area equaled 1. Therefore, each treatment's scaled BP values represented a deviation from the scaled control BP, on a pixel-by-pixel basis, which could then be compared among study areas. All analyses that follow were conducted using these scaled values.

To determine the influence of each bottom-up factor on BP patterns, we developed ratios between the treatment BP and the control BP (hereafter termed the 'treatment ratio') whereby the magnitude of the treatment ratio was proportional to the departure in BP at each pixel, regardless of whether or not the treatment had a higher or lower value than that of the control. In addition, the sign of the ratio indicated whether the treatment BP was less than (negative) or greater than (positive) the control:

$$\text{Treatment.ratio} = \begin{cases} -(\text{BP.control}_i \div \text{BP.trt}_i) + 1, & \text{BP.control}_i > \text{BP.trt}_i \\ (\text{BP.trt}_i \div \text{BP.control}_i) - 1, & \text{BP.control}_i < \text{BP.trt}_i \end{cases} \quad (3)$$

where BP.control_i represents the BP of the control at the i th pixel and BP.trt_i is the BP of the treatment at the i th pixel. For any pixel with a BP of zero (for the control or treatments), the treatment ratio was not calculated. The resulting ratios appropriately quantified the differences between each treatment and the control. For example, a pixel whose treatment value that was one half the value of the control had the same treatment ratio (-1.0), but a different sign, as a pixel whose treatment value was twice the value of the control (1.0). This equation was also applied directly to the BP maps for visualization purposes.

We evaluated the influence of ignitions, fuel configuration and topography using two metrics: the 'absolute' and 'proportional' contributions. The absolute contribution was simply the absolute value of the treatment ratio averaged across all pixels. For example, an absolute contribution = 1 implied that, on a pixel-wise basis, the average BP of the treatment was either half (50% less) or double (100% more) that of the control. The absolute contribution inherently includes some minor noise from stochastic variability among model simulations. To adjust for this,

we estimated the degree of noise by comparing the BP differences among multiple BP maps produced with identical inputs and subsequently subtracted it from the absolute contribution. The proportional contribution simply rescaled the absolute contribution of each factor so that the contribution of the three factors totaled 1.0; that is, the absolute contribution of all factors within each study area was summed, and the proportional contribution of each factor equaled the proportion of that summed value. The absolute contribution was used to compare the influence of factors among study areas, whereas the proportional contribution was used to evaluate influences within an individual study area.

To determine if spatial pattern in BP of each treatment was significantly different from the control, we calculated bootstrap 95% confidence intervals of 100 random samples of 250 pixels each. The confidence intervals of the treatment ratios of all 100 random samples were averaged, and those confidence intervals that overlapped with zero were considered not significantly different from the control. These calculations were conducted using the 'boot' package (Davison and Hinkley 1997, Canty and Ripley 2011) in the R statistical program (R Development Core Team 2007).

RESULTS

The control BP maps (Fig. 5) show that BP patterns are highly heterogeneous within each study area. Visual comparison of these maps to the treatment BP maps reveals that some treatments result in qualitatively different spatial patterns from their control. Generally, the spatial patterns in the fuel configuration treatment are noticeably different from the control, whereas the topography and ignitions treatments have more subtle impacts on BP spatial patterns. The effect of the treatments on mean BP (i.e., BP averaged over all pixels) also varies (Fig. 5). The ignitions and fuel configuration treatments have a low-to-negligible effect on mean BP in all study areas except SS. The topography treatment has a large effect on mean BP in all study areas except WBNP (Fig. 5).

Although mean BP reveals broad landscape-scale effects, the treatment ratio maps highlight the fine-scale spatially variable effect of each

treatment relative to the control and also illustrates the direction and magnitude of those effects (Fig. 6). For example, although the mean BP of the control and fuel configuration treatment in WBNP are nearly identical, the spatial differences are considerable, as illustrated by the patterns in the treatment ratio map. Some treatments result in very high and very low treatment ratios. With the exception of SBW, the highest and lowest ratios are seen in the fuel configuration treatment. The topography treatment almost universally has a lower BP than that of the control, as evidenced by a lower mean BP relative to the control (Fig. 5) and negative treatment ratios over broad swaths of each study area (except WBNP) (Fig. 6). Results from the bootstrap analysis indicate that all treatments are significantly ($p \leq 0.05$) spatially different from the control except for the topography treatment in WBNP.

Scatterplots comparing the treatment BP values to the control BP values show the varying effects of the treatments both within and among study areas (Fig. 7). For example, the ignitions treatment in SS generally results in higher BP than the control, but the same treatment has a less uniform effect in GALWC and SBW. The tight relationship around the 1:1 line for the ignitions and topography treatments in WBNP suggests that neither ignition pattern nor topography has a strong influence on BP patterns in that study area. Conversely, the considerable scatter in the fuel configuration treatment suggests this factor plays a moderate-to-large role in all study areas, corroborating the information gleaned from the treatment ratio maps (Fig. 6).

Substantial differences among study areas can be seen in the absolute contribution of each bottom-up factor (Fig. 8). Ignitions contributed relatively little to BP in all study areas, especially in WBNP. In contrast, fuel configuration contributed the most in all study areas except SBW, where topography was more important. Topography contributed more in SBW and SS than in GALWC and WBNP. The proportional contribution of each factor to BP indicated the influence of each factor within a study area. In SBW, topography was dominant, accounting for more than half the proportional contribution to BP. In GALWC and SS, fuel configuration was about four times more important than ignitions and

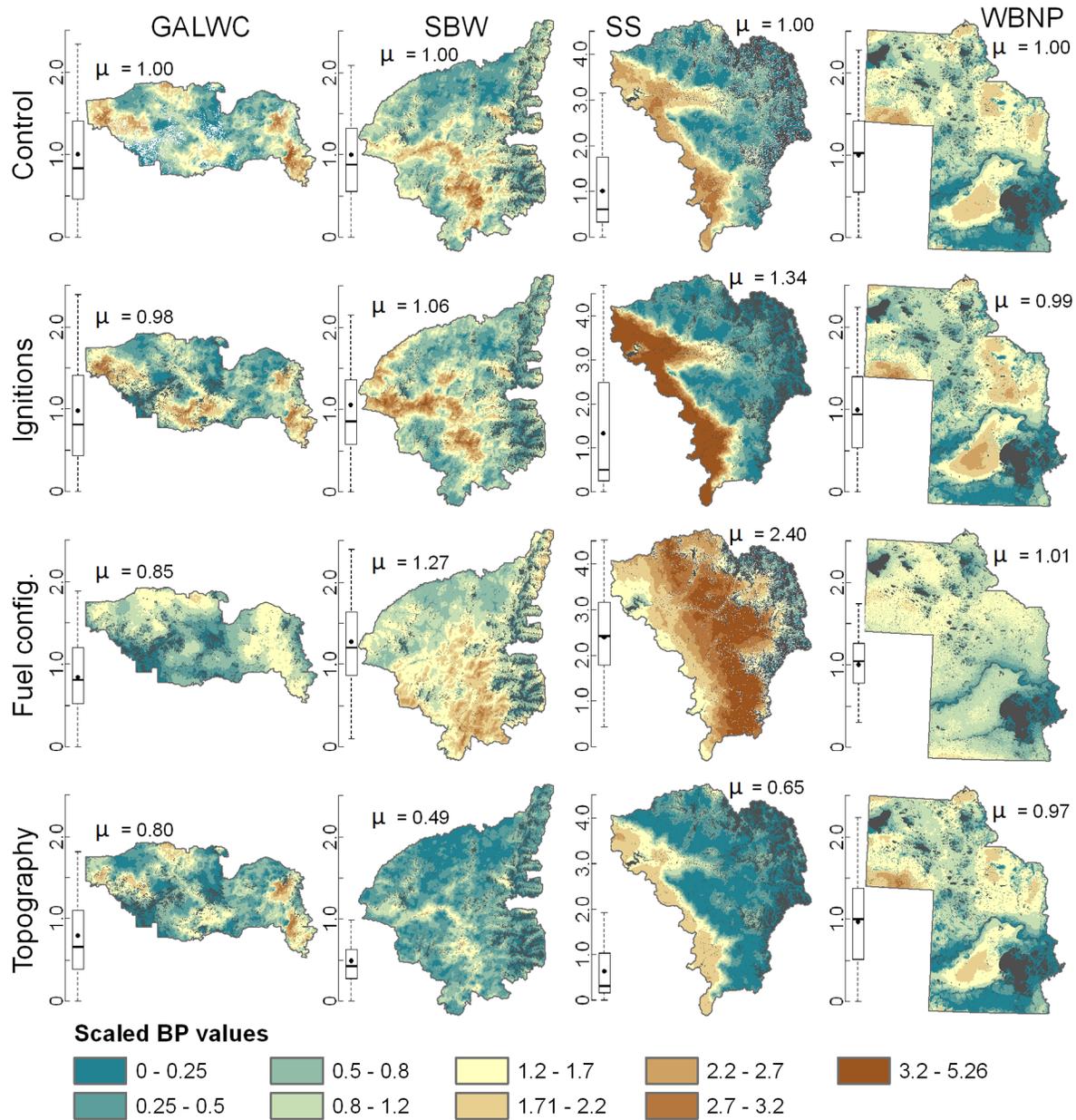


Fig. 5. The scaled burn probability (BP) maps for the control and experimental treatments for each study area. The box-and-whisker plots represent the distribution of values in each map, as well as the median (thick black line) and mean (black dot).

topography combined. In WBNP, fuel configuration was by far the dominant contributor to the spatial pattern of BP.

Finally, to evaluate our working hypotheses (Fig. 2), we show the relationship of the absolute and proportional contributions of each bottom-up factor (Fig. 8) to the spatial autocorrelation

(averaged among radii) of each factor (Fig. 9). The rank order among study areas of the contributions (absolute and proportional) of fuel configuration and ignitions fulfilled our working hypotheses based on the spatial structure of these factors. Although the proportional contribution of topography followed the hypothesized rank

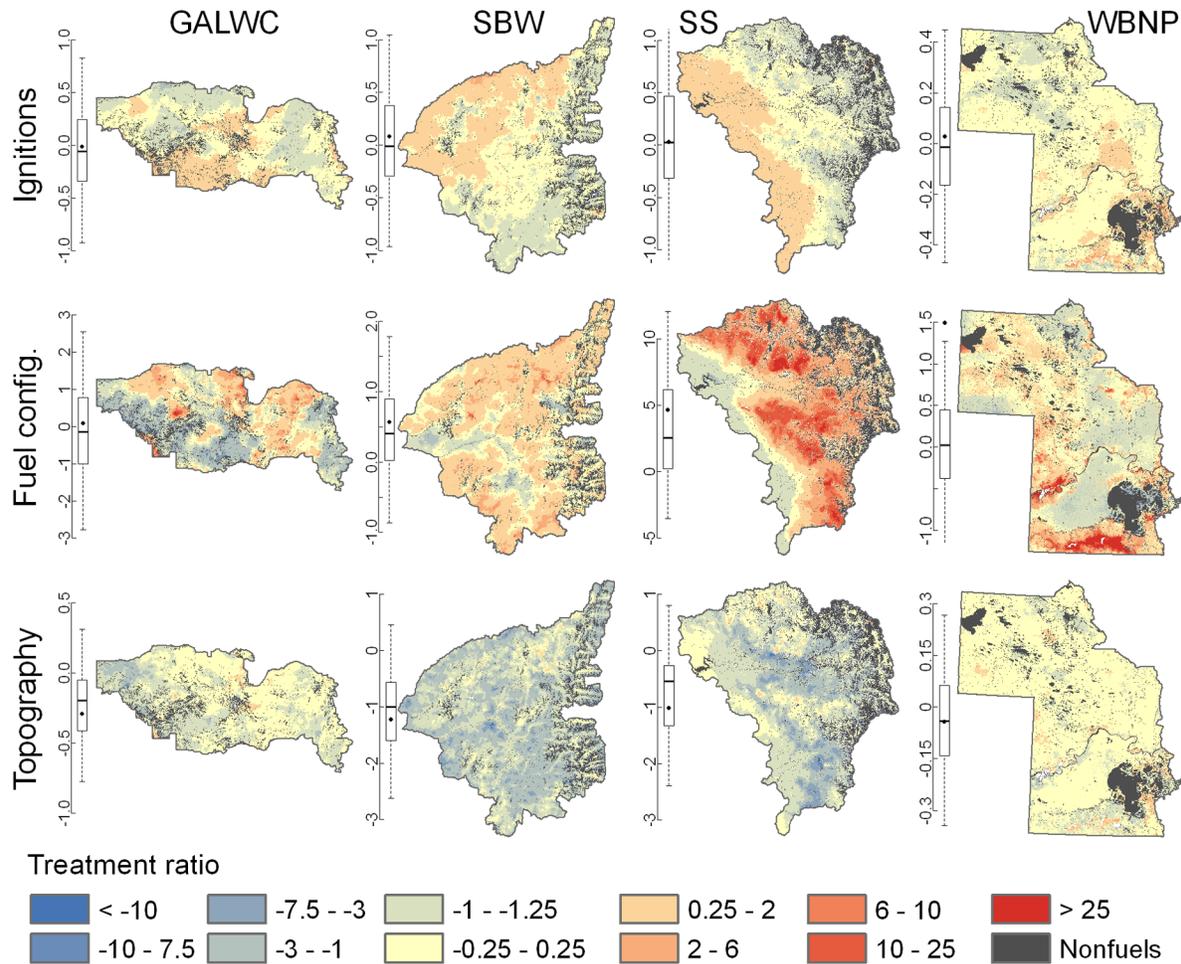


Fig. 6. The burn probability (BP) ratio maps created using Eq. 3. Positive (red) values indicate higher treatment BP than in the control; negative (blue) values indicate lower treatment BP in the control. The box-and-whisker plots represent the distribution of values in each map, as well as the median (thick black line) and mean (black dot).

order among study areas, the absolute contribution did not.

DISCUSSION

Although a synthetic model of top-down and bottom-up controls on fire regimes exists (Meyn et al. 2007, Krawchuk and Moritz 2011), it is generally not known to what extent the bottom-up controls of ignitions, fuels, and topography promote (or limit) spatial variability in fire in different ecosystems. In this study, we used BP as a standard for comparison and a simulation experiment to evaluate and quantify the influ-

ence of bottom-up controls on four biophysically divergent fire-prone landscapes in western North America. BP models represent simplifications of real-world processes, but provide a robust way to measure the sensitivity of simulated BP to bottom-up controls. Our results suggest that the influence of bottom-up factors on fire regimes is highly dependent on ecosystem type, but also on the idiosyncrasies of the specific landscape. Furthermore, our results lend support to studies of detailed fire history (e.g., Rollins et al. 2002) by solidifying the ideas that fine-scale variability in fire likelihood is usually a function of not one but several bottom-up controls (Heyerdahl et al.

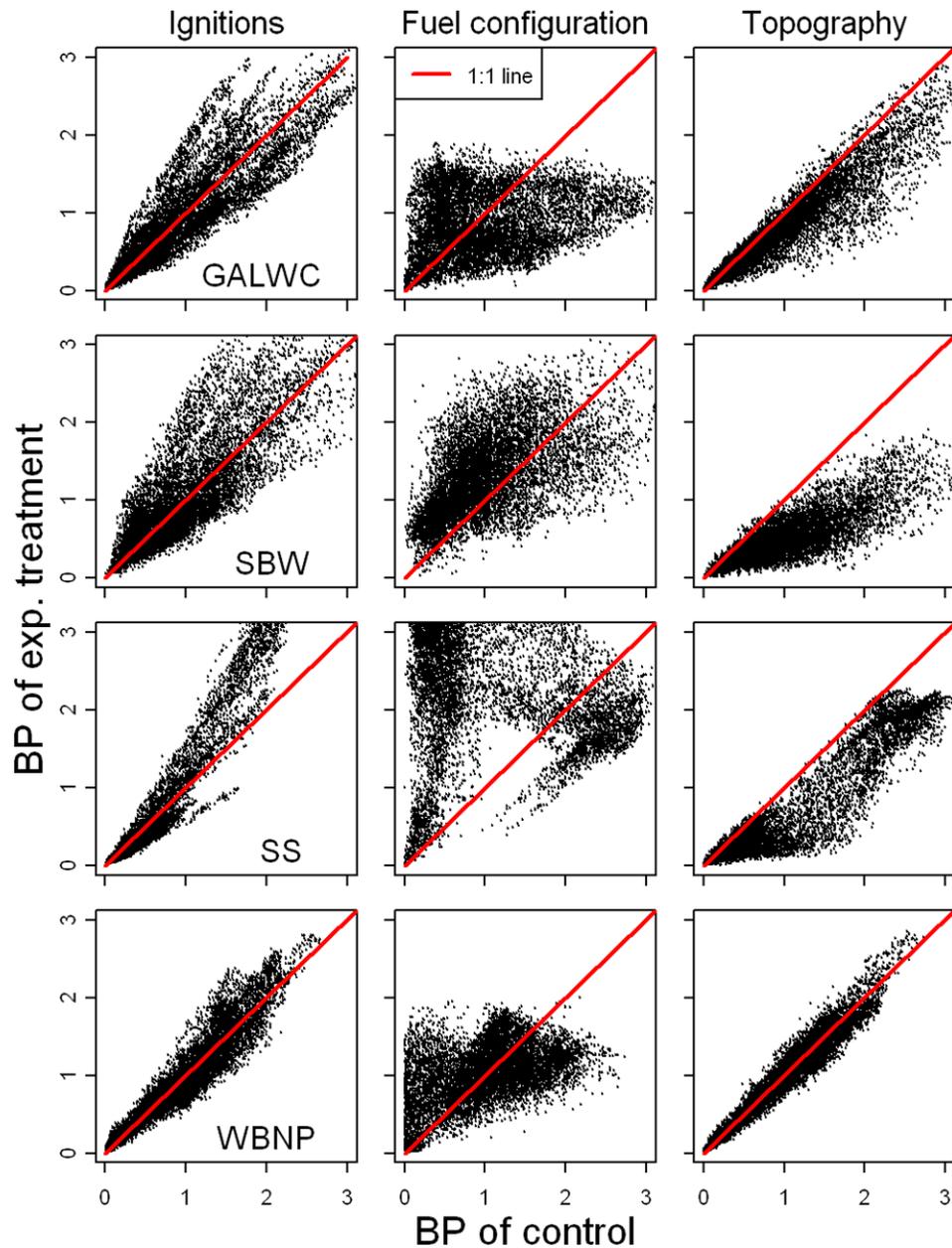


Fig. 7. Scatterplots of 10,000 random pixels depicting the scaled BP of each treatment (y-axis) vs. the scaled BP of the control (x-axis). The red line represents the 1:1 line.

2001).

We hypothesized that the spatial structure—specifically spatial autocorrelation—of bottom-up factors would largely account for their respective influence on fire likelihood. Our results support this hypothesis for at least two of the three factors: ignitions and fuels. Plotting

the absolute contribution of ignitions and fuel configuration against a measure of autocorrelation (Moran's I) (Fig. 9) reveals that the rank order of influence among study areas is exactly as hypothesized. For topography, the rank order of GALWC and SS was opposite to what we hypothesized. However, when the proportional

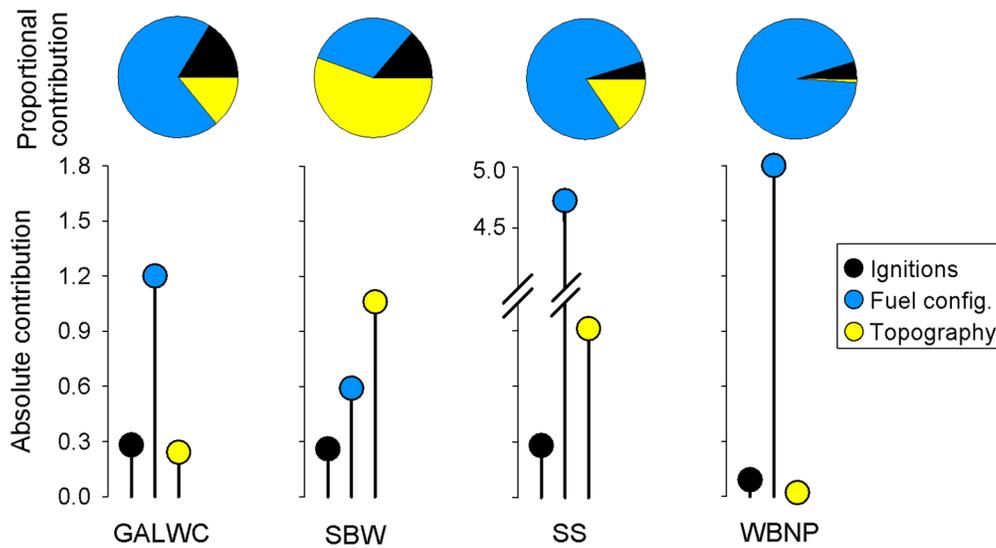


Fig. 8. The proportional (pie charts) and absolute (dot plots) contributions of bottom-up factors for each treatment in each study area.

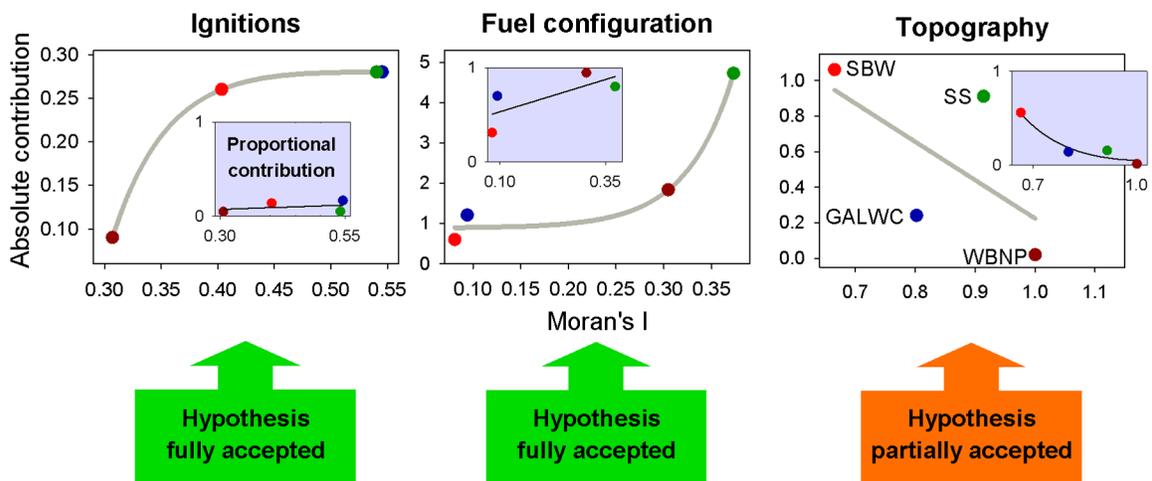


Fig. 9. The proportional and absolute contributions of bottom-up factors to BP as a function of spatial clustering. This is used as a semi-quantitative test of our working hypotheses. The spatial structure (x-axes) consists of the mean of all Moran's *I* values shown in Fig. 2. Note that both the x and y axes vary among plots.

contribution (i.e., the within-study area measure of influence) of topography was plotted against autocorrelation, the ranking of study areas was consistent with our expectations. We therefore conclude that the hypothesis is at least partly accepted in the case of topography. Hence, we illustrate how the spatial structure of bottom-up factors is a key determinant of spatial fire likelihood, and can also act as a proximal metric

for bottom-up contributions when in-depth analysis may not be possible or practical.

Although we have only four data points (Fig. 9), our results suggest a nonlinear relationship between the influence of a bottom-up factor on fire patterns and the spatial structure of that factor. This enhances our ecological understanding of spatial nonlinearities among fire and its environment (Turner 2005b). For example, the

influence of fuels increases sharply as spatial autocorrelation increases. These findings and those of Ryu et al. (2007) could have important implications for fuels reduction treatments intended to reduce the probability of wildland fire. That is, in addition to ‘area treated’, spatial configuration of fuels may be an important consideration (Finney 2001). Other studies have also found nonlinearities relating to fire regimes (Peters et al. 2004), including the influence of both top-down (Hu et al. 2011) and bottom-up controls (Finney 2001, McKenzie et al. 2006).

The influence of landscape-level fuel connectivity on fire spread is well documented and has important implications for the dynamics of fire prone ecosystems (Turner and Romme 1994, Miller and Urban 2000). Our findings show that, similar to Viedma et al. (2009), landscapes with more heterogeneous fuels (i.e., low spatial autocorrelation) contribute less to the fire patterns than landscapes with more highly connected and spatially autocorrelated fuels. We found that randomizing the already highly heterogeneous fuels in SBW did not have as large of an influence as randomizing fuels in landscapes that are more strongly spatially structured (e.g., SS and WBNP) (Figs. 2 and 7). However, the degree of temporal stability in the importance of fuel configuration is, to some extent transient, as vegetation changes through disturbance and succession. In fact, the degree to which spatial patterns in fuels are reinforced or erased by fires (Miller and Urban 1999, Peterson 2002), or merely the result of the biophysical template, is an area ripe for further research (McKenzie et al. 2011).

In addition to spatial structure, the contribution of fuels on spatial fire likelihood depends on the magnitude of the potential spread rate among fuel types. For example, the fuels of SBW and GALWC have similarly low spatial autocorrelation, but the influence of fuel configuration was greater in GALWC. This is likely because the fuel types in GALWC promote faster fire spread than those of SBW: about two times faster under average weather conditions (potential spread rate of 9.3 m/min. vs. 4.6 m/min.). Similarly, the contribution of fuel configuration in SS far outweighs the contribution of the other two factors both within and among study areas. This is likely due to its fuels being highly

clustered, as well as being fairly diverse across the entire study area in terms of the potential spread rate of fire, with about twice the standard deviation in potential spread rate compared to SBW and WBNP (std. dev. of 8.3 m/min. in SS, 4.1 m/min. in SBW and 5.1 m/min. in WBNP). The influence of a bottom-up factor on fire regimes is thus likely an interaction between the spatial structure, strength (or magnitude), and variability of that factor in a given landscape.

Compared to the influence of fuels, the spatial patterns of ignitions contributed relatively little to fire likelihood patterns in the four study areas. Because all four study areas are managed, to varying degrees, with a goal of restoring natural fire regimes, we modeled only lightning-caused ignitions and did not model fire suppression; therefore, the simulated fires were relatively large. In landscapes with a larger human impact, ignition patterns may contribute more to spatial fire patterns. Human-caused ignitions are substantially more clustered than lightning-caused ignitions (Veblen et al. 2000, Krawchuk et al. 2006, Syphard et al. 2009) and human-dominated landscapes are generally more fragmented and experience more fire suppression, leading to smaller fires (Sturtevant and Cleland 2007, Bar Massada et al. 2011). In other words, although the effect of ignition patterns on fire patterns is important where fires are relatively small (Yang et al. 2008, Carmel et al. 2009), it is diminished in landscapes that experience large fires (Bar Massada et al. 2011).

Fire patterns have been shown to vary with topography, especially in areas of steep and complex terrain (Heyerdahl et al. 2001, Taylor and Skinner 2003, Kellogg et al. 2008, Kennedy and McKenzie 2010). We were surprised at the low influence of topography in GALWC relative to SS, especially given the high degree of spatial autocorrelation in elevation and previously reported importance of topography on fire patterns in GALWC (Rollins et al. 2000). However, we do note that GALWC is not as steep as SS; the average slope in GALWC is 15.1° compared to 18.7° in SS, suggesting that spatial autocorrelation in elevation may not be the most appropriate measure of topographic variability as it relates to fire likelihood.

Although topography did substantially contribute to BP patterns in the mountainous study

areas, its contribution may be underestimated if one considers its indirect effect on patterns of ignitions and vegetation. For example, topography can sometimes be a strong driver of vegetation and ignition patterns in rugged landscapes, which also affect BP patterns. These indirect effects can be challenging to quantify because they are based on complex interactions. For example, Parks et al. (2011) showed through statistically isolating the “unique” and “shared” contributions of the environmental controls on BP, topography had an over-arching effect on the fire environment in the Southern Sierra. In light of their results, one could expect topography to exert a non-trivial effect on ignitions and fuels in any landscape with substantial relief. Although a detailed analysis of the indirect effect of the controls on fire likelihood, as undertaken by Parks et al. (2011), was beyond the scope of this study, it does provide an interesting arena for future research.

Simulation models represent a simplification of the real world and simulated fire behavior does not always reflect observed behavior (Cruz and Alexander 2010). The BP grids generated for this study are therefore synthetic measures of the spatial pattern in fire likelihood for the current state of the landscape, rather than a reconstruction of fire regimes. However, because fire atlas data are too sparse to reconstruct fire regimes, simulation modeling represents an attractive alternative for evaluating bottom-up controls for multiple landscapes. Furthermore, studies conducted over the past decade indicate that simulations can yield fairly realistic fire patterns, as long as relevant natural variability is incorporated (Lertzman et al. 1998, Parisien et al. 2010, Finney et al. 2011).

CONCLUSION

Clear-cut partitioning of bottom-up vs. top-down controls is difficult (Peters et al. 2004, Zinck and Grimm 2009), in part because bottom-up factors usually interact amongst themselves, as well as with top-down controls (Gavin et al. 2006, Parisien et al. 2010). Simulation modeling provided the means, through input manipulation, to isolate the effect of bottom-up environmental factors on spatial fire likelihood in four fire-prone landscapes of North America. Because

fire–environment relationships can be idiosyncratic to a particular landscape and are known to vary at different spatial and temporal frames of study (Cyr et al. 2007, Parks et al. 2011), we provided a standard baseline for comparison among these study areas. The standard baseline using simulated burn probabilities allowed us to quantify the influence of ignitions, fuel configuration, and topography. The results obtained provided some new insights with respect to bottom-up controls of fire regimes that, to some degree, can be generalized to the sub-continental extent. However, because all four study areas have a ‘light’ human imprint, our results may not be representative of more human-influenced landscapes (Cardille and Lambois 2010).

Existing frameworks of fire regime controls (Meyn et al. 2007, Krawchuk and Moritz 2011) have focused on global measures of fire activity (e.g., area burned). Furthermore, fire activity at the regional scale is often associated with climate variability (e.g., Westerling et al. 2006, Heyerdahl et al. 2008); such studies are focused on *temporal* variability of fire activity and climate. In this study, we focused on the *spatial* variability of fire activity and specific bottom-up factors. In doing so, we offer a different lens through which to view dominant controls on fire regimes. For example, we found that fuel configuration is the dominant control of spatial variability in fire activity in most study areas, and that the influence of topography varies dramatically, from insignificant to the largest driving factor, depending on the study area. This does not imply that top-down factors such as climate are unimportant—they are—but rather, studies with different temporal and spatial windows of analysis will not have consistent results. This comparative study therefore sheds further light on the factors most influencing variability in fire likelihood. In fact, we suggest that, through a greater appreciation of the tremendous spatial variability in fire likelihood, the results of this study could be used to extend synthetic frameworks of environmental controls on fire regimes.

ACKNOWLEDGMENTS

We acknowledge funding from the Joint Fire Science Program under Project JFSP 06-4-1-04. We thank Xianli Wang for thoughtful comments that significantly improved this manuscript and Mark Finney and Alan

Ager for their computer and software support. We also thank those who helped us gather data and expert knowledge of the study areas, including Dennis Fahl, John Kramers, Fred Hernandez and Charles Maxwell (GALWC), Erin Law, Mike Lubke, Matt Young, Tobin Kelly, Matt Young, Guy Williams and Rick Stratton (SBW), Dave Bartlett (SS), and Keith Hartery, Mark Heathcott, and Rita Antoniak (WBNP).

LITERATURE CITED

- Anderson, H. E. 1982. Aids to determining fuel models for estimating fire behavior. General Technical Report INT-GTR-122. USDA Forest Service, Intermountain Forest and Range Experimental Station, Ogden, Utah, USA.
- Balshi, M. S., A. D. McGuire, P. Duffy, M. Flannigan, J. Walsh, and J. Melillo. 2009. Assessing the response of area burned to changing climate in western boreal North America using a Multivariate Adaptive Regression Splines (MARS) approach. *Global Change Biology* 15:578–600.
- Bar Massada, A., A. D. Syphard, T. J. Hawbaker, S. I. Stewart, and V. C. Radeloff. 2011. Effects of ignition location models on the burn patterns of simulated wildfires. *Environmental Modelling & Software* 26:583–592.
- Bond, W. J. and B. W. van Wilgen. 1996. *Fire and plants*. Chapman and Hall, London, UK.
- Bradshaw, B. and E. McCormick. 2000. *FireFamily Plus user's guide*. Version 2.0. General Technical Report RMRS-GTR-67WWW. USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, USA.
- Bradstock, R. A., K. A. Hammill, L. Collins, and O. Price. 2010. Effects of weather, fuel and terrain on fire severity in topographically diverse landscapes of south-eastern Australia. *Landscape Ecology* 25:607–619.
- Brown, J. K., S. F. Arno, S. W. Barrett, and J. P. Menakis. 1994. Comparing the prescribed natural fire program with presettlement fires in the Selway-Bitterroot Wilderness. *International Journal of Wildland Fire* 4:157–168.
- Brown, T. J., B. L. Hall, C. R. Mohrle, and H. J. Reinbold. 2002. Coarse assessment of the Federal Wildland Fire Occurrence Data: Report for the national wildfire coordinating group. Program for Climate, Ecosystem and Fire Applications. Desert Research Institute, Reno, Nevada, USA.
- Canty, A. and B. Ripley. 2011. *boot: Bootstrap R (S-Plus) Functions*. R package version 1.3-2. R Foundation for Statistical Computing, Vienna, Austria.
- Cardille, J. A. and M. Lambois. 2010. From the redwood forest to the Gulf Stream waters: human signature nearly ubiquitous in representative US landscapes. *Frontiers in Ecology and the Environment* 8:130–134.
- Carmel, Y., S. Paz, F. Jahashan, and M. Shoshany. 2009. Assessing fire risk using Monte Carlo simulations of fire spread. *Forest Ecology and Management* 257:370–377.
- Cary, G. J., R. E. Keane, R. H. Gardner, S. Lavorel, M. D. Flannigan, I. D. Davies, C. Li, J. M. Lenihan, T. S. Rupp, and F. Mouillot. 2006. Comparison of the sensitivity of landscape-fire-succession models to variation in terrain, fuel pattern, climate and weather. *Landscape Ecology* 21:121–137.
- Cruz, M. G. and M. E. Alexander. 2010. Assessing crown fire potential in coniferous forests of western North America: a critique of current approaches and recent simulation studies. *International Journal of Wildland Fire* 19:377–398.
- Cyr, D., S. Gauthier, and Y. Bergeron. 2007. Scale-dependent determinants of heterogeneity in fire frequency in a coniferous boreal forest of eastern Canada. *Landscape Ecology* 22:1325–1339.
- Daly, C., W. P. Gibson, G. H. Taylor, G. L. Johnson, and P. Pasteris. 2002. A knowledge-based approach to the statistical mapping of climate. *Climate Research* 22:99–113. <http://www.prism.oregonstate.edu>
- Davison, A. C. and D. V. Hinkley. 1997. *Bootstrap methods and their applications*. Cambridge University Press, Cambridge, UK.
- Duncan, B. W. and P. A. Schmalzer. 2004. Anthropogenic influences on potential fire spread in a pyrogenic ecosystem of Florida, USA. *Landscape Ecology* 19:153–165.
- Finney, M. A. 1998. FARSITE: Fire Area Simulator—model development and evaluation. Research Paper RMRS-RP-4. USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, USA.
- Finney, M. A. 2001. Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. *Forest Science* 47:219–228.
- Finney, M. A. 2002. Fire growth using minimum travel time methods. *Canadian Journal of Forest Research* 32:1420–1424.
- Finney, M. A. 2006. An overview of FlamMap fire model capabilities. Pages 213–219 in P. L. Andrews and B. W. Butler, editors. *Proceedings of Fuels management: How to measure success*, Portland, Oregon, USA. Proceedings RMRS-P-41. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado, USA.
- Finney, M. A., C. W. McHugh, I. C. Grenfell, K. L. Riley, and K. C. Short. 2011. A simulation of probabilistic wildfire risk components for the continental United States. *Stochastic Environmental Research and Risk Assessment* 25:973–1000.
- Forestry Canada Fire Danger Group. 1992. Development and structure of the Canadian forest fire behaviour prediction system. Forestry Canada, Fire

- Danger Group and Science and Sustainable Development Directorate, Ottawa, Ontario, Canada.
- Gardner, R. H., B. T. Milne, M. G. Turner, and R. V. O'Neill. 1987. Neutral models for the analysis of broad-scale landscape pattern. *Landscape Ecology* 1:19–28.
- Gavin, D. G., F. S. Hu, K. Lertzman, and P. Corbett. 2006. Weak climatic control of stand-scale fire history during the late Holocene. *Ecology* 87:1722–1732.
- Gedalof, Z., D. L. Peterson, and N. J. Mantua. 2005. Atmospheric, climatic, and ecological controls on extreme wildfire years in the northwestern United States. *Ecological Applications* 15:154–174.
- Heyerdahl, E. K., L. B. Brubaker, and J. K. Agee. 2001. Spatial controls of historical fire regimes: A multi-scale example from the interior west, USA. *Ecology* 82:660–678.
- Heyerdahl, E. K., P. Morgan, and J. P. Riser. 2008. Multi-season climate synchronized historical fires in dry forests (1650-1900), northern Rockies, USA. *Ecology* 89:705–716.
- Hirsch, K. G. 1996. Canadian forest fire behavior prediction (FBP) system: user's guide. Special report 7. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta, Canada.
- Holden, Z. A., P. Morgan, and J. S. Evans. 2009. A predictive model of burn severity based on 20-year satellite-inferred burn severity data in a large southwestern US wilderness area. *Forest Ecology and Management* 258:2399–2406.
- Hu, F. S., P. E. Higuera, J. E. Walsh, W. L. Chapman, P. A. Duffy, L. B. Brubaker, and M. L. Chipman. 2011. Tundra burning in Alaska: Linkages to climatic change and sea ice retreat. *Journal of Geophysical Research-Biogeosciences* 115.
- Jensen, O. C. and G. A. Sanchez-Azofeifa. 2006. Satellite-derived ecosystems classification: image segmentation by ecological region for improved classification accuracy, a boreal case study. *International Journal of Remote Sensing* 27:233–251.
- Keane, R. E., S. A. Mincemoyer, K. M. Schmidt, D. G. Long, and J. L. Garner. 2000. Mapping vegetation and fuels for fire management on the Gila National Forest Complex, New Mexico. General Technical Report GTR-RMRS-046. USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, USA.
- Kellogg, L. K. B., D. McKenzie, D. L. Peterson, and A. E. Hessler. 2008. Spatial models for inferring topographic controls on historical low-severity fire in the eastern Cascade Range of Washington, USA. *Landscape Ecology* 23:227–240.
- Kennedy, M. C. and D. McKenzie. 2010. Using a stochastic model and cross-scale analysis to evaluate controls on historical low-severity fire regimes. *Landscape Ecology* 25:1561–1573.
- Krawchuk, M. A., S. G. Cumming, M. D. Flannigan, and R. W. Wein. 2006. Biotic and abiotic regulation of lightning fire initiation in the mixedwood boreal forest. *Ecology* 87:458–468.
- Krawchuk, M. A. and M. A. Moritz. 2011. Constraints on global fire activity vary across a resource gradient. *Ecology* 92:121–132.
- Krawchuk, M. A., M. A. Moritz, M.-A. Parisien, J. Van Dorn, and K. Hayhoe. 2009. Global pyrogeography: the current and future distribution of wildfire. *PLoS ONE* 4:e5102.
- Lertzman, K., J. Fall, and B. Dorner. 1998. Three kinds of heterogeneity in fire regimes: at the crossroads of fire history and landscape ecology. *Northwest Science* 72:4–23.
- Littell, J. S., D. McKenzie, D. L. Peterson, and A. L. Westerling. 2009. Climate and wildfire area burned in western U.S. ecoprovinces, 1916-2003. *Ecological Applications* 19:1003–1021.
- McKenney, D. W., J. H. Pedlar, P. Papadopol, and M. F. Hutchinson. 2006. The development of 1901-2000 historical monthly climate models for Canada and the United States. *Agricultural and Forest Meteorology* 138:69–81.
- McKenzie, D., A. E. Hessler, and L. K. B. Kellogg. 2006. Using neutral models to identify constraints on low-severity fire regimes. *Landscape Ecology* 21:139–152.
- McKenzie, D., C. Miller, and D. A. Falk. 2011. Toward a theory of landscape fire. Pages 3–25 in D. McKenzie, C. Miller, and D. A. Falk, editors. *The landscape ecology of fire*. Springer, New York, New York, USA.
- Mermoz, M., T. Kitzberger, and T. T. Veblen. 2005. Landscape influences on occurrence and spread of wildfires in Patagonian forests and shrublands. *Ecology* 86:2705–2715.
- Meyn, A., P. S. White, C. Buhk, and A. Jentsch. 2007. Environmental drivers of large, infrequent wildfires: the emerging conceptual model. *Progress in Physical Geography* 31:287–312.
- Miller, C., M. A. Parisien, A. A. Ager, and M. A. Finney. 2008. Evaluating spatially-explicit burn probabilities for strategic fire management planning. Pages 245–252 in J. De las Heras, C. A. Brebbia, D. Viegas, and V. Leone, editors. *Modeling, monitoring, and management of forest fires*. WIT Press, Boston, Massachusetts, USA.
- Miller, C. and D. L. Urban. 1999. Interactions between forest heterogeneity and surface fire regimes in the southern Sierra Nevada. *Canadian Journal of Forest Research* 29:202–212.
- Miller, C. and D. L. Urban. 2000. Connectivity of forest fuels and surface fire regimes. *Landscape Ecology* 15:145–154.
- Moritz, M. A., P. F. Hessburg, and N. A. Povak. 2011.

- Native fire regimes and landscape resilience. Pages 51–86 in D. McKenzie, C. Miller, and D. A. Falk, editors. *The landscape ecology of fire*. Springer, New York, New York, USA.
- Parisien, M. A., V. G. Kafka, K. G. Hirsch, J. B. Todd, S. G. Lavoie, and P. D. Maczek. 2005. Mapping wildfire susceptibility with the BURN-P3 simulation model. Information Report NOR-X-405. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta, Canada.
- Parisien, M. A., C. Miller, A. A. Ager, and M. A. Finney. 2010. Use of artificial landscapes to isolate controls on burn probability. *Landscape Ecology* 25:79–93.
- Parisien, M. A., S. A. Parks, C. Miller, M. A. Krawchuk, M. Heathcott, and M. A. Moritz. 2011. Contributions of ignitions, fuels, and weather to the burn probability of a boreal landscape. *Ecosystems* 14:1141–1155.
- Parks, S. A., M. A. Parisien, and C. Miller. 2011. Multi-scale evaluation of the environmental controls on burn probability in a southern Sierra Nevada landscape. *International Journal of Wildland Fire* 20:815–828.
- Peters, D. P. C., R. A. Pielke, B. T. Bestelmeyer, C. D. Allen, S. Munson-McGee, and K. M. Havstad. 2004. Cross-scale interactions, nonlinearities, and forecasting catastrophic events. *Proceedings of the National Academy of Sciences of the United States of America* 101:15130–15135.
- Peterson, G. D. 2002. Contagious disturbance, ecological memory, and the emergence of landscape pattern. *Ecosystems* 5:329–338.
- Podur, J. and B. M. Wotton. 2011. Defining fire spread event days for fire-growth modelling. *International Journal of Wildland Fire* 20:497–507.
- R Development Core Team. 2007. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
- Rollins, M. G. 2009. LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire* 18:235–249.
- Rollins, M. G., P. Morgan, and T. Swetnam. 2002. Landscape-scale controls over 20(th) century fire occurrence in two large Rocky Mountain (USA) wilderness areas. *Landscape Ecology* 17:539–557.
- Rollins, M. G., T. Swetnam, and P. Morgan. 2000. Twentieth-century fire patterns in the Selway-Bitterroot Wilderness Area, Idaho/Montana, and the Gila/Aldo Leopold Wilderness Complex, New Mexico. In D. N. Cole, S. F. McCool, W. T. Borrie, and J. O’Loughlin, editors. *Wilderness science in a time of change conference*, Missoula, MT. *Proceedings RMRS-P-15-VOL-5*. USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, USA.
- Ryu, S. R., J. Chen, D. Zheng, and J. J. Lacroix. 2007. Relating surface fire spread to landscape structure: An application of FARSITE in a managed forest landscape. *Landscape and Urban Planning* 83:275–283.
- Scott, J. H. and R. E. Burgan. 2005. Standard fire behavior fuel models: A comprehensive set for use with Rothermel’s surface fire spread model. General Technical Report RMRS-GTR-153. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado, USA.
- Sturtevant, B. R. and D. T. Cleland. 2007. Human and biophysical factors influencing modern fire disturbance in northern Wisconsin. *International Journal of Wildland Fire* 16:398–413.
- Swetnam, T. W. and J. H. Dieterich. 1985. Fire history of ponderosa pine forests in the Gila Wilderness, New Mexico. Pages 390–397 in J. E. Lotan, B. M. Kilgore, W. C. Fischer, and R. W. Mutch, editors. *Proceedings: symposium and workshop on wilderness fire*. USDA Forest Service, Ogden, Utah, USA.
- Syphard, A. D., V. C. Radeloff, T. J. Hawbaker, and S. I. Stewart. 2009. Conservation threats due to human-caused increases in fire frequency in Mediterranean-climate ecosystems. *Conservation Biology* 23:758–769.
- Taylor, A. H. and C. N. Skinner. 2003. Spatial patterns and controls on historical fire regimes and forest structure in the Klamath Mountains. *Ecological Applications* 13:704–719.
- Turner, M. G. 2005a. Landscape ecology in North America: past, present, and future. *Ecology* 86:1967.
- Turner, M. G. 2005b. Landscape ecology: What is the state of the science? *Annual Review of Ecology Evolution and Systematics* 36:319–344.
- Turner, M. G. and W. H. Romme. 1994. Landscape dynamics in crown fire ecosystems. *Landscape Ecology* 9:59.
- Tymstra, C., R. W. Bryce, B. M. Wotton, S. W. Taylor, and O. B. Armitage. 2010. Development and Structure of Prometheus: the Canadian wildland fire growth simulation model. Report Number NOR-X-417. Canadian Forest Service, Natural Resources Canada, Northern Forestry Centre, Edmonton, Alberta, Canada.
- USDA Forest Service. 2008. MODIS fire and thermal anomalies product for Terra and Aqua MODIS. Salt Lake City, Utah, USA. <http://activefiremaps.fs.fed.us/gisdata.php>
- van Wageningen, J. W. and D. R. Cayan. 2008. Temporal and spatial distribution of lightning in California in relation to large-scale weather patterns. *Fire Ecology* 4:34–56.
- Vankat, J. L. 1982. A gradient perspective on the vegetation of Sequoia National Park, California.

- Madroño 29:200–214.
- Veblen, T. T., T. Kitzberger, and J. Donnegan. 2000. Climatic and human influences on fire regimes in ponderosa pine forests in the Colorado front range. *Ecological Applications* 10:1178–1195.
- Viedma, O., D. G. Angeler, and J. M. Moreno. 2009. Landscape structural features control fire size in a Mediterranean forested area of central Spain. *International Journal of Wildland Fire* 18:575–583.
- Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam. 2006. Warming and earlier spring increase western US forest wildfire activity. *Science* 313:940–943.
- Yang, J., H. S. He, and S. R. Shifley. 2008. Spatial controls of occurrence and spread of wildfires in the Missouri Ozark Highlands. *Ecological Applications* 18:1212–1225.
- Zinck, R. D. and V. Grimm. 2009. Unifying wildfire models from ecology and statistical physics. *American Naturalist* 174:E170–E185.