Ecological Applications, 28(2), 2018, pp. 573–586

Fine-scale spatial climate variation and drought mediate the likelihood of reburning

Sean A. Parks,[1,4] Marc-André Parisien,[2] Carol Miller,[1] Lisa M. Holsinger,[1] and Larry Scott Baggett[3]

[1]*Aldo Leopold Wilderness Research Institute, Rocky Mountain Research Station, USDA Forest Service, 790 E. Beckwith Avenue, Missoula, Montana 59801 USA*

[2]*Northern Forestry Centre, Canadian Forest Service, Natural Resources Canada, 5320 122nd Street, Edmonton, Alberta T5H 3S5 Canada*

[3]*Rocky Mountain Research Station, USDA Forest Service, 240 West Prospect Road, Fort Collins, Colorado 80526 USA*

Abstract. In many forested ecosystems, it is increasingly recognized that the probability of burning is substantially reduced within the footprint of previously burned areas. This self-limiting effect of wildland fire is considered a fundamental emergent property of ecosystems and is partly responsible for structuring landscape heterogeneity (i.e., mosaics of different age classes), thereby reducing the likelihood of uncharacteristically large fires in regions with active fire regimes. However, the strength and longevity of this self-limiting phenomenon is not well understood in most fire-prone ecosystems. In this study, we quantify the self-limiting effect in terms of its strength and longevity for five fire-prone study areas in western North America and investigate how each measure varies along a spatial climatic gradient and according to temporal (i.e., annual) climatic variation. Results indicate that the longevity (i.e., number of years) of the self-limiting effect ranges between 15 yr in the warm and dry study area in the southwestern United States to 33 yr in the cold, northern study areas in located in northwestern Montana and the boreal forest of Canada. We also found that spatial climatic variation has a strong influence on wildland fire's self-limiting capacity. Specifically, the self-limiting effect within each study area was stronger and lasted longer in areas with low mean moisture deficit (i.e., wetter and cooler settings) compared to areas with high mean moisture deficit (warmer and drier settings). Last, our findings show that annual climatic variation influences wildland fire's self-limiting effect: drought conditions weakened the strength and longevity of the self-limiting effect in all study areas, albeit at varying magnitudes. Overall, our study provides support for the idea that wildland fire contributes to spatial heterogeneity in fuel ages that subsequently mediate future fire sizes and effects. However, our findings show that the strength and longevity of the self-limiting effect varies considerably according to spatial and temporal climatic variation, providing land and fire managers relevant information for effective planning and management of fire and highlighting that fire itself is an important factor contributing to fire-free intervals.

Key words: age dependence; annual climate variation; drought; fire frequency; fire interval; self-limiting effect; self-regulation; spatial climate variation; wildland fire.

Introduction

Although the area burned by wildland fire has increased in recent decades (Westerling 2016), there is growing recognition that fire often exhibits self-limiting properties, whereby it reduces subsequent fire activity (Peterson 2002, McKenzie et al. 2011). As wildland fire consumes fuel, and hence reduces biomass, the probability of burning is lessened compared to sites with an extended fire-free interval (Héon et al. 2014). The overall reduction in the likelihood of fire within the footprint of previously burned areas can be described as the self-limiting effect. The self-limiting effect is a manifestation of at least two separate phenomena that have been previously documented in the literature. The first of these concerns ignitions: fires are less likely to ignite within the footprint of previously burned areas (Krawchuk et al. 2006, Penman et al. 2013, Parks et al. 2016). The second of these phenomena concerns fire spread: fires are less likely to spread into recently burned areas (Collins et al. 2009, Parks et al. 2015). In other words, previously burned areas oftentimes act as an absolute barrier to subsequent fire spread. Consequently, the self-limiting effect is an emergent property of recently burned areas that depends on the two processes mentioned here.

The self-limiting effect can be quantified using two measures. The strength of self-limiting effect (i.e., the reduced probability burning) is generally strong immediately after fire and diminishes as time since fire increases (e.g., Fontaine et al. 2012). As such, the effect is more or less negligible after sufficient time has passed for fuels to accumulate to flammable levels (Holsinger et al. 2016, Thompson et al. 2017), and the length of time (i.e., number of years) this process takes is hereafter referred to as

Manuscript received 6 November 2017; accepted 11 December 2017. Corresponding Editor: Bradford P. Wilcox.

[4] E-mail: sean_parks@fs.fed.us

the longevity of the self-limiting effect. Although several studies have successfully documented some of the processes resulting in a reduced probability of burning, the overall self-limiting effect is for the most part unquantified in a replicated manner spanning multiple study areas and fire environments (but see Price et al. 2015). Indeed, it is these metrics (i.e., the strength and longevity of the self-limiting effect) that managers will find most useful in determining the benefit that past wildland fires will provide with respect to limiting future fires.

Ample evidence suggests that the strength and longevity of wildland fire's self-limiting effect varies geographically (cf. Holsinger et al. 2016, Prichard et al. 2017), likely an outcome of top-down climatic controls on productivity, vegetation, and fire regime characteristics (Krawchuk and Moritz 2011, Pausas and Ribeiro 2013). For example, in shrubland systems in California, USA, Moritz (2003) and Price et al. (2012) found that fires had virtually no influence on subsequent fire activity. Evidence from dry and warm forest ecosystems in both Australia and the United States, however, suggest that wildland fire inhibits the ignition and spread of subsequent fire for up to 10 years (Collins et al. 2009, Price and Bradstock 2010, Holsinger et al. 2016). In cooler and wetter forested settings in the United States and Canada, wildland fire limits subsequent fire activity and extent for up to 25–50 yr (Parks et al. 2015, Erni et al. 2017). Although these studies do not explicitly evaluate variation in self-regulating processes along spatial climatic gradients, the differing results across such wide-ranging geography collectively suggest that spatial climatic variation undoubtedly plays a key role in influencing wildland fire's self-limiting capacity. However, all studies to date pertaining to self-regulating processes aggregate results within individual study areas (e.g., Collins et al. 2009, Parks et al. 2015, 2016). An explicit evaluation of the self-limiting effect in relation to fine-scale climatic variation (i.e., within individual study areas) is needed because fire managers must make decisions on landscapes comprised of highly diverse climatic settings and vegetation types.

There is active debate as to whether, and under which circumstances, temporal climatic variation (i.e., extreme fire weather) influences the self-limiting capacity of wildland fire (Fernandes et al. 2012). Some studies concluded that extreme weather can override any self-regulating properties of fire (Johnson et al. 2001, Moritz et al. 2004, Schoennagel et al. 2004, Van Wilgen et al. 2010), whereas others found no clear evidence that this effect lessens as fire weather becomes more severe (Price et al. 2014, Storey et al. 2016). However, as the findings of Collins et al. (2009) and Parks et al. (2015) showed, there may in fact be a middle ground where extreme fire weather reduces the strength and longevity of wildland fire's self-regulating properties but does not completely override it. Given the divergent findings of these studies, the influence of temporal climatic variation on the self-limiting capacity of wildland fire is an open question that is clearly in need of further research.

Managing landscapes that are resilient to natural disturbances such as fire is an increasingly important goal for many land management agencies in North America (e.g., Forests and Rangelands 2017). In light of increasing fire activity and ever-growing fire-suppression expenditures (Calkin et al. 2015), it is imperative that we understand how wildland fire influences subsequent disturbance processes. In North America, wildland fire "treats," so to speak, substantially more area than traditional fuel treatment strategies such as thinning or prescribed burning (USDA Forest Service 2016*a*, NIFC 2017) and as such, land management agencies are keenly interested in how long, and under what weather conditions, previous burns act as fuel treatments (cf. Miller 2003, North et al. 2012, Hessburg et al. 2015). In addition, improved knowledge of what factors (i.e., spatial and temporal variation in climate) enhance or constrain wildland fire's self-limiting effect could also be useful to those who model fire likelihood and risk across large landscapes (Finney et al. 2011, Parisien et al. 2011, Parks et al. 2012) and potentially inform efforts to predict fire activity under a warming climate (Batllori et al. 2013, McKenzie and Littell 2017, Parks et al. 2017).

Because many fire-prone forested landscapes of western North America have been transformed by a century of fire exclusion and management activities (e.g., logging; Heyerdahl et al. 2001, Keane et al. 2002), they are often thought to be susceptible to uncharacteristically large and severe wildland fire that may lead to ecological degradation (Mallek et al. 2013, Harris and Taylor 2015, Coop et al. 2016). As such, there is mounting interest in restoring landscapes that are resilient to wildland fire (Hessburg et al. 2015, Stephens et al. 2016) and, motivated by increased fire activity in recent decades (Westerling 2016), there is a strong need for detailed information pertaining to wildland fire's ability to limit future fire activity. Yet, few studies have specifically analyzed the self-limiting capacity of wildland fire, nor its relationship with both spatial and temporal variation in climate. In this study, we evaluate wildland fire's self-limiting effect in five fire-prone study areas in western North America using detailed fire history spatial data spanning 1972–2015. Specifically, we aimed to (1) quantify the strength and longevity of the self-limiting effect in each study area, (2) evaluate whether or not the self-limiting effect varies according to a spatial climatic gradient, and (3) evaluate whether or not the self-limiting effect is influenced by temporal climatic variation. Our results could provide valuable information that is necessary to better manage forested systems and may reveal opportunities to restore resilience to fire-adapted ecosystems.

Methods

Study areas

We conducted our investigation within five study areas composed entirely of protected lands in western North America (Fig. 1). We focused on these protected study

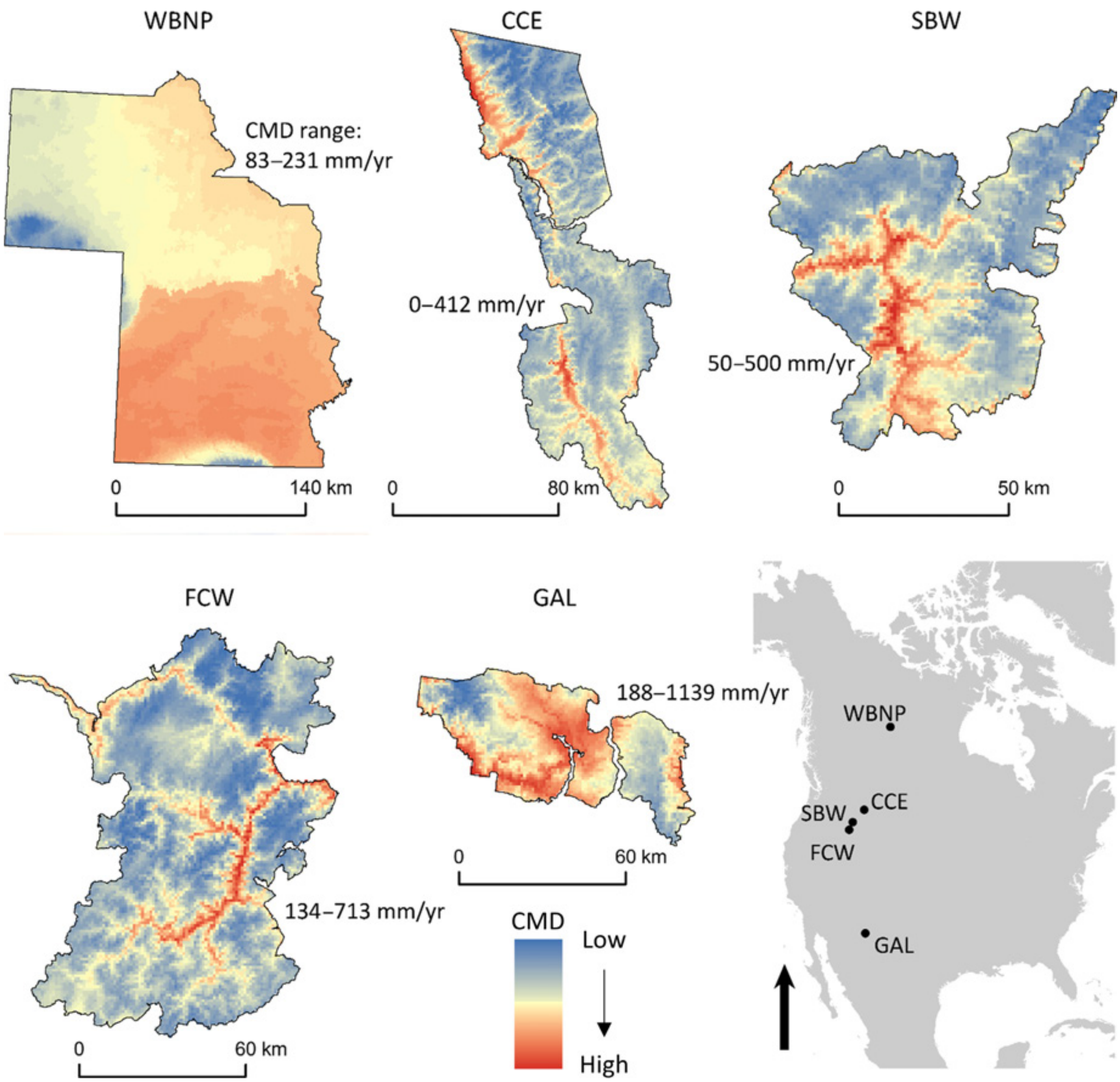

FIG. 1. Climatic moisture deficit (CMD) representing the 1981–2010 time period for each study area. CMD is scaled differently for each study areas.

areas for two reasons. First, the protected areas we chose all have policies whereby wildland fire is allowed to burn with little to no fire suppression. Second, our focus on protected areas limits potential confounding effects of land-management activities (e.g., forestry, agriculture) and anthropogenic features (e.g., roads) that are more common outside such areas. These study areas cover a broad latitudinal range that corresponds to climate gradients ranging from cold and moist to warm and dry. All study areas have experienced substantial fire activity in recent decades (Fig. 2).

WBNP (Wood Buffalo National Park).—WBNP is Canada's largest national park (44,800 km^2) and a UNESCO world heritage site. The park has little topographic relief and is underlain by discontinuous permafrost. Vegetation in WBNP is representative of the western Canadian boreal forest and is composed of wetlands (fens and bogs; ~70%), upland forest (~20%), and open water (10%). The dominant tree species on well drained sites include jack pine (*Pinus banksiana*), white spruce (*Picea glauca*), trembling aspen (*Populus tremuloides*), and balsam poplar (*Populus balsamifera*). Black spruce (*Picea mariana*) and tamarack (*Larix laricina*) are common in treed bogs and fens, respectively. Wetland areas, most of which are dominated by graminoids, *Sphagnum* spp. mosses, or shrubs, have varying degrees of cover. The fire season runs from May through mid-September, peaking between June and August (Kochtubajda et al. 2006). Wildland fires are mainly

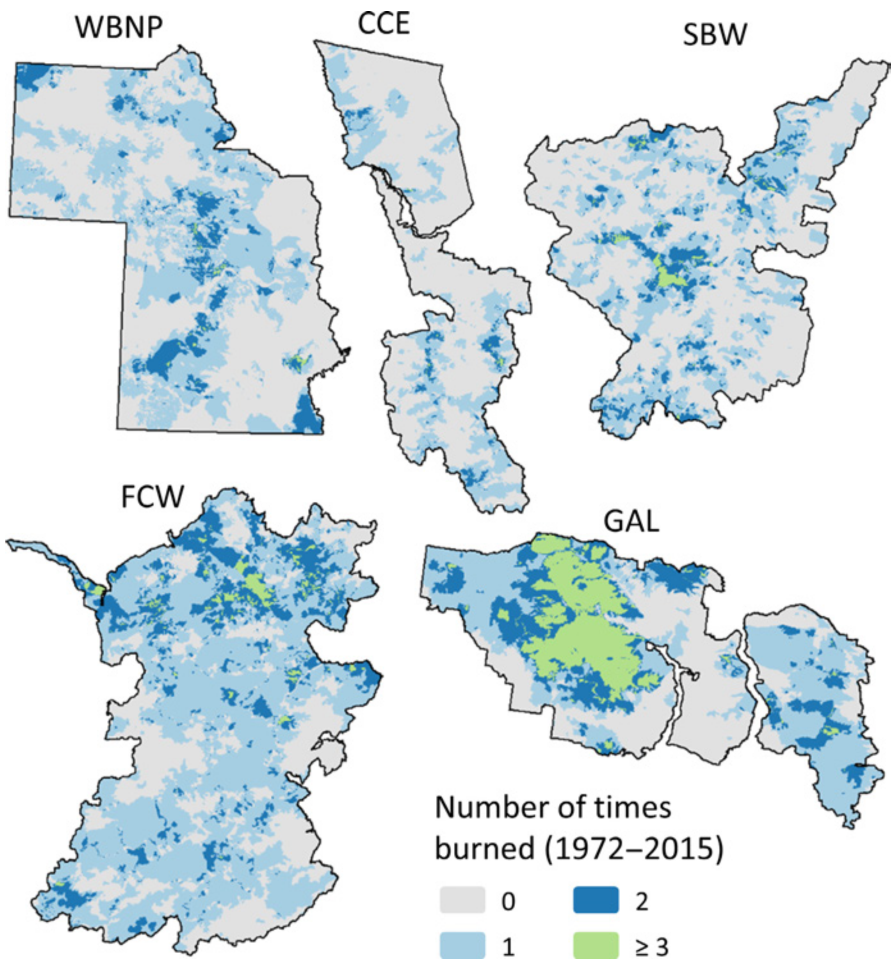

FIG. 2. Fire history (fires ≥20 ha) of each study area. WBNP, Wood Buffalo National Park; CCE, Crown of the Continent Ecosystem; SBW, Selway-Bitterroot Wilderness; FCW, Frank Church–River of No Return Wilderness; GAL, Gila and Aldo Leopold Wilderness.

stand replacing and can grow very large (>100,000 ha). From 1972 to 2015, about 2.5 million hectares burned in WBNP.

CCE (Crown of the Continent Ecosystem).—The CCE (10,331 km^2) is comprised of Glacier National Park and the Great Bear, Bob Marshall, and Scapegoat Wilderness Areas in Montana, USA. Elevations range from 950 m to over 3100 m. In this rugged study area, alpine glacial canyons and cirques drain into major river valleys (Barrett et al. 1991, Keane et al. 1994). Areas of ponderosa pine and mixed-conifer forest comprise a relatively small proportion of CCE (about 15%; Rollins 2009) and were historically maintained by low- and mixed-severity fire regimes (Arno et al. 2000). Most of the study area (>60%), however, is composed of subalpine forest types and characterized by a mixed- to high-severity fire regime. The fire season runs from mid-July through September (USDA Forest Service 2016*b*). Nearly 351,000 ha burned from 1972 to 2015.

SBW (Selway-Bitterroot Wilderness).—The SBW (5,471 km^2) is located in western Montana and north-central Idaho. Elevations range from 531 m to over 3,000 m. Subalpine forest types comprise a large portion of the study area (50%), followed by Douglas fir and mixed conifer forests (~30%; Rollins 2009). The fire season runs from late-June through mid-September (Brown et al. 1994). 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). About 287,000 ha of SBW burned from 1972 to 2015.

FCW (Frank Church–River of No Return Wilderness).—The FCW (9,777 km^2) is located in central Idaho. Elevations range from 600 to 3,136 m and topographic features include river breaks, deep canyons, mountains, and glaciated basins (USDA Forest Service 2003). The fire season runs from early-July to mid-September (USDA Forest Service 2016*b*). Vegetation is dominated by mixed-conifer (~40%) and subalpine forest types (~30%) (Rollins 2009). FCW has a mainly mixed-severity fire regime where low-elevation, open ponderosa pine forests typically experience frequent, low-intensity fires, and, generally, fire frequency decreases and severity increases with increasing elevation, moisture, and tree density (Crane and Fischer 1986). From 1972 to 2015, about 885,000 ha burned in FCW.

GAL (Gila and Aldo Leopold Wilderness).—The GAL (3,087 km^2) incorporates the Gila and Aldo Leopold Wilderness Areas in western New Mexico, USA. Elevations range from 1,462 to 3,314 m and the topography is diverse, composed of mountains, broad valleys, steep canyons, and extensive mesas. Vegetation in GAL is composed largely of ponderosa pine forest (about 30%), juniper–pinyon pine woodland (40%), and mixed-conifer forest types (20%; Rollins 2009). The fire season runs early May through mid-July (USDA Forest Service 2016*b*), although fires are less likely after mid-June due to rains associated with monsoonal storms from the Gulf of Mexico (Rollins et al. 2002). Fires in GAL often burn as low-severity surface fires, but fire severity tends to increase with elevation (Swetnam and Dieterich 1985) and varies with aspect, incident radiation, and topographic position (Holden et al. 2009). About 380,000 ha burned from 1972 to 2015.

Fire data

Our analysis approach involved a comparison of the observed fire history to a randomly generated fire history and therefore required two geospatial fire history data sets (i.e., observed and random) for each study area. Observed fire history atlases for each study area span 1972–2015 and depict all fires ≥20 ha (Fig. 2). Fire history data sets covering 1972–2012 for the U.S. study areas were obtained from Parks et al. (2015). These fire atlases were updated through 2015 with fire perimeters obtained from the Monitoring Trends in Burn Severity project (Eidenshink et al. 2007) and the Geospatial Multi-Agency Coordination Group (data *available online*).[5,6] However, because these data sources generally do not map smaller fires (those <~400 ha), we identified and mapped smaller fires that occurred from 2013 to 2015 using Landsat imagery following the methods described in Parks et al. (2015). The observed fire atlas for WBNP was obtained from the Canadian National Fire Database (2017). Fires that occurred prior to ~1995 in WBNP may be mapped less accurately and likely overestimate area burned to some degree since they were not delineated with satellite imagery as they were in the U.S. study areas. However, given the sheer size of fires and annual area burned in WBNP, this artifact likely has a negligible influence on our results. The polygon-based fire history data for WBNP were converted to raster data sets (30-m resolution) for each year in which a fire occurred.

The purpose of the randomly generated fire atlas was to serve as a neutral expectation with which to compare observed fire intervals. Within each study area and for each year 1972–2015, we randomly assigned "burned" pixels in the same proportion as the actual observed area burned in each year (Appendix S1), thus preserving the overall temporal pattern of burning for each study area. To preserve the spatial aspects of the observed fire history patterns, we also ensured that the probability that any given pixel was randomly assigned as burned was proportional to the number of observed times burned during the study period (1972–2015); pixels that burned multiple times have more random fires compared to pixels that burned only once over the study period (Fig. 2). Preserving these aspects of the observed data in the random fire atlas allowed us to statistically assess the departure of the observed fire intervals from those of a neutral expectation and evaluate how these departures vary according to spatial and temporal climatic variation. This approach also ensured that we did not randomly assign pixels as burned in regions that may have (1) bioclimatic or fuel conditions that inhibit fire occurrence (e.g., alpine environments) or (2) burned prior to 1972 (the first year in our fire history atlases) and may be influencing fire activity during our study period.

Statistical analysis

Survival analysis is a statistical approach used in many fields for analyzing "time-to-event" data. In the biomedical context, the event of interest is often the death of a patient, and can be used to quantify, for example, how long cancer patients survive on a drug treatment compared to a placebo (cf. Fizazi et al. 2012). Survival analysis is becoming an increasingly important tool for analyzing fire-interval data (e.g., Moritz 2003, Cyr et al. 2007, Senici et al. 2010, Parks et al. 2016) and we apply this approach here to evaluate wildland fire's self-limiting capacity. In the lexicon of survival analysis, the event of interest is a fire and the elapsed time between successive fires (i.e., the fire interval) is used to generate our models. Survival analysis can account for censored data (Klein and Moeschberger 2005), meaning some data are incomplete because the true interval between fires is unknown. This would be the case, for example, for a pixel that burned only once during the study period (1972–2015) in 2005. This observation is censored because, although the pixel was fire free for at least 33 yr (2005 minus 1972), we cannot know the true fire-free interval. We also assume that the pixel will experience another fire at some time after our study period ends (in 2015), but we cannot know when (this record is also censored). For each pixel that experienced a fire, we recorded the elapsed time (number of years) between the

[5] http://www.mtbs.gov/
[6] http://www.geomac.gov/

fire and the previous fire. Observations are censored in cases where there is no record of a previous or subsequent fire (Moritz et al. 2009). The identical approach was used on the random fire data sets. This resulted in fire interval data (i.e., time-to-event) for both the observed record and the control (i.e., random fire data sets) for each study area.

We used the hazard ratio to quantify the strength and longevity of wildland fire's self-limiting effect. In the context of our study, the hazard ratio is the ratio between the hazard rate of the observed and random data sets and should be interpreted as the probability that a fire will occur in a previously burned area compared to that expected by chance. A hazard ratio <1 indicates that fire is less likely to occur in a previously burned area compared to that expected by chance. To compute the hazard ratio, we used Cox proportional hazard modelling (Cox 1992) with the survival package (Therneau 2015) within the R statistical environment (R Core Team 2016). However, an assumption of proportional hazards regression is that the hazard ratio is constant over time (Spruance et al. 2004). This is not a realistic assumption, as several studies have shown that strength of the self-limiting effect is strong in the first few years after fire but weakens as time since fire increases (Collins et al. 2009, Bradstock et al. 2010, Holsinger et al. 2016, Parks et al. 2016). To counter the proportional hazards assumption, we used the timeSplitter() function in the Greg package (Gordon and Seifert 2016) and, with guidance from the associated vignette, we created time-dependent model coefficients (vignette *available online*).[7] Consequently, we used the Cox proportional hazard model to plot the hazard ratio as a function of time since fire.

To explore how the self-limiting effect varies along a spatial climatic gradient, we added the climatic moisture deficit (CMD; Fig. 1) as an independent variable to the Cox proportional hazard models (Eqs. 1 and 2). CMD is a simplification of the multi-decadal climatic water deficit (Stephenson 1990), which is a measure of the difference between reference evaporation and evapotranspiration. As a robust metric describing the aridity gradient, CMD and similar metrics are strongly correlated with fire regime characteristics (e.g., Littell and Gwozdz 2011, Parks et al. 2014*b*, Kane et al. 2015*b*). Gridded CMD (1-km resolution) was obtained from AdaptWest (Wang et al. 2016) and represents a 30-yr average over the 1981–2010 time period (data *available online*).[8] CMD was extracted for all observed and random fire samples. For each study area, we built two models describing the hazard ratio (HR); one model assumes proportional hazard (Eq. 1) and the other recognizes that the HR changes as time since fire increases (Eq. 2). The simplified form of the models are as follows:

[7] https://cran.r-project.org/web/packages/Greg/vignettes/timeSplitter.html

[8] https://adaptwest.databasin.org/

$$\mathrm{HR} \sim \mathrm{CMD} \tag{1}$$

$$\mathrm{HR} \sim \mathrm{CMD} + \mathrm{FI} + \mathrm{CMD} \times \mathrm{FI} \tag{2}$$

(Eq. 1 assumes proportional hazard and Eq. 2 includes time-varying coefficients) where CMD is the climatic moisture deficit, FI is the fire interval, and CMD × FI is an interaction term.

To explore how the self-limiting effect varies according to temporal climatic variation, we incorporated the Palmer Drought Severity Index (PDSI) into the models. We used the PDSI from the month with the average highest fire activity (June in WBNP and GAL, August in CCE, SBW, and FCW). Gridded monthly PDSI values (4-km resolution) for the U.S. study areas were obtained from PRISM (Daly et al. 2002); for WBNP, gridded June PDSI (2.5° resolution) was obtained from Dai et al. (2004). For WBNP, PDSI was available only until 2014, so fire data for 2015 are not included in the PDSI analysis for WBNP. Gridded PDSI values were averaged within each study area to obtain a single value for each year. PDSI values were thus assigned to each record in which an observed or random pixel burned. However, we do not know the PDSI for samples that were censored at the end of our fire record (i.e., those samples that burned prior to 2015 but will reburn at some point after 2015 [but 2014 in WBNP]). For these samples, we assigned a PDSI value randomly drawn from the observed fire record. Again, we built two models for each study area, one assuming proportional hazards (Eq. 3) and the other using timeSplitter() to ensure that time since fire and PDSI were time-dependent variables (Eq. 4); The simplified form of the models are as follows:

$$\mathrm{HR} \sim \mathrm{PDSI} \tag{3}$$

$$\mathrm{HR} \sim \mathrm{PDSI} + \mathrm{FI} + \mathrm{PDSI} \times \mathrm{FI} \tag{4}$$

(Eq. 3 assumes proportional hazard and Eq. 4 includes time-varying coefficients) where PDSI is the Palmer Drought Severity Index, FI is the fire interval, and PDSI × FI is an interaction term.

Due to the potential for strong spatial autocorrelation in fire data (Kane et al. 2015*a*, Holsinger et al. 2016), we conducted all statistical procedures 100 times using 100 data subsets. Each subset was randomly selected from both the observed and random fire data sets at a sampling rate of 0.1%. This sampling rate was intended to reduce the effect of spatial autocorrelation and was chosen based the range of the semivariograms generated with gridded (30-m resolution) fire data described in Parks et al. (2014*a*). All of the results and figures presented in this paper depict the 50th percentile values of the 100 models. Confidence intervals (90th percentile) were also generated from the predicted response of the 100 models. We evaluated statistical significance using the mean P value of the 100 models for the independent variable in Eqs. 1 and 3 and the interaction term in

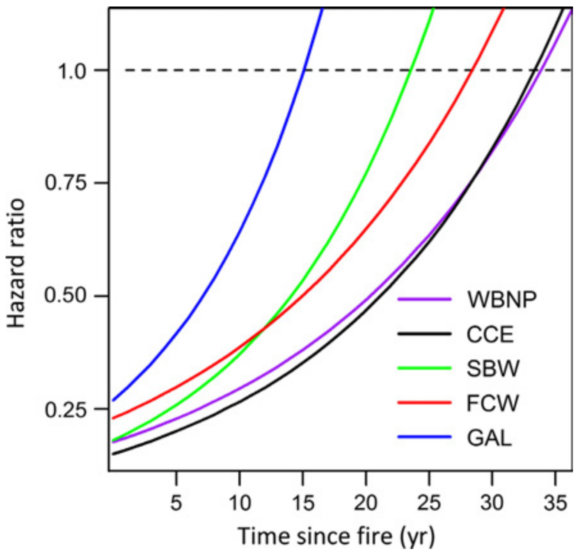

FIG. 3. Hazard ratio as a function of time since fire for the five study areas. Values represent the relative probability (compared to the null model) that fire will burn within the perimeter of a previous fire. Values <1 indicate that fire is less likely to burn within the footprint of a previous fire compared to that expected by chance. Confidence intervals (90%) shown in Appendix S2.

Eqs. 2 and 4. Specifically, we scaled (i.e., multiplied) the mean P value by two as described by Vovk (2012).

RESULTS

Wildland fire substantially reduces the probability of burning in all five study areas (Fig. 3; see Appendix S2 for CIs; $P \leq 0.001$ in all study areas). The strength of this effect is strongest immediately after fire and decays as time since fire increases. The self-limiting longevity (i.e., the length of time that the hazard ratio remains <1) varies among study areas: 33 yr in WBNP and CCE, 23 yr in SBW, 28 yr in FCW, and 15 yr in GAL (Fig. 3; Appendix S2). To emphasize stronger self-limiting effects, we also calculated the length of time the hazard ratio remains <0.5, which is the number of years in which there is a reduction of at least 50% in the probability of burning compared to what's expected by chance. These stronger self-limiting effects persist for 20 yr in WBNP, 21 yr in CCE, 13 yr in SBW, 14 yr in FCW, and 7 yr in GAL.

Spatial variation in CMD influences the strength of wildland fire's self-limiting effect (Fig. 4; $P \leq 0.05$ in all study areas). This relationship is positive, with the hazard ratio increasing with CMD, indicating a weakening of the self-limiting effect as CMD increases. When incorporated into models using time-varying coefficients, the interaction between CMD and the fire interval is also statistically significant in all study areas ($P \leq 0.05$; Fig. 5). At higher CMD values, the strength and longevity of the self-limiting effect is reduced compared to lower CMD values. This highlights that there is substantial spatial variation within each study area in terms of wildland fire's self-limiting capacity. In SBW, for example, the fire's self-limiting longevity is 28 yr at 10th percentile CMD values but only 15 yr at 90th percentile CMD values (Fig. 5).

PDSI, which varies annually, also influences the strength of wildland fire's self-limiting effect (Fig. 4; $P \leq 0.05$ in all study areas). This relationship is negative; as PDSI increases (indicating increasingly wetter years), the hazard ratio decreases, indicating that the self-limiting effect strengthens. When PDSI is incorporated into the models using time-varying coefficients, it is apparent that

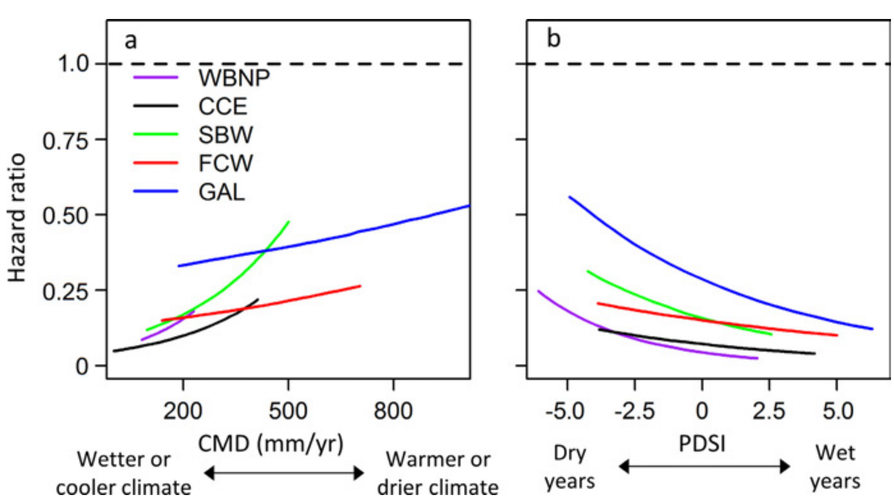

FIG. 4. Hazard ratio as a function of (a) the Climatic Moisture Deficit (CMD; evaluates spatial climatic variation; Eq. 1) and (b) the Palmer Drought Severity Index (PDSI; temporal climatic variation; Eq. 3). Because these relationships assume proportional hazards (i.e., the hazard ratio does not change as time since fire increases), we built additional models incorporating time varying coefficients for time since fire and CMD (Fig. 5) and time since fire and PDSI (Fig. 6).

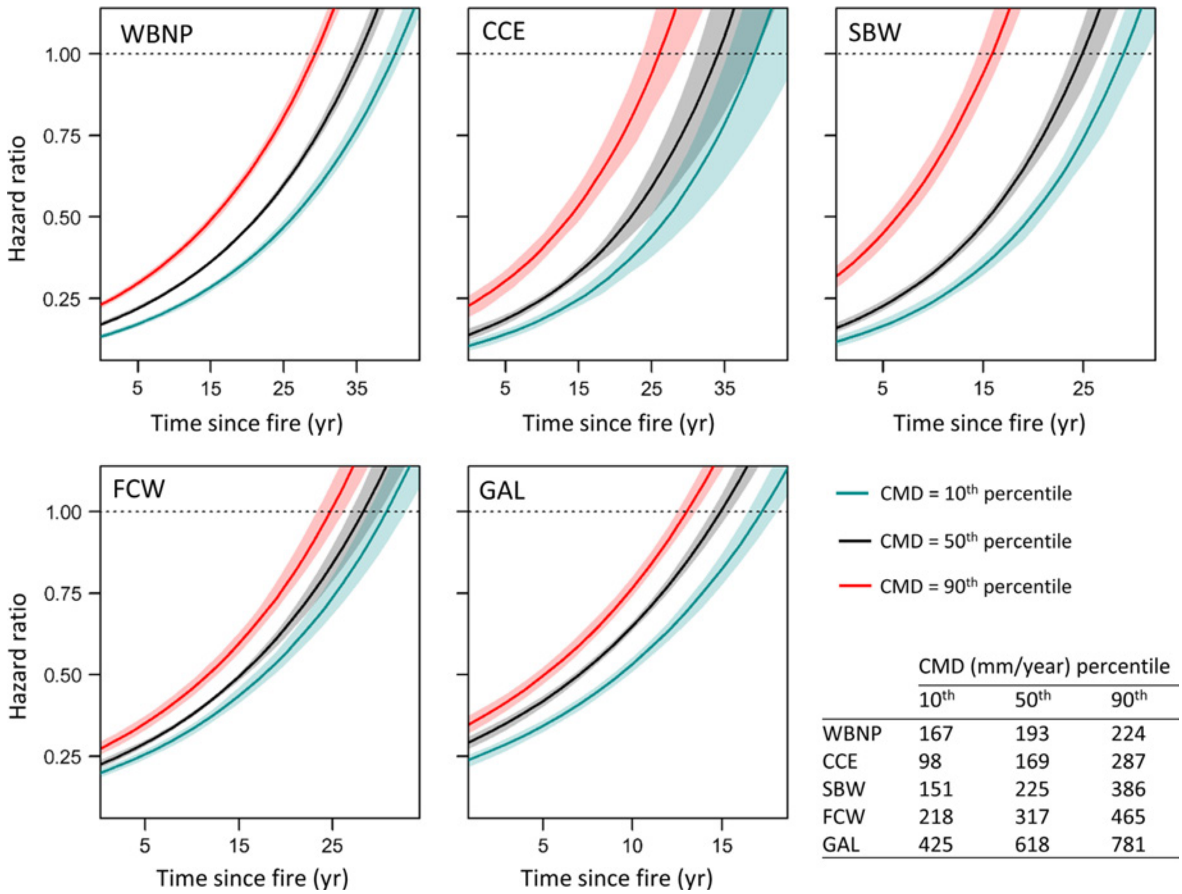

FIG. 5. Hazard ratio with confidence intervals (90th percentile) as it varies by time since fire and climatic moisture deficit (CMD) (Eq. 2). CMD percentiles are based on burned areas only and not the study area as a whole.

temporal climatic variation substantially influences the strength and longevity of wildland fire's self-limiting effect ($P \leq 0.05$ in all study areas; Fig. 6). The strength and longevity of the self-limiting effect is weaker in drier years (lower PDSI) compared to wetter years (higher PDSI). For example, in SBW, the self-limiting longevity lasts 27 yr under average moisture conditions (PDSI = 0) but only 18 yr under drought conditions (PDSI = −4).

Discussion

Our study clearly shows that wildland fire reduces the probability of subsequent fire, thereby reinforcing that the "ecological memory" of fire has a substantial influence on subsequent fire–vegetation dynamics across landscapes in western North America (Turner 1989, Peterson 2002). Indeed, fire itself is often cited as a key factor in restoring resilience to future fire (McKenzie et al. 2011, Schoennagel et al. 2017) and, in light of this, land managers should explicitly acknowledge fire as an important factor contributing to fire-free intervals. Whereas this fire–fuels feedback is increasingly recognized, our results reveal important subtleties: the strength and longevity of wildland fire's self-limiting capacity varies substantially across fairly fine-scale environmental gradients, likely corresponding to different vegetation types, and as a result of inter-annual climatic variation (i.e., drought).

Wildland fire consumes fuel, and therefore, subsequent fire is unlikely within burned areas until sufficient fuels reaccumulate. This self-limiting feedback is considered a fundamental ecosystem process and is critical in creating mosaics of fuel ages across landscapes that in turn result in heterogeneity in fire behavior and effects (Agee 1993, McKenzie et al. 2011). Our finding that wildland fire limits subsequent fire activity is in strong agreement with several previous evaluations of related phenomena (Collins et al. 2009, Fernandes et al. 2012, Héon et al. 2014, Holsinger et al. 2016, Parks et al. 2016, Erni et al. 2017). However, our results contrast with some studies that concluded burned areas have little-to-no influence on subsequent fire activity (Johnson et al. 2001, Moritz 2003, Price et al. 2015). One reason for this discrepancy is likely due to differences in the dominant vegetation type (thus in fire behavior) or fire environment. For example, a lack of fuel age dependence in shrubland

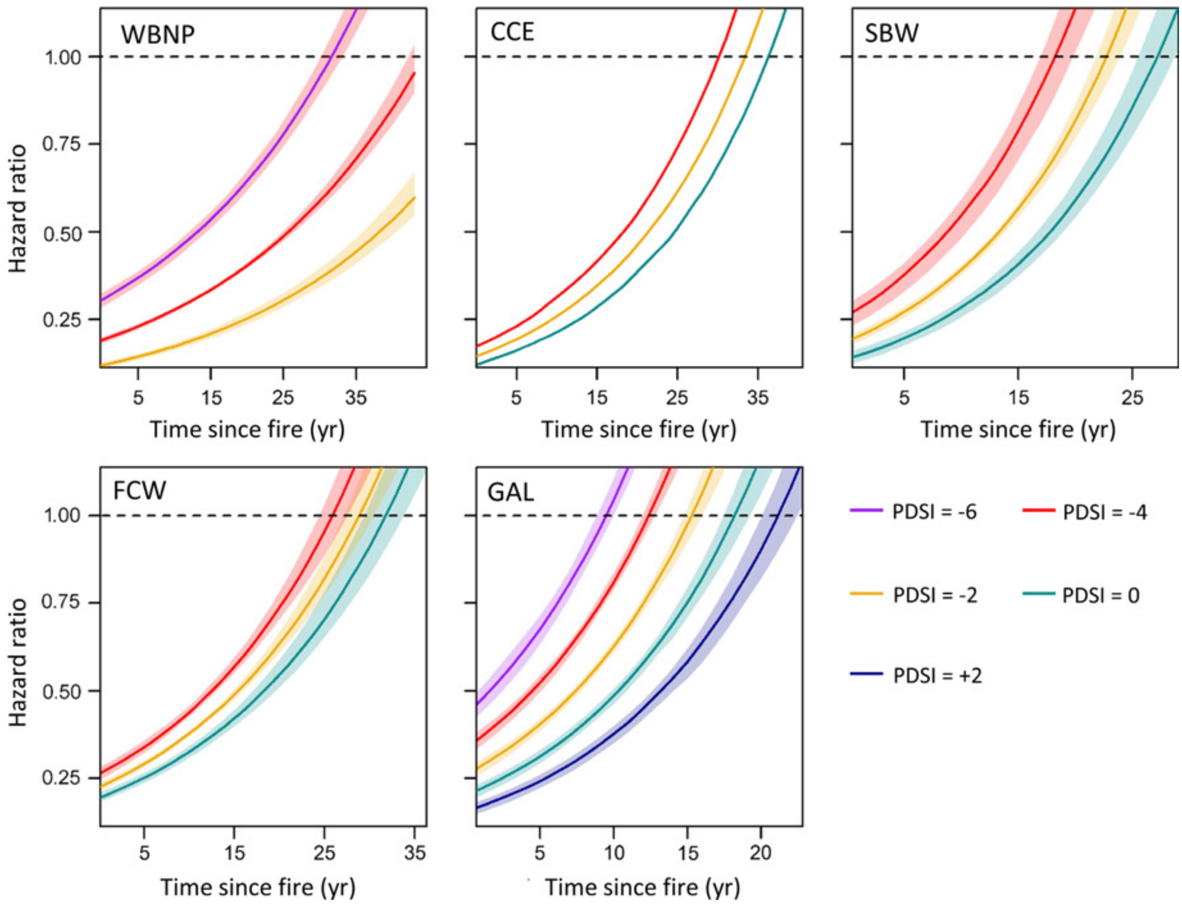

Fig. 6. Hazard ratio as a function of time since fire and PDSI (Eq. 4); decreasing PDSI values represent increasing drought conditions. Note that the displayed PDSI values may differ among study areas because fires did not generally occur under certain PDSI conditions over the course of our study. Confidence intervals (90th percentile) are not shown for CCE because of the large degree of overlap among them.

ecosystems has been documented in California, USA and South Africa (e.g., Moritz et al. 2004, Van Wilgen et al. 2010, Price et al. 2012); we did not evaluate such ecosystems. Another potential reason for these contrasting results is that fires only burn under extreme fire-weather conditions in some regions due to effective fire suppression, in that fires are more likely to be extinguished under moderate compared to extreme weather conditions (Arienti et al. 2006, Thompson et al. 2016). In contrast, fire suppression is discouraged in our study areas and, consequently, the fires we studied may have burned under a wider range of fire weather. Nevertheless, because our analysis used consistent methodology across numerous fire-prone study areas, our results are robust, compelling, and likely applicable to other forested fire-prone regions.

Variation in terms of the strength and longevity of the wildland fire's self-limiting effect is evident among the various ecological settings represented by our study areas: in the coldest and most northern study areas (CCE and WBNP), the self-limiting longevity is over twice that of the warmest, most southern study area (GAL). These regional discrepancies are a result of an ecological setting defined by top-down controls on productivity (i.e., climate), hence post-fire fuel accumulation rates, and bottom-up constraints on fire ignition and spread (Meyn et al. 2007, Krawchuk and Moritz 2011, Parks et al. 2012). For example, fire in the most southern study area (GAL) is largely characterized as a surface fire regime and is primarily carried by fine fuels (i.e., grass and pine litter) that recover quickly after fire (Swetnam and Baisan 1996), whereas fires in the northern study areas are increasingly stand-replacing and carried by ladder and canopy fuels that develop over longer periods (Schimmel and Granström 1997, Schoennagel et al. 2004). Hence, top-down and bottom-up controls on fire, fuels, and their interactions (Bond et al. 2005, Keane et al. 2015) are responsible for the general pattern we observed: the self-limiting effect is overall stronger and has greater longevity in the north compared to the south in the forested study areas we evaluated, which contrasts with the results of Price et al. (2015), who found no discernable trend. It is worth noting, however, that Price et al. (2015) examined wildfires across extremely large areas, portions of which are subjected to effective fire suppression or otherwise do not exhibit high fire activity. This is an important consideration because the occurrence of fire interactions are partly a function of the overall fire activity (i.e., greater activity translates to a highly probability of interaction; Héon et al. 2014).

In addition to the observed variation among study areas, our findings clearly show that, within a study area, fine-scale spatial climatic variation influences wildland fire's self-limiting effect. The climatic moisture deficit (CMD) concurrently incorporates moisture availability (i.e., precipitation) and moisture demand (i.e., temperature), and consequently, lower CMD sites generally correspond to wetter and cooler areas, whereas higher CMD sites to drier and warmer areas (Stephenson 1998). In all study areas, wildland fire's self- limiting capacity is stronger and lasts longer in wet and cool settings vs. dry and warm settings, providing evidence that some forest types generally exert a stronger negative feedback on wildland fire than others. Our results are thus consistent with studies who concluded that spatial climate variation is a strong control on fire frequency (McKenzie et al. 2000, Guyette et al. 2012). More importantly, however, fine-scale variation in fuel accumulation rates corresponding to spatial climatic variation (Cleveland et al. 1999, Anderson et al. 2006) clearly influences the strength and longevity of wildland fire's self-limiting capacity.

Our results show that the self-limiting effect is weaker and has reduced longevity when fires burn under drought conditions, although antecedent conditions (both drought and above-average precipitation) are known to influence both productivity and fire activity in some ecosystems (Swetnam and Baisan 1996, McKenzie and Littell 2017). Our findings are therefore consistent with previous investigations that concluded that previous fires were less likely to act as a barrier to subsequent fire spread under extreme fire weather (Collins et al. 2009, Parks et al. 2015, Erni et al. 2017) and with various other studies highlighting the importance of weather in influencing fire activity (Abatzoglou and Kolden 2013, Wang et al. 2014, Lydersen et al. 2017).

Our findings shed some light on the debate as to whether or not previously burned areas limit subsequent fire activity even under extreme weather conditions. In agreement with Collins et al. (2009) and Parks et al. (2015), our results show that extreme fire weather weakens but does not completely override the self-limiting effect of fire. However, our results contrast with studies that found that extreme fire weather has either no effect (Price et al. 2014, Storey et al. 2016) or completely overrides the self-limiting effect of fire (e.g., Johnson et al. 2001, Price et al. 2012). As previously discussed, we suggest these discrepancies are due to differences in methods, ecosystems evaluated, and fire regime. Nevertheless, in the context of a warming climate, our results suggest that recently burned areas will still limit subsequent fire activity, but the strength and longevity of the effect may be reduced if the frequency of fire-conducive conditions increases as anticipated (Stocks et al. 1998, Wang et al. 2017).

Because many fire-prone forested landscapes of western North America have been transformed by a century of fire exclusion and management activities (e.g., logging; Heyerdahl et al. 2001, Keane et al. 2002), they are often thought to be susceptible to uncharacteristically large and severe wildland fire that may lead to ecological degradation (Mallek et al. 2013, Harris and Taylor 2015, Coop et al. 2016). Consequently, there is mounting interest in restoring landscapes that are resilient to wildland fire (Hessburg et al. 2015, Stephens et al. 2016). Given that many regions in western North America have experienced a 2- to 10-fold increase in fire activity in recent decades (i.e., since the 1970s; Westerling 2016) despite aggressive fire-suppression policies (Calkin et al. 2014), there is a strong need for detailed information pertaining to wildland fire's ability to limit future fire activity. As such, our results suggest that this recent fire activity might be used as an opportunity to restore fire as a fundamental ecosystem process (McKenzie et al. 2011). Policies of continued aggressive fire suppression could forego such opportunities and will likely return landscapes to a state that is not resilient to fire (Calkin et al. 2015, North et al. 2015). Simply put, contemporary landscape patterns and fuel loads in regions that have experienced recent fire may provide a respite from uncharacteristically large fires in future years (Turner 1989). Bypassing these opportunities may not be prudent for the long term sustainability and health of forested ecosystems in western North America (Moritz et al. 2014).

By design, our study was focused on the likelihood of subsequent burning and did not account for variation in fire severity. However, fire severity is known to influence post-fire successional trajectories, other ecosystem functions, and the severity of subsequent fires (Collins et al. 2009, Miller et al. 2012, Chambers et al. 2016, Kemp et al. 2016, Stevens-Rumann et al. 2016, Morgan et al. 2017). We might therefore expect severity of previous fire to also influence subsequent fire likelihood. Incorporating fire severity would have certainly painted a more complete picture of the self-limiting effect of wildfires, but adding this component was not only beyond the scope of this study, but was not possible given our statistical approach since we have no information on the severity of censored observations. Nevertheless, this knowledge gap should be addressed in future research efforts.

Several factors should be considered when interpreting our findings. For example, fires that occurred prior to 1935 have been shown to limit fire activity in the late-20th and early 21st century despite the passing of several decades in at least one of our study areas (SBW; Morgan et al. 2017). As such, our sampling approach and statistical design that included only those areas that burned during the 1972–2015 time period may actually underestimate the self-limiting longevity. In other words, our observed fire intervals (censored and uncensored) can never exceed 43 yr due to our fire record (spanning 1972–2015), but fire intervals could be longer were we to have data spanning a longer time period. Also, we may have underestimated the influence of temporal climatic variation because the PDSI data we used were resolved monthly and fire spread is known to respond to sub-daily to daily variation in weather (e.g., Wang et al. 2014, Holsinger et al. 2016). Although this was likely a reasonable approach given the timeframe of our study (1972–2015), it is possible to estimate the exact dates at which fires burned for recent fires (2002–present) by interpolating satellite fire detection data, thereby enabling the analysis of daily weather (cf. Parks 2014, Veraverbeke et al. 2014). Furthermore, although the probability of burning (i.e., the hazard ratio) increases beyond the value of one at the self-limiting longevity threshold (e.g., Fig. 3), this should not be interpreted as a higher probability of burning compared to areas with extended fire-free intervals. The Cox proportional models used log-linear terms and, as a result, the probability of burning by necessity increases above one. Future investigations using similar methods could explore non-linear or asymptotic responses. In particular, non-linear response terms may be important in study regions that include extremely hot and dry bioclimatic settings where fuel accumulation rates are low and the self-limiting effect may be quite strong; in such cases, we might expect the hazard ratio to exhibit a unimodal response along a spatial climatic gradient (cf. Krawchuk and Moritz 2011, Pausas and Ribeiro 2013).

Conclusions

Our study provides three important insights concerning the influence of burned areas on the probability of subsequent fire in forested landscapes of western North America. First, wildland fire clearly exhibits self-limiting characteristics, in that burned areas show a reduced probability of burning; the strength of this effect decays over time and lasts 15–33 yr, generally increasing from south to north. Second, fine-scale spatial climatic variation has a strong influence; within each study area, the self-limiting effect is stronger and lasts longer in wetter and cooler sites compared to drier and warmer sites. Third, temporal climatic variation influences wildland fire's self-limiting capacity; the strength and longevity of the self-limiting effect were reduced during years of drought. Our study areas are protected lands with little to no anthropogenic infrastructure (e.g., roads) and have policies that de-emphasize fire suppression and encourage the role of wildland fire as a natural process. As such, these study areas are somewhat atypical. Nevertheless, our findings are highly relevant to other fire-prone forested regions in North America and elsewhere where the human imprint on the fire regime is stronger (Parisien et al. 2016, Camp and Krawchuk 2017).

Acknowledgments

We acknowledge National Fire Plan Funding from the Rocky Mountain Research Station. We also thank two anonymous reviewers whose feedback substantially improved this manuscript.

Literature Cited

Abatzoglou, J. T., and C. A. Kolden. 2013. Relationships between climate and macroscale area burned in the western United States. International Journal of Wildland Fire 22:1003–1020.

Agee, J. K. 1993. Fire ecology of Pacific Northwest forests. Island Press, Washington, D.C., USA.

Anderson, K. J., A. P. Allen, J. F. Gillooly, and J. H. Brown. 2006. Temperature-dependence of biomass accumulation rates during secondary succession. Ecology Letters 9: 673–682.

Arienti, M. C., S. G. Cumming, and S. Boutin. 2006. Empirical models of forest fire initial attack success probabilities: the effects of fuels, anthropogenic linear features, fire weather, and management. Canadian Journal of Forest Research 36:3155–3166.

Arno, S. F., D. J. Parsons, and R. E. Keane. 2000. Mixed-severity fire regimes in the northern Rocky Mountains: consequences of fire exclusion and options for the future. Pages 225–232 *in* D. Cole, S. F. McCool, W. T. Borrie, and O. Jennifer, editors. Wilderness science in a time of change conference-Volume 5: Wilderness ecosystems, threats, and management. USDA Forest Service. https://www.fs.usda.gov/treesearch/pubs/21867

Barrett, S. W., S. F. Arno, and C. H. Key. 1991. Fire regimes of western larch–lodgepole pine forests in Glacier National Park, Montana. Canadian Journal of Forest Research 21:1711–1720.

Batllori, E., M.-A. Parisien, M. A. Krawchuk, and M. A. Moritz. 2013. Climate change-induced shifts in fire for Mediterranean ecosystems. Global Ecology and Biogeography 22:1118–1129.

Bond, W. J., F. I. Woodward, and G. F. Midgley. 2005. The global distribution of ecosystems in a world without fire. New Phytologist 165:525–538.

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.

Calkin, D. E., C. S. Stonesifer, M. P. Thompson, and C. W. McHugh. 2014. Large airtanker use and outcomes in suppressing wildland fires in the United States. International Journal of Wildland Fire 23:259–271.

Calkin, D. E., M. P. Thompson, and M. A. Finney. 2015. Negative consequences of positive feedbacks in US wildfire management. Forest Ecosystems 2:9.

Camp, P. E., and M. A. Krawchuk. 2017. Spatially varying constraints of human-caused fire occurrence in British Columbia, Canada. International Journal of Wildland Fire 26:219–229.

Canadian Forest Service. 2017. Canadian National Fire Database—Agency fire data. Canadian Forest Service, Edmonton, Alberta, Canada.

Chambers, M. E., P. J. Fornwalt, S. L. Malone, and M. A. Battaglia. 2016. Patterns of conifer regeneration following high severity wildfire in ponderosa pine–dominated forests of the Colorado Front Range. Forest Ecology and Management 378:57–67.

Cleveland, C. C., et al. 1999. Global patterns of terrestrial biological nitrogen (N2) fixation in natural ecosystems. Global Biogeochemical Cycles 13:623–645.

Collins, B. M., J. D. Miller, A. E. Thode, M. Kelly, J. W. van Wagtendonk, and S. L. Stephens. 2009. Interactions among wildland fires in a long-established Sierra Nevada Natural Fire Area. Ecosystems 12:114–128.

Coop, J. D., S. A. Parks, S. R. Mcclernan, and L. M. Holsinger. 2016. Influences of prior wildfires on vegetation response to subsequent fire in a reburned southwestern landscape. Ecological Applications 26:346–354.

Cox, D. R. 1992. Regression models and life-tables. Pages 527–541 *in* S. Kotz and N. L. Johnson, editors. Breakthroughs in statistics. Springer, New York, New York, USA.

Crane, M. F., and W. C. Fischer. 1986. Fire ecology of the forest habitat types of central Idaho. US Forest Service, Intermountain Research Station, GTR INT-218. https://www.fs.fed.us/rm/pubs_int/int_gtr218.pdf

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.

Dai, A., K. E. Trenberth, and T. Qian. 2004. A global dataset of Palmer Drought Severity Index for 1870–2002: relationship with soil moisture and effects of surface warming. Journal of Hydrometeorology 5:1117–1130.

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.

Eidenshink, J. C., B. Schwind, K. Brewer, Z.-L. Zhu, B. Quayle, and S. M. Howard. 2007. A project for monitoring trends in burn severity. Fire Ecology 3:3–21.

Erni, S., D. Arseneault, M.-A. Parisien, and Y. Bégin. 2017. Spatial and temporal dimensions of fire activity in the fire-prone eastern Canadian taiga. Global Change Biology 23:1152–1166.

Fernandes, P. M., C. Loureiro, M. Magalhães, P. Ferreira, and M. Fernandes. 2012. Fuel age, weather and burn probability in Portugal. International Journal of Wildland Fire 21: 380–384.

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.

Fizazi, K., et al. 2012. Abiraterone acetate for treatment of metastatic castration-resistant prostate cancer: final overall survival analysis of the COU-AA-301 randomised, double-blind, placebo-controlled phase 3 study. Lancet Oncology 13:983–992.

Fontaine, J. B., V. C. Westcott, N. J. Enright, J. C. Lade, and B. P. Miller. 2012. Fire behaviour in south-western Australian shrublands: evaluating the influence of fuel age and fire weather. International Journal of Wildland Fire 21:385–395.

Forests and Rangelands. 2017. National cohesive wildland fire management strategy. U.S. Department of Agriculture and U.S. Department of the Interior, Washington, D.C., USA. https://www.forestsandrangelands.gov/strategy/

Gordon, M., and R. Seifert. 2016. Greg: regression helper functions. https://cran.r-project.org/web/packages/Greg/index.html

Guyette, R. P., M. C. Stambaugh, D. C. Dey, and R.-M. Muzika. 2012. Predicting fire frequency with chemistry and climate. Ecosystems 15:322–335.

Harris, L., and A. H. Taylor. 2015. Topography, fuels, and fire exclusion drive fire severity of the rim fire in an old-growth mixed-conifer forest, Yosemite National Park, USA. Ecosystems 18:1192–1208.

Héon, J., D. Arseneault, and M.-A. Parisien. 2014. Resistance of the boreal forest to high burn rates. Proceedings of the National Academy of Sciences USA 111:13888–13893.

Hessburg, P. F., et al. 2015. Restoring fire-prone Inland Pacific landscapes: seven core principles. Landscape Ecology 30: 1805–1835.

Heyerdahl, E. K., L. B. Brubaker, and J. K. Agee. 2001. Spatial controls of historical fire regimes: a multiscale example from the interior west, USA. Ecology 82:660–678.

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.

Holsinger, L., S. A. Parks, and C. Miller. 2016. Weather, fuels, and topography impede wildland fire spread in western US landscapes. Forest Ecology and Management 380:59–69.

Johnson, E. A., K. Miyanishi, and S. R. J. Bridge. 2001. Wildfire regime in the boreal forest and the idea of suppression and fuel buildup. Conservation Biology 15:1554–1557.

Kane, V. R., C. A. Cansler, N. A. Povak, J. T. Kane, R. J. McGaughey, J. A. Lutz, D. J. Churchill, and M. P. North. 2015*a*. Mixed severity fire effects within the Rim fire: Relative importance of local climate, fire weather, topography, and forest structure. Forest Ecology and Management 358: 62–79.

Kane, V. R., J. A. Lutz, C. Alina Cansler, N. A. Povak, D. J. Churchill, D. F. Smith, J. T. Kane, and M. P. North. 2015*b*. Water balance and topography predict fire and forest structure patterns. Forest Ecology and Management 338:1–13.

Keane, R. E., P. Morgan, and J. P. Menakis. 1994. Landscape assessment of the decline of whitebark pine (albicaulis) in the Bob Marshall Wilderness Complex, Montana, USA. Northwest Science 68:213–229.

Keane, R. E., K. C. Ryan, T. T. Veblen, C. D. Allen, J. A. Logan, B. Hawkes, and J. Barron. 2002. The cascading effects of fire exclusion in Rocky Mountain ecosystems. Pages 133–152 *in* J. Baron, editor. Rocky Mountain futures: an ecological perspective. Island Press, Washington, D.C., USA.

Keane, R. E., D. McKenzie, D. A. Falk, E. A. H. Smithwick, C. Miller, and L.-K. B. Kellogg. 2015. Representing climate, disturbance, and vegetation interactions in landscape models. Ecological Modelling 309:33–47.

Kemp, K. B., P. E. Higuera, and P. Morgan. 2016. Fire legacies impact conifer regeneration across environmental gradients in the US northern Rockies. Landscape Ecology 31:619–636.

Klein, J. P., and M. L. Moeschberger. 2005. Survival analysis: techniques for censored and truncated data. Springer Science & Business Media, New York.

Kochtubajda, B., M. D. Flannigan, J. R. Gyakum, R. E. Stewart, K. A. Logan, and T.-V. Nguyen. 2006. Lightning and fires in the Northwest Territories and responses to future climate change. Arctic 59:211–221. http://www.jstor.org/stable/40512795?seq=1page_scan_tab_contents

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., 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.

Littell, J. S., and R. B. Gwozdz. 2011. Climatic water balance and regional fire years in the Pacific Northwest, USA: linking regional climate and fire at landscape scales. Pages 117–139 *in*

D. McKenzie, C. Miller, and D. A. Falk, editors. The landscape ecology of fire. Springer, Dordrecht, The Netherlands.

Lydersen, J. M., B. M. Collins, M. L. Brooks, J. R. Matchett, K. L. Shive, N. A. Povak, V. R. Kane, and D. F. Smith. 2017. Evidence of fuels management and fire weather influencing fire severity in an extreme fire event. Ecological Applications 27:2013–2030.

Mallek, C., H. Safford, J. Viers, and J. Miller. 2013. Modern departures in fire severity and area vary by forest type, Sierra Nevada and southern Cascades, California, USA. Ecosphere 4:art153.

McKenzie, D., and J. S. Littell. 2017. Climate change and the eco-hydrology of fire: Will area burned increase in a warming western USA? Ecological Applications 27:26–36.

McKenzie, D., D. L. Peterson, and J. K. Agee. 2000. Fire frequency in the interior Columbia River Basin: building regional models from fire history data. Ecological Applications 10:1497–1516.

McKenzie, D., C. Miller, and D. A. Falk. 2011. The landscape ecology of fire. Springer Science & Business Media, New York.

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. 2003. Wildland fire use: a wilderness perspective on fuel management. Pages 379–385 *in* P. N. Omi and L. A. Joyce, editors. Fire, fuel treatments, and ecological restoration: Conference Proceedings; 2002 16–18 April. USDA Forest Service Rocky Mountain Research Station, Fort Collins, Colorado, USA.

Miller, J. D., C. N. Skinner, H. D. Safford, E. E. Knapp, and C. M. Ramirez. 2012. Trends and causes of severity, size, and number of fires in northwestern California, USA. Ecological Applications 22:184–203.

Morgan, P., A. T. Hudak, A. Wells, S. A. Parks, L. S. Baggett, B. C. Bright, and P. Green. 2017. Multidecadal trends in area burned with high severity in the Selway-Bitterroot Wilderness Area 1880–2012. International Journal of Wildland Fire 26:930–943.

Moritz, M. A. 2003. Spatiotemporal analysis of controls on shrubland fire regimes: age dependency and fire hazard. Ecology 84:351–361.

Moritz, M. A., J. E. Keeley, E. A. Johnson, and A. A. Schaffner. 2004. Testing a basic assumption of shrubland fire management: how important is fuel age? Frontiers in Ecology and the Environment 2:67–72.

Moritz, M. A., T. J. Moody, L. J. Miles, M. M. Smith, and P. de Valpine. 2009. The fire frequency analysis branch of the pyrostatistics tree: sampling decisions and censoring in fire interval data. Environmental and Ecological Statistics 16:271–289.

Moritz, M. A., et al. 2014. Learning to coexist with wildfire. Nature 515:58.

NIFC. 2017. NIFC. https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html

North, M., B. M. Collins, and S. Stephens. 2012. Using fire to increase the scale, benefits, and future maintenance of fuels treatments. Journal of Forestry 110:392–401.

North, M. P., S. L. Stephens, B. M. Collins, J. K. Agee, G. Aplet, J. F. Franklin, and P. Z. Fulé. 2015. Reform forest fire management. Science 349:1280–1281.

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 spatial patterns of burn probability of a boreal landscape. Ecosystems 14:1141–1155.

Parisien, M.-A., C. Miller, S. A. Parks, E. R. Delancey, F.-N. Robinne, and M. D. Flannigan. 2016. The spatially varying influence of humans on fire probability in North America. Environmental Research Letters 11:075005.

Parks, S. A. 2014. Mapping day-of-burning with coarse-resolution satellite fire-detection data. International Journal of Wildland Fire 23:215–223.

Parks, S. A., M. A. Parisien, and C. Miller. 2012. Spatial bottom-up controls on fire likelihood vary across western North America. Ecosphere 3:20.

Parks, S. A., C. Miller, C. R. Nelson, and Z. A. Holden. 2014*a*. Previous fires moderate burn severity of subsequent wildland fires in two large western US Wilderness Areas. Ecosystems 17:29–42.

Parks, S. A., M. A. Parisien, C. Miller, and S. Z. Dobrowski. 2014*b*. Fire activity and severity in the western US vary along proxy gradients representing fuel amount and fuel moisture. PLoS ONE 9:e99699.

Parks, S. A., L. M. Holsinger, C. Miller, and C. R. Nelson. 2015. Wildland fire as a self-regulating mechanism: the role of previous burns and weather in limiting fire progression. Ecological Applications 25:1478–1492.

Parks, S. A., C. Miller, L. M. Holsinger, L. S. Baggett, and B. J. Bird. 2016. Wildland fire limits subsequent fire occurrence. International Journal of Wildland Fire 25:182.

Parks, S. A., L. M. Holsinger, C. Miller, and M.-A. Parisien. 2018. Analog-based fire regime and vegetation shifts in mountainous regions of the western US. Ecography. http://onlinelibrary.wiley.com/doi/10.1111/ecog.03378/abstract, *in press*.

Pausas, J. G., and E. Ribeiro. 2013. The global fire-productivity relationship. Global Ecology and Biogeography 22:728–736.

Penman, T. D., R. A. Bradstock, and O. Price. 2013. Modelling the determinants of ignition in the Sydney Basin, Australia: implications for future management. International Journal of Wildland Fire 22:469–478.

Peterson, G. D. 2002. Contagious disturbance, ecological memory, and the emergence of landscape pattern. Ecosystems 5:329–338.

Price, O. F., and R. A. Bradstock. 2010. The effect of fuel age on the spread of fire in sclerophyll forest in the Sydney region of Australia. International Journal of Wildland Fire 19:35.

Price, O. F., R. A. Bradstock, J. E. Keeley, and A. D. Syphard. 2012. The impact of antecedent fire area on burned area in southern California coastal ecosystems. Journal of Environmental Management 113:301–307.

Price, O. F., R. Borah, and S. W. Maier. 2014. Role of weather and fuel in stopping fire spread in tropical savannas. Austral Ecology 39:135–144.

Price, O. F., J. G. Pausas, N. Govender, M. Flannigan, P. M. Fernandes, M. L. Brooks, and R. B. Bird. 2015. Global patterns in fire leverage: the response of annual area burnt to previous fire. International Journal of Wildland Fire 24: 297–306.

Prichard, S. J., C. S. Stevens-Rumann, and P. F. Hessburg. 2017. Tamm review: Shifting global fire regimes: Lessons from reburns and research needs. Forest Ecology and Management 396:217–233.

R Core Team. 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. www.r-project.org

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 20th century fire occurrence in two large Rocky Mountain (USA) wilderness areas. Landscape Ecology 17:539–557.

Schimmel, J., and A. Granström. 1997. Fuel succession and fire behavior in the Swedish boreal forest. Canadian Journal of Forest Research 27:1207–1216.

Schoennagel, T., T. T. Veblen, and W. H. Romme. 2004. The interaction of fire, fuels, and climate across rocky mountain forests. BioScience 54:661–676.

Schoennagel, T., et al. 2017. Adapt to more wildfire in western North American forests as climate changes. Proceedings of the National Academy of Sciences USA 114:4582–4590.

Senici, D., H. Y. H. Chen, Y. Bergeron, and D. Cyr. 2010. Spatiotemporal variations of fire frequency in central boreal forest. Ecosystems 13:1227–1238.

Spruance, S. L., J. E. Reid, M. Grace, and M. Samore. 2004. Hazard ratio in clinical trials. Antimicrobial Agents and Chemotherapy 48:2787–2792.

Stephens, S. L., B. M. Collins, E. Biber, and P. Z. Fulé. 2016. US federal fire and forest policy: emphasizing resilience in dry forests. Ecosphere 7:e01584.

Stephenson, N. L. 1990. Climatic control of vegetation distribution: the role of the water balance. American Naturalist 135:649–670.

Stephenson, N. 1998. Actual evapotranspiration and deficit: biologically meaningful correlates of vegetation distribution across spatial scales. Journal of Biogeography 25:855–870.

Stevens-Rumann, C., S. Prichard, E. Strand, and P. Morgan. 2016. Prior wildfires influence burn severity of subsequent large fires. Canadian Journal of Forest Research 46:1375–1385.

Stocks, B. J., et al. 1998. Climate change and forest fire potential in Russian and Canadian boreal forests. Climatic Change 38:1–13.

Storey, M., O. Price, and E. Tasker. 2016. The role of weather, past fire and topography in crown fire occurrence in eastern Australia. International Journal of Wildland Fire 25:1048–1060.

Swetnam, T. W., and C. H. Baisan. 1996. Historical fire regime patterns in the southwestern United States since AD 1700. Pages 11–32 *in* C. D. Allen, editor. Fire effects in Southwestern Forests, Proceedings of the Second La Mesa Fire Symposium, Los Alamos, New Mexico, March 29–31, 1994; General Technical Report RM-GTR-286.

Swetnam, T. W., and J. H. Dieterich. 1985. Fire history of ponderosa pine forests in the Gila Wilderness, New Mexico. Page Proceedings—Symposium and Workshop on Wilderness Fire. Gen. Tech. Rep. INT-GTR-182. US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, Utah, USA.

Therneau, T. M. 2015. A package for survival analysis in S. https://cran.r-project.org/web/views/Survival.html

Thompson, M. P., P. Freeborn, J. D. Rieck, D. E. Calkin, J. W. Gilbertson-Day, M. A. Cochrane, and M. S. Hand. 2016. Quantifying the influence of previously burned areas on suppression effectiveness and avoided exposure: a case study of the Las Conchas Fire. International Journal of Wildland Fire 25:167.

Thompson, D. K., M.-A. Parisien, J. Morin, K. Millard, C. P. S. Larsen, and B. N. Simpson. 2017. Fuel accumulation in a high-frequency boreal wildfire regime: from wetland to upland. Canadian Journal of Forest Research 47:957–964.

Turner, M. G. 1989. Landscape ecology: the effect of pattern on process. Annual Review of Ecology and Systematics 20: 171–197.

USDA Forest Service. 2003. The Frank Church–River of No Return Wilderness Management Plan. USDA Forest Service, Washington, D.C., USA.

USDA Forest Service. 2016*a*. Fiscal year 2017 budget justification. USDA Forest Service, Washington, D.C., USA.

USDA Forest Service. 2016*b*. MODIS fire detection GIS data.

Van Wilgen, B. W., et al. 2010. Fire management in Mediterranean-climate shrublands: a case study from the Cape Fynbos, South Africa. Journal of Applied Ecology 47:631–638.

Veraverbeke, S., F. Sedano, S. J. Hook, J. T. Randerson, Y. Jin, and B. M. Rogers. 2014. Mapping the daily progression of large wildland fires using MODIS active fire data. International Journal of Wildland Fire 23:655.

Vovk, V. 2012. Combining p-values via averaging. arXiv preprint arXiv:1212.4966.

Wang, X., M.-A. Parisien, M. D. Flannigan, S. A. Parks, K. R. Anderson, J. M. Little, and S. W. Taylor. 2014. The potential and realized spread of wildfires across Canada. Global Change Biology 20:2518–2530.

Wang, T., A. Hamann, D. Spittlehouse, and C. Carroll. 2016. Locally downscaled and spatially customizable climate data for historical and future periods for North America. PLoS ONE 11:e0156720.

Wang, X., M.-A. Parisien, S. W. Taylor, J.-N. Candau, D. Stralberg, G. A. Marshall, J. M. Little, and M. D. Flannigan. 2017. Projected changes in daily fire spread across Canada over the next century. Environmental Research Letters 12:25005.

Westerling, A. L. 2016. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. Philosophical Transactions of the Royal Society B 371:20150178.

Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.1671/full