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QUANTIFYING THE INFLUENCE OF PAST WILDFIRES ON THE SEVERITY
AND SIZE OF SUBSEQUENT WILDFIRES

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Dissertation

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Quantifying the influence of past wildfires on the severity and size of subsequent wildfires

Chairperson: Cara R. Nelson

Wildfire is arguably one of the most important and widespread natural disturbance agents in western U.S. forests. It has a substantial impact on ecosystem structure and function by influencing soils, nutrients, carbon budgets, wildlife habitat, and vegetation. Wildfires also influence fuel amount, type, and structure, potentially influencing the severity and size of subsequent wildfires through site- and landscape-level feedback mechanisms. Until relatively recently, the ability to quantitatively evaluate how these feedback mechanisms operate has not been feasible because of data limitations (i.e. there has not been enough wildfire). However, due to increased fire activity over the last ~25 years, there are a number of examples of wildfires “interacting” with subsequent fires, where a wildfire either burns within the perimeter of a previously burned area (i.e. it reburns) or burns up to (but not in to) a previously burned area. This recent surge in fire activity, along with increased availability of remotely sensed data, now makes it possible to evaluate how wildfires influence subsequent fire severity and size over large landscapes. Some studies have suggested that extreme weather conditions may decrease the strength of the feedback mechanisms associated with interacting fires, and consequently, evaluating the influence of weather on such relationships is increasingly important, especially given that climate change is expected to result in more extreme weather events.

This dissertation is composed of three chapters. The first chapter quantifies how previous wildfire influences the severity of subsequent fires. In my second chapter, I develop and evaluate several approaches to estimate day-of-burning for each point within a fire perimeter using coarse-resolution MODIS fire detection data. Knowing the day-of-burning is essential in order to evaluate the influence of observed weather (e.g., from a nearby weather station) on observed fire-related effects, such as smoke production or the previously mentioned feedback mechanisms of fire. My third chapter evaluates the ability of wildfire to act as a fuel break by limiting the extent (i.e. size) of subsequent fire. Using the methods from Chapter Two to estimate day-of-burning, I was also able to evaluate the influence of weather in weakening the strength of this feedback.

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In addition to those previously acknowledged, other individuals substantially contributed to my dissertation research. Lisa Holsinger in particular was instrumental in processing very large amounts of satellite data. Zack Holden provided field data and research ideas. Andy Scalise collated and organized a number of fire progression maps.

Lastly, I would like to thank my awesome wife, Ashley, and my two wonderful daughters. Without Ashley’s support, it would have been nearly impossible to juggle work, school, and our children (not that I would juggle my children) – thank you, Ashley. And though my daughters are too young to realize it, their humor, smiles, and curiosity make every day worthwhile. I love you all.

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Chapter 1:

Previous fires moderate burn severity of subsequent wildland fires in two large western US wilderness areas

Abstract

Wildland fire is an important natural process in many ecosystems. However, fire exclusion has reduced frequency of fire and area burned in many dry forest types, which may affect vegetation structure and composition, and potential fire behavior. In forests of the western U.S., these effects pose a challenge for fire and land managers who seek to restore the ecological process of fire to ecosystems. Recent research suggests that landscapes with unaltered fire regimes are more ‘self-regulating’ than those that have experienced fire-regime shifts; in self-regulating systems, fire size and severity are moderated by the effect of previous fire. To determine if burn severity is moderated in areas that recently burned, I analyzed 117 wildland fires in two wilderness areas in the western U.S. that have experienced substantial recent fire activity. Burn severity was measured using a Landsat satellite-based metric at a 30-meter resolution. I evaluated 1) whether pixels that burned at least twice since 1984 experienced lower burn severity than pixels that burned once, 2) the relationship between burn severity and fire history, pre-fire vegetation, and topography, and 3) how the moderating effect of a previous fire decays with time. Results show burn severity is significantly lower in areas that have recently burned compared to areas that have not. This effect is still evident at ~22 years between wildland fire events. Results further indicate that burn severity generally increases with time since and severity of previous wildfire. These findings may assist land managers anticipate the

consequences of allowing fires to burn and provide rationale for using wildfire as a ‘fuel treatment’.

Introduction

Wildland fire is an important ecological process in many ecosystems (Agee, 1993), altering vegetation composition and structure, consuming biomass, and creating or maintaining landscape heterogeneity. However, fire exclusion has caused a dramatic reduction in fire frequency and area burned, particularly in dry forests of the western U.S. (Kilgore and Taylor, 1979; Heyerdahl et al., 2001; Taylor and Skinner, 2003), and is considered one of the major causes of increased tree density and homogenization of such forests (Taylor, 2000; Hessburg et al., 2005; Naficy et al., 2010). Such changes are thought to be partly responsible for recently observed increases in area burned and burn severity (Stephens, 2005; North et al., 2009), although a warming climate has also been implicated (McKenzie et al., 2004; Westerling et al., 2006; Miller et al., 2009).

Increasing awareness of the ecological role of wildland fire (Hutto, 2008), coupled with recognition of the adverse ecological and socio-economic consequences of fire suppression (Backer et al., 2004), have led to criticisms of fire suppression policies (Stephens and Ruth, 2005). Though the idea of allowing more fires to burn has gained favor, implementing ‘resource benefit’ fires is still relatively uncommon due to numerous economic, social and, air quality concerns (Zimmerman et al., 2006). How best to effectively and safely restore the natural process of fire to landscapes that have been altered by decades of fire exclusion remains a dilemma (Arno et al., 2000).

Theory suggests that landscapes with intact fire regimes are more ‘self-regulating’ than those with disrupted regimes (Agee, 1999; Peterson, 2002; McKenzie et al., 2011). That is, wildland fires create fuel breaks and reduce fuel loads and, if fires recur before fuels can recover, the size and severity of subsequent fires are limited. This negative feedback is a fundamental ecosystem property (McKenzie et al., 2011) and the primary rationale for prescribed and resource benefit fires in forested ecosystems (Stephens et al., 2009). The concept of self-regulation is complementary to that of ‘ecological memory’, which is defined as the degree to which ecological processes are shaped by past disturbance events (Peterson, 2002). As such, increased fire intervals due to fire exclusion may have lessened or erased the effects – or reduced the ecological memory – of previous fires in many dry conifer forests of the western US. This may have led to landscape patterns and processes that interrupt the self-regulating effect of active fire regimes.

Empirical evidence for self-regulation is limited because data on recurring fires exist for relatively few areas. However, there is some evidence that a previous wildland fire can moderate the burn severity of subsequent fires. For example, a mixed-conifer forest in central Idaho previously treated with prescribed fire burned with lower severity than untreated forest (Arkle et al., 2012) and forests in northwestern California that burned at least twice had proportionally less high severity fire compared to forests that burned once (Miller et al., 2012). Numerous other studies have focused solely on areas that have burned twice or more in recent decades (i.e. reburn studies) (Thompson et al, 2007; Collins et al., 2009; Holden et al., 2010; van Wagtenonk et al., 2012). A key finding among these reburn studies was that areas that previously experienced high-severity fire were more likely to burn again at high severity; this is particularly interesting because these studies span a broad range of forest types, fire regimes, and climate. Most of these

reburn studies, however, found no noticeable trends in the burn severity of subsequent fires when the initial fire burned at low or moderate severity (but see Holden et al., 2010). Although these reburn studies contribute to understanding the role of successive wildfires, it is difficult to place their findings in the context of self-regulation since no comparisons were made to areas that have not experienced recent fire.

I investigated how previous fires affect the burn severity of subsequent fires across two large and diverse wilderness landscapes. Though these areas have both experienced significant fire activity in recent decades, they differ in topographic complexity and climate. I define burn severity as the degree of fire-induced environmental change, as measured with a satellite-derived index. This study has three objectives. (1) Determine whether the presence or absence of previous wildland fires influences the burn severity of subsequent fires; I hypothesize that burn severity in areas that have reburned (i.e. burned at least twice during the study period) is lower compared to severity in those areas that have not reburned. (2) Assuming a reburn effect is found in objective 1, examine how this effect varies with fire history, pre-fire vegetation, and topography, as such variables have been shown to influence burn severity elsewhere (Thompson et al., 2007). (3) Assuming a reburn effect is found in objective 1, examine how this effect varies over time; I hypothesize it decays.

Methods

Study areas

This study focuses on The Gila-Aldo Leopold Wilderness Complex (GAL) in New Mexico and the Frank Church – River of No Return Wilderness (FCW) in Idaho. Potentially confounding effects of human disturbances are reduced in wilderness areas, as they have

experienced little vegetation management (i.e. logging). Furthermore, many fires have been allowed to burn in recent decades (Swetnam and Dieterich, 1985; Beckman, 2008), although historical fire exclusion has likely left a legacy in both study areas. As such, these areas are the most appropriate natural laboratories for my study, containing diverse vegetation types and a sufficient number wildland fires and reburns to analyze.

Gila-Aldo Leopold Wilderness Complex (GAL)

The GAL (3190 km²) comprises both the Gila and Aldo Leopold Wilderness Areas (Fig. 1). Elevations range from 1462 to 3314 m; the topography is diverse, composed of mountains, broad valleys, steep canyons, and extensive mesas. At the lowest elevations, the vegetation is desert scrub and grasslands (*Ceanothus*, *Artemisia*, and *Yucca* spp.). As elevation increases, it transitions to piñon-oak-juniper woodland (*P. edulis engelmannii*, *Juniperus deppeana*, *J. monosperma*, and *Quercus* spp.), and then to ponderosa pine (*Pinus ponderosa*) woodland and forest. The highest elevations are composed of Douglas-fir, Englemann spruce (*Picea engelmannii*), white fir (*A. concolor*), subalpine fir (*Abies lasiocarpa*), southwestern white pine (*P. strobiformis*), and aspen (*Populus tremuloides*) forests (Rollins et al., 2002).

Although the fire season runs April through September, mid-summer fires are uncommon due to rains associated with monsoonal storms from the Gulf of Mexico (Rollins et al., 2002). Fires in GAL are generally frequent and low-severity surface fires, but burn severity tends to increase with elevation (Swetnam and Dieterich, 1985) and varies with aspect, incident radiation and topographic position (Holden et al., 2009). Extensive cattle and sheep grazing began in the 1890's, which substantially reduced fine fuel amount and continuity and caused a decrease in fire frequency (Swetnam and Dieterich, 1985; Swetnam and Baisan, 1996). Resource benefit fires

began to occur in ~1975 (Swetnam and Dieterich, 1985). Between 1984 and 2008, a total of 72,226 ha burned once, while of 50,004 ha reburned (Fig. 1).

Frank Church – River of No Return Wilderness (FCW)

The FCW (9574 km²) is the second largest wilderness area in the lower 48 states. FCW is rugged; elevations range from 600 to 3136 m. Topographic features include river breaks, deep canyons, mountains, and glaciated basins (USDA Forest Service, 2003). Park-like groves of ponderosa pine exist below about 1500 m on south and west slopes (Barrett, 1988). Denser ponderosa pine and Douglas-fir (*Pseudotsuga menziesii*) forests occupy north and east aspects, up to elevations of about 2100 m. Still higher, the vegetation transitions to grand fir (*Abies grandis*), lodgepole pine (*Pinus contorta*), and Englemann spruce. At the highest elevations, subalpine fir, whitebark pine (*Pinus albicaulis*), and alpine environments are common (Barrett, 1988; Finklin, 1988).

The fire season runs from early-July to mid-September (USDA Forest Service, 2013). Low-elevation, open ponderosa pine forests tend to experience frequent, low-intensity fires, and, generally, fire frequency decreases and severity increases with increasing elevation, moisture, and tree density (Crane and Fischer, 1986). Fire suppression became effective in about 1935 (Finklin, 1988) although sheep grazing may have excluded fire earlier (Steele et al, 1981). Resource benefit fires began to occur in ~1988 (Beckman, 2008). Between 1984 and 2008, a total of 498,067 ha burned once, while 91,671 ha reburned (Fig. 1).

Data

Burn severity data were obtained from the Monitoring Trends in Burn Severity (MTBS) project (Eidenshink et al., 2007), which has mapped burn severity as the differenced normalized burn ratio (dNBR) of large (≥ 400 ha) wildland fires in the U.S. since 1984 (through 2008 when this study was conducted) at a 30-m resolution using Landsat 4 and 5 Thematic Mapper and Landsat 7 Enhanced Thematic Mapper-Plus satellite imagery (Fig. 2). Specifically, the normalized burn ratio (NBR) is computed for both pre- and post-fire satellite images, and then the pre-fire NBR is subtracted from the post-fire NBR (Key and Benson, 2006). The post-fire imagery is usually acquired one year after the fire, but this may be shorter or longer depending on image quality and availability (which varies due clouds, smoke, snow, and sun angle). As dNBR values increase, there is generally a corresponding increase in char, consumption of downed fuels, exposure of mineral soil and ash, and scorched/blackened vegetation; there is also a corresponding decrease in moisture content, above-ground green biomass, and vegetative cover (Key and Benson, 2006). The index has been shown to be predictive ($R^2 > 0.65$) of field assessed measures of burn-severity within or near my study areas (Holden et al, 2009; Arkle et al., 2012). MTBS also provides *relative* differenced normalized burn ratio (RdNBR) data (Miller and Thode, 2007), as well as discrete severity classes (e.g., low, moderate, and high). I used dNBR (vs. RdNBR) because it is generally equal to or better than RdNBR at representing field-based measures of burn severity (Soverel et al., 2010; Cansler and McKenzie, 2012). I also used dNBR (vs. the discrete severity classes) because I required a continuous representation of burn severity.

To minimize the effect of minor mapping errors, I used a ‘reverse buffer’ and analyzed only pixels ≥ 100 meters from the edge of each MTBS perimeter; this reduced the probability of including pixels that did not burn. Pixels classified as water, perennial snow, or barren/rock

(Rollins, 2009) were removed prior to analysis. Data from 1984-2008 were analyzed; to qualify as a 'reburn', a pixel must have burned at least twice during this time period. I refer to pixels that burned only once during this time period as 'no-reburn.'

Additional spatial data to evaluate objective 2 (i.e. how the reburn effect varies with fire history, pre-fire vegetation, and topography) were obtained from a variety of sources (Table 1) and are similar to those used in other studies of reburns (Thompson et al. 2007). The fire history variables (severity of previous fire [P.dNBR] and time since previous fire [TIME]) were generated using MTBS data (Eidenshink et al., 2007). Because fuels data (amount, type, and structure) were not available for every year of the study period, I used two variables as proxies of live fuel: pre-fire normalized difference vegetation index (NDVI) and LANDFIRE fire-regime group (FRG) (Rollins, 2009). NDVI is a satellite index of photosynthetic capacity, or vegetation greenness, and was calculated using the pre-fire Landsat imagery provided by MTBS. FRG characterizes presumed historical fire regimes and basically combines the numerous LANDFIRE biophysical setting (BpS) categories (BpS is the presumed vegetation under a normal disturbance regime; Rollins, 2009) into five classes representing the fire regime (frequency and severity). For example, one FRG category indicates a fire return interval of < 35 years with low or mixed severity and is composed of BpS types such as 'northern rocky mountain ponderosa pine woodland and savanna'. The topographic variables I evaluated (Table 1) were found to be predictive of high-severity fire (Dillon et al., 2011) and included factors that directly or indirectly influence fuel (live and dead biomass) type, configuration, and moisture. For example, solar radiation (SRAD) may directly influence fuel moisture and indirectly influence biomass production and the rate of fuel accumulation. None of the independent variables were highly correlated ($r < 0.7$). All spatial data used in my analyses had a cell size of 30 m.

Analyses

Influence of presence or absence of previous wildland fires on the burn severity of subsequent fires

To determine if the presence of previous wildland fires affect burn severity of subsequent fires (hereafter, I term this the ‘reburn effect’), I calculated the mean and median dNBR in reburn and no-reburn pixels in each study area. I also used a Kolmogorov-Smirnov test to determine if the dNBR frequency distributions of reburn and no-reburn pixels were significantly different. For this objective, I used a truncated subset of the severity data from 1999 to 2008 to ensure that no-reburn pixels represented a substantially long fire-free period (i.e. at least 15 years). The cut-off year of 1999 was a somewhat arbitrary choice but reflects a balance between retaining sufficient data for analysis and avoiding labeling pixels that had recently burned as no-reburn. I considered using fire atlas data that exist for fires before 1984 (e.g., Rollins et al. 2001) so that I might use the entire length of the MTBS dataset (1984-2008). However, these data are inconsistent and vary in accuracy (Haire et al., 2013); I opted to use only the more consistently generated MTBS data.

dNBR values are unitless and somewhat difficult to interpret ecologically. Therefore, I relate some of the dNBR values reported in this section and elsewhere in the results to a field-based measure of burn severity, the composite burn index (CBI). CBI values are more ecologically relevant, as they incorporate factors such as amount of vegetation consumed, consumption or charring of substrate materials, and amount of newly exposed mineral soil (van Wagendonk et al., 2004; Key and Benson, 2006). CBI values have a strong relationship to dNBR values in and near my study areas ($R^2 > 0.65$) (Holden et al., 2009; Arkle et al., 2012). Miller and Thode (2007) suggest that low severity fire corresponds to CBI values ≤ 1.25 ,

moderate severity to CBI values > 1.25 and ≤ 2.25 , and high severity CBI values > 2.25 .

Therefore, I used the data presented in Holden et al. (2009) and Arkle et al. (2012) and nonlinear models (*cf.* Miller and Thode, 2007) to determine the relationship between dNBR and CBI, thereby better allowing key dNBR values to be placed in the context of an ecologically relevant field-based measure of burn severity.

Influence of fire history, pre-fire vegetation, and topography on reburn severity

To determine how reburn severity varies with fire history, pre-fire vegetation and topography, I generated multivariate models for each study site using generalized linear models (GLMs, family=Gaussian) and the R statistical program (R Development Core Team, 2007). In these models, dNBR is the dependent variable and a suite of fire history, vegetation, and topographic variables (Table 1) were evaluated as independent variables.

Given the high degree of autocorrelation present in the data, a two-stage process was used to ensure that the models were not over fit (Legendre, 1993). In stage one, I subsampled the data to diminish the effect of pseudoreplication associated with spatially autocorrelated data (Legendre and Fortin, 1989). I based the subsampling frequency on the distance at which pixels are spatially independent (Krawchuk et al., 2009; Parisien et al., 2011a). To determine this distance, I generated semivariograms using the residuals of naïve models (i.e. including all predictor variables) and calculated the ‘range’, which is the distance at which pixels are no longer correlated. For GAL, the range was 819 m, corresponding to a subsampling frequency of 0.13% (823 pixels). For FCW, the range was 1004 m, corresponding to a subsampling frequency of 0.08% (644 pixels).

In stage two, 2500 subsamples were generated for each study area by randomly selecting pixels with the subsampling frequency determined in the previous step (Krawchuk et al., 2009; Parisien et al., 2011a). A candidate model was generated for each subsample (n=2500) through forward and backward stepwise regression, which is an automated model-selection procedure based on Bayesian information criterion (BIC). Both the linear and quadratic (i.e. 2nd degree polynomial) forms of each variable were evaluated for inclusion. Each candidate model represents the independent variable(s) that best explain burn severity for each subsample; due to the infrequent subsampling frequency, the variables explaining burn severity may vary substantially among candidate models. Therefore, the final model for each study area was selected based on the most frequently identified model (i.e. set of independent variables) in the 2500 candidate models. Model parameters were generated by averaging across the most frequently identified candidate models, thereby creating an ensemble model (i.e. a multi-model average). The use of an ensemble model limits the stochasticity of model outcomes caused by randomly subsampling the data (Parisien et al., 2011b). The fits of the final models were evaluated based on the average coefficient of determination (i.e., the R^2 between the observed and predicted dNBR values) in the ensemble model.

Variation in reburn effect over time

To quantify how reburn effect varies over time, I plotted the mean dNBR of reburn pixels against time since previous fire (i.e. time between fire events). Using all reburn pixels, linear regression (dNBR as explained by time since previous fire) was conducted to generate a trend line and better depict how the relationship varies through time. I tested whether the slope of each trend line was significantly different from zero using a 500 model ensemble, each model using a

different subset of data sampled at the frequency described in the previous section. To test for significance, I averaged the p-values of the slope coefficient from the model ensemble.

Results

Influence of presence or absence of previous wildland fires on the burn severity of subsequent fires

In both study areas, mean and median dNBR were substantially lower in reburn pixels than in no-reburn pixels. In GAL, mean and median dNBR for reburn pixels were 89 and 68, respectively, compared to mean and median values of 213 and 178 for no-reburn pixels. In FCW, mean and median dNBR for reburn pixels were 158 and 112, respectively, compared to mean and median values of 339 and 272 for no-reburn pixels. A Kolmogorov-Smirnov test revealed that the dNBR frequency distributions of reburn and no-reburn pixels (Fig. 3) were significantly different in both study areas ($p < 0.001$).

The relationship between dNBR and CBI (Fig. 4) allows the unitless dNBR values to be better placed in an ecological context. As such, in GAL, the corresponding mean and median CBI for reburn pixels were both < 0.5 (low severity), whereas the mean and median CBI values for no-reburn pixels were 1.6 and 1.3 (moderate severity), respectively. In FCW, the mean and median CBI for reburn pixels were 1.1 and 0.8 (low severity), respectively, compared to mean and median CBI values of 1.9 and 1.6 (moderate severity) for no-reburn pixels.

Influence of fire history, pre-fire vegetation, and topography on reburn severity.

The models for each study area include those variables that were selected during the stepwise regression (Fig. 5; Table 2). In both study areas, the interaction between P.dNBR and

TIME indicates that burn severity increases with P.dNBR and that dNBR values are highest at the highest values of both P.dNBR and TIME (Fig. 5). The models for both study areas also indicate that dNBR increases with pre-fire NDVI. In GAL, no topographic variables were selected, whereas in FCW, dNBR increases with ELEV and decreases with SRAD and TPI2000. Based on the spatial autocorrelation of the residuals, the subsampling frequency I employed did not violate the assumption of independence; that is, the variogram ranges of the model residuals was less than the distance values I used to subsample the data.

Variation in reburn severity over time

Mean dNBR of reburn pixels tended to increase with time since previous fire (Fig. 6). The slope of the regression line is significantly different from zero in GAL ($p = 0.02$) and FCW ($p=0.08$) as determined from the ensemble regression model. The effect is still evident at for the longer intervals between fires (~22 years), with mean dNBR values remaining substantially lower than the mean dNBR of no-reburn pixels (Fig. 6). The slopes of the regression lines indicate that dNBR increases by 3.2 and 4.0 units/year since last burn in GAL and FCW, respectively.

Discussion

One of the key concepts in landscape ecology is that, not only are landscapes shaped by disturbance events, but disturbances themselves are shaped by the history and pattern of landscapes (Turner, 1989; Peterson, 2002). This core concept underscores that feedbacks associated with, for example, fire history are critical mechanisms of the self-regulation process. Our findings complement this concept and add to increasing evidence for the self-regulation of burn severity in areas where relatively short-interval successive fires have occurred.

The presence or absence of previous wildland fires influences the burn severity of subsequent fires

As I hypothesized, areas that reburned since 1984 experienced lower burn severity than areas of no-reburn, indicating that previous wildland fires moderate burn severity of subsequent fires. Our results are consistent with Arkle et al. (2012), who found that burn severity was lower in areas that were treated by prescribed burns compared to untreated areas. These results are also consistent with Miller et al. (2012), who found that there was proportionally less high severity fire in reburn compared to no-reburn.

Several ecological mechanisms are likely responsible for the observed lower severity in reburns compared to no-reburns. The lower severity I found in reburns compared to no-reburns is likely due, at least in part, to the consumption of dead and down fuel by the earlier fire, thereby reducing fuel availability for subsequent fires. Another explanation, however, could be that changes in vegetation amount, structure, and composition were caused by the earlier fire, thereby reducing ladder fuels and the likelihood of torching of the upper canopy during subsequent fire events.

The reburn effect varies with fire history, pre-fire vegetation, and topography

Several studies have found that areas that previously burned at high severity were more likely to burn at high severity during subsequent wildland fires (Thompson et al. 2007, Collins et al. 2009, Holden et al. 2010, van Wagendonk et al. 2012). I also found that severity generally increases with the severity of previous fire. That reburn severity increases with the severity of the previous fire is somewhat counterintuitive because one might expect a high-severity fire to leave

behind little flammable biomass that would contribute to the severity of a reburn. One explanation could lie with fire regime dynamics associated with shrubs, as sites dominated by shrubs generally experience crown fires (Baker, 2009) and typically regenerate with shrubs, perpetuating a high-severity regime (McKenzie et al., 2011). I suggest that this explanation is at least partly responsible in FCW, as 11.2% of the biophysical setting (i.e., presumed vegetation with disturbance) in the reburn area is shrub dominated compared to 1.8% in GAL (Rollins, 2009). Alternatively, forested landscapes that experience high-severity fire may also experience a post-fire conversion from tree to shrub life form (which could be either a change in the ecological state or the natural successional pathway). Reburns occurring during the shrub state will generally burn at high severity (Thompson and Spies, 2010; van Wagtenonk et al., 2012). Finally, severe fires in forests may beget severe fires when fire-killed trees create heavy fuel loads (Odion et al., 2004) that provide conditions for a subsequent severe wildland fire (cf. Arno et al., 2000). Although the last two explanations are difficult to quantify without field data or time-series vegetation data, they should not be discounted in either of my study areas.

Burn severity increased with vegetation greenness, measured as NDVI, in both study areas. This follows other studies that have found more vegetation generally corresponds to higher burn severity (Cocke et al., 2005; Arkle et al., 2012). This highlights the importance of biomass productivity, but also the influence of topographic variables, on burn severity. For example, the increase in dNBR with ELEV in FCW is likely explained by a combination of enhanced productivity (due to increased moisture) and increasing fuel load (due to reduced fire frequency) with elevation; Dillon et al. (2011) also found that elevation was a major influence in explaining high-severity fire in the northern Rocky Mountain, USA and suggested it was due to increased biomass in upper elevations. The negative relationship between dNBR and SRAD in FCW is

potentially because moisture limitations on south-facing slopes leads to decreased productivity. The relationship between dNBR and TPI2000 in FCW could be due differences in the relative rates of post-fire vegetation recovery in valley bottoms compared to ridge tops.

Although three topographic variables (ELEV, SRAD, and TPI2000) were predictive of burn severity in FCW, no topographic variables were retained in the model in GAL. I suggest that the presence and absence of topographic influence on burn severity in FCW and GAL, respectively, may be due to varying importance of bottom-up controls. Although topography is by no means ‘gentle’ in GAL, it is considerably more diverse and rugged in FCW (standard deviation of ELEV, SRAD, and TPI2000 are all higher in FCW). Thus, as also suggested by other fire studies (Kennedy and McKenzie, 2010; Parks et al., 2012), it is probable that the higher topographic variability in FCW provides stronger bottom-up controls compared to GAL.

The reburn effect decays over time

Our results add to a growing body of research that has found that severity of reburns increases with time since previous fire (Collins et al., 2009; Bradstock, 2010; van Wagtendonk et al., 2012) and that such an effect can be persistent for decades (Miller et al., 2012). As expected, I found that severity of reburns increases with time since the previous fire, likely due to biomass accumulation associated with longer fire-free intervals (Mack et al., 2008). Thus, the moderating effect of previous fire on the burn severity of subsequent fire diminishes with time. The effect appears to last at least the ~22 years I analyzed, even in the short fire interval system of GAL. Given the temporal extent of my study, I am unable to make inferences beyond 22 years.

The longevity of the reburn effect is of great interest to land managers and likely varies by ecosystem type and geographic regions. I suggest that the longevity of the reburn effect –

measured by how long takes for the previous fire to have no effect on the burn severity of subsequent fires – is influenced by a number of factors including the severity of the initial fire, the dominant type of vegetation establishing at the site, and the productivity of the site. For example, the longevity of the reburn effect from a low-severity fire will be relatively short because there is less change in ecological conditions from which to recover. Conversely, the longevity of the reburn effect will be longer in cases where sites experience high severity fire. The reburn effect will also persist for sites that are revegetated by low-flammability vegetation (which may vary by life stage [e.g., lodgepole pine]) (Romme, 1982) or have low productivity. Fires in GAL are generally less severe than in FCW, so the re-accumulation of fuels for subsequent fires is comparatively quick. Conversely in FCW, the prevalence of higher severity fires and, therefore, a higher degree of change, suggest that more time is needed to recover than in GAL. Thus, I expect that the longevity of the reburn effect is generally shorter in GAL than in FCW, although the temporal extent of my data was too short for us to directly test this.

Other considerations

Despite their designation as wilderness and being the best available examples of naturally functioning ecosystems, GAL and FCW have likely been affected by fire suppression to some degree. Fire-use policies (i.e. allowing fires to burn for resource benefit) have only been in place for ~25-40 years (Swetnam and Dieterich, 1985; Beckman, 2008), and even with the advent of fire use, many fires were suppressed. As such, I acknowledge that fire exclusion in previous decades may have led to higher severity fires than would have occurred otherwise (Barrett, 1988).

Although I considered numerous variables in my models, the variation explained (0.29 – 0.32) suggests that future modeling should include an even broader set of variables. Variables related to pre-fire vegetation structure and dead fuels may be particularly important, but unfortunately are not yet available for large landscapes, especially on an annual basis. Using the soil-adjusted vegetation index (SAVI) (Huete, 1988) instead of NDVI may be appropriate for future analyses, especially in GAL, as soils influence NDVI where canopy cover is low (Huete et al., 1985). Weather variables, such as wind speed and temperature at the time of burning, are likely important drivers of burn severity due to their strong influence on potential fire behavior (Schwilk et al., 2006; Miller et al., 2009; Thompson and Spies, 2010). Including such temporally variable data is currently challenging because of the uncertainty in knowing when a pixel burned. However, remotely sensed fire progression maps or daily MODIS data (Roy et al., 2002; USDA Forest Service, 20013) may make it possible to link day of burning with weather station data to models explaining burn severity. Finally, because fire activity may be better explained at broader scales (Parks et al., 2011) due to the contagious nature of fire spread (Peterson, 2002), incorporating variables representing the stand or neighborhood may improve future modeling efforts.

Conclusion and management implications

The three most important findings in this study are that 1) burn severity is significantly lower in areas that have recently burned compared to areas that have not, 2) as the time interval between fires increases, the severity of the subsequent fire increases, and 3) the moderating effect of a previous fire on the burn severity of the subsequent fire lasts at least 22 years. By providing quantitative information about future reductions in burn severity, these results provide

land managers a longer timeframe in which to view the benefits and costs of an individual fire. Our findings indicate that fires can and do self-regulate from a burn severity perspective and provide rationale and insight to using wildfire as an effective ‘fuel treatment’.

A high proportion of each study area burned between 1984 and 2008, suggesting that future wildfires will interact with previous fires. Based on my results, these future reburns will likely burn at relatively low severity when they occur. In fact, from 2009 to 2012, GAL had eight reburn fires (since 1984) and FCW had six reburn fires (USDA Forest Service, 2013; GeoMAC, 2013). Furthermore, some areas in GAL have burned five times since 1950 (Rollins et al., 2001; Eidenshink et al., 2007); such areas are likely restored in terms of vegetation structure and fire regime characteristics, at least partially explaining the relatively high proportion of low-severity fire seen in GAL.

Considering that a fire will inevitably burn most forested areas at some point in the future (North et al., 2009), land managers need to weigh the short-term ‘costs’ associated with letting a fire burn with the long-term consequences of suppressing a fire. Larson et al. (2014) suggest that reintroducing frequent fire to unlogged, historically low-density ponderosa pine and mixed-conifer forests may restore and maintain conditions that were present in the pre-suppression era due to ‘latent resilience’ of large, fire resistant trees in these forests. Such forest types are fairly common in GAL and, at low-to-mid elevations, in FCW. However, longer intervals between any previous fire and a subsequent fire may diminish the capabilities of the forest to absorb the disturbance and restore pre-suppression conditions. After an excessively long fire-free interval, fire severity may be too high for even large, fire resistant trees to survive, potentially causing the ecosystem to ‘reset’ or change to an alternative state (Gunderson, 2000).

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Tables

Table 1. Predictor variables evaluated for inclusion into the models. None of the variables are highly correlated ($r < 0.7$).

Variable type	Variable name	Variable description	Data range (5 th – 95 th percentile)*	Source
Fire history	P.dNBR	dNBR of the previous fire	-64 - 782 (FCW) -29 - 351 (GAL)	Eidenshink et al., 2007
	TIME	Elapsed time since the previous fire burned (years)	6 - 20 (FCW) 3 - 17 (GAL)	
	P.dNBR:TIME	Interaction term between P.dNBR and Time (this is specified within the statistical model equation)	na	
Veg.	NDVI	Pre-fire normalized differenced vegetation index	0.20 - 0.65 (FCW) .25 - .49 (GAL)	Landsat 4 and 5 TM; Landsat 7 ETM+
	FRG	Fire regime group (LANDFIRE) (factor variable)	na (categorical data)	Rollins, 2009
Topography	ELEV	Elevation (meters)	1028 - 2333 (FCW) 2079 - 2569 (GAL)	USGS
	SLOPE	Slope (degrees)	6 - 40 (FCW) 2 - 35 (GAL)	Burrough and McDonnell, 1998
	SRAD	Potential solar radiation (kWh/m ²)	761 - 1555 (FCW) 1288 - 1932 (GAL)	Fu and Rich, 2002
	TPI300	Topographic position index: 300 m scale	-50 - 54 (FCW) -42 - 42 (GAL)	Weiss, 2001
	TPI2000	Topographic position index: 2000 m scale	-307 - 288 (FCW) -124 - 155 (GAL)	Weiss, 2001

*These values characterize those areas that reburned during my analysis window.

Table 2. Parameters of the ensemble model for each study area; these models examine how reburn severity varies with fire history, pre-fire vegetation, and topography.

	Variable	β	SE	<i>P</i>
GAL	NDVI	1415.2	89.4	< 0.001
	NDVI ²	482.3	88.1	0.004
	P.dNBR	-0.17	0.07	0.050
	TIME	0.133	1.06	0.132
	P.dNBR:TIME	0.026	0.01	0.001
R² = 0.29				
FCW	NDVI	1786.8	180.8	< 0.001
	NDVI ²	-37.98	180.2	0.490
	P.dNBR	-0.367	0.08	0.001
	TIME	-3.857	1.81	0.125
	ELEV	2367	256.1	< 0.001
	ELEV ²	181.5	187.4	0.390
	SRAD	-960.6	203.9	< 0.001
	SRAD ²	-328.6	178.1	0.163
	TPI2000	-791.8	206.0	0.002
	TPI2000 ²	-300.5	184.8	0.220
P.dNBR:TIME	0.024	0.01	< 0.001	
R² = 0.33				

Figures

Figure 1. The general location of the study areas within the U.S. (a) and areas that have experienced no-reburn (green shading) vs. areas that reburned (red shading) between 1984 and 2008 within GAL (b) and FCW (c).

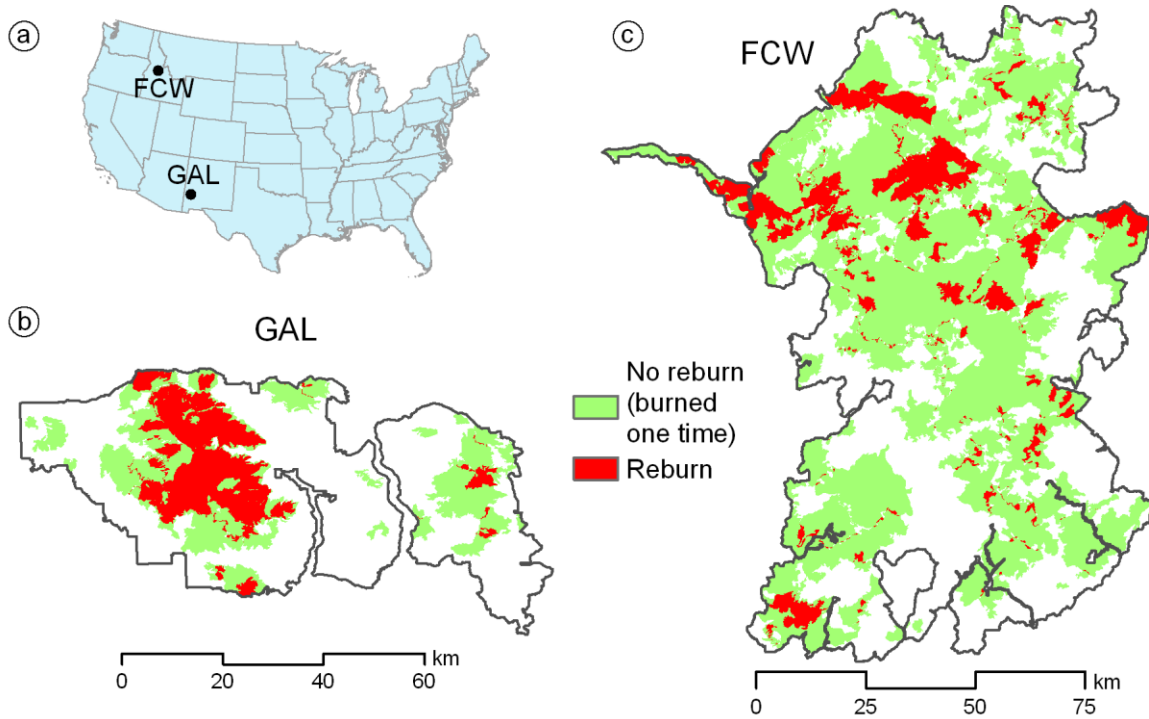


Figure 2. Burn severity (dNBR) for the 2004 Granny fire in GAL. The thick black line represents the Granny fire perimeter; the hatched area represents the perimeter of the 2000 Bloodgood fire. Qualitatively, areas that had previously burned in 2000 appear to have lower dNBR than areas that had not. The inset shows the location of the Granny fire within GAL.

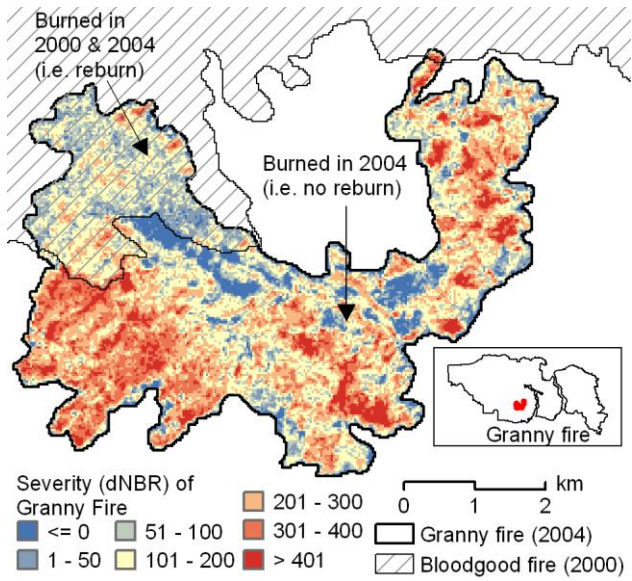


Figure 3. Frequency distributions of dNBR for reburn (red) and no-reburn (blue) pixels in each study area. A two-sided Kolmogorov-Smirnov test indicates that the distributions within each study area are significantly different ($p < 0.001$).

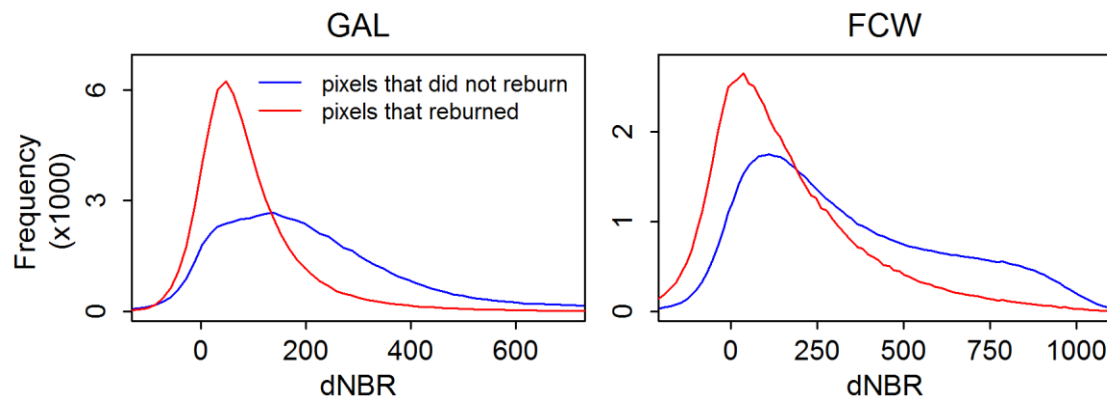


Figure 4. The relationship between dNBR and CBI for the 2003 Dry Lakes Fire in GAL (left) (Holden et al., 2009) and the 2007 East Zone Complex near FCW (right) (Arkle et al., 2012).

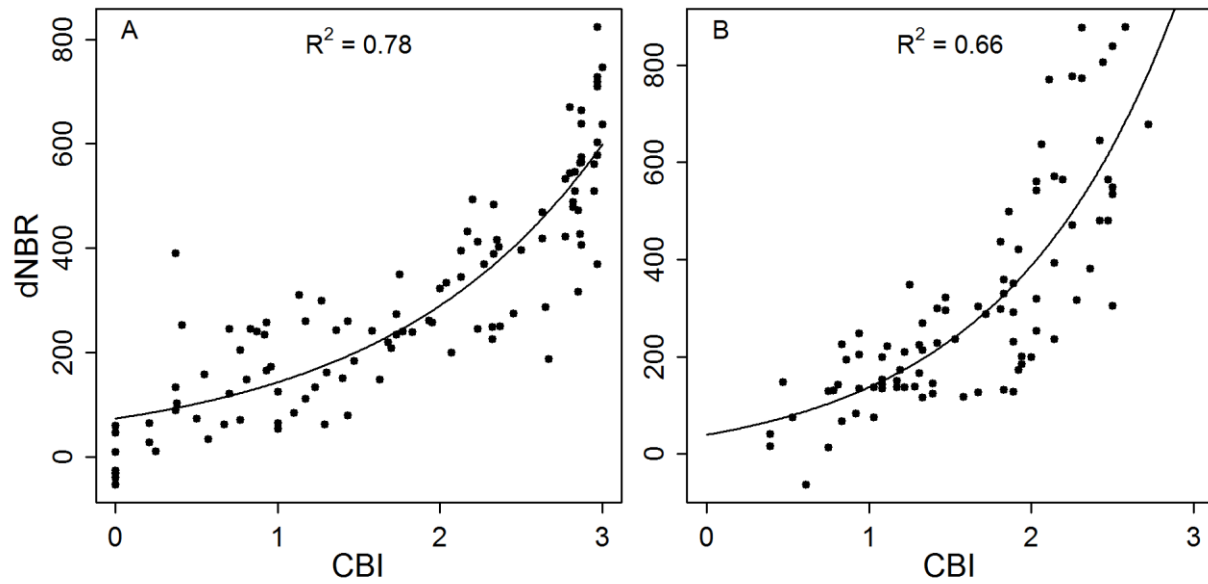


Figure 5. Partial dependence plots for GAL (top row) and FCW (bottom row) models for those variables selected by the stepwise regression (Table 2). These plots represent the relationship between each variable and dNBR when all other variables are held constant at their mean.

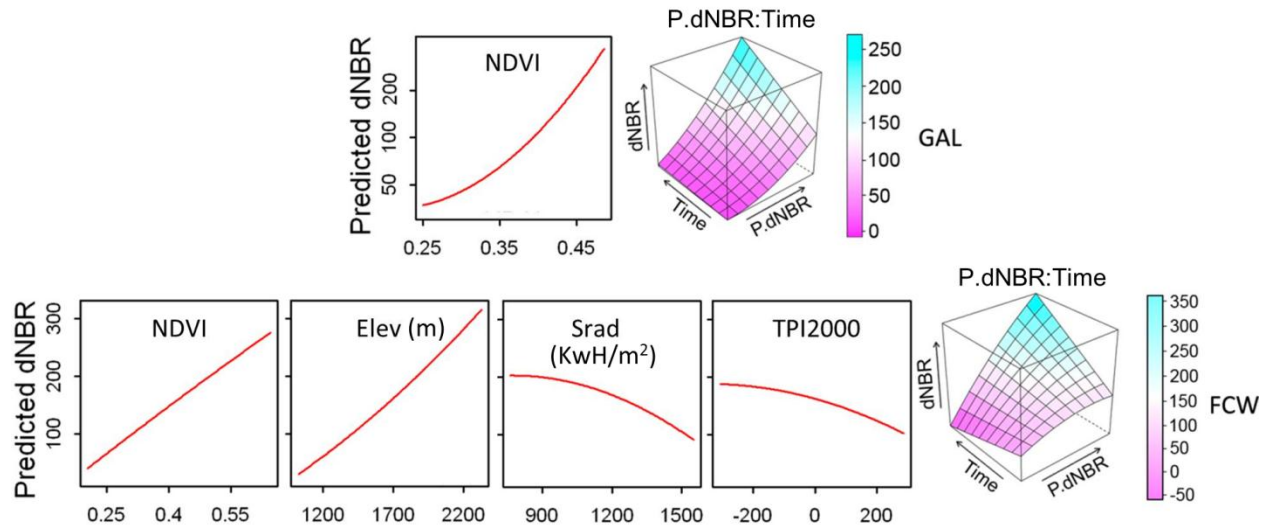
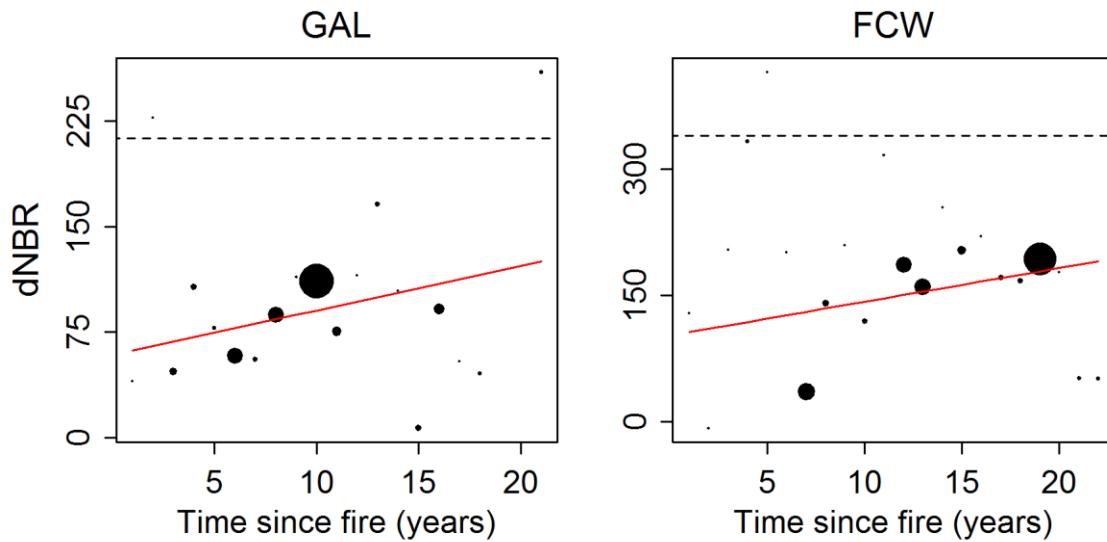


Figure 6. Mean dNBR of reburn pixels plotted against time since fire. The dashed horizontal line represents the mean dNBR of all pixels that burned from 1999-2008 but did not burn between 1984-1998. That is, this line represents the burn severity of pixels that had not burned for a minimum of 15 years, corresponding to a dNBR of 213 and 339 in GAL and FCW, respectively, and CBI values of 1.6 and 1.9. Size of circles represents the number of pixels in each time since previous fire. Trend lines (red) are shown of the fit between dNBR and time since previous fire. The trend is significant in GAL ($p=0.02$) and FCW ($p=0.08$).



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Chapter 2:

Mapping day-of-burning with coarse-resolution satellite fire-detection data

Abstract

Evaluating the influence of observed daily weather on observed fire-related effects (e.g., smoke production, carbon emissions, and burn severity) often involves knowing exactly what day any given area has burned. As such, a number of studies have used fire progression maps – in which the perimeter of an actively burning fire is mapped at a fairly high temporal resolution – or MODIS satellite data to determine the day-of-burning, thereby allowing an evaluation of the influence of daily weather. However, fire progression maps have many caveats, the most substantial being that they are rarely mapped on a daily basis and may not be available in remote locations. Although MODIS fire detection data provide an alternative due to its global coverage and high temporal resolution, its coarse spatial resolution (1 km²) often requires that it be downscaled. An objective evaluation of how to best downscale, or interpolate, MODIS fire detection data is necessary. I evaluated ten spatial interpolation techniques on 21 fires by comparing the day-of-burning as estimated with spatial interpolation of MODIS fire detection data to the day-of-burning that was recorded in fire progression maps. The day-of-burning maps generated with the best performing interpolation technique showed reasonably high quantitative and qualitative agreement with fire progression maps. Consequently, the methods described in this chapter provide a viable option for producing day-of-burning data where fire progression maps are of poor quality or unavailable.

Introduction

There have been numerous fire-related studies that depended upon knowing the day-of-burning for any given point of any given fire. These studies, for the most part, needed to know the day-of-burning in order to use daily weather (e.g., from a nearby weather station) to explain or predict fire-related phenomena. For example, some studies have evaluated the influence of weather on fire effects (i.e. burn severity) (Collins et al. 2007; Bradstock et al. 2010; Thompson and Spies 2010) and others have used observed weather data to parameterize their models of fuel consumption and carbon emissions (de Groot et al. 2007, de Groot et al. 2009). Furthermore, some researchers have parameterized fire simulation models with weather conditions conducive to high spread days (Parisien et al. 2011; Parks et al. 2011; Podur and Wotton 2011).

The studies described above relied on either fire progression maps or satellite data to infer day-of-burning (and therefore, the ability to determine the associated daily weather). Fire progression maps are often generated by land management and fire agencies, in which the perimeter of an actively burning fire is mapped at a fairly high temporal resolution (every few days to daily). Such fire progression maps are generated using aircraft with GPS or thermal mapping capabilities, aerial photos, ground-based GPS, or other field-based intelligence (C. McHugh personal communication). These maps are primarily generated to provide fire managers and the public with information on how a particular wildfire has grown over time. However, they also allow the research community the ability to conduct studies that evaluate, for example, the influence of daily weather on fire effects (e.g., Collins et al. 2009; Roman-Cuesta et al. 2009)

There are some challenges, however, with using day-of-burning data from fire progression maps. First, fire progression maps are rarely created at the resolution of single days due to resource limitation (e.g., no available aircraft during periods of peak fire activity), safety

concerns (e.g., high winds or heavy smoke), or remote location (Fig. 1). Generally, only a small number of fires are mapped on a daily basis; these fires tend to be the ones that threaten human life and infrastructure (e.g., 2102 High Park Fire in Colorado). More commonly, fire progression maps have temporal gaps, some of them spanning multiple days (Fig. 1). To deal with such gaps, researchers typically average daily weather values over the days where temporal gaps exist in fire progression maps (e.g., Collins, Kelly et al. 2007). Such an approach, however, likely understates the influence of weather because extreme conditions are masked by averaging (Collins et al. 2009). Furthermore, because of the limited availability of fire progression maps with adequate temporal resolution, many studies have been limited to only one or a few fires, making their findings highly localized. Other caveats of fire progression maps are that collection flight times vary by day, may be attributed with the incorrect day, and are sometimes drawn to reflect containment lines and not actual area burned (C. McHugh personal communication; B. Quayle, personal communication). Finally, and perhaps most importantly, fire progression maps are often not generated in extremely remote locations (e.g., the Canadian boreal forest).

Where fire progression maps are not available or are of inadequate quality, some researchers have used MODIS fire detection data (NASA MCD14ML product, Collection 5, Version 1) to infer day-of-burning. These satellite data contain the date and location of actively burning pixels but have a coarse spatial resolution (pixel size = 1 km²). As such, various approaches have been used to downscale them. For example, de Groot et al. (2007, 2009) used nearest neighbor interpolation to estimate day-of-burning, whereas Parisien et al. (2011) and Parks et al. (2012) buffered individual fire detections. Because MODIS fire detection data are collected globally and at a high temporal frequency, they offer an alternative to agency-generated

fire progression maps. However, an objective evaluation of how to best interpolate, or downscale, these coarse data is necessary.

There is a clear need by the fire management and research communities for reliable information regarding the day-of-burning for each point within a fire perimeter. Such data would allow a consistent and unbiased method for incorporating daily weather data into fire-related analyses. As such, this study has two objectives: 1) use ten spatial interpolation techniques to generate fine-scale day-of-burning maps and 2) evaluate each technique using fire progression maps.

Methods

Estimating day-of-burning

I estimated the day-of-burning (DOB) for 21 fires (Table 1) that are greater than 5000 ha and, for comparative purposes, have at least six mapped fire progression perimeters. These fires have broad geographic dispersion (Table 1) to ensure that the methods evaluated here are applicable across geographic regions. DOB was estimated for each pixel within each fire perimeter using several interpolation techniques (Table 2). Although these estimates can be generated at any resolution, I generated DOB using a pixel size of 30 x 30m, matching the resolution of Landsat TM imagery and associated products (e.g., burn severity data; Eidenshink et al. 2007). All procedures described below are implemented using the R statistical program (R Development Core Team 2007); the code is available from the corresponding author with no restrictions.

Estimating DOB was a three step process. In step one, all MODIS fire detection data (NASA MCD14ML product, Collection 5, Version 1) overlapping and within 1-km of the final

fire perimeter were selected for use in the interpolation process. Fire perimeters were obtained from the Geospatial Multiagency Coordinating Group (GeoMAC) (2013); non-contiguous polygons (e.g., spot fires) $< \sim 100$ ha were removed. MODIS fire detection data were obtained from USDA Forest Service Active Fire Mapping Program (<http://activefiremaps.fs.fed.us/>) and serve as the input data for the interpolations. Hereafter, these point data are referred to as MODIS-DOB; they represent MODIS pixel centroids and are attributed with the date that a fire is detected (Fig. 2). MODIS-DOB have a coarse spatial resolution of 1 km^2 ; however, the high temporal resolution of these data (there are two MODIS sensors, each passing overhead twice per day) provide useful information for mapping fine-scale day-of-burning. In cases where there were two or more spatially coincident fire detections (i.e. fire was detected in the same pixel but on a different day), the one with the earliest date was retained and others were removed.

In step two, I estimated DOB for each pixel within each fire perimeter using ten interpolation methods (Table 2); hereafter, these day-of-burning estimates are referred to as interpolated-DOB. The interpolation techniques vary in complexity and not all of them are described in this paragraph; however, the details and equations for all ten are presented in tabular format (Table 2). The simplest is called nearest neighbor (NN) interpolation, in which each pixel within a fire perimeter is assigned a DOB based on the nearest MODIS-DOB. Moving along the complexity gradient, another is called average date (AD), in which each pixel is assigned a DOB based on the average date of nearby MODIS-DOB data. There are also a number of interpolation methods that assign DOB to each pixel based on weighted averages of nearby MODIS-DOB data; the most common is inverse-distance weighting (IDW) interpolation (see Fig. 2 for an illustration of how IDW operates). For those interpolation methods that calculate the average (i.e. AD) or weighted average (i.e. WMD) of nearby MODIS-DOB, I limited the interpolated-DOB to

only those dates observed in the nearby MODIS-DOB (Table 2). This ensured that the interpolated-DOB corresponded to days of detected fire growth and was not an artifact of averaging. This was accomplished for each pixel by selecting the date of the temporally nearest MODIS-DOB to the average or weighted average of each interpolation method.

In step three, I reassigned all spatially contiguous interpolated-DOB regions that were \leq 25 ha to DOB values of the nearest regions larger than 25 ha. This size threshold is admittedly arbitrary; however, this step was necessary because the process described in step two often produced small interpolated-DOB regions that were not in agreement with surrounding estimates. This presumably occurred because of flare ups (and therefore MODIS-DOB detections) that occurred days after the flaming front passed through an area.

Comparison to fire progression maps

To evaluate each interpolation technique, I compared interpolated-DOB to the day-of-burning recorded in fire progression maps obtained from GeoMAC (2013); hereafter, GeoMAC-DOB. For any perimeter that was recorded before 12 PM (noon) on any given day, I changed the recorded day-of-burning to that of the previous day on the assumption that most of the area likely burned the previous afternoon and evening. For example, if a perimeter was recorded at 4 AM on July 2, I modified the date of the perimeter and shifted it to July 1. For this comparison, the GeoMAC-DOB data are considered the ‘observed’ data. However, the observed day-of-burning in the GeoMAC-DOB is not necessarily the actual day-of-burning due to temporal gaps in the mapped fire perimeters (Fig. 1); in such cases, I compared the ‘recording dates’ of the DOB-GeoMAC to aggregated interpolated-DOB. For example, consider a GeoMAC-DOB fire perimeter that was mapped on August 1 and then again on August 3 (i.e. a two-day gap): I used

the mapped fire perimeter (GeoMAC-DOB) on August 3 and compared that to the interpolated-DOB for August 2 and 3. I quantified the percentage of pixels in the interpolated-DOB that *spatially* and *temporally* agreed with the GeoMAC-DOB (i.e. percent of pixels that exactly matched). I also quantified the percent of pixels in the interpolated-DOB that were within ± 1 and ± 2 recording dates of the GeoMAC-DOB. These comparisons, hereafter termed ‘percent agreement’, were then used to evaluate each interpolation technique.

Results

Day-of-burning maps (i.e. interpolated-DOB) for each of the ten spatial interpolation techniques were generated. Interpolated-DOB, as expected, varied among interpolation techniques, as evaluated qualitatively by the maps (Fig. 3) and quantitatively by the percentage agreement between interpolated-DOB and GeoMAC-DOB (Table 3). Among the 21 fire analyzed, the nearest date method (ND) had the lowest mean percent agreement for the exact match (42.8%), ± 1 recording date (69.4%), and ± 2 recording dates (80.7%). The weighted by mean and distance method (WMD) had the highest mean percent agreement for the exact match (46.1%; tied with MAJ10), ± 1 recording date (75.8%; tied with WMD.sq), and ± 2 recording dates (85.8%; tied with IDW.half and WMD.sq). Taking into account the percent agreement values for the exact match, ± 1 , and ± 2 recording dates, I conclude that the WMD method performed marginally best overall. However, several other interpolation methods had percent agreement values that were almost as high as WMD, notably AD, IDW, IDW.sq, IDW.half, and WMD.sq. Relative to these top performing methods, the NN, ND, MAJ5, and MAJ10 methods had low percent agreement with GeoMAC-DOB. Visual inspection of the interpolated-DOB (WMD method) and GeoMAC-DOB also shows good agreement (Fig. 4).

Discussion

Several interpolation methods were effective for mapping DOB for a broad range of ecosystem types, including grass (Mustang Corner [Florida]), grass/shrub (Rockhouse [Texas]), and conifer-dominated types (Fool Creek [Montana]). The average percent agreement for the WMD method was 46.1%, 75.8, and 85.8% for the exact match, ± 1 , and ± 2 recording dates, respectively. This is roughly in line with the average percent agreement reported by de Groot et al. (2007), who used nearest neighbor interpolation to estimate day-of-burning for one fire in British Columbia, Canada using AVHRR and MODIS fire detections; they found that the percent agreement for ± 1 and ± 2 recording dates to be 80% and 90%, respectively (they did not report the exact match). Although I concluded that the WMD method had the highest percent agreement when compared to fire progression maps, this was only a marginal improvement over some of the other methods; I therefore suggest that the IDW, IDW.sq, IDW.half, and WMD.sq (and to a lesser degree, the AD method) also generate reasonable interpolated-DOB. In fact, these six top-performing interpolation techniques, based on the kappa statistic (Landis and Koch 1977), are nearly identical using a kappa=0.95 threshold (Table 4).

Although MODIS data have fairly coarse spatial resolution, the high temporal resolution of these data supports the use of spatial interpolation techniques and allows day-of-burning maps to be generated at any resolution. This is particularly important, because although fire behavior and effects are a function of fuels, weather, and topography (Agee 1993), the influence of weather is of particular interest (McKenzie et al. 2004; Abatzoglou and Kolden 2011) because of its high temporal variability (Bessie and Johnson 1995; Anderson et al. 2007) and its dominant influence during extreme years (Moritz 2003; Gedalof et al. 2005). As such, the methodology

developed here will allow for incorporating weather data into fire-related analyses covering broad regions and literally hundreds or thousands of fires (e.g., Parks et al. 2014). For example, studies that tie weather to wildfire smoke and carbon emissions (McKenzie et al. 2006; Lavoué et al. 2007) would benefit tremendously from the methods described here. Studies analyzing the effect of weather on fire effects (i.e. burn severity) (e.g., Thompson and Spies 2010) would also benefit, as would fire simulation studies that parameterize their models with weather conditions conducive to high spread days (e.g., Parisien et al. 2011). A related benefit of using the methods describe here is simply the ability to quantify daily fire growth of individual fires. For example, such an ability would benefit studies like those of Lavoué and Stocks (2011) who used a sigmoidal growth function, based on fire duration and final size, to estimate daily fire growth.

Although I used fire progression maps for quasi-validation purposes, it should be noted that these data are imperfect, as previously described, and are not likely correct themselves. The lack of adequate ground-truthed data is challenging and, as such, complicates the validation procedure: it is not possible to know with 100% confidence how well the interpolations in this study perform. For example, the WMD method, on average, ‘under-predicted’ the day-of-burning by 0.2 recording dates (average difference between interpolated- and observed-DOB among the 21 fires; range: -1.3 – 0.4); that is, the interpolated day-of-burning was generally earlier than the recorded day-of-burning in the fire progression maps. In some cases, this under-prediction was substantial (four fires were < -0.5 recording dates and two fires were < -1.0). Such bias in the interpolations are likely due to incorrect recording dates of the fire progression maps, as it is highly unlikely that the MODIS satellite would systematically detect a fire before it actually burned. Considering the previously described caveats with fire progression maps and that they may, on average, systematically record the fire date later than it occurred, it is possible

that the percent agreement values reported in this study underestimate the quality of the interpolations.

The methodology developed in this paper has been shown to generate, on average, robust DOB estimates. However, there are some reasons why estimated DOB may be incorrect in some areas. Clouds, heavy smoke, and tree canopy may limit the ability of the MODIS sensors from detecting fire (Giglio 2010). Also, individual pixels within fast moving or low intensity fires may not be detected. Additional mischaracterization of DOB is likely due to the coarse resolution of the fire detection data. Also due to the coarse resolution of the MODIS data, it is likely that the methods described here are inappropriate for small fires (< ~500 ha); note that the smallest fire I analyzed was ~6300 ha. There are other inherent caveats associated with the fire detection algorithm (e.g., varying levels of detection confidence) (Giglio 2010) and remote sensing in general (Verstraete et al. 1996). Finally, it may be that the methods developed here are not necessary when high-quality daily fire progression maps are available. Although these caveats are important considerations, the methods described in this paper provide a viable option for producing day-of-burning data where agency-generated fire progression maps are of poor quality or unavailable.

Finally, it is worth noting that the MODIS burned area product (MCD45A1) (Roy et al. 2005) also estimates day-of-burning by evaluating change in vegetation. However, it has an eight-day precision (Roy and Boschetti 2009) and oftentimes has spatial gaps within a fire perimeter (i.e. no data on estimated day-of-burning for some MODIS pixels) (Fig. 5). As such, the methods presented in this paper can potentially be used to complement other algorithms that estimate day-of-burning (e.g., Giglio et al. 2009).

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Table 1. General information about the 21 study fires, including name, year of burning, size, location (U.S. state), and duration.

Fire Name	Year	Size (ha)	Location	Duration (days)*
Columbia Cx	2006	53,200	Washington	41
Tripod Cx	2006	74,121	Washington	81
Ahorn	2007	22,699	Montana	57
Corporal	2007	6,337	Montana	35
Fool Creek	2007	25,847	Montana	73
Railley Mountain	2007	8,576	Montana	48
Showerbath	2007	24,999	Idaho	43
South Barker	2008	13,819	Idaho	53
Twitchell Canyon	2010	18,391	Utah	73
High Park	2012	36,546	Colorado	17
Waldo Canyon	2012	7,340	Colorado	8
Rock House	2011	127,640	Texas	22
Miller	2011	36,087	New Mexico	32
Whitewater Baldy	2012	120,508	New Mexico	41
Wallow	2011	221,043	Arizona	28
Day	2006	66,459	S. California	25
Zaca	2007	98,759	S. California	61
Hancock	2006	8,964	N. California	81
Pigeon	2006	40,842	N. California	94
Deep	2009	12,242	Florida	6
Mustang Corner	2008	16,166	Florida	6

*Based on first and last MODIS fire detection

Table 2. Abbreviation, name, and description of interpolation methods (ordered from simplest to most complex) used to estimate day-of-burning (DOB-interpolated) using coarse resolution MODIS fire detection data (MODIS-DOB). For those interpolation methods that calculate the average (i.e. AD) or weighted average (i.e. WMD) of nearby MODIS-DOB, I limited the interpolated-DOB to only those dates observed in the nearby MODIS-DOB (See Methods).

Interpolation abbreviation	Interpolation name	Interpolation description
NN	Nearest neighbor	Each pixel is assigned the Julian day of the nearest MODIS fire detection.
ND	Nearest date	Each pixel is assigned the earliest Julian day of the three nearest MODIS fire detections.
AD	Average date	Each pixel is assigned the averaged Julian day of the three nearest MODIS fire detections.
MAJ5	Majority of five nearest neighbors	Each pixel is assigned the most common Julian day among the five nearest fire detections. In case of a tie, the earlier Julian day is assigned.
MAJ10	Majority of ten nearest neighbors	Each pixel is assigned the most common Julian day among the ten nearest fire detections. In case of a tie, the earlier Julian day is assigned.
IDW	Inverse distance weighted	Each pixel is assigned a weighted average of the five nearest MODIS fire detections (See Fig. 2). The weight of each fire detection (w_i) is based on the distance (d) and is defined as: $w_i = \left(\frac{1}{d_i}\right) / \sum_{i=1}^5 1/d_i$
IDW.sq	Inverse distance weighted-squared	Each pixel is assigned a weighted average of the five nearest MODIS fire detections. The weight of each fire detection (w_i) is based on the distance (d) and is defined as: $w_i = \left(\frac{1}{d_i^2}\right) / \sum_{i=1}^5 1/d_i^2$
IDW.half	Inverse distance weighted-square root	Each pixel is assigned a weighted average of the five nearest MODIS fire detections. The weight of each fire detection (w_i) is based on the distance (d) and is defined as: $w_i = \left(\frac{1}{d_i^{0.5}}\right) / \sum_{i=1}^5 1/d_i^{0.5}$
WMD	Weighed by mean and distance	Each pixel is assigned a weighted average of the five nearest MODIS fire detections. The weight of each fire detection (w_i) is based on the date ($jday_i$) and distance (d_i) and is defined as: $w_i = \left(\frac{1}{\left(\left jday_i - \frac{\sum_{i=1}^5 jday_i}{5} \right + 1 \right) * d_i} \right)$
WMD.sq	Weighted by mean and	Each pixel is assigned a weighted average of the five nearest MODIS

distance-squared

fire detections. The weight of each fire detection (w_i) is based on the date ($jday_i$) and distance (d_i) and is defined as:

$$w_i = \left(\frac{1}{\left(\left| jday_i - \frac{\sum_{i=1}^5 jday_i}{5} \right| + 1 \right)^2 * d_i} \right)$$

Table 3. For each fire, percent agreement for each interpolation method between the interpolated-DOB and the GeoMAC-DOB for the exact match (± 0), within one recording date (± 1), and within two recording date (± 2).

Fire Name	NN			ND			AD			MAJ5			MAJ10		
	± 0	± 1	± 2	± 0	± 1	± 2	± 0	± 1	± 2	± 0	± 1	± 2	± 0	± 1	± 2
Columbia Cx	66.3	84.0	90.4	70.6	86.2	92.2	67.4	86.1	92.0	69.9	85.4	91.1	71.5	86.1	91.5
Tripod Cx	38.7	66.3	77.5	31.5	51.1	59.6	39.2	68.8	79.9	37.3	67.3	78.0	38.5	69.7	80.3
Ahorn	28.5	49.2	63.1	35.0	57.2	70.7	27.2	50.1	67.5	32.4	54.9	70.5	28.4	52.1	69.7
Corporal	31.0	54.2	65.3	35.8	53.4	59.9	32.4	57.5	68.7	33.0	53.8	63.1	34.2	55.0	64.3
Fool Creek	48.1	70.6	79.8	49.1	67.0	77.0	47.9	73.7	80.3	54.9	73.8	81.3	54.5	75.4	83.4
Railley Mtn.	45.9	59.4	72.3	77.3	93.9	96.6	44.6	62.3	73.1	43.5	58.7	70.9	43.3	59.9	71.6
Showerbath Cx	36.1	65.9	78.8	45.7	77.7	86.9	38.2	67.8	82.4	31.4	63.1	77.7	31.7	59.4	74.8
South Barker	47.5	78.2	86.5	33.1	60.3	74.1	52.4	84.2	91.4	48.8	82.1	90.3	50.9	82.6	90.9
Twitchell	28.8	51.1	58.3	35.3	59.2	75.6	29.1	54.6	61.1	33.6	54.3	60.0	34.7	54.8	60.0
High Park	51.9	80.6	86.8	49.4	77.3	84.6	54.8	82.6	88.7	54.9	81.2	87.6	56.8	81.9	88.3
Waldo Canyon	59.7	85.1	94.3	54.6	83.5	92.0	63.0	84.8	94.2	64.3	86.5	93.9	64.8	87.7	94.3
Rockhouse	78.4	95.5	97.7	26.2	61.1	75.8	79.4	96.3	97.8	77.9	95.3	97.2	78.7	95.4	97.2
Miller	40.0	69.7	88.3	38.2	63.9	84.7	41.1	72.7	90.4	38.7	68.4	87.7	38.5	66.0	85.9
Whitewater Baldy	41.3	77.6	88.1	43.5	75.8	86.4	42.6	81.3	89.5	42.4	78.7	87.8	41.2	78.8	88.1
Wallow	36.0	75.3	90.1	40.3	78.0	90.7	37.1	77.6	92.2	38.6	77.7	92.2	39.2	76.7	93.1
Day	49.3	83.0	91.8	49.0	83.0	92.1	52.5	85.7	93.1	52.6	85.5	93.0	54.5	86.4	93.4
Zaca	39.2	78.5	87.1	34.0	74.2	86.2	40.5	81.6	90.2	40.9	79.9	88.7	43.0	81.6	89.7
Hancock	50.6	73.3	86.1	42.5	61.9	74.4	51.3	75.3	88.3	46.8	68.0	80.5	50.6	71.4	84.2
Pigeon	38.3	63.5	78.3	41.5	55.6	70.3	40.0	67.2	82.1	37.8	60.3	75.8	39.2	61.4	77.0
Deep	28.4	68.6	84.4	9.9	48.1	72.2	23.6	69.0	85.0	19.6	61.5	79.9	15.4	58.5	75.5
Mustang Corner	60.3	91.9	96.3	55.6	88.5	93.6	57.8	93.7	97.2	58.8	92.6	94.2	58.7	90.8	92.5
MEAN	45.0	72.5	82.9	42.8	69.4	80.7	45.8	74.9	85.0	45.6	72.8	82.9	46.1	72.9	83.1

Table 3 (continued)

Fire Name	IDW			IDW.sq			IDW.half			WMD			WMD.sq		
	±0	±1	±2	±0	±1	±2	±0	±1	±2	±0	±1	±2	±0	±1	±2
Columbia Cx	66.9	86.5	92.5	66.9	85.9	92.0	66.3	86.8	92.7	67.5	86.7	92.7	67.4	86.9	92.7
Tripod Cx	39.6	69.2	80.6	39.5	69.0	80.1	39.4	69.1	80.8	39.7	69.7	80.9	39.8	69.6	80.9
Ahorn	26.3	49.0	66.4	28.0	49.9	66.6	26.2	49.4	66.3	26.0	49.3	66.7	25.5	48.8	66.5
Corporal	32.4	59.7	70.5	31.9	58.5	69.3	32.5	60.0	70.6	32.3	60.6	71.1	31.8	60.8	71.1
Fool Creek	46.4	73.9	80.3	46.4	73.6	80.1	45.7	74.0	80.5	46.6	74.1	80.7	46.6	74.1	80.8
Railley Mtn.	44.8	62.6	74.0	45.2	62.0	73.8	43.5	62.0	73.4	44.0	62.3	73.5	43.9	62.2	73.3
Showerbath Cx	39.9	69.1	84.4	39.5	68.5	83.2	39.6	68.8	84.9	39.7	68.5	84.3	39.6	68.3	84.5
South Barker	52.4	85.3	92.1	51.3	84.6	91.5	52.4	85.4	92.5	52.6	85.1	92.7	53.1	85.5	92.9
Twitchell	29.1	56.7	62.4	28.8	56.0	61.9	29.2	57.2	63.0	29.5	56.7	62.4	29.7	56.8	62.8
High Park	55.0	83.1	89.5	54.8	82.7	88.7	54.4	83.1	89.5	55.0	83.5	89.7	54.8	83.4	89.7
Waldo Canyon	64.2	86.8	95.2	62.3	86.9	95.1	65.5	86.9	95.0	66.0	87.3	95.6	66.2	87.2	95.3
Rockhouse	79.6	96.3	97.8	79.1	96.2	97.8	79.6	96.3	97.7	79.5	96.3	97.7	79.5	96.3	97.7
Miller	41.4	73.6	91.8	41.5	73.3	91.1	41.2	73.0	91.4	41.4	73.5	91.7	41.3	73.2	91.5
Whitewater Baldy	42.9	82.3	90.2	43.3	82.0	90.1	42.4	82.0	90.2	42.7	82.3	90.1	42.7	82.2	90.1
Wallow	37.5	78.3	93.3	37.4	78.0	92.7	37.3	78.0	93.4	37.8	78.6	93.7	37.6	78.3	93.6
Day	53.0	85.9	93.3	52.4	85.6	93.1	53.4	86.0	93.4	53.8	86.2	93.4	54.0	86.2	93.4
Zaca	40.6	82.0	90.4	40.7	81.4	89.9	40.6	81.9	90.4	41.3	82.5	90.6	41.0	82.5	90.6
Hancock	53.7	76.6	89.0	54.8	75.9	89.2	53.4	76.1	89.2	54.6	76.6	88.8	53.7	76.0	89.2
Pigeon	39.4	67.9	83.5	40.0	67.4	83.2	39.3	67.8	83.6	39.5	67.9	83.9	39.5	67.8	83.7
Deep	20.3	69.6	85.7	22.8	69.3	85.5	19.9	69.5	85.5	20.3	69.5	85.5	20.2	69.9	85.5
Mustang Corner	58.4	93.8	97.3	59.2	93.7	97.1	57.3	94.3	97.2	58.0	94.8	97.0	57.8	95.5	97.0
MEAN	45.9	75.6	85.7	46.0	75.3	85.3	45.7	75.6	85.8	46.1	75.8	85.8	46.0	75.8	85.8

Table 4. Average (among all 21 fires) kappa statistic (Landis and Koch 1977) between all pairwise interpolation techniques.

	NN	ND	AD	MAJ5	MAJ10	IDW	IDW.sq	IDW.half	WMD	WMD.sq
NN	--	--	--	--	--	--	--	--	--	--
ND	0.84	--	--	--	--	--	--	--	--	--
AD	0.92	0.88	--	--	--	--	--	--	--	--
MAJ5	0.87	0.90	0.92	--	--	--	--	--	--	--
MAJ10	0.85	0.88	0.89	0.91	--	--	--	--	--	--
IDW	0.92	0.87	0.96	0.92	0.90	--	--	--	--	--
IDW.sq	0.94	0.87	0.96	0.91	0.89	0.98	--	--	--	--
IDW.half	0.91	0.88	0.96	0.93	0.90	0.99	0.97	--	--	--
WMD	0.91	0.88	0.96	0.93	0.90	0.99	0.97	0.99	--	--
WMD.sq	0.91	0.88	0.96	0.93	0.90	0.98	0.96	0.99	0.99	--

Figures

Figure 1. Julian day the perimeter was recorded (i.e. observed; left) and the number of days that elapsed between perimeter observations (right) for the Day fire in southern California. These maps illustrate that temporal gaps often exist in fire progression maps.

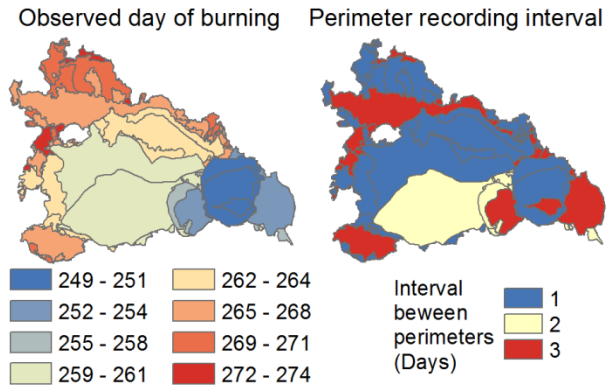
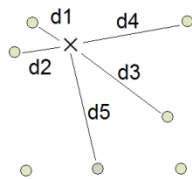
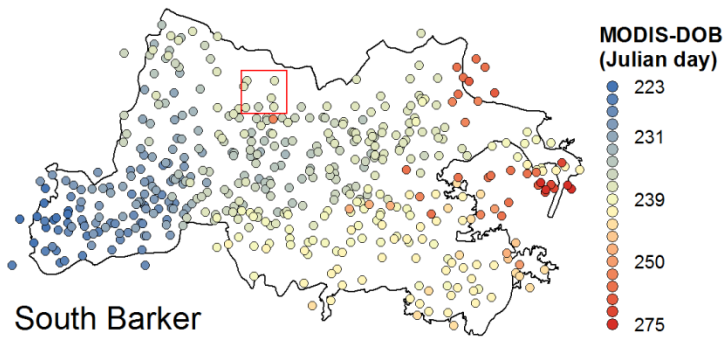


Figure 2. Illustration of how the inverse distance weighting (IDW) interpolation method operates. For the pixel labeled with an 'X', DOB is estimated using a weighted averaged of the five nearest MODIS fire detections. w_1 is the weight (in the IDW weighted average equation [bottom]) of the closest MODIS fire detection, d_1 is the distance of the closest fire detection, and DOB1 is the day-of-burning of the closest fire detection. w_2 is the weight of the second closest MODIS fire detection, etc.



$$w_1 = (1/d_1) / (1/d_1 + 1/d_2 + 1/d_3 + 1/d_4 + 1/d_5)$$

$$w_2 = (1/d_2) / (1/d_1 + 1/d_2 + 1/d_3 + 1/d_4 + 1/d_5)$$

$$w_3 = (1/d_3) / (1/d_1 + 1/d_2 + 1/d_3 + 1/d_4 + 1/d_5)$$

$$w_4 = (1/d_4) / (1/d_1 + 1/d_2 + 1/d_3 + 1/d_4 + 1/d_5)$$

$$w_5 = (1/d_5) / (1/d_1 + 1/d_2 + 1/d_3 + 1/d_4 + 1/d_5)$$

$$\text{Interpolated-DOB} = ((\text{DOB1} * w_1) + (\text{DOB2} * w_2) + (\text{DOB3} * w_3) + (\text{DOB4} * w_4) + (\text{DOB5} * w_5))$$

Figure 3. Visual comparison of five of the interpolation techniques for the Fool Creek fire.

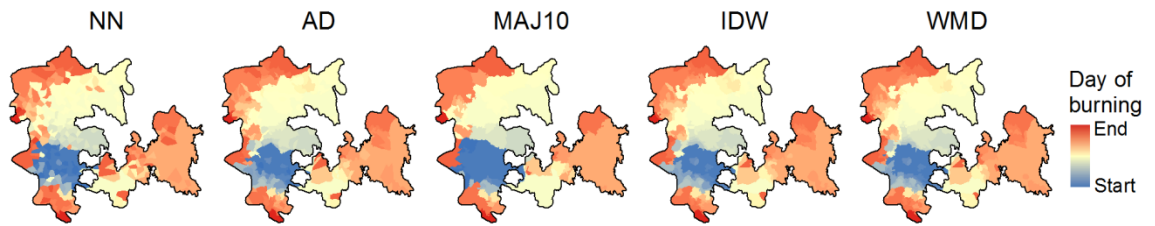


Figure 4. Maps showing DOB-GeoMAC vs. DOB-interpolated (WMD) for each of the 21 study fires.

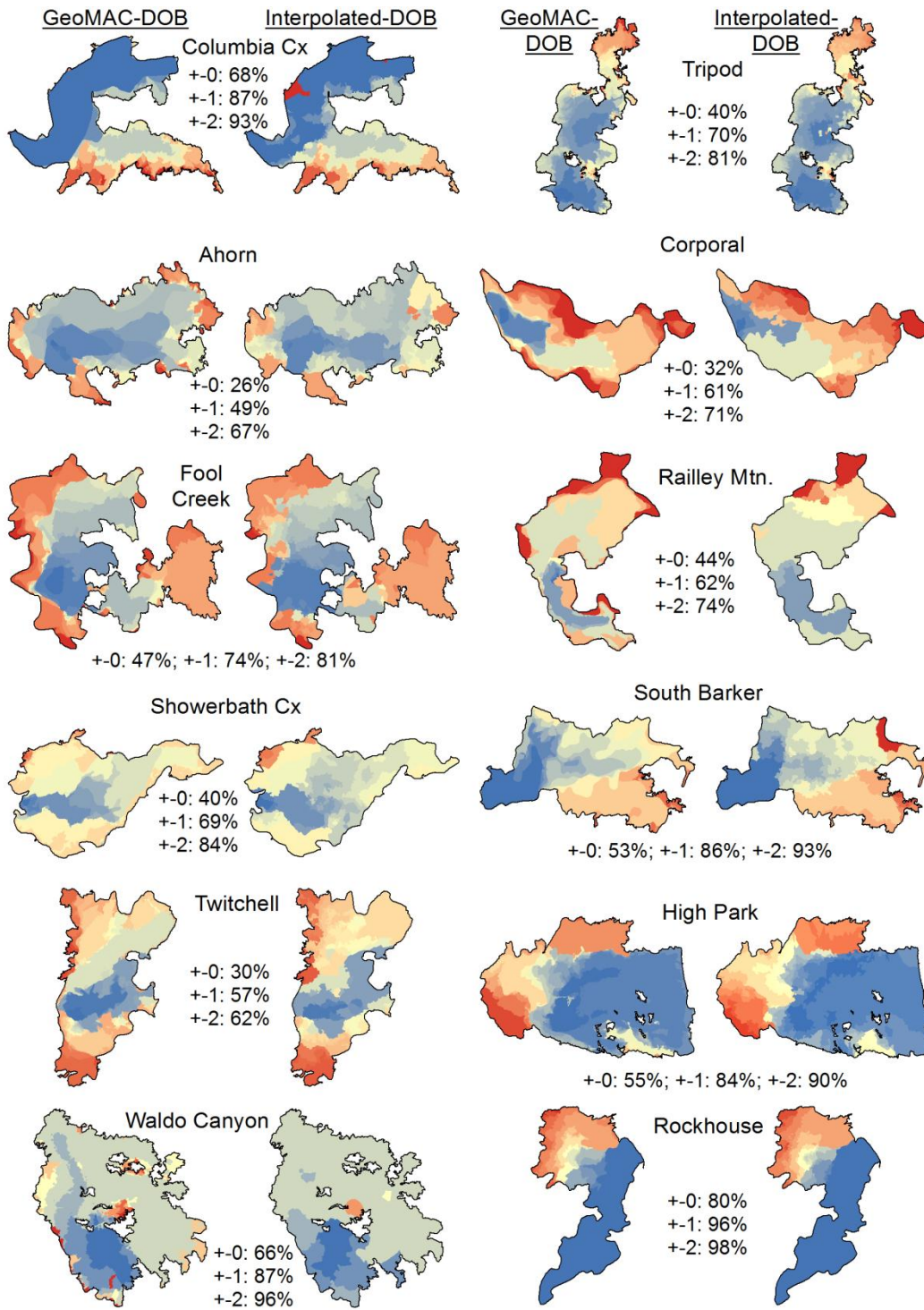


Figure 4. (continued)

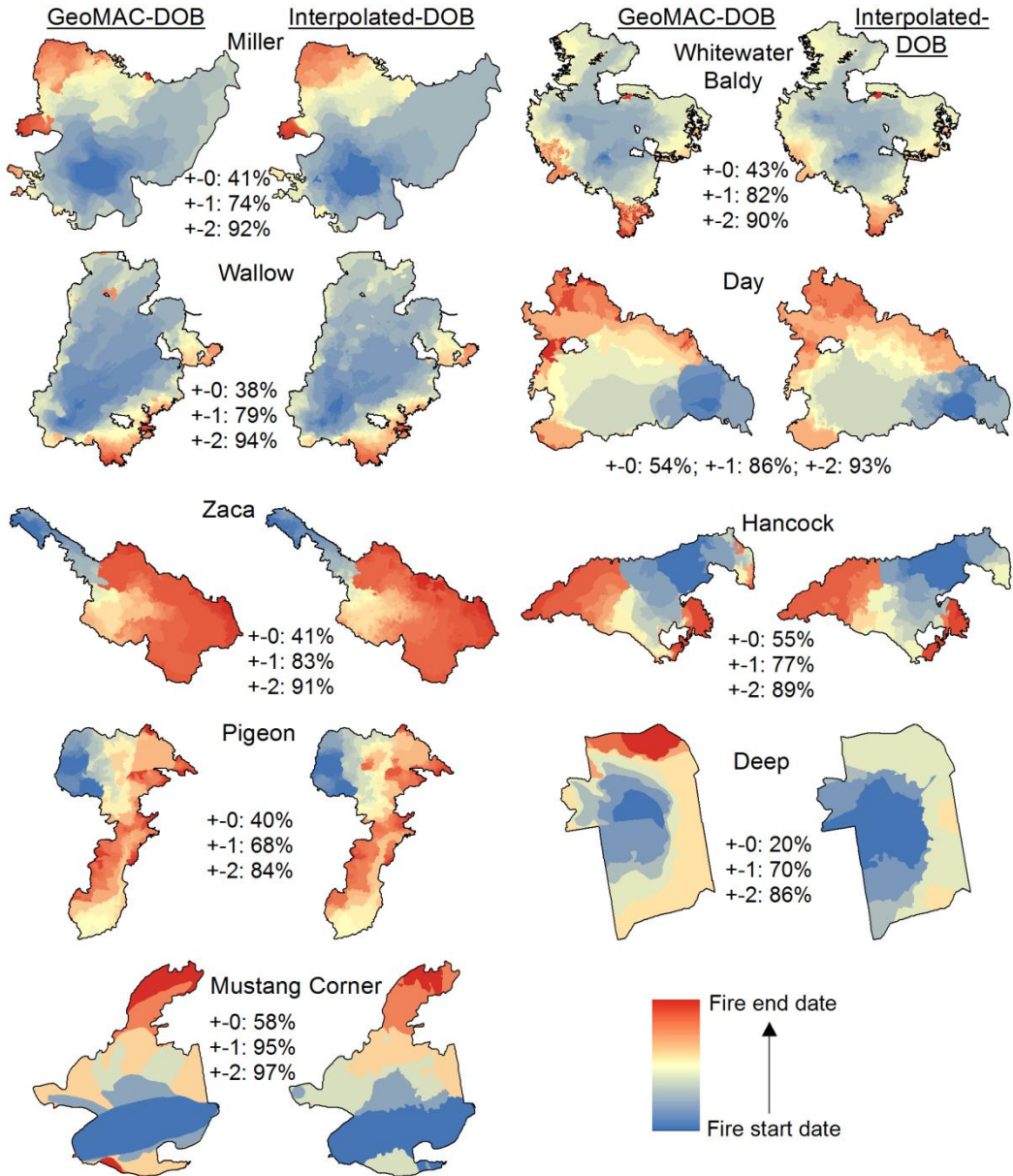
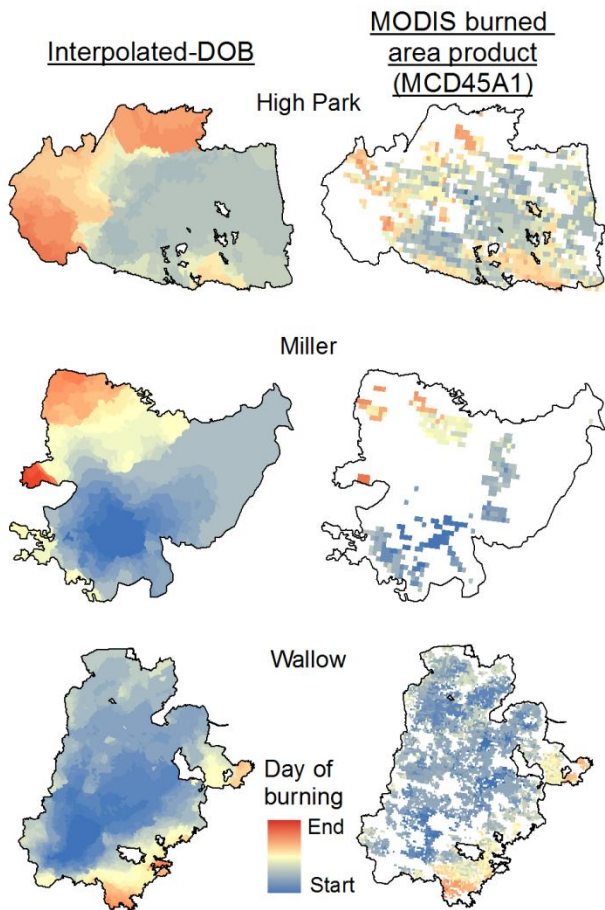


Figure 5. Interpolated (left) and MODIS burned area product (MCD45A1; right) day-of-burning for High Park, Miller, and Wallow fires.



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Chapter 3:

Ability of wildfires to limit the extent of subsequent fires

Abstract

Theory suggests that fire size can be limited by previous fires in landscapes with active fire regimes. However, empirical examples of this pattern-process feedback (also termed ‘self-regulation’) are surprisingly rare due to data limitations resulting from an overall lack of fires on the landscape due to fire exclusion policies. Given the increase in fire activity over the last ~25 years in the western US, there are now opportunities to evaluate these spatial feedbacks and explicitly quantify the ability of wildfire to limit the size, or extent, of subsequent fires. Understanding weather’s influence on the ability of wildfires to act as future fuel breaks is also necessary given that extreme fire-conducive weather may moderate this effect and may become more common in the future due to climate change. In this study, I evaluated the ability of wildfire to limit the extent of subsequent fires along a temporal gradient in four large study areas in the western US that have experienced substantial fire activity in recent decades. Using fire progression maps in conjunction with weather station data, I also evaluated the influence of daily weather in modifying the effectiveness of wildfire as a fuel break. Results indicate that wildfires do limit subsequent wildfire spread, but this effect decays over time; wildfires no longer act as fuel breaks ~6-17 years after a fire, depending on the study area. I also found that extreme weather substantially moderates this effect; the ability of wildfire to act as a fuel break is ~halved or more under extreme compared to more moderate weather

conditions in three of the study areas. These results will be useful to fire managers who seek to restore natural fire regimes or to exploit recent burns when managing fire.

Introduction

Wildland fire is an important ecological process in many ecosystems (Agee 1993); it alters vegetation composition and structure, consumes biomass, and influences landscape heterogeneity. Such fire-induced changes can influence subsequent fire behavior and effects via site- and landscape-level feedbacks (Agee 1999; Peterson 2002; McKenzie et al. 2011). For example, wildfires reduce fuel loads, and if fires recur before sufficient biomass has accumulated, the size and severity of subsequent fires may be limited (Collins et al. 2009; Parks et al. 2014). These feedback mechanisms are considered fundamental ecosystem properties of fire-adapted ecosystems of the western US (McKenzie et al. 2011) but have been largely disrupted in many ecosystems due to successful fire exclusion dating back to the 1930s (Heyerdahl et al. 2001; Taylor and Skinner 2003). Some areas of the western US, however, have experienced substantial fire over the last three decades, partially because some fires were not actively suppressed (termed “resource benefit fires”); these areas provide crucial natural laboratories to explicitly evaluate how these feedback mechanisms function.

Land managers are increasingly recognizing that fire exclusion is problematic for a number of ecological and social reasons. For example, fire exclusion is often cited as the cause of increased tree density and homogenizations in several forest types (Hessburg et al. 2005; Naficy et al. 2010), which in turn has contributed to increases in area burned and fire severity (Stephens 2005; Mallek et al. 2013). Fire suppression activities are

expensive (Gebert et al. 2007) and have a number of adverse ecological consequences such as high-intensity backburns, fireline construction, and fire retardant pollution (Backer et al. 2004). Finally, there is an increasing awareness that wildland fire is a necessary component of healthy ecosystems (Kilgore 1973; Hutto 2008). These factors, combined with acknowledgement that climate change will likely lead to more frequent fire (Littell et al. 2010; Westerling et al. 2011), have increased interest in explicitly and quantitatively evaluating how feedbacks between wildfire and subsequent wildfire operate.

Several recent studies have shown that fire severity is lower in areas that reburned within a previously recorded fire perimeter compared to those that did not (Arkle et al. 2012; Miller et al. 2012; Parks et al. 2014), clearly indicating a strong feedback between wildfire and subsequent fire severity. However, barring those that are inferential (Price et al. 2012; Parisien et al. In press) or involve fire simulation modeling (e.g., Davis et al. 2010), studies explicitly evaluating feedbacks between wildfires and subsequent wildfire size are extremely limited and inconsistent in their results. For example, Collins et al. (2009) found that wildfire indeed limited the size of subsequent fires in upper mixed-conifer forest in the Sierra Nevada, California, whereas Teske et al. (2012) found this effect in only one of three study areas in central Idaho and northern Montana. The ability of wildfires to act as a fuel breaks depends upon underlying contingencies such as time between fires (Peterson 2002), but only a couple of studies have evaluated this factor (Collins et al. 2009; Price and Bradstock 2010). There is a clear need for more information on how wildfires serve as fuel breaks and how this may change as time

between fires increases over a broad range of ecosystems and geographies of the western US.

Another understudied aspect of feedbacks between wildfire and subsequent fire size is the influence of weather. Mortiz (2003) suggested that extreme fire weather may override or moderate the effect of a previously burned area in limiting the extent of subsequent fires; this was substantiated by Collins et al. (2009) and Price and Bradstock (2010), who showed that the ability of a wildfire to act as a fuel break decreased as fire weather became more extreme. Further investigation over a broader range of geography and ecosystem types is needed to develop a more comprehensive understanding of fire-weather relationships, especially given the varying influence of bottom-up and top-down controls on fire regimes (e.g., fuels vs. weather) (Heyerdahl et al. 2001; Mermoz et al. 2005; Parks et al. 2012). Such information would be useful in anticipating how the effectiveness of wildfire as a fuel break may weaken under future climatic conditions, which is important considering that extreme fire weather is expected to become more common in the future (Nitschke and Innes 2008).

The first objective of this study was to determine if wildfires limit the extent of subsequent fires, and if so, how this effect changes as time between fires increases. I hypothesized that the effectiveness of wildfire as a fuel break will be greatest immediately after a fire and decay through time. Assuming a fuel break effect is found, my second objective was to determine if extreme fire-conducive weather conditions modify this effect. I hypothesized that the ability of wildfires to act as a fuel break will be weaker and decay faster with increasing fire weather conditions.

Methods

Study area

I conducted this study within four study areas composed entirely of protected areas (wilderness and national park) (Fig. 1), thereby limiting the confounding effects of mechanical fuel treatments that are common outside such areas. The FCW study area is composed of the Frank Church – River of No Return Wilderness in central Idaho. The adjacent SBW encompasses the Selway-Bitterroot Wilderness in western Montana and north-central Idaho. CCE (Crown of the Continent Ecosystem) is comprised of Glacier National Park and the Great Bear, Bob Marshall, and Scapegoat wilderness areas. Finally, GAL incorporates the Gila and Aldo Leopold Wilderness Areas in western New Mexico. These study areas were chosen because they have experienced substantial fire activity in recent decades and thus have enough data to evaluate the effectiveness of wildfire as a fuel break. Although a proportion of ignitions were managed as resource benefit fires in all study areas, some were also actively suppressed.

FCW (Frank Church – River of No Return Wilderness)

The FCW (9777 km²) is the second largest wilderness area in the lower 48 states. Mean annual precipitation is 871 mm and mean annual temperature is 2.7 °C (Daly et al. 2002). However, there is substantial intra-area variation in both mean annual precipitation and temperature (Fig. 2). In this and all study areas, mean annual precipitation is generally lowest in the low elevation river bottoms and highest on the mountain peaks; temperature exhibits the opposite pattern. FCW is rugged; elevations range from 600 to 3136 m. Topographic features include river breaks, deep canyons,

mountains, and glaciated basins (USDA Forest Service 2003). Park-like groves of ponderosa pine (*Pinus ponderosa*) exist below about 1500 m on south and west slopes (Barrett 1988). Denser ponderosa pine and Douglas-fir (*Pseudotsuga menziesii*) forests occupy north and east aspects, up to elevations of about 2100 m. Still higher, the vegetation transitions to grand fir (*Abies grandis*), lodgepole pine (*P. contorta*), and Englemann spruce (*Picea engelmannii*). At the highest elevations, subalpine fir (*A. lasiocarpa*), whitebark pine (*P. albicaulis*), and alpine environments predominate (Barrett 1988; Finklin 1988). The fire season runs from early-July to mid-September (USDA Forest Service 2013). Low-elevation, open ponderosa pine forests tend to experience frequent, low-intensity fires, and, generally, fire frequency decreases and severity increases with increasing elevation, moisture, and tree density (Crane and Fischer 1986). Fire suppression became effective in about 1935 (Finklin 1988) although sheep grazing may have excluded fire earlier (Steele et al. 1981). Resource benefit fires began to occur in ~1988 (Beckman 2008).

SBW (Selway-Bitterroot Wilderness)

The SBW (5471 km²) is the third-largest wilderness area in the lower 48 states. It includes the Bitterroot mountain range along the Montana and Idaho border and large portions of the Selway and Lochsa watersheds in Idaho. Mean annual precipitation in SBW is 1221 mm and mean annual temperature is 3.5 °C (Daly et al. 2002). Elevations range from 531 m in the Selway River drainage on the western edge to over 3000 m in the southeast portion of the study area. The vegetation of SBW is diverse. Lower elevations (up to ~1500 m) in the west and northwest portion of the study area are

characterized by Pacific maritime forests composed of western hemlock (*Tsuga heterophylla*), western red cedar (*Thuja plicata*), western white pine (*P. monticola*), and Douglas-fir (Rollins et al. 2002). Ponderosa pine is common at lower elevations in other portions of the study area, particularly on dry south-facing slopes (Brown et al. 1994). As elevation increases, Douglas-fir and grand fir are prominent on mesic sites and ponderosa pine, 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, whitebark pine, lodgepole pine, subalpine fir, and alpine larch (*L. lyallii*) (Rollins et al. 2002). At the highest elevations, alpine environments (i.e., barren or snow/ice) are common, especially along the Bitterroot divide. The fire season in SBW 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). Fires were actively suppressed until 1972; resource benefit fires were allowed to burn after this point (van Wagtenonk 2007). Cattle and sheep grazing was evident in the early 1900's (USDA Forest Service 1924), which may have decreased fire frequency within portions of SBW.

CCE (Crown of the Continent Ecosystem)

The CCE is the largest (10,331 km²) of the four study areas. Mean annual precipitation in CCE is 1243 mm and mean annual temperature is 2.2 °C (Daly et al. 2002) (Fig. 2). The CCE straddles both the east and west slopes of the continental divide.

The northern portion of is composed of Glacier National Park (GNP), where alpine glacial canyons drain into major river valleys (Barrett et al. 1991). South of GNP lays the Great Bear, Bob Marshall, and Scapegoat Wilderness Areas. Elevations in CCE range from 950 m near Lake McDonald in GNP to over 3100 m on the highest mountain peak (also in GNP). Although dependent upon fire history and soil texture, ponderosa pine, lodgepole pine, Douglas fir, western larch are the dominant tree species in low-elevation areas (< ~1500 m) (Arno 1980; Keane et al. 1994; Keane et al. 2006). Western hemlock and western red cedar are present in low-elevation (< 1500 m) wet areas that have been free of fire for extended periods of time (> ~100 years). As elevation increases the dominant species become lodgepole pine, subalpine fir, and Engelmann spruce. Whitebark pine and alpine larch are present near treeline (1800-2300 m elevation, depending on latitude); alpine environments are common above this elevation. Areas of ponderosa pine and mixed-conifer in CCE were historically maintained by low- and mixed-severity regimes (Arno et al. 2000; Keane et al. 2006); the effects of fire exclusion (dense understory and duff accumulation) are evident in these areas. Most of the study area (excluding alpine environments), however, is characterized by a mixed- to high-severity fire regime (Arno et al. 2000). The fire season runs from mid-July through September (USDA Forest Service 2013). Resource benefit fires began in the Bob Marshall wilderness in 1981 and in GNP in 1994.

GAL (Gila and Aldo Leopold Wilderness)

The GAL (3087 km²) is the driest and warmest of the four study areas; mean annual precipitation is 578 mm and mean annual temperature is 10.4 °C (Daly et al.

2002) (Fig. 2). Elevations range from 1462 to 3314 m. The topography is diverse, composed of mountains, broad valleys, steep canyons, and extensive mesas. At the lowest elevations, the vegetation is desert scrub and grasslands (*Ceanothus*, *Artemisia*, and *Yucca* spp.). As elevation increases, it transitions to piñon-oak-juniper woodland (*P. edulis engelmannii*, *Juniperus deppeana*, *J. monosperma*, and *Quercus* spp.), and then to ponderosa pine woodland and forest. The highest elevations are composed of Douglas-fir, Englemann spruce, white fir (*A. concolor*), subalpine fir, southwestern white pine (*P. strobiformis*), and aspen (*Populus tremuloides*) forests (Rollins et al. 2002). Although the fire season runs April through September, mid-summer fires are uncommon due to rains associated with monsoonal storms from the Gulf of Mexico (Rollins et al. 2002). Fires in GAL are generally frequent and 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). Extensive cattle and sheep grazing began in the 1890's, which substantially reduced fine fuel amount and continuity and caused a decrease in fire frequency (Swetnam and Dieterich 1985; Swetnam and Baisan 1996). Resource benefit fires began to occur in 1975 (Swetnam and Dieterich 1985).

Analyses

Development of geospatial fire atlas

Creating the geospatial fire atlas for each study area was a multi-step process. First, I obtained fire perimeters from the Monitoring Trends in Burn Severity (MTBS) project (Eidenshink et al. 2007), which has mapped the perimeter and severity of fires \geq

400 ha in the western US from 1984-2011. Next, I supplemented the MTBS fire perimeters by identifying and mapping all fires ≥ 20 ha from 1972-2012 using the entire record of Landsat data, including the multi-spectral sensor (MSS), thematic mapper (TM), enhanced thematic mapper plus (ETM+), and operational land imager (OLI) sensors. This was conducted by obtaining virtually all snow-free images for each study area from the US Geological Survey Center for Earth Resources Observation and Science (USGS-EROS) (available from <http://earthexplorer.usgs.gov/>) and identifying and mapping areas of change between image dates. Identifying and mapping fires with the MSS imagery (circa 1972-1984) relied primarily on evaluating differences between pre- and post-fire NDVI (normalized differenced vegetation index) (dNDVI). For the Landsat TM, ETM+, and OLI data (1984-2012), however, I delineated fire perimeters by evaluating differences between pre- and post-fire NBR (normalized burn ratio) (dNBR) (Key and Benson 2006). I converted the reflective and thermal bands of each Landsat scene into top-of-atmosphere reflectance and brightness temperature respectively, and produced multi-date comparisons of all NDVI/NBR scenes within each year. A linear grayscale was assigned to dNDVI and dNBR imagery typically in the range of -800 to +1100 for best contrast in delineating fire perimeters. To identify and map fires in GAL, I also used two relativized metrics of fire-induced change (RdNBR, Miller and Thode 2007; RBR, Parks et al. 2014) since these severity indices provided higher contrast in the more sparsely vegetated study area. Supplementary spatial data were also used to confirm the presence of fire, including Moderate Resolution Imaging Spectroradiometer (MODIS) fire detections (USDA Forest Service 2013) (2001-2012), National Interagency Fire Management Integrated Database (<https://fam.nwcg.gov/fam->

web/kcfast/html/ocmenu.htm) (1972-2012), Geospatial Multi-Agency Coordination Group fire perimeters (<http://www.geomac.gov/index.shtml>) (2001-2011), and various regional fire atlases for the Gila Wilderness (Rollins et al. 2001) (1972-1997), Northern Rocky mountains (Gibson 2006) (1972-2003), and the Flathead National Forest (<http://www.fs.usda.gov/detailfull/flathead/landmanagement/gis>) (1980-2012). All geospatial operations were conducted using either ArcMap 10.1 (ESRI Inc. 2012) or the “raster” package (Hijmans and van Etten 2011) within the R statistical program (R Development Core Team 2007).

Numerous MTBS fire perimeters were modified because they incorrectly mapped two fires from different years as one fire or where multiple MTBS fires in a year actually represented one contiguous fire or fire complex. The final product is a geospatial fire atlas for all fires ≥ 20 ha from 1972-2012. All fire perimeters were converted to raster format with a 30 x 30 meter pixel size (matching the resolution of Landsat TM, ETM, and OLI data).

Identifying limiting fire perimeters

Previous wildfires interact with subsequent fire by either stopping the spread or getting reburned by a subsequent fire. As such, I developed an objective and consistently applied rule-set to identify wildfire perimeters, or portions thereof, that either limited or did not limit the spread of subsequent fires. First, each pixel of each fire perimeter was evaluated to determine if it interacted with a subsequent fire, defined by either 1) a fire perimeter pixel is within 375 m of a subsequent fire or 2) a fire perimeter pixel is reburned by a subsequent fire. The 375 m distance threshold allows for error in wildfire

perimeter mapping due to the spatial and spectral diversity caused by variability in fire severity, vegetation type, and speed of vegetation recovery (Holden et al. 2005). Next, I determined whether interacting pixels did or did not limit the extent of subsequent fires. If a subsequent fire perimeter was ≤ 375 m as measured outwards from the initial fire perimeter and ≤ 750 m as measured inwards (i.e. the subsequent fire infiltrated the initial fire perimeter by ≤ 750 m), then I assumed that the pixel was limiting the extent of the subsequent fire (Fig. 3); hereafter, these proximal and interacting pixels are referred to as LIMITING. In this case, the 750 m threshold acknowledges that wildfires may limit subsequent fire size even though it may reburn along the perimeter of a previous fire. If a pixel from a subsequent fire perimeter infiltrated > 750 meters and reburned a previous fire, then I assumed that the subsequent fire was not limited in extent by the initial wildfire; hereafter, these interacting pixels are referred to as NOT LIMITING. If a pixel from a subsequent fire was > 375 m from a fire perimeter, I assumed that that there was no interaction and the pixel was excluded from further analyses (Fig. 3). Preliminary analyses indicated that many false-positives resulted from this rule-set (e.g. pixels were mislabeled as LIMITING, see Fig. 3d), prompting an additional step to minimize this occurrence: if greater than 35% of the area of the initial or subsequent wildfire overlapped, then all proximal pixels were identified as NOT LIMITING. All pixels from all fires were thus labeled as LIMITING, NOT LIMITING, or excluded from the analyses. To clarify, the analyses units are pixels along the perimeter boundary, or edge, of the initial wildfire; no pixels from the interior of the initial fire perimeter are analyzed.

Exploratory analyses indicated there are individual cases where the thresholds described above failed and perimeter pixels were seemingly mislabeled as LIMITING or

NOT LIMITING. I found that, although changing the thresholds may alleviate this issue for individual cases, it seemingly mislabeled pixels of other fires. I evaluated alternative thresholds in these exploratory analyses (250 and 500 m vs. 375 and 750 m); the results were surprisingly similar to those reported here, which suggests that minor changes in threshold values do not substantially change the findings of this study.

Statistical model

To quantify the ability of wildfires to serve as fuel breaks, and how this ability may change as time between fires increases, I built logistic regression models (using the logit function) with LIMITING vs. NOT LIMITING as the binary response variable and time between fires (years) as the explanatory variable. I built these models with two sets of data for each study area, one with all fires (≥ 20 ha) and another with large fires (≥ 400 ha). I built two models for two reasons. First, it is probable that some of the smaller fires in my study did not burn in a subsequent fire event although the fire perimeter data would indicate that it did (falsely labeling such pixels as NOT LIMITING). This is due to difficulty in identifying and mapping unburned islands within a fire perimeter. A model including only large fires reduces the chance of this occurring. Second, some have suggested that small fuel treatments are ineffective at limiting fire spread (e.g., Graham 2003); excluding small fires (< 400 ha) acknowledges this notion. Although the fire perimeter data span 41 years, I removed all interactions older than 25 years from the analysis. This was because initial data exploration indicated that there were only small amounts of data beyond 25 years between fires and there appeared to be no effect of wildfire as a fuel break beyond this time, although this could simply be due to the lack of

data. Model fits are evaluated with the area under curve calculation for the receiver operating characteristic curve (ROC) as calculated with the ‘verification’ package in R (NCAR - Research Applications Laboratory 2013).

To test for model significance while minimizing the effects of spatial autocorrelation, which tends to overfit models and inflate statistical significance (Legendre and Fortin 1989; Legendre 1993), I used a subsampling and multi-model approach similar to that described by Parisien et al. (2011). Specifically, for each logistic regression model described above and below, I generated a model ensemble using 2500 random subsets of data; the subsampling frequency was 1% of the full dataset. The model ensemble p-value for each variable (which is the average p-value of each of the 2500 models) was used to test whether or not the independent variables were statistically significant. I chose a 1% subsampling frequency based on Parks et al. (2014) who used ~0.1% subsampling frequency for two-dimensional data; since fire perimeter edges are linear, one-dimensional features, I assumed that this sampling frequency was appropriate. A 1% sampling frequency indicates that, on average, one pixel is selected for every 3 km of interacting fire perimeter in each random subset of data.

Incorporating weather into statistical models

To evaluate how weather conditions may affect the ability of a wildfire to limit subsequent fire extent, I built a second set of logistic regression models for each study area that also included a fire weather index (in addition to time between fires) as an explanatory variable. I used the energy release component (ERC) to represent fire weather, which is commonly used in fire studies (e.g., Abatzoglou and Kolden 2013;

Riley et al. 2013). ERC is related to the amount of heat released per unit area at the flaming front of a fire (Bradshaw et al. 1983) but can also be considered a fuel moisture metric that represents long term drying (Andrews et al. 2003). Daily ERC was generated using Fire Family Plus software (Bradshaw and McCormick 2000) and remote automated weather station (RAWS) data for stations within or in close proximity to each study area (Lodgepole RAWS for FCW, Hells Half Acre for SBW, Spotted Bear Ranger Station for CCE, and Beaverhead for GAL). ERC was calculated using the NFDRS fuel model G for all study areas except GAL, in which I used fuel model K.

I then assigned these daily ERC values to each 30 x 30 m pixel within each large fire that burned between 2001 and 2012 based on the estimated day of burning. Because agency generated fire progression maps were not available for a large number fires in my study, I estimated day-of-burning using the methods developed by Parks (2014), where day-of-burning for each 30 x 30 m pixel, and hence fire progression, was calculated by spatially interpolating Moderate Resolution Imaging Spectrometer (MODIS) fire detection data (NASA MCD14ML product, Collection 5, Version 1). Due to the coarse nature of the MODIS input data (1 km²), this process was limited to large fires and to fires burning after 2000 to coincide with the operational timeline of the MODIS sensors. MODIS fire detection data depict the date and location (i.e. pixel centroid) of actively burning MODIS pixels, and although the spatial resolution is relatively coarse (pixel size = 1km²), the fine temporal resolution (there are two MODIS sensors, each passing two times per day) allows day-of-burning to be mapped at finer spatial resolution via interpolation.

The models that incorporate weather employ a subset of data; they include only large fires (≥ 400 ha), and further, those large fires must interact with fires that occurred between 2001 and 2012. For example, a 1000 ha fire from 1990 that interacts with a 1500 ha fire from 1999 is excluded from the analysis because the 1999 fire occurred prior to MODIS; it is also excluded if it interacts with a 300 ha fire from 2003 because the 2003 fire was too small to use day-of-burning interpolation. However, if the same fire interacts with a 1500 ha fire from 2003, then it is included in the analysis since MODIS data can be used to estimate day of burning for the subsequent 2003 fire. For each interacting fire perimeter pixel, I extracted the daily ERC value that was associated with the subsequent fire. In those cases when a wildfire did not technically overlap but was within 375 m from a subsequent fire, I used the day-of-burning estimate, and hence the ERC value, of the nearest pixel of the subsequent fire. I assessed significance of ERC using the subsampling and model ensemble approach described above. Interactions between time and ERC were not evaluated for simplicity.

Results

A total of 1038 fires and 437 large fires were identified between 1972 and 2012 across all study areas. A majority of these ($> 60\%$) interacted with a subsequent fire (Table 1). The FCW had the highest number of large fires and the greatest amount of total area burned. SBW had the most fires (≥ 20 ha) ($n=373$) during this time period, but on average, those fires were smaller compared to the other study areas (average fire size in SBW = 685 ha). GAL (the smallest study area), on the other hand, experienced the

least number of fires (≥ 20 ha). Proportionally, CCE burned the least (0.30) over the 1972-2012 time period whereas GAL burned the most (1.12) (Table 1).

In all study areas, the proportion of pixels defined as LIMITING generally decreased as time until subsequent fire increases (Fig. 4) for both sets of wildfires analyzed (all fires and large fires). Consequently, the logistic regression models indicate that the ability of wildfires to limit the extent of subsequent fires is strongest immediately after a fire but decays over time (Figs. 4 and 5). Wildland fires no longer act as an effective fuel break (defined here as a ≤ 0.30 probability of limiting extent of subsequent fire) after ~ 6 years in GAL and ~ 16 in the three northern study areas (Figs 4 and 5; Table 2). Overall, the relationship between the effectiveness of fire as a fuel break and time between fires is distinctly different in GAL (i.e. it is weaker and decays faster) compared to the northern study areas of FCW, SBW, and CCE (Fig. 5). Large wildfires in FCW, SBW, and CCE are over 75% effective at limiting the extent of subsequent wildfires for up to four years, diminishing to $\sim 50\%$ 11 years after wildfire (Fig. 5). Model fits, as measured with the ROC statistic, range from 0.72 (FCW) to 0.82 (GAL) for the models including all fires and range from 0.77 (FCW and SBW) to 0.87 (CCE) for those including large fires. The model ensembles with randomly subset data indicate that all models are statistically significant ($p \leq 0.001$).

In all study areas, the ability of wildfire to act as a fuel break weakens with increasing fire-conducive weather conditions (Fig. 6). For example, ten years after wildfire in CCE, the ability of fire to act as a fuel break is very high under moderate conditions (probability = 0.97; 50th percentile ERC) but is very weak and no longer acts as an effective fuel break under extreme conditions (probability < 0.30 ; 99th percentile

ERC). The length of time in which wildfire no longer acts as an effective fuel break (again defined as ≤ 0.30 probability of limiting extent of subsequent fire) is substantially shorter under extreme vs. moderate weather conditions (99th vs. 50th percentile ERC) (Fig. 6; Table 2). In GAL, for example, wildfire no longer acts as a fuel break after two years under extreme conditions compared to eight years under moderate conditions. The influence of ERC was statistically significant ($p \leq 0.03$ in all study areas) according to the model ensembles. Delta ROC values (comparing a model with and without ERC) ranged from 0.00 (FCW) to 0.05 (CCE).

Discussion

Theory suggests that in landscapes with an active fire regime, landscape pattern is shaped by wildfire, but wildfire is also shaped by landscape pattern. This pattern-process feedback loop, also termed self-regulation, is a fundamental concept in disturbance ecology (Turner 1989; Agee 1999) and underscores the importance of wildfire in creating and maintaining resilient landscapes (McKenzie et al. 2011). The results of this study clearly indicate that wildfires act as fuel breaks and limit the extent of subsequent wildfires across my four western US study areas, supporting the notion of self-regulation in landscapes with active fire regimes. The strength of this feedback, however, decays over time and is completely diminished by ~6-16 years after a wildfire, depending on the study area. This suggests that the “ecological memory”, defined as the degree to which ecological processes are shaped by past disturbance events (Peterson 2002), at least in terms of wildfire’s ability to act as a fuel break, is relatively short. However, the pattern-process feedback loop of wildfire not only limits subsequent fire extent, but limits

subsequent fire severity (Parks et al. 2014), an effect that can last for decades (Miller et al. 2012), suggesting that the ecological memory of wildfire in terms of subsequent fire severity is much longer. Since federal agencies spend millions of dollars each year on fuel treatments to reduce fire hazard and risk in fire prone landscapes (Allen et al. 2002), it is critical to understand how wildfires may also serve as fuel treatments, both in terms of how they limit subsequent fire extent and severity. As such, my study has the potential to help managers make more informed decisions about how to best manage a particular wildfire through assessing its potential longevity for constraining future fires and understanding the limitations under extreme weather conditions.

In terms of time between fire events, my findings are broadly similar to those of Collins et al. (2009), who also found that the ability of fire to act as a fuel break decays over time. My findings, however, are less consistent with those of Teske et al. (2012), who found that wildfire limited the extent of subsequent wildfires in only one of the three study areas they examined. I evaluated the same three study areas (FCW, SBW, and CCE) as Teske et al. (2012) and found that wildfires definitively act as fuel breaks in all three areas, especially in the immediate years following a fire, so it is somewhat surprising that our findings are not in agreement. The likely explanation for the lack of agreement involves methodological differences; Teske et al. (2012) did not include a statistical evaluation of time between fires in their analyses, and in not doing so, may have muted the statistical signal of fire as a fuel break. Given my findings that wildfire's ability to act as a fuel break decays relatively quickly and is completely diminished by ~16 years after a fire in these study areas, investigations of this sort should explicitly address time between fires.

In all study areas, the effectiveness of wildfire as a fuel break weakens with increasing fire weather, which was also noted Collins et al. (2009). In fact, my results indicate that, in three out of four study areas, the longevity of the ability of fire to act as a fuel break effect is at least ~halved or more under extreme (99th percentile ERC) compared to more moderate fire-season weather conditions (50th percentile), thereby supporting the assertion that the importance of fuels diminishes during extreme weather events (Bessie and Johnson 1995; Price and Bradstock 2011). Nevertheless, my results indicate that fuels, or lack thereof due to burning, strongly limit fire (probability of limiting subsequent fire ≥ 0.65) in the northern study areas for at least three years following fire even under extreme conditions. Conversely, in GAL, which is generally comprised of dry conifer forest, the ability of fire to act as a fuel break lasts for only two years (probability ≤ 0.3) under extreme fire weather conditions; a study by Price and Bradstock (2010) revealed similar findings in a dry forest in Australia. From a climate change perspective, extreme weather conditions are projected to become more common (Salinger 2005; Nitschke and Innes 2008), and in fact, there is evidence that such changes are already occurring (Collins 2014). As such, the strength and longevity of wildfire in limiting the extent of subsequent fires will be likely be reduced in future years, reinforcing the results from other studies suggesting that climate change will result in higher fire activity in many areas of the western US (Westerling and Bryant 2008; Littell et al. 2010; Moritz et al. 2012).

Some studies have argued that the distribution of fire sizes is dictated by endogenous factors, implicitly implying that fuel availability solely drives fire sizes (Malamud et al. 1998; Turcotte and Malamud 2004). Others, however, have argued that

exogenous factors such as weather are responsible for fire size distributions (Boer et al. 2008). Our results suggest that both fuel availability and weather (endogenous and exogenous factors) are responsible for fire sizes, supporting the assertion of Moritz et al. (2005) who posit that fire size is controlled by multiple factors. Our results further suggest that the influence of weather may vary among regions, being more influential in CCE and GAL (based on improved model fits and relative decreases in the longevity of wildfire to act as a fuel break under extreme conditions [Table 2]). These differences may be due to factors such as variability in vegetation and drought frequency (Wang et al. In press). However, these differences could also be because the fire weather data may imperfectly represent the conditions influencing some fires because the procedure I used to estimate day-of-burning, and therefore ERC, has a moderate degree of uncertainty (Parks 2014), meteorological conditions are highly spatially heterogeneous (Holden and Jolly 2011), and weather station siting may bias observations (Myrick and Horel 2008).

Pyrogeographic differences among the study areas are evident and are likely due to differences in climate and ecosystem response to fire (Keeley et al. 2008; Freeman and Kobziar 2011). The southwest study area in particular, composed of the Gila and Aldo Leopold Wilderness areas (GAL), is strikingly different than the other three study areas in terms of the strength and longevity of wildfire to act as a fuel break. This difference is likely a reflection of differences in climate and fire regime characteristics in GAL. The fire regime in GAL is for the most part characterized by frequent surface fire dependent upon fine fuel availability and continuity (Schoennagel et al. 2004). As such, large fire years tend to occur one to three years after a wet (i.e. high precipitation) year (Swetnam and Baisan 1996); fine fuel growth and accumulation stimulated during wet years

therefore erases the effects of the previous fire in terms of its ability to act as a fuel break and, consequently, wildfires are not likely to act as fuel breaks for periods of time exceeding ~6 years. In contrast, the other study areas generally experience less frequent but higher severity fires (Parks et al. 2014) that are more dependent upon ladder and canopy fuels (Schoennagel et al. 2004). Such ladder and canopy fuels take longer to recover after fire, hence the increased longevity of fire as a fuel break in FCW, SBW, and CCE. I suggest similar studies should be conducted in other study areas representing different ecosystems (e.g., chaparral and boreal systems) to gain a broader pyrogeographic perspective. Broader theoretical perspectives may also be necessary, because although fire may act as a fuel break *if* a subsequent fire occurs nearby, the probability of a subsequent fire interacting with a previous fire may be quite low (e.g., Price et al. 2012).

Several aspects of my analyses likely influence the results of this study. First, I assumed that a wildfire limited the extent of a subsequent wildfire if pixels on the perimeters of both wildfires were proximal. Because other features such as mountain ridges or rivers may influence fire boundaries, this assumption may not always hold true. However, given the strong signal of time between fire events, I surmise this assumption has a negligible influence on my results. Second, it is possible that a wildfire limited the extent of a subsequent wildfire even if infiltrated it by more than 750 m (I labeled these pixels as NOT LIMITING). Due to the logistic regression framework utilized in this study, it was necessary to define perimeter pixels in a binary fashion. The implication of this second issue is that I potentially underestimate the strength and longevity of wildfire's ability to limit the extent of subsequent fires. Third, when mapping the fire

perimeters with satellite data, it is possible that I may have falsely identified other types of disturbance as fire. I assume, however, that the errors of this sort are negligible since fuel treatments do not occur in my study areas (because they are inside wilderness or national parks) and vegetation changes due to insect and disease (e.g., bark beetle) are too subtle to be detected using my methods given that their full effects often take multiple years to manifest (Meigs et al. 2011).

Conclusion

My findings show that wildfires clearly limit subsequent fire size. This effect is strongest immediately after fire, decays over time, and lasts for ~6-16 years, depending on the study area. Furthermore, my findings show that increasing fire weather diminishes the ability of fire to act as a fuel break. As such, fire managers can potentially use my results to aid in assessing whether any particular fire scar will act as a fuel break based its age and the projected weather. However, managers should also consider that, even if a past fire scar does not stop the progression of a wildfire and it reburns within a past fire perimeter, the fire severity will likely be limited (Miller et al. 2012; Parks et al. 2014).

More broadly, however, the numerous fires that have occurred over the last couple of decades in the western US potentially provide opportunities for managing fire in a different manner. That is, in forested landscapes that have experienced relatively recent fire (< ~25 years), there are now opportunities to reevaluate fire suppression policies and allow more fires to play their natural ecological role. Although this management strategy may not be advantageous in some landscapes, such as those at risk of invasion by non-native species (Keeley et al. 2011), it has several potential benefits.

For example, allowing more fires to burn in certain situations will reduce landscape homogeneity and create more resilient landscapes in which the self-regulating feedback mechanisms of fire can be better realized (Keane et al. 2002), thereby reducing fire suppression costs and increasing firefighter safety. Furthermore, landscapes with active fire regimes may be more resilient to other types of disturbance (i.e. insect and disease outbreaks) (Bebi et al. 2003; Kulakowski et al. 2012). Lastly, ongoing fire disturbance offers the opportunity for establishment of species that are better aligned with the emerging climate, thereby acknowledging that vegetation communities and fire regime characteristics will change with shifts in climate (Westerling et al. 2011; Smith et al. 2014).

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Tables

Table 1. Summary of fires in each study area from 1972-2012.

Study area	Number of fires	<u>All fires</u>		Number of fires	<u>Large fires</u>	
		Number that interact with subsequent fire ^a	Area burned (ha) [proportion of study area]		Number that interact with subsequent fire ^a	Area burned (ha) [percent of study area]
FCW	297	234	862,373 [0.88]	147	123	843,574 [0.86]
SBW	373	225	255,454 [0.47]	125	71	225,698 [0.41]
CCE	189	78	307,228 [0.30]	77	33	297,678 [0.29]
GAL	179	138	345,334 [1.12]	88	56	334,137 [1.08]
Total	1038	675	1,770,389	437	283	1,701,087

^aThese values reflect only those fires that interact with a subsequent fire within 25 years (see Methods).

Table 2. Number of years until wildfires no longer serve as an effective fuel break (defined as having a ≤ 0.30 probability of limiting the extent of subsequent fire). Values reflect model fits (e.g., Figs. 5 and 6) with and without ERC as an explanatory variable.

Study area	<u>Time only models</u>			<u>Time plus ERC models</u>			
	All fires ^a	Large fires ^b	No ERC (n) ^c	ERC 50 th	ERC 75 th	ERC 90 th	ERC 99 th
FCW	16	16	16 (111)	18	17	15	13
SBW	18	18	17 (66)	24	20	17	13
CCE	15	14	14 (32)	24	19	16	10
GAL	6	7	5 (54)	8	5	4	2

^aThese values reflect the model that include fires ≥ 20 ha (Fig. 5a).

^bThese values reflect the model that include fires ≥ 400 ha (Fig. 5b).

^cThese values reflect a model using the subset of fires used in the models that include elapsed time and ERC, but excludes ERC (see Methods); these values are more directly comparable to the values in the columns to the right that include both elapsed time and ERC. The number of fires evaluated in the models evaluating elapsed time and ERC is provided in parentheses.

Figures

Figure 1. Locations of the four study areas in the western US.

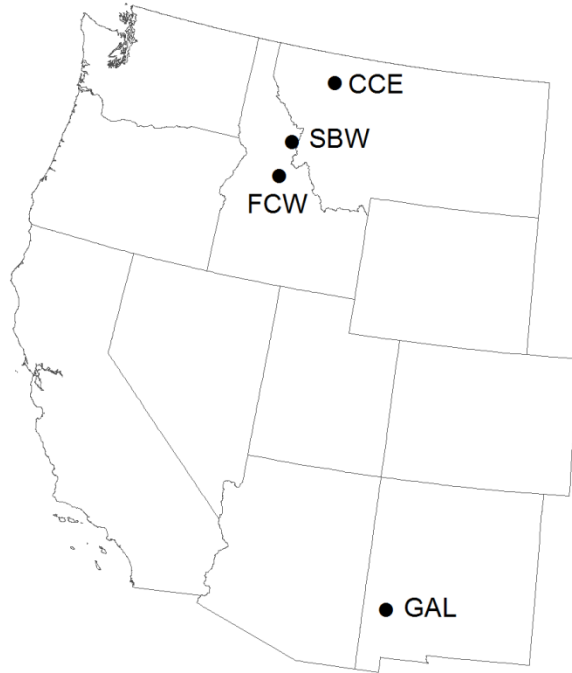


Figure 2. The four study areas for which I evaluated the ability of previous wildfires to limit the extent of subsequent wildfires. The boxplots depict the variability in mean annual precipitation and mean annual temperature within each study area (Daly et al. 2002); boxes represent the inter-quartile range, whiskers extend to the 5th and 95th percentiles, horizontal lines represent the median, and solid dots the mean.

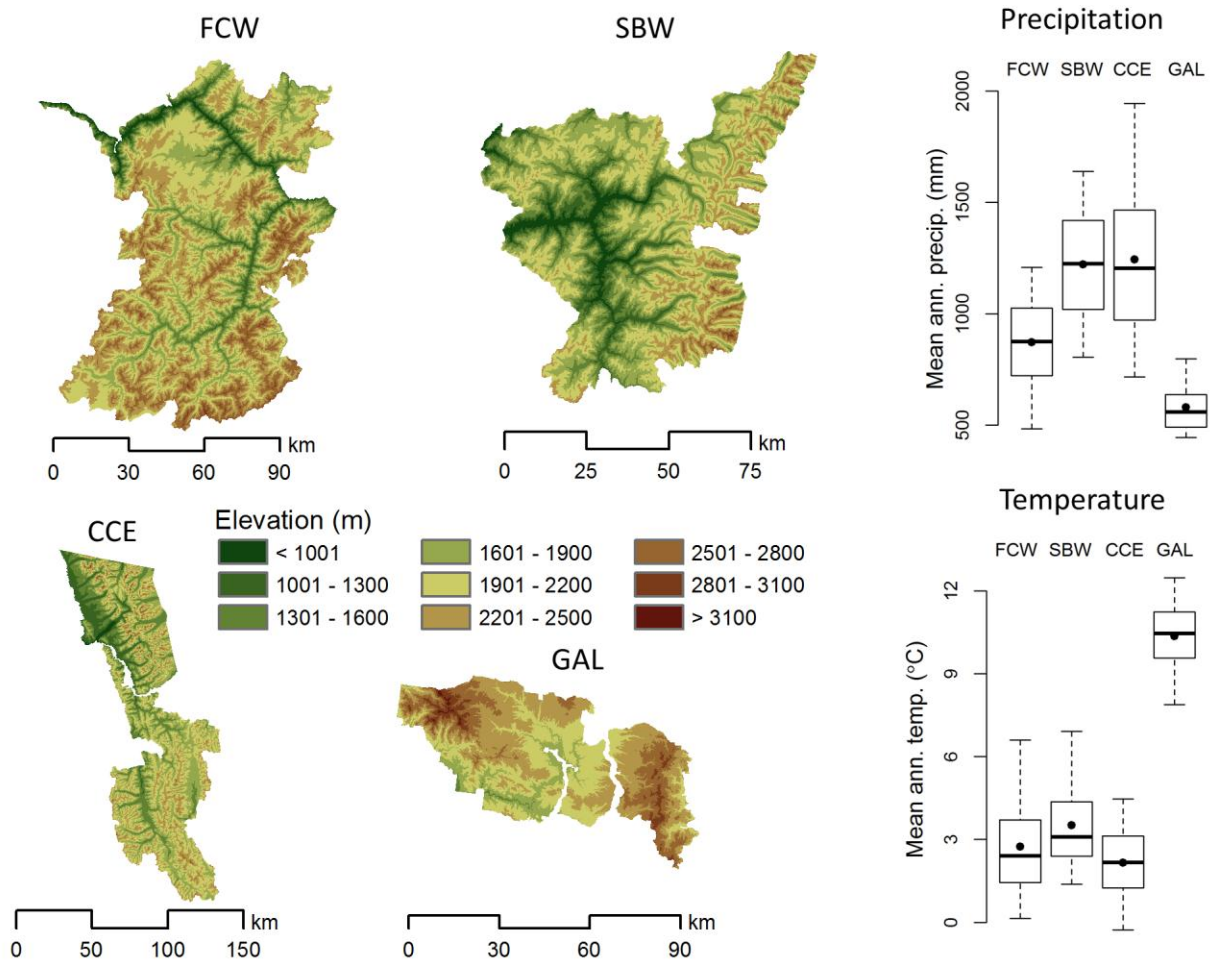


Figure 3. Examples from SBW depicting how pixels were defined as LIMITING or NOT LIMITING. In all examples, the initial wildfire has a blue (LIMITING), red (NOT LIMITING), or brown (not analyzed) perimeter and the subsequent fire is solid gray. In panel (a), a 2007 wildfire that interacts with a subsequent 2008 wildfire. Blue pixels are those defined as LIMITING and are ≤ 375 m (as measured outwards) or ≤ 750 m (as measured inwards) from the subsequent fire perimeter. Those pixels that do not interact with a subsequent fire (brown line) are excluded from the analyses. In panel (b), all pixels from the 2000 wildfire are NOT LIMITING since the 2007 wildfire burned over the entire 2000 wildfire and are > 750 m from the 2007 fire perimeter boundary (as measured inwards). In panel (c), some portions of the 2008 wildfire infiltrate the 2007 wildfire beyond 750 m; such pixels are defined NOT LIMITING. In panel (d), a large proportion of the perimeter of the 2005 wildfire is proximal to the perimeter of the 2012 wildfire. However, since $> 35\%$ of the 2005 wildfire overlaps with the 2012 wildfire, all proximal pixels are labeled NOT LIMITING (see Methods).

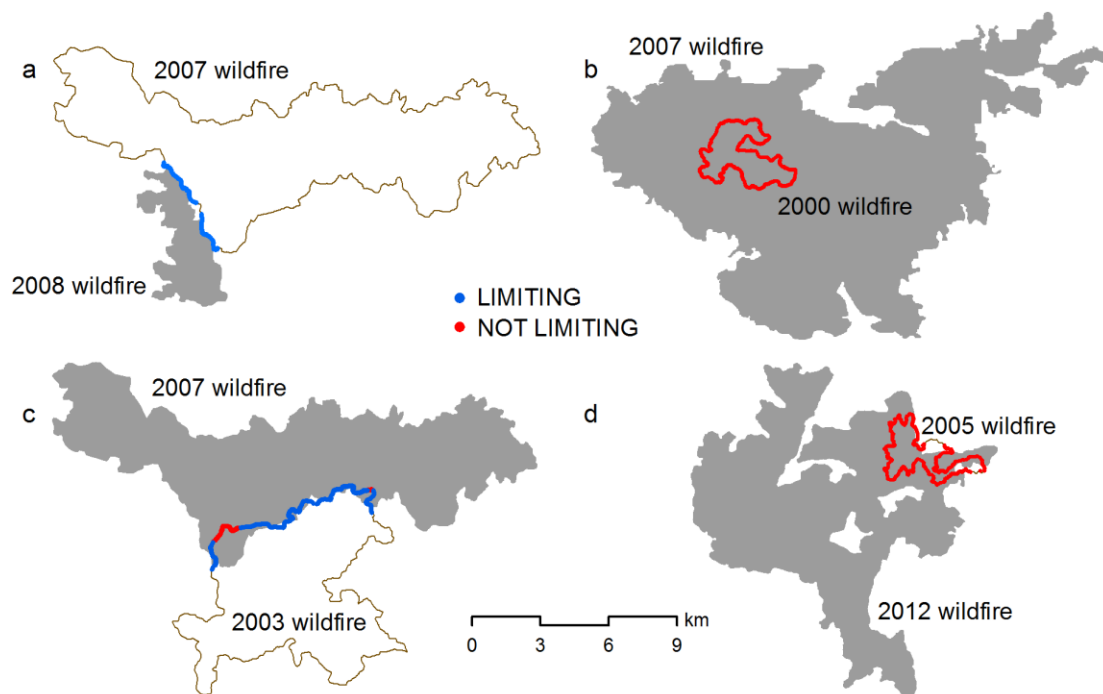


Figure 4. Data depicting proportion of pixels defined as LIMITING (y-axis) along a gradient depicting time until subsequent fire (x-axis). Sizes of circles represent the relative number of pixels for each time until subsequent fire within each study area. Red lines show the predicted logistic regression fit. ROC values are provided in Fig 5.

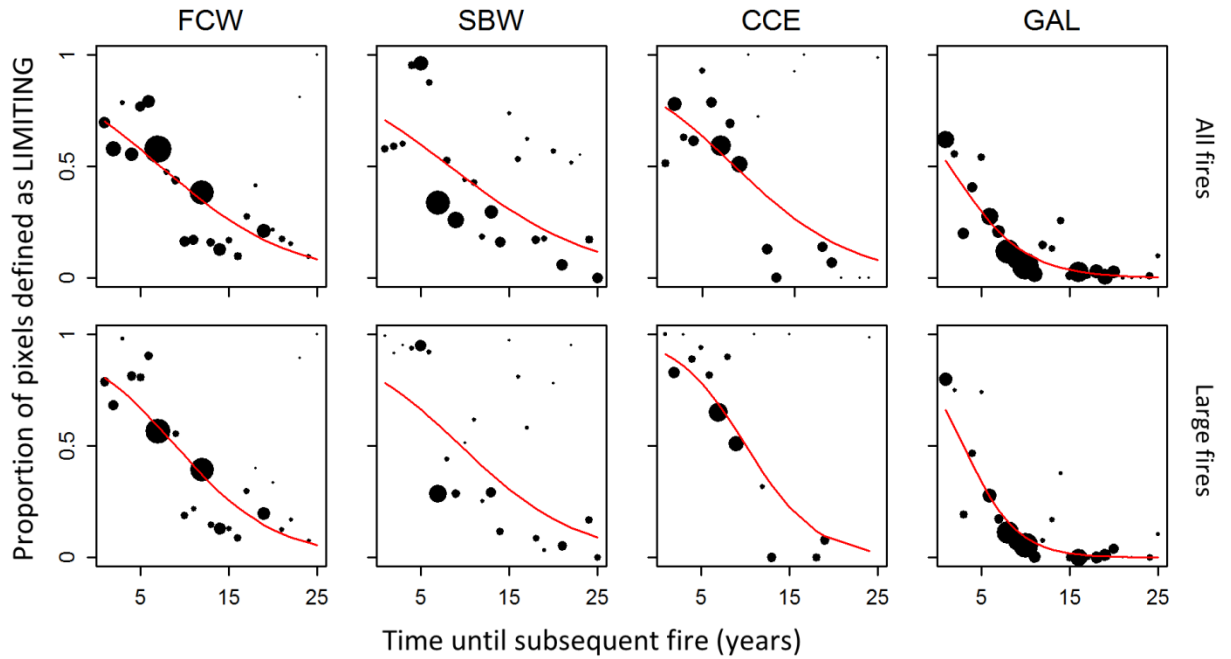


Figure 5. Response curves depicting the probability of a wildfire limiting the extent of subsequent fire over time for each study area for small (a) and large fires (b). The receiver operating characteristic, area under the curve statistic (ROC) is shown for each fit. These models fits were generated using all pixels (the model ensembles were used to test for statistical significance). The horizontal dashed line represents the threshold (0.30 probability) at which wildfires no longer act as an effective fuel break.

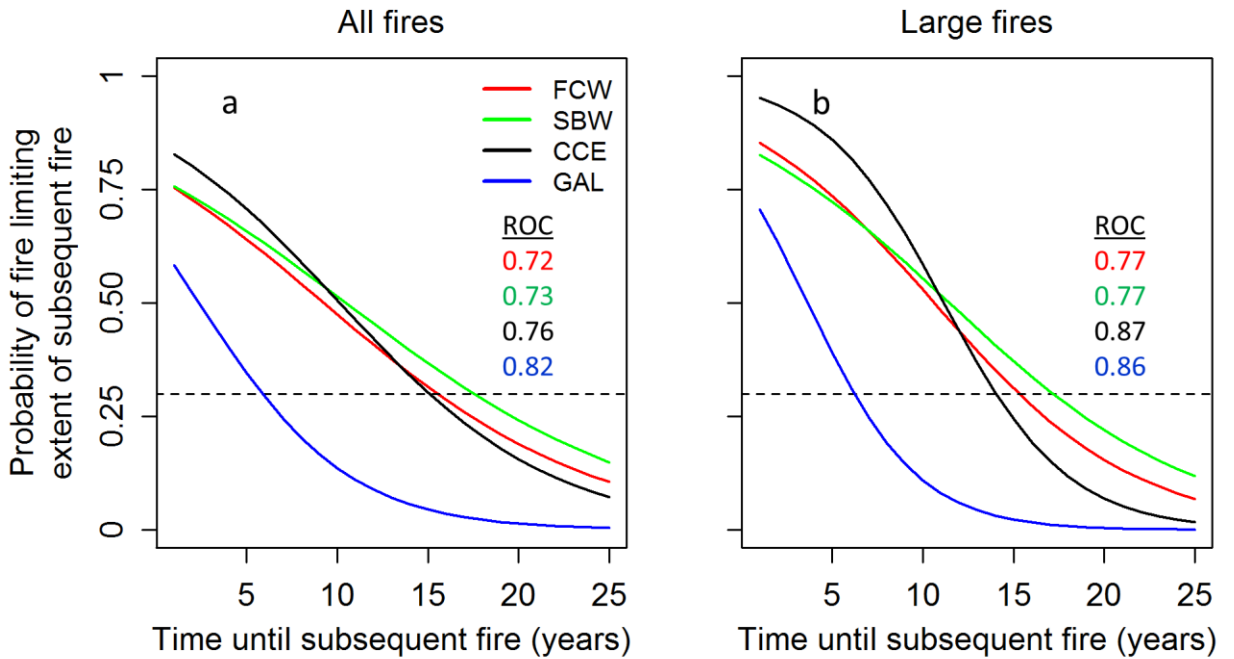
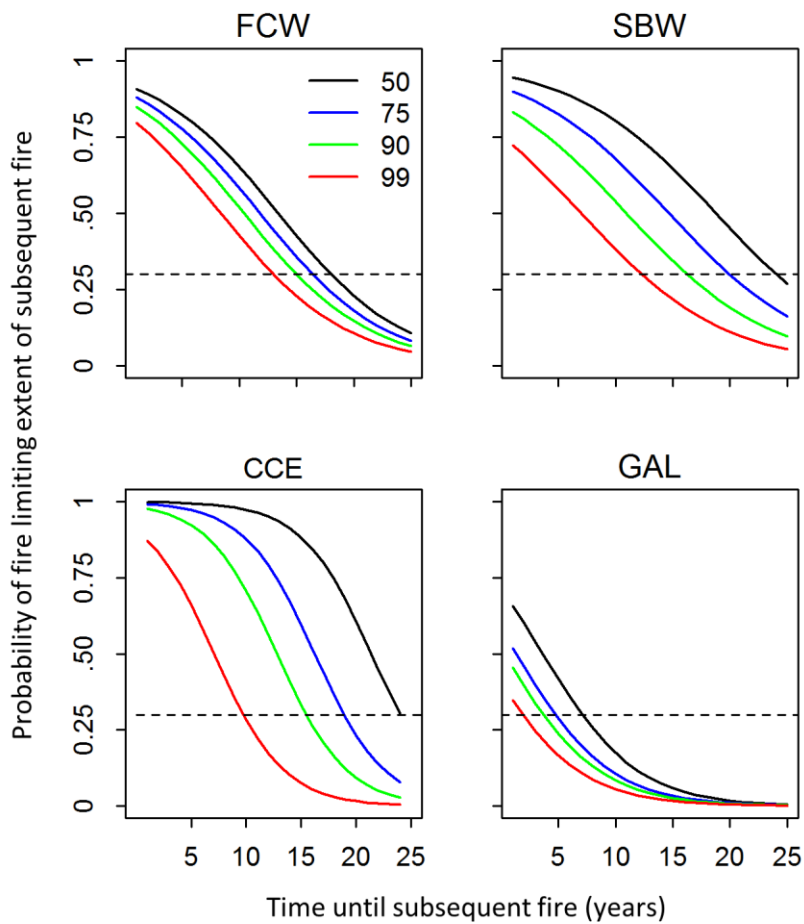


Figure 6. Response curves depicting how the probability of fire limiting the extent of subsequent fire varies by ERC. The contribution of ERC is statistically significant ($p \leq 0.05$) in all study areas according to each 2500 model ensemble. All ERC percentiles are study area specific and determined using ERC values occurring within the fire season; I defined the fire season as the beginning and ending date that encompassed 95% of the MODIS fire detections (USDA Forest Service 2013) for each study area. The horizontal dashed line represents the threshold (0.30 probability) at which wildfires no longer act as an effective fuel break.



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