

# Previous Fires Moderate Burn Severity of Subsequent Wildland Fires in Two Large Western US Wilderness Areas

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## 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, we analyzed 117 wildland fires in 2 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-m resolution. We 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 around 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 to anticipate the consequences of allowing fires to burn and provide rationale for using wildfire as a “fuel treatment”.

**Key words:** burn severity; dNBR; fire history; interacting fires; reburn; wilderness; wildland fire use.

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## 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 and others 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 and others 2005; Naficy and others 2010). Such changes are thought to be partly responsible for recently observed increases in area burned and burn severity (Stephens 2005; North and others 2009), although a warming climate has also been implicated (McKenzie and others 2004; Westerling and others 2006; Miller and others 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 (Backer and others 2004), has 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 and others 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 and others 2000).

Theory suggests that landscapes with intact fire regimes are more “self-regulating” than those with disrupted regimes (Agee 1999; Peterson 2002; McKenzie and others 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 and others 2011) and the primary rationale for prescribed and resource benefit fires in forested ecosystems (Stephens and others 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 U.S. 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 and others 2012) and forests in northwestern California that burned at least twice had proportionally less high severity fire compared to forests that burned once (Miller and others 2012). Numerous other studies have focused solely on areas that have burned twice or more in recent decades (that is, reburn studies) (Thompson and others 2007; Collins and others 2009; Holden and others 2010; van Wagtenonk and others 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 and others 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 because no comparisons were made to areas that have not experienced recent fire.

We 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. We 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; we hypothesize that burn severity in areas that have reburned (that is, burned at least twice during the study period) is lower compared to severity in those areas that have not reburned. (2) Assuming a re-burn 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 and others 2007). (3) Assuming a re-burn effect is found in objective 1, examine how this effect varies over time since previous burn; we 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 to no vegetation management (that is, logging), even before they were legally established as wilderness (1964/1980 [Gila/Aldo Leopold] and 1980 [FCW]). 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 our study, containing diverse vegetation types and a sufficient number of wildland fires and reburns to analyze.

#### Gila-Aldo Leopold Wilderness Complex (GAL)

The GAL (3,190 km<sup>2</sup>) comprises both the Gila and Aldo Leopold Wilderness Areas (Figure 1). Elevations range from 1,462 to 3,314 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 (*Abies concolor*), subalpine fir (*A. lasiocarpa*), southwestern white pine (*P. strobiformis*), and aspen (*Populus tremuloides*) forests (Rollins and others 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 and others 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 and others 2009). Extensive cattle and sheep grazing began in the 1890s, 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 around 1975 (Swetnam and Dieterich 1985). Between 1984 and 2008, a total of 72,226 ha burned once, whereas 50,004 ha reburned (Figure 1).

#### Frank Church—River of No Return Wilderness (FCW)

The FCW (9,574 km<sup>2</sup>) is the second largest wilderness area in the lower 48 states. FCW is rugged; elevations range from 600 to 3,136 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 1,500 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 2,100 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*

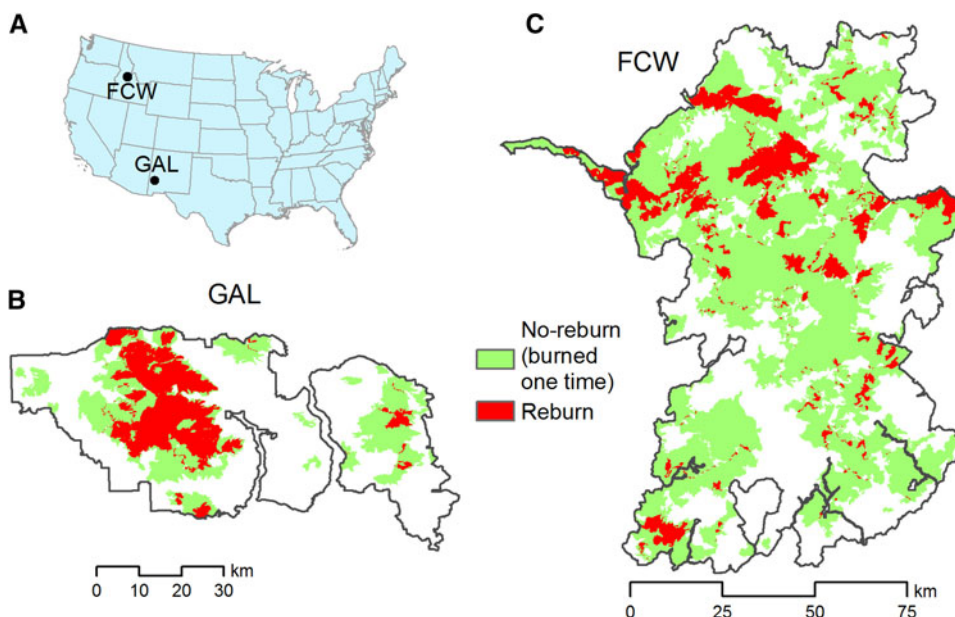


Figure 1. The general location of the study areas within the U.S. (A) and areas that have experienced no-reburn (green shading) versus areas that reburned (red shading) between 1984 and 2008 within GAL (B) and FCW (C).

*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 and others 1981). Resource benefit fires began to occur in about 1988 (Beckman 2008). Between 1984 and 2008, a total of 498,067 ha burned once, whereas 91,671 ha reburned (Figure 1).

## Data

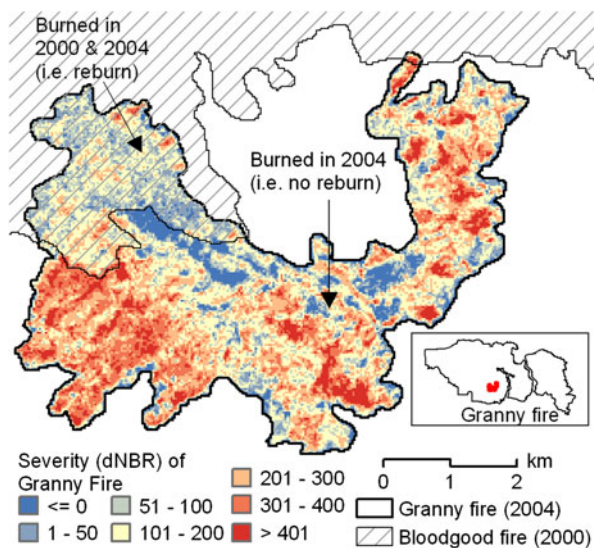
Burn severity data were obtained from the Monitoring Trends in Burn Severity (MTBS) project (Eidenshink and others 2007), which has mapped burn severity as the differenced normalized burn ratio (dNBR) of large ( $\geq 400$  ha) wildland fires in the U.S. since 1984 (through 2008 when this study was conducted) at a 30-m resolution using Landsat 4 and 5 Thematic Mapper and Landsat 7 Enhanced Thematic Mapper-Plus satellite imagery (Figure 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 1 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 our study areas (Holden and others 2009; Arkle and others 2012).

MTBS also provides *relative* differenced normalized burn ratio (RdNBR) data (Miller and Thode 2007), as well as discrete severity classes (for example, low, moderate, and high). We used dNBR (vs. RdNBR) because it is generally equal to or better than RdNBR at representing field-based measures of burn severity (Soverel and others 2010; Cansler and McKenzie 2012). We also used dNBR (vs. the discrete severity classes) because we required a continuous representation of burn severity.

To minimize the effect of minor mapping errors, we used a “reverse buffer” and analyzed only pixels at least 100 m 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 to 2008 were analyzed; to qualify as a “reburn”, a pixel must have burned at least twice during this time period. We refer to pixels that burned only once during this time period as “no-reburn.”

Additional spatial data to evaluate objective 2 (that is, 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 and others 2007). The fire history variables (severity of previous fire [P.dNBR] and time since previous fire [TIME]) were generated using MTBS data (Eidenshink and others 2007). Because fuels data (amount, type, and structure) were not available for every year of the study period, we 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



**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.



**Table 1.** Predictor Variables Evaluated for Inclusion into the Models

Variable type	Variable name	Variable description	Data range (5th–95th percentile) <sup>1</sup>	Source
Fire history	P.dNBR	dNBR of the previous fire	–64 to 782 (FCW) –29 to 351 (GAL)	Eidenshink and others (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	
Vegetation	NDVI	Pre-fire normalized differenced vegetation index	0.20–0.65 (FCW) 0.25–0.49 (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 <sup>2</sup> )	761–1555 (FCW) 1288–1932 (GAL)	Fu and Rich (2002)
	TPI300	Topographic position index: 300 m scale	–50 to 54 (FCW) –42 to 42 (GAL)	Weiss (2001)
	TPI2000	Topographic position index: 2000 m scale	–307 to 288 (FCW) –124 to 155 (GAL)	Weiss (2001)

None of the variables are highly correlated ( $r < 0.7$ ).

<sup>1</sup>These values characterize those areas that returned during our analysis window.

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 less than 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 we evaluated (Table 1) were found to be predictive of high-severity fire (Dillon and others 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 our 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*

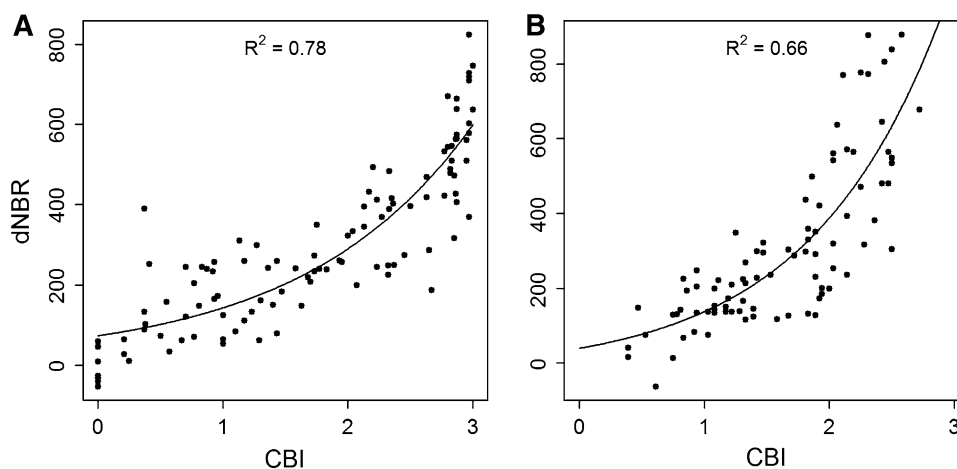
To determine if the presence of previous wildland fires affect burn severity of subsequent fires (hereafter, we term this the “reburn effect”), we calculated the mean and median dNBR in reburn and no-reburn pixels in each study area. We also used a Kolmogorov–Smirnov test to determine if the dNBR frequency distributions of reburn and no-reburn pixels were significantly different. For this objective, we 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 (that is, 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. We considered using fire atlas data that exist for fires before 1984 (for example, Rollins and others 2001) so that we might use the entire length of the MTBS data set (1984–2008). However, these data are inconsistent and vary in accuracy (Haire and others 2013); we opted to use only the more consistently generated MTBS data.

dNBR values are unitless and somewhat difficult to interpret ecologically. Therefore, we 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 Wageningen and others 2004; Key and Benson 2006). CBI values have a strong relationship to dNBR values in and near our study areas ( $R^2 > 0.65$ ) (Figure 3) (Holden and others 2009; Arkle and others 2012). Miller and Thode (2007) suggest that low severity fire corresponds to CBI values  $\leq 1.25$ , moderate severity to CBI values  $> 1.25$  and  $\leq 2.25$ , and high severity to CBI values  $> 2.25$ . Therefore, we used the data presented in Holden and others (2009) and Arkle and others (2012) and nonlinear models (compare 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 (Figure 3).

### *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, we



**Figure 3.** The relationship between dNBR and CBI for the 2003 Dry Lakes Fire in GAL (left) (Holden and others 2009) and the 2007 East Zone Complex near FCW (right) (Arkle and others 2012).

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, we subsampled the data to diminish the effect of pseudoreplication associated with spatially autocorrelated data (Legendre and Fortin 1989). We based the subsampling frequency on the distance at which pixels are spatially independent (Krawchuk and others 2009; Parisien and others 2011a). To determine this distance, we generated semivariograms using the residuals of naïve models (that is, 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 1,004 m, corresponding to a subsampling frequency of 0.08% (644 pixels).

In stage two, 2,500 subsamples were generated for each study area by randomly selecting pixels with the subsampling frequency determined in the previous step (Krawchuk and others 2009; Parisien and others 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 (that is, second 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 (that is, set of independent variables) in the 2,500 candidate models. Model parameters were generated by averaging across the most frequently identified candidate models, thereby creating an ensemble model (that is, a multi-model average). The use of an ensemble model limits the stochasticity of model outcomes caused by randomly subsampling the data (Parisien and others 2011b). The fits of the final models were evaluated based on the average coefficient of determination (that is, the  $R^2$  between the ob-

served and predicted dNBR values) in the ensemble model.

#### *Variation in Reburn Effect Over Time*

To quantify how reburn effect varies over time, we plotted the mean dNBR of reburn pixels against time since previous fire (that is, 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. We 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. Similar to the approach described in the previous section, the subsampling strategy and ensemble model were necessary to avoid overinflating the significance of our model parameters, as would have occurred had we used all pixels. To test for significance, we 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 (Figure 4) were significantly different in both study areas ( $P < 0.001$ ).

The relationship between dNBR and CBI (Figure 3) 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 less than 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.

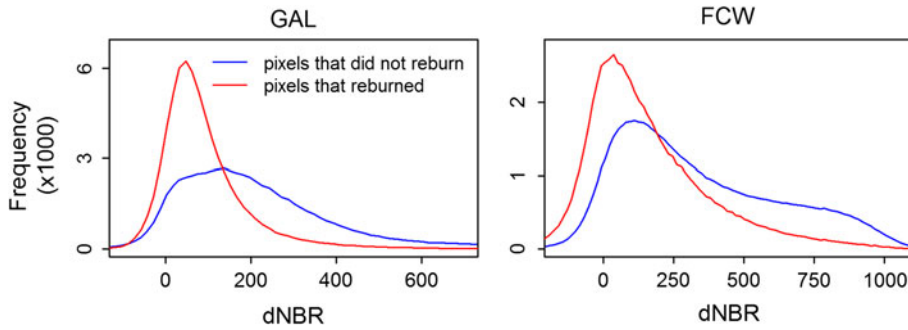


Figure 4. Frequency distributions of dNBR for reburn (red) and no-reburn (blue) pixels in each study area. A two-sided Kolmogorov–Smirnov test indicates that the distributions within each study area are significantly different ( $P < 0.001$ ).

### 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 (Figure 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 (Figure 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 we employed did not violate the assumption of independence; that is, the variogram ranges of the model residuals were less than the distance values we used to subsample the data.

### Variation in Reburn Severity Over Time

Mean dNBR of reburn pixels tended to increase with time since previous fire (Figure 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 for the longer intervals between fires (~22 years), with mean dNBR values remaining substantially lower than the mean dNBR of no-reburn pixels (Figure 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.

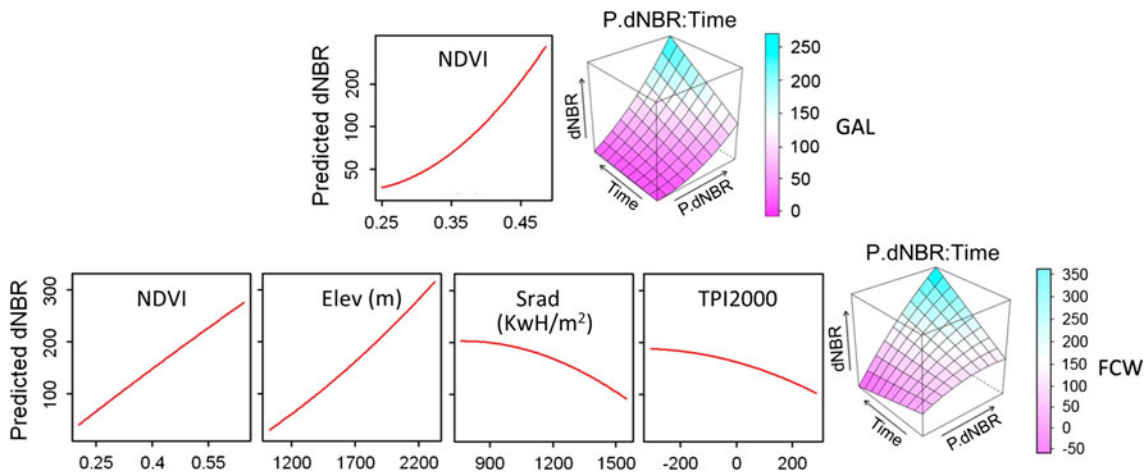


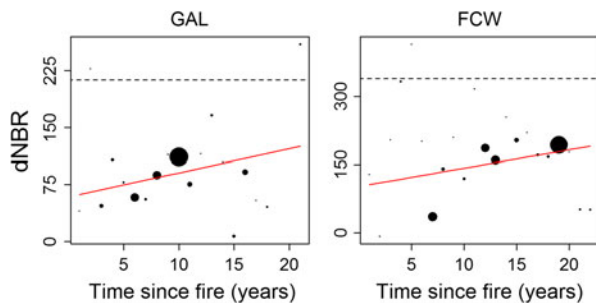
Figure 5. Partial dependence plots for GAL (top row) and FCW (bottom row) models for those variables selected by the stepwise regression (Table 2). These plots represent the relationship between each variable and dNBR when all other variables are held constant at their mean.



**Table 2.** Parameters of the Ensemble Model for Each Study Area

	Variable	$\beta$	SE	P
GAL	NDVI	1415.2	89.4	<0.001
	NDVI <sup>2</sup>	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
	$R^2 = 0.29$			
FCW	NDVI	1786.8	180.8	<0.001
	NDVI <sup>2</sup>	-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 <sup>2</sup>	181.5	187.4	0.390
	SRAD	-960.6	203.9	<0.001
	SRAD <sup>2</sup>	-328.6	178.1	0.163
	TPI2000	-791.8	206.0	0.002
	TPI2000 <sup>2</sup>	-300.5	184.8	0.220
	P.dNBR:TIME	0.024	0.01	<0.001
	$R^2 = 0.33$			

*These models examine how reburn severity varies with fire history, pre-fire vegetation, and topography.*



**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 to 2008 but did not burn between 1984 and 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*) show the fit between dNBR and time since previous fire value. The slope is significantly different from zero in both study areas ( $P = 0.02$  and  $0.08$  in GAL and FCW, respectively).

### The Presence or Absence of Previous Wildland Fires Influences the Burn Severity of Subsequent Fires

As we 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 and others (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 and others (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 we 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 and others 2007; Collins and others 2009; Holden and others 2010; van Wagtenonk and others 2012). We 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 and others 2011). We suggest that this explanation is at least partly responsible in FCW, as 11.2% of the biophysical setting (that is, 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 and others 2012). Finally, severe

fires in forests may beget severe fires when fire-killed trees create heavy fuel loads (Odion and others 2004) that provide conditions for a subsequent severe wildland fire (Arno and others 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 our 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 and others 2005; Arkle and others 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 and others (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 limitation on south-facing slopes leads to decreased productivity. The relationship between dNBR and TPI2000 in FCW could be due to 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. We 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 and others 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 and others 2009; Bradstock 2010; van Wagtenonk and others 2012) and that such an effect can be persistent for decades (Miller and others 2012). As expected, we found

that severity of reburns increases with time since the previous fire, likely due to biomass accumulation associated with longer fire-free intervals (Mack and others 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 approximately 22 years we analyzed, even in the short fire interval system of GAL. Given the temporal extent of our study, we are unable to make inferences beyond 22 years. Although the slopes of the relationship are different (3.2 and 4.0 dNBR units/year in GAL and FCW, respectively), it is difficult to make meaningful inferences given that the differences are not substantial, the relationship between dNBR and field-based measures of burn severity are nonlinear, and the temporal extent of our study is limited. Furthermore, we note that the mean dNBR we used in this analysis is influenced by extreme values, and as such, the dNBR and CBI values reported here are higher than those had we used a different statistic such as the median.

The longevity of the reburn effect is of great interest to land managers and likely varies by ecosystem type and geographic regions. We suggest that the longevity of the reburn effect—measured by how long it 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 greater 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 [for example, lodgepole pine]) (Romme and Knight 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, suggests that more time is needed to recover than in GAL. Thus, we expect that the longevity of the reburn effect is generally shorter in GAL than in FCW, although the temporal extent of our 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 function-

ing ecosystems, GAL and FCW have likely been affected by fire suppression to some degree. Fire-use policies (that is, allowing fires to burn for resource benefit) have only been in place for around 25–40 years (Swetnam and Dieterich 1985; Beckman 2008), and even with the advent of fire use, many fires were suppressed. As such, we acknowledge that fire exclusion in previous decades may have led to higher severity fires than would have occurred otherwise (Barrett 1988).

Although we considered numerous variables in our models, the variation explained (0.29–0.32) suggests that future modeling should include a broader set of variables that incorporate different temporal and spatial scales. 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 and others 1985). Weather variables, such as wind speed and temperature at the time of burning, are highly temporally variable and may be important drivers of burn severity due to their strong influence on potential fire behavior (Schwilk and others 2006; Miller and others 2009; Thompson and Spies 2010). Including such temporally variable data is currently challenging because of the uncertainty in knowing when a pixel burned. However, it may be possible to estimate day of burning using MODIS data (Roy and others 2002; USDA Forest Service 2013), thereby allowing daily weather conditions (obtained from nearby weather stations) to be incorporated into models explaining burn severity; fire progression maps can also be used in the same fashion (for example, Collins and others 2007; Thompson and Spies 2009). Finally, because fire activity may be better explained at broader scales (Parks and others 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; this result, along with those of Teske and others (2012) who found that fires also self-regulate from a *fire size* perspective (in FCW), provides 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 our 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 and others 2001; Eidenshink and others 2007); this suggests a functioning and self-regulating disturbance regime that at least partially explains the relatively high proportion of low-severity fire observed in GAL.

Considering that a fire will inevitably burn most forested areas at some point in the future (North and others 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 and others (2013) 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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