

# Influence of Landscape Gradients in Wilderness Management and Spatial Climate on Fire Severity in the Northern Rockies USA, 1984 to 2010

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**Abstract**—Management activities, applied over broad scales, can potentially affect attributes of fire regimes including fire severity. Wilderness landscapes provide a natural laboratory for exploring effects of management because in some federally designated wilderness areas the burning of naturally ignited fires is promoted. In order to better understand the contribution of fire management activities to fire effects, we examined patterns of severity across a management gradient defined by wilderness—non-wilderness boundaries in a northern Rocky Mountain study region. We identified a significant positive effect of the management gradient on severity for the time period 1984 to 2010, but the magnitude and direction of effects varied from year to year. However, the influence of management on severity was subsumed by the influence of spatial climate. Our findings represent an important step in constructing predictive models of severity with changes in both climate and fire management practices.

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## Introduction

Understanding the contribution of management policies and practices to emerging attributes of fire regimes is increasingly important, given the broad scales at which fire suppression, prescribed burning, vegetation management and other strategies continue to be applied. A primary example is found in some federally designated wilderness areas in the western U.S., where management policies have encouraged so-called “natural burning,” that is, allowing lightning-ignited fires to burn with little human interference (Parsons and others 1986). The likelihood that fires will burn of their own accord in wilderness is increased because the practice is favored by policy; in addition, natural burning is favored in wilderness during times when suppression in non-wilderness areas takes higher priority, or when remoteness prevents timely and effective suppression response. However, natural burning policies are not applied uniformly across wilderness areas; the need to protect property and respect management policies on adjacent lands plays an important role in deciding when and where fires are allowed to burn in wilderness (Kelson and Lilieholm 1999; Karieva and others 2007).

In a previous study, we found indications that the distribution of fire sizes, and in particular, the predominance of the largest fires, was influenced by differences in management along a non-wilderness—wilderness continuum (Haire and others 2013). Based on analysis of contemporary fire size distributions (1984 to 2007), the magnitude and direction of

change along the wilderness gradient varied among three study regions. Results for the northern Rockies study region were particularly striking: conditions favorable to large fire events increased dramatically toward wilderness interiors.

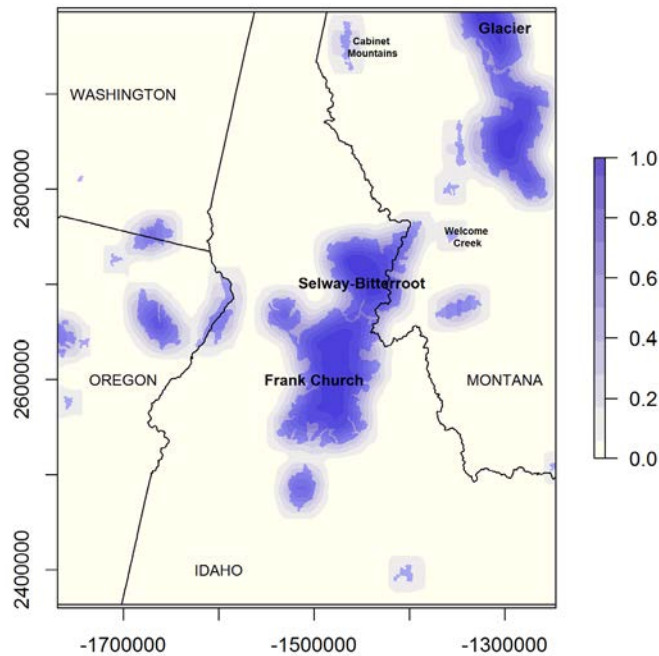
If large fire events are apparently influenced by wilderness management context, what about the ecological changes resulting from those fires? Several recent projects have examined the dynamics of severity with re-burning that has occurred within wilderness areas in recent decades (Holden and others 2010; van Wagendonk and others 2012; Parks and others 2014b). These studies suggested that previously burned areas moderate the severity of subsequent fire. Importantly, however, outcomes can vary in relation to several factors including climate and weather conditions, vegetation type, time-interval since fire, and effects of the previous fire. Following on the findings of these studies, we derived two research hypotheses which we tested in a northern Rockies study region across a wilderness gradient (figure 1).

H<sub>1</sub>: Fire severity varies primarily in relation to management and fire history. Burning practices in wilderness contribute to the heterogeneity of fuels in such a way that limits imposed on severity at local scales (e.g., Parks and others 2014b) will be apparent at the regional scale of our study.

H<sub>2</sub>: Variability in spatial climate is the primary driver of severity at regional scales through its effects on fire season length, vegetation type, productivity, and fuels. These patterns are more important than management in determining trends in severity; effects of management are superimposed on this basic template.

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**Figure 1**—The northern Rockies study area included several wilderness areas (dark blue shading; those mentioned in the text are labeled, as is Glacier National Park). Legend colors represent the wilderness gradient (WG) which formed the basis of our study design.

## Methods

### Study Region

The study region includes several northern Rockies wilderness areas and their surrounding landscapes (figure 1). Regional-fire years in the northern Rockies are associated with broad scale synoptic climate (Baker 2003; Heyerdahl and others 2008; Morgan and others 2008). Infrequent high-pressure blocking systems promote extremely dry regional climate patterns (Romme and Despain 1989; Bessie and Johnson 1995) and may respond to global climate anomalies (Baker 2003).

Ecosystem characteristics vary across the region with elevation. Higher elevation forest species include white-bark pine (*Pinus albicaulis*), lodgepole pine (*P. contorta*), subalpine fir (*Abies lasiocarpa*), grand fir (*A. grandis*), and Engelmann spruce (*Picea engelmannii*); ponderosa pine (*P. ponderosa*), Douglas-fir (*Pseudotsuga menziesii*), and western larch (*Larix occidentalis*) are present at middle elevations (Rollins and others 2002; Morgan and others 2008). In wetter climates, including areas of the Cabinet Mountains Wilderness, western redcedar (*Thuja plicata*) and western hemlock (*Tsuga heterophylla*) are found in valleys with heath-shrublands inhabiting open ridges (www.wilderness.net). Upmost elevations are known for their sparsely vegetated rocky and often icy conditions.

Wilderness areas range in size, with Frank Church-River of No Return (957,820 ha) and Selway-Bitterroot (542,516 ha) located adjacent to each other, separated by the Magruder Corridor. Glacier National Park was also included as a “wilderness area” due to its large size (200,075 ha)

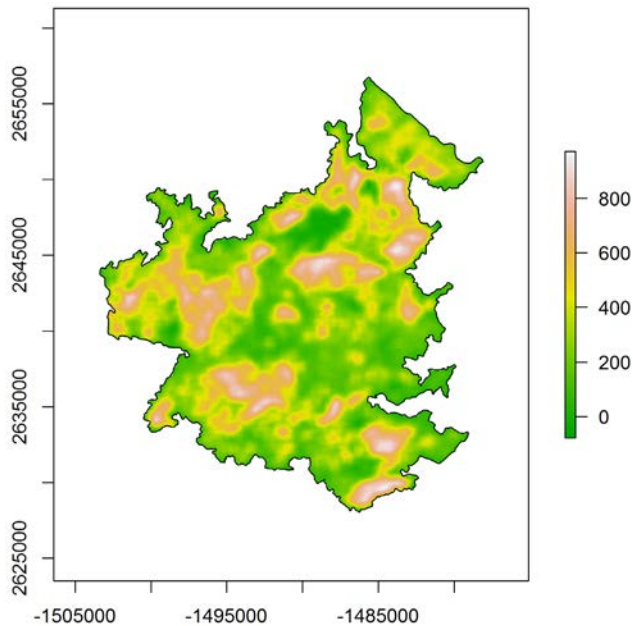
and fire management history which includes allowance of natural burning. Some relatively smaller wilderness areas are scattered on the surrounding landscape, for example, Welcome Creek (11,385 ha). Wilderness areas are surrounded by publicly owned lands managed for multiple uses including livestock grazing, timber harvest, and recreation ([www.nationalmap.gov](http://www.nationalmap.gov)), and also about parcels of private land.

### Sampling Design

We sampled fire severity data and other variables across a wilderness gradient (WG; figure 1) which was constructed using the following steps. First, we added Glacier National Park to a base map of wilderness boundaries ([www.nationalmap.gov](http://www.nationalmap.gov)). Then, we derived a gridded map (400 m cell size) of wilderness/non-wilderness (assigned values of 1/0 respectively), based on the wilderness (plus one Park) boundaries. Next, we applied a uniformly weighted kernel within ~130,000 ha moving windows across the region. Variations in the shape and size of the wilderness areas resulted in a continuous gradient of values ( $0 < x < 1$ ; figure 1). The WG achieved its maximum value (1) in interior portions of large wilderness areas, and the minimum value (0) in areas farthest outside wilderness boundaries. The WG surface matched the projection of all other spatial datasets used in the study (i.e., severity and climate data; Albers Equal Area Projection, North American Datum of 1983). All spatial and tabular data analyses were accomplished in R (R Core Team 2014).

### Neighborhood Severity Models

We used burn severity data for 1984 to 2010 (Differenced Normalized Burn Ratio,  $\Delta$ NBR; [www.mtbs.gov](http://www.mtbs.gov)) to develop a response variable for the analysis. Recognizing that new burn severity metrics continue to be developed and tested for their utility (Parks and others 2014a), we judged  $\Delta$ NBR appropriate to our need for a continuous measure of landscape change. Burn severity images ( $n = 895$ ) were resampled from 30 m to 100 m cell size and a uniformly weighted kernel ( $7 \times 7$  cells/ ~50 ha) was applied to create a measure of neighborhood severity (NS; figure 2). The goal of resampling and kernel smoothing was to identify and map concentrations of similar values of burn severity at a scale that better corresponded to regional conditions in spatial climate. The kernel models were randomly sampled at a consistent density (1 point/100 ha); points were then subsampled to achieve uniform distribution across the WG ( $n = 2000$ ). Thus, points fell primarily within and immediately adjacent to wilderness areas. Twenty of the sampled burn images were striped due to failure of the forward motion of Landsat 7 ([http://landsat.usgs.gov/products\\_slcutoffbackground.php](http://landsat.usgs.gov/products_slcutoffbackground.php)), but we were able to obtain alternative burn images in 15 cases (JFSP project 12-1-03-19: Quantifying the effectiveness and longevity of wildland fire as a fuel treatment). Samples from the remaining five striped images were dropped from the analysis, resulting in a final sample of  $n = 1979$ .



**Figure 2**—Neighborhood severity (NS) was modeled using burn severity images ( $n = 895$ ). Images were smoothed by resampling from 30-m to 100-m cell size and applying a uniformly weighted kernel. The ~36,000 ha Flossie Complex (Idaho, 2000) NS model is shown here.

### Spatial Climate Models

We used 19 Bioclim layers to represent variability in fuel conditions across the study region based on the assumption that ecosystem and associated fuel characteristics are strongly driven by climate. Staff at the U.S. Geological Survey, Fort Collins Science Center developed the data set employed in our study using 400 m climate normals data (1971 to 2000) which were downscaled from PRISM data (<http://www.prism.oregonstate.edu/>) by Climate Source, Inc. Conditions in temperature or precipitation are modeled annually (e.g., Annual Precipitation), and within time periods defined by variability at each grid cell location (e.g., Precipitation in the Driest Period). Definitions of the 19 variables are available on the WorldClim website (<http://www.worldclim.org/bioclim>; see also Hijmans and others 2005). All layers were sampled at the random locations ( $n = 1979$ ) and used as predictor variables in the analysis.

### Analysis

We used quantile regression (Koenker 2013) to analyze patterns of severity (NS) across gradients of spatial climate (Bioclim layers) and management (WG). Compared to ordinary least squares regression, quantile regression allows a more complete picture of relationships between variables when a single rate of change based on central tendency may not adequately characterize patterns in the data (Cade and Noon 2003; Cade and others 2005). Quantile regression models have the same interpretation as ordinary least squares models, but the models can be developed for specific portions of the data distribution. For any given quantile ( $\tau$ ), slope coefficients represent rates of change after adjusting

for the effects of the other variables in the model. At upper and lower quantiles, results can be interpreted as constraints because a majority of the sample data occurs below or above the modeled interval ( $\tau$ ), in contrast with other regression techniques where interpretation focuses on the mean response (Cade and Noon 2003).

The goal of our modeling process was to evaluate the effects of the WG on NS at upper  $\tau$  after accounting for the effects of ecosystem and associated fuel characteristics. We were most interested in modeling upper limits to NS because constraints on higher severity would be expected under  $H_1$ ; thus, we estimated rates of change of the response distribution (NS) conditional on the matrix of predictor variables (19 Bioclim variables, WG) for  $\tau = 0.70$  to  $\tau = 0.90$  at intervals of 0.05. We used the linear quantile regression method to estimate parameters for each  $\tau$  and the rank score-based method to compute confidence intervals assuming independent but not identically distributed errors; these options are available in the *quantreg* package written in R (Koenker 2013).

First, we tested each predictor in a separate univariate model to identify patterns in relationships between NS and the WG and between NS and each of the 19 Bioclim variables. We then derived 1) a full model containing all Bioclim predictors found to be significant in univariate models and 2) a minimally adequate (reduced) model which contained variables found to be significant in the full model. Finally, we added WG to the reduced model, to test for its importance after taking into account effects of the Bioclim representations of ecosystem and associated fuel characteristics. A variable was considered an active constraint if the upper and lower bounds of 90 percent confidence intervals were either both greater than zero or both less than zero for the upper range of  $\tau$ . We repeated the univariate WG model using data from three years which were both well represented in the data set and had a fairly even distribution of data points across the WG (1988, 2000, and 2007), to compare outcomes for these large fire years (Morgan and others 2008) with the result for all years.

We used  $AIC_c(\tau)$  to compare models with spatial climate variables only (reduced model, described above), to models containing the WG as an additional predictor (reduced model + WG):

$$NS = \beta_0 + \beta_{1,\dots,n}Climate + WG + \varepsilon$$

where NS = neighborhood severity, Climate = Bioclim spatial climate variables and WG = wilderness gradient. The  $AIC_c(\tau)$  is a modification of Akaike's Information Criterion for small sample size (Hurvich and Tsai 1990) that incorporates differences in coefficients of determination, that is, the weighted sum of absolute deviations minimized in estimating the  $\tau$ th quantile regression with  $p$  parameters (Cade and others 2005). We compared differences between  $AIC_c(\tau)$  for the more complex models and the simplest model with a constant only ( $\beta_0$ ) to represent model improvement with addition of parameters ( $\Delta AIC_c(\tau)$  as defined in Cade and others 2005). The resulting scale of  $\Delta AIC_c(\tau)$  provides a positive measure that is proportional to model fit, as well as a measure of relative improvement as variables are added to

simpler models. We calculated  $\Delta AIC_c(\tau)$  across all  $\tau$  (0.05 to 0.95 in increments of 0.05) to observe changes in models representing lower, middle, and upper constraints on NS while focusing on outcomes at upper  $\tau$ .

As a final exploratory step we constructed a spatial model of predicted values using a set of variables selected, above, for the 75<sup>th</sup> quantile. We used the “predict” function in the raster package (Hijmans 2014) which outputs a raster object with predictions from a fitted model object. The spatial model was evaluated qualitatively for the purpose of generating ideas for research to follow.

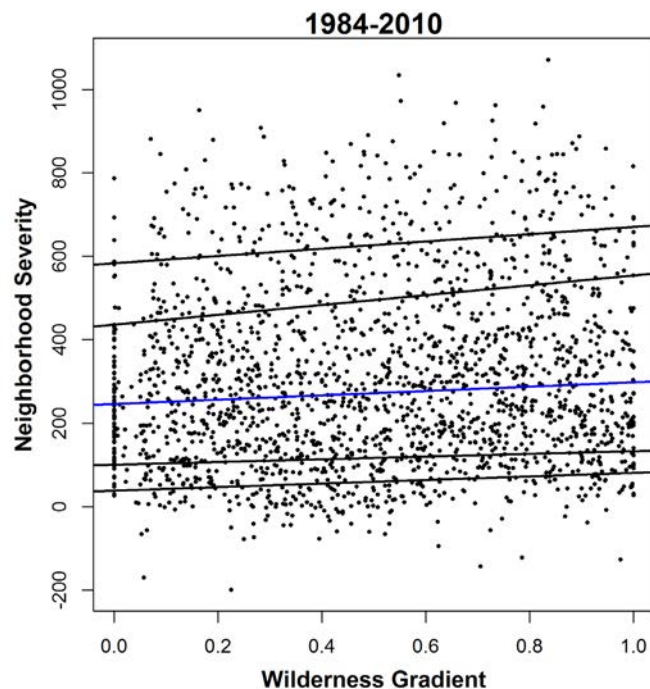
## Results

Wilderness management context had a marked influence on fire effects at the regional scale of the study, based on consideration of the wilderness gradient alone. We identified a gradual, positive constraint on NS at upper quantiles ( $\tau = 0.70$  to  $\tau = 0.90$ ) wherein severity increased along the WG (figure 3). However, the direction and magnitude of

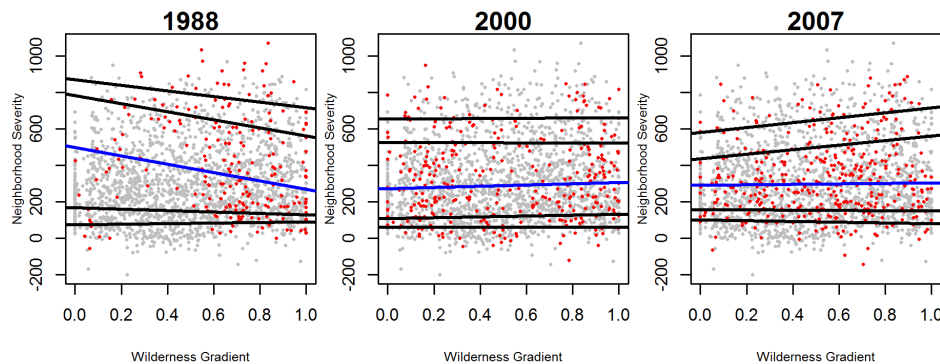
effects varied when viewed in different time frames (figure 4). Patterns of NS in 1988 showed a steep, negative upper limit indicating *decreased* severity along the WG. In 2000, however, no significant trends were evident, and in 2007, an *increasing* trend in NS was seen across the WG at upper  $\tau$ .

Gradients in spatial climate, represented in Bioclim variables, were major contributors to patterns of severity across the region from 1984 to 2010. Specifically, all significant predictors worked to increase NS at the upper range of the data distribution (table 1). Among the seven Bioclim variables which were significant in univariate models, Precipitation in the Wettest Period, Precipitation in the Driest Period, and Precipitation in the Coldest Quarter emerged as important, positive predictors of NS in multiple regression models (table 1, Models 2 and 3). The contribution of WG to trends in severity became insignificant when considered in combination with the spatial climate gradients (table 1, Model 4).

Although the positive, upper limit to NS imposed by the WG was statistically significant in univariate models (table 1), it added relatively little information to models representing constraints across the range of lower, middle, or upper  $\tau$



**Figure 3**—Plots of regression quantile model fits using fire severity data for all years, where  $y$  = neighborhood severity (NS) and  $x$  = wilderness gradient (WG). The black lines represent regression quantile fits for  $\tau = 0.10, 0.20, 0.80, 0.90$ ; the blue line is the median fit ( $\tau = 0.50$ ), and data points are shown as black points. Neighborhood severity increased gradually but significantly at upper quantiles, indicating increasing magnitude of fire effects along the wilderness gradient.



**Figure 4**—Plots of regression quantile model fits, as in Figure 3, but using fire severity data for 1988, 2000, and 2007 (show as red dots in each plot; gray dots represent data from all other years). At upper quantiles, a decreasing trend was observed for 1988, trends were non-significant for 2000, and neighborhood severity increased across the wilderness gradient in 2007.

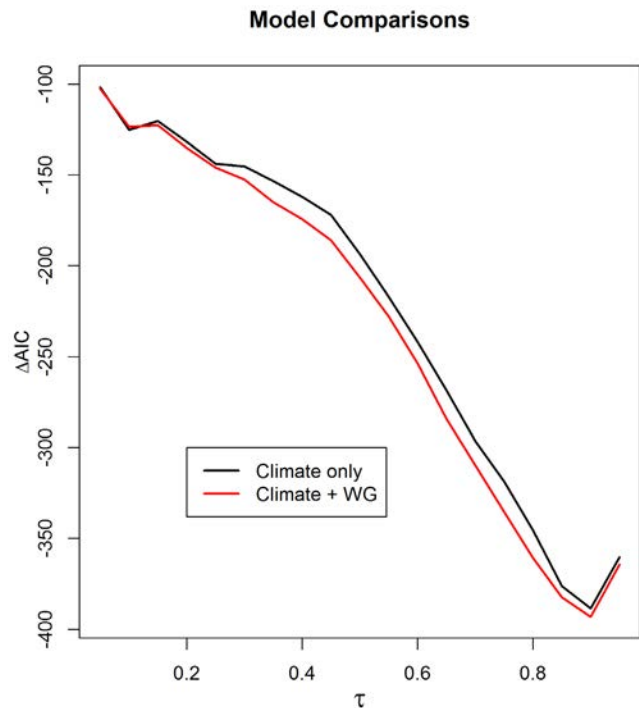
**Table 1**—Regression results for  $\tau = 0.70$  to  $\tau = 0.90$  at intervals of 0.05 (direction of effect: +/- or non-significant: ns). Seven out of 19 Bioclim variables and the wilderness gradient (WG) were significant predictors of neighborhood severity (NS) in univariate models (1). Results are also shown for univariate regression of NS~WG by year. Three of the seven Bioclim predictors retained importance in a full multivariate model (2), but only Precipitation in the Driest Period held its influence in a reduced model (3). After adding WG to the reduced model, Precipitation in the Driest Period and Precipitation in the Coldest Quarter were positive predictors, but WG was not important (4). Significance was determined by tests of 90 percent confidence intervals.

Model	Ann. PPT	PPT Wettest Period	PPT Driest Period	PPT Wettest Quarter	PPT Driest Quarter	PPT Warmest Quarter	PPT Coldest Quarter	WG 1984-2010	WG 1988	WG 2000	WG 2007
1. Univariate	+	+	+	+	+	+	+	+	-	ns	+
2. Multiple regression (full)	ns	+	+	ns	ns	ns	+				
3. Multiple regression (reduced)		ns	+				ns				
4. Multiple regression (reduced) + WG		ns	+				+	ns			

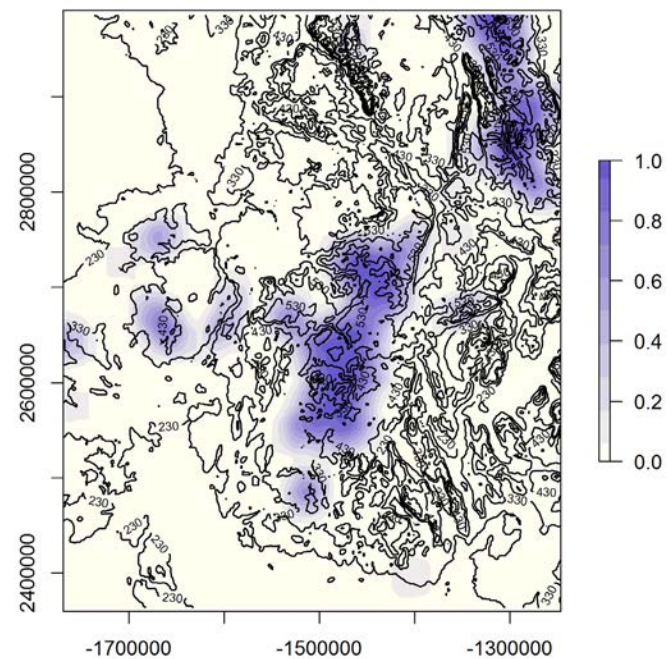
(figure 5). Models tended to be better overall, in terms of fit and explanatory power, at the highest values of  $\tau$ , indicating that landscape gradients included in the models became operative at the upper range of severity.

Predicted patterns of severity at its upper limits were highly variable across wilderness landscapes. Some of the

highest predicted values, and steepest gradients in NS, occurred higher along the WG, that is, in wilderness interiors (e.g., in the Frank Church–River of No Return and Glacier; see figure 1); however, a wide range of values were observed across the study region and relative to location across the WG (figure 6).



**Figure 5**—Differences between  $AIC_c(\tau)$  ( $y$ -axis) for the more complex models and the simplest model ( $\beta_0$ ) were plotted across  $\tau$  ( $x$ -axis) to represent model improvement with addition of parameters. Larger absolute values of  $\Delta AIC_c(\tau)$  also signal better model fit. The models included three Bioclim precipitation variables before and after adding the wilderness gradient (WG). Model fit improved across quantiles, but the WG added very little to models at lower, middle, or upper  $\tau$ .



**Figure 6**—Spatial prediction for the neighborhood severity (NS) gradient (black contour lines) at upper limits of the data distribution ( $\tau = 0.75$ ). Two Bioclim variables were included in the model: Precipitation in the Driest Period and Precipitation in the Coldest Quarter. The wilderness gradient (WG) is shaded in the background, with wilderness interiors dark blue as in Figure 1.

## Discussion

In an earlier study, the wilderness—non-wilderness gradient had a strong correspondence with the influence of large fires in structuring fire size distributions in the northern Rockies (Haire and others 2013). Our current findings indicate that the severity of fires also varies spatially in relation to the shape and size of wilderness areas which define the wilderness gradient. Although management history cannot be assumed to vary uniformly across the gradient, the coincidence of multiple factors along the gradient, including management activities, led to measurable consequences for both fire size distributions and fire severity at the regional scale of the study.

Natural burning practices which are known to affect landscape heterogeneity of fire effects at particular locations (Holden and others 2010; van Wagtenonk and others 2012; Parks and others 2014b) also influence patterns of severity at a regional scale in the northern Rockies. However, across all years of our study, rather than leading to lower severity, wilderness management was implicated in producing a gradual, but statistically meaningful positive trend in severity at locations associated with its upper range of values. It is possible that the agency of wilderness management in lessening fire effects is only quantifiable in particular years (figure 4), or that interactions between management and environment constitute primary drivers of increased severity across the study landscape.

In the northern Rockies study region, patterns of severity adhere to underlying templates which are closely related to gradients in spatial climate. Our findings reinforce the basic premise of studies which focus on patterns of burning differentiated by major ecological zones (e.g., Anderson and McCleary 2014). Precipitation during specific seasons defined this template in our study region, reflecting dynamics of fuel condition and connectivity in both space and time. Wetter conditions were the predominant contributors to increased severity at locations associated with its upper range of values, and their influence subsumed the role of management in multiple regression models (table 1; figure 5).

Our results are best interpreted with consideration of other landscape attributes that can influence fire effects and are potentially confounded with the wilderness gradient. In particular, outside of wilderness, anthropogenic landscape fragmentation caused by roads and other human structures, as well as land use practices such as agriculture, livestock grazing, and timber harvest can alter fuel type, condition, and continuity (Parisien and Moritz 2009; Shinneman and others 2010). In contrast, fragmentation in wilderness areas is more often defined by natural boundaries that modulate fire spread and intensity including rock, ice, and topographic variability. These landscape attributes may affect our ability to accurately detect changes in severity along the management gradient at regional scales.

Concern regarding climate change has led to strong interest in predictive models which utilize spatial climate data. These spatial models require establishment of a functional relationship between climate variability and a process of

interest, often species presence or abundance (Elith and Leathwick 2009). Our work represents a successful first step in the modeling process for fire severity and, with further development, could ultimately provide predictions under future climate scenarios.

For example, steep gradients in severity were predicted relative to management boundaries in some places (figure 6). Examining changes in these gradients under different climate scenarios could be useful in understanding the role of more static landscape properties (e.g., management boundaries and topography) compared to dynamic shifts in the composition and arrangement of ecosystems. More robust models would be achieved through inclusion of additional environmental data, further exploration and quantification of scales of importance in pattern-process relationships, and assessment of predictive performance and model uncertainty. Resulting insights into the dynamics of fire effects across space and time could provide useful perspectives for managers and conservationists alike.

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