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Pattern and process of prescribed fires influence effectiveness at reducing wildfire severity in dry coniferous forests

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ABSTRACT

We examined the effects of three early season (spring) prescribed fires on burn severity patterns of summer wildfires that occurred 1–3 years post-treatment in a mixed conifer forest in central Idaho. Wildfire and prescribed fire burn severities were estimated as the difference in normalized burn ratio (dNBR) using Landsat imagery. We used GIS derived vegetation, topography, and treatment variables to generate models predicting the wildfire burn severity of 1286–5500 30-m pixels within and around treated areas. We found that wildfire severity was significantly lower in treated areas than in untreated areas and significantly lower than the potential wildfire severity of the treated areas had treatments not been implemented. At the pixel level, wildfire severity was best predicted by an interaction between prescribed fire severity, topographic moisture, heat load, and pre-fire vegetation volume. Prescribed fire severity and vegetation volume were the most influential predictors. Prescribed fire severity, and its influence on wildfire severity, was highest in relatively warm and dry locations, which were able to burn under spring conditions. In contrast, wildfire severity peaked in cooler, more mesic locations that dried later in the summer and supported greater vegetation volume. We found considerable evidence that prescribed fires have landscape-level influences within treatment boundaries; most notable was an interaction between distance from the prescribed fire perimeter and distance from treated patch edges, which explained up to 66% of the variation in wildfire severity. Early season prescribed fires may not directly target the locations most at risk of high severity wildfire, but proximity of these areas to treated patches and the discontinuity of fuels following treatment may influence wildfire severity and explain how even low severity treatments can be effective management tools in fire-prone landscapes.

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1. Introduction

Prescribed fires are often implemented to lower the probability of severe wildfires that could damage ecosystems and property (Agee and Skinner, 2005; Peterson et al., 2005; Reinhardt et al., 2008). This is generally accomplished through reductions in surface, ladder, and canopy fuels (Hunter et al., 2007). In ponderosa pine and mixed conifer forests, these treatments are typically conducted under cooler, moister conditions in the spring or fall (relative to the warmer, dryer conditions under which wildfires burn) when fire spread and size can be controlled. Burning under these conditions generally results in low severity, patchy fires that consume low to moderate amounts of fuels. Despite the low severity of prescribed fires, there is considerable empirical evidence that prescribed fires successfully reduce severity and modify behavior (e.g. spread) of subsequent wildfires (Pollet and Omi, 2002; Finney et al., 2005; Lezberg et al., 2008; Wimberly et al., 2009; Prichard et al., 2010; Fulé et al., 2012).

There are many environmental variables that influence fire severity, including weather, climate, topography, and the types, amounts, and moisture content of vegetation (Pyne et al., 1996; Dillon et al., 2011). Wildfires in the northern Rocky Mountains typically burn during summer when living and dead vegetation is particularly dry. Windy, low humidity conditions tend to increase fire intensity, resulting in increased fire spread (usually via crown fire) and burn severity (Graham et al., 2004). Steeper slopes often have higher burn severities because flames can easily propagate into canopies and fire moving uphill tends to pre-heat air and fuels resulting in better combustion (Lentile et al., 2006). Forest structural characteristics, such as canopy base height and tree density, are also important factors influencing burn severity patterns within landscapes (Scott and Reinhardt, 2001; Pollet and Omi, 2002; Peterson et al., 2005; Lentile et al., 2006; Jain and Graham, 2007).

Prescribed fires are generally intended to alter forest structure in a manner that decreases surface fuels, ladder fuels, and small tree densities (Graham et al., 2004; Agee and Skinner, 2005). Most fires are small and target individual stands (usually <1000 ha), but

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landscape-level treatments are becoming more common (Hunter et al., 2007). Prescribed fires are generally effective at reducing surface and some ladder fuels, but generally do not alter canopy fuels (Kilgore and Sando, 1975; Knapp and Keeley, 2006; Stephens and Moghaddas, 2005; Stephens et al., 2009). Some studies suggest that mechanical thinning implemented prior to prescribed burning is more effective than prescribed burning alone at reducing canopy bulk density and wildfire hazard (Pollet and Omi, 2002; Symons et al., 2008; Stephens et al., 2009), whereas others indicate that thinning alone has little effect on wildfire severity (Prichard et al., 2010). Rapid understory regeneration and litter accumulation following prescribed fire may require repeat treatments up to once per decade (Fernandes and Botelho, 2003; Skinner, 2005; Knapp et al., 2007; Battaglia et al., 2008).

The ecological patterns and processes that influence the effectiveness of prescribed fires are still relatively unknown. This lack of understanding is the result of simple comparisons of wildfire severity within prescribed fire perimeters relative to surrounding untreated areas. This approach, while informative, does not identify the conditions within the prescribed fire perimeter that contributed to its effectiveness at reducing wildfire severity. These may include prescribed fire severity and continuity (i.e. patchiness of burned areas interspersed amongst areas where little organic matter was consumed), as well as pre-fire vegetation conditions, the patchiness of this vegetation, topography, and other characteristics. Further, no studies have examined the conditions where these treatments are the most and least effective at reducing wildfire severity, nor whether prescribed fires burn the same areas of the landscape that are likely to burn at high severity in a wildfire. Finally, to quantify treatment effectiveness, no studies have compared the observed burn severity of an area to model estimates of how the area would have burned in a wildfire had it not been treated previously with prescribed fire.

The goal of this paper was to examine how prescribed fire characteristics interact with vegetation and topographic conditions to influence subsequent wildfires. We addressed four questions: (1) do prescribed fires reduce subsequent wildfire severity relative to potential wildfire severity had treatments not been implemented, (2) how do vegetation, topography, and prescribed fire severity influence prescribed fire effectiveness, (3) how does landscape context (i.e. position within vegetation patches, treatment patches, and treatment boundary) combine with local conditions to influence wildfire severity, and (4) do prescribed fires treat locations most at risk of high severity wildfires?

2. Methods

2.1. Study area

This study was conducted in the South Fork Salmon River drainage on the Payette National Forest, ID, USA (Fig. 1). Our study sites were in steep terrain with elevations ranging from 1106–2467 m. Upland vegetation was dominated by Douglas fir (*Pseudotsuga menziessi*) on north-facing slopes, and by mixed ponderosa pine (*Pinus ponderosa*) and fir, shrubland, and grassland communities on south-facing slopes. Climate was characterized by cold, snowy winters, and hot, dry summers. From 1471 to 1948, the fire return interval in these catchments averaged 10 years (Barrett, 2000), but likely varied with forest type and climate trends (Agee, 1998; Pierce et al., 2004). Since 1948 a fire suppression program limited the size and severity of most wildfires. The area is mostly roadless and has had no timber harvest or livestock grazing in the past 40–50 years. Prescribed fire treatments were conducted under dry, low-wind conditions in early May 2004 (Parks site) and early May 2006 (Fitsum and Williams sites) using incendiary objects dropped from a helicopter and hand-held drip torches near treatment perimeters. Methods, guidelines, and treatment objectives were the same for all three prescribed fires and are described in Arkle and Pilliod (2010). The Parks treatment burned within a 1052 ha area (29% Unburned-Low, 57% Low, 13% Moderate, and 0.7% High severity). The Fitsum prescribed fire burned within an area of 696 ha (58% Unburned-Low severity and 41% Low severity) and the Williams treatment burned 1035 ha (77% Unburned-Low severity and 22% Low severity). Less than 1% of the Fitsum and Williams sites burned at Moderate or High prescribed fire severity. In 2007, the Zena, Loon, Monumental, and Riordan Wildfires burned much of the area, including the three treated sites, between late July and September in a mosaic of burn severities and unburned patches (Fig. 1).

2.2. Data sources and variable development

We used 30-m raster GIS data for each variable in our analyses. The burn severity of prescribed fires (RXSEV) and the 2007 wildfires (WILDSEV) was quantified in each pixel using the differenced normalized burn severity ratio (dNBR) from Landsat imagery obtained before and after each fire (Supplemental Table 1). We used dNBR data and burn severity class breakpoints (for descriptive purposes) obtained from the Monitoring Trends in Burn Severity database (MTBS; Eidenshink et al., 2007) when available. We found that dNBR correlated well with ground-based assessments of burn severity at these sites (Supplemental Fig. 1; Table 1) and it is an accurate index of burn severity at the 30-m spatial scale (Holden et al., 2010). We used unclassified, square root transformed dNBR values of RXSEV and WILDSEV in all of our models (Table 1). We employed the $(\mathrm{dNBR}+700)^{0.5}$ transformation used by Finney et al. (2005) to facilitate comparisons between studies and to normalize, re-scale, and aid in the interpretation of our burn severity data.

For each pixel, we used data from digital elevation models to quantify the following topographic variables: ELEVATION, SLOPE, ASPECT, heat load index (HEATLOAD), and topographic relative moisture index (TRMI). HEATLOAD values are unitless and were obtained by transforming ASPECT such that the coolest slopes (northeast-facing) have a value of 0 and the warmest slopes (southwest-facing) have a value of 1 (McCune and Grace, 2002). TRMI data, also unitless, ranged from 1–27, with high values indicating mesic areas (Manis et al., 2001). Table 2 contains descriptions of all variables.

We used LANDFIRE data (Rollins and Frame, 2006) to quantify the vegetation conditions of each pixel. Variables include vegetation type (VEGTYPE), percent canopy cover (VEGCOV), vegetation height (VEGHT), and vegetation volume (VEGVOL; calculated as in Table 2) as a proxy for biomass or vegetation bulk density.

Using GIS processes, we developed several variables representing the landscape context of each pixel (Table 2 and Supplemental Fig. 2). For each pixel we determined the closest distance (meters) to the prescribed fire treatment perimeter (RXPERIMDIST). We also calculated the distance from each pixel to the nearest edge of a contiguous patch where prescribed fire burn severity was $\geqslant 27$ (RXPATCHDIST; i.e. RXSEV $\geqslant$ low severity). Some pixels that were outside of the prescribed fire treatment boundary exhibited spectral changes analogous to those of low severity prescribed fire. We included these pixels in our analyses of RXPATCHDIST because they likely represent areas of some other disturbance (e.g. beetle kill or blow-down) that could potentially explain variation in wildfire severity in the areas surrounding prescribed fire treatments. We developed two variables that represent the vegetation patch conditions surrounding each pixel. The first variable (HIVOLDIST) is the distance from a given pixel to the edge of a patch of high vegetation volume (contiguous area where VEGVOL > 10×10^3 m^3). The 10×10^3 m^3 cutoff was selected because approximately 50%

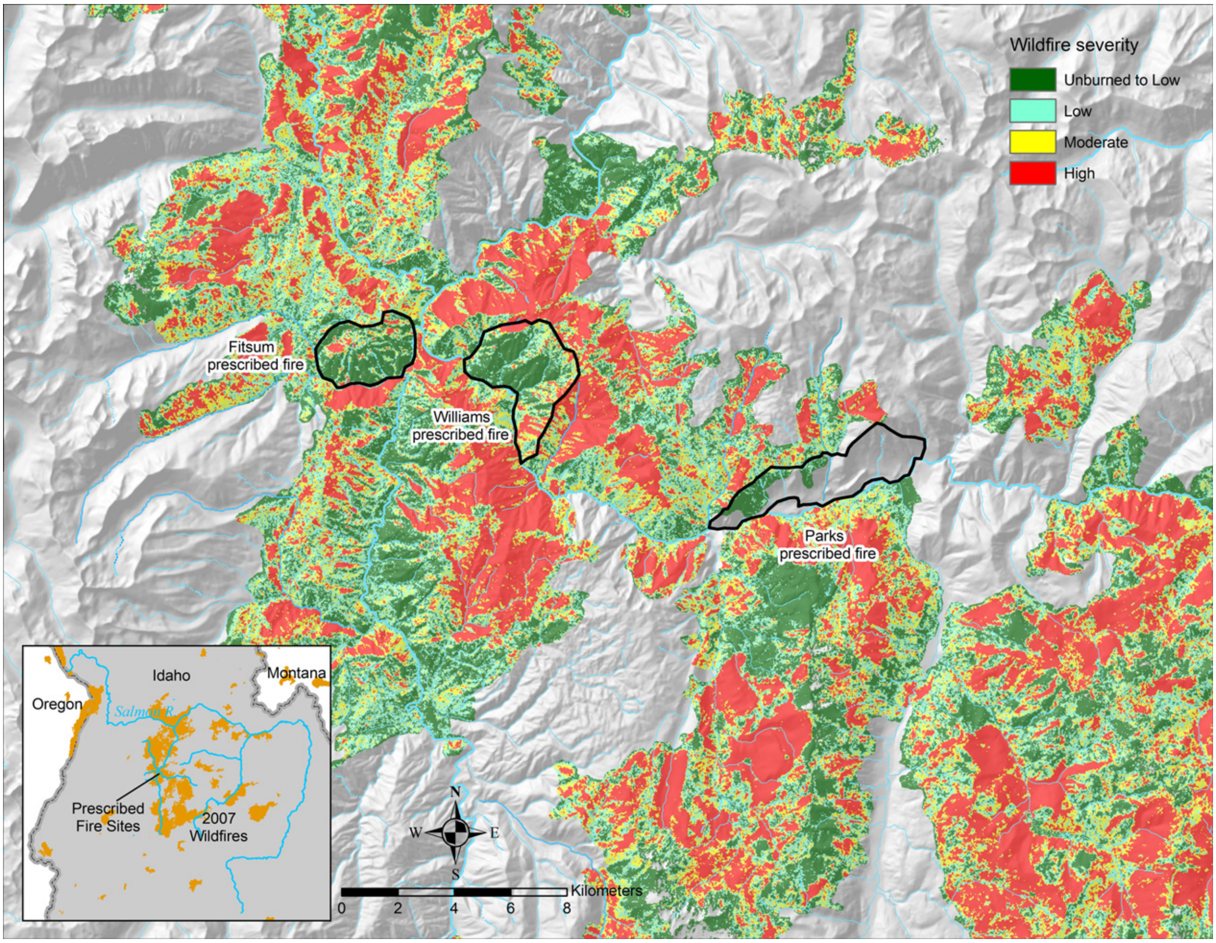

Fig. 1. Map of prescribed fire treatment perimeters (polygons) within the South Fork Salmon River drainage, Payette National Forest, Idaho. Landsat derived wildfire severity is shown. Inset gives the location of the treatment sites and the 2007 wildfires that burned one to three years post-treatment.

Table 1
MTBS derived burn severity ranges for each burn severity class. Equivalent square root transformed ranges are given for predictor and response variables (WILDSEV and RXSEV) used in NPMR analyses. For validation purposes, the number of field plots falling within each burn severity class is given along with the mean percentage of canopy identified by field crews as black and brown within those plots.

Class	ΔNBR	WILDSEV or RXSEV	*n* Field Plots	Ave.% Plot Canopy Black	Ave.% Plot Canopy Brown
Unburned-Low	−254 to 75	21.12–27.85	10	0.25	1.94
Low	76 to 225	27.86–30.42	38	1.5	8.19
Moderate	226 to 410	30.43–33.32	25	8.5	40.1
High	411 to 1081	33.33–42.21	23	69.1	28.7

of the forested pixels had vegetation volumes greater, and 50% had vegetation volumes lower than this value. The second variable (LOVOLDIST) is the distance from a given pixel to the edge of a patch of low vegetation volume (contiguous area where VEGVOL < 2×10^3 m^3). The 2×10^3 m^3 cutoff was selected because most non-forested pixels had vegetation volumes below this value. For each of these four landscape context variables, more negative distance values indicate that the pixel was further outside of a patch (or treatment perimeter), and more positive values indicate that the pixel was further inside the patch (or treatment perimeter). Values close to 0 m indicate that the pixel was either near a patch edge, or that the pixel was in the interior of a relatively small patch. The three patch variables were created using a 3 by 3 moving window average to smooth the raster data into contiguous patches prior to calculating the distance from each pixel to a patch edge.

2.3. Data analysis

Using GIS processing, we buffered each prescribed fire treatment boundary by 1 km to obtain pixels from the landscape surrounding each treatment. From the population of pixels within a treatment and within the treatment buffer (i.e. site), we subsampled on a regular spacing interval of 60 m (*sensu* Wimberly et al., 2009) to minimize coregistration error and to increase independence among sample units. Data used to address questions 1 and 4 were subset into treated or untreated areas prior to analysis. For each model used to address questions 2 and 3, we equalized sample sizes of pixels inside and outside of the prescribed fire boundary by randomly selecting pixels from the region with an excess. This step ensured that the effects of predictor variables on wildfire severity are not biased by a low sample size, since data from both treated and untreated areas were included in each of these models. Only pixels that were burned by wildfire, or by prescribed fire and wildfire, were used to develop predictive models. This provides more conservative estimates of prescribed fire effectiveness. For example, portions of the Parks site that were treated with prescribed fire, but unburned in the wildfire, were excluded from analyses despite observational evidence suggesting

Table 2
Descriptions of variables used, or potentially used, in NPMR analyses.

Variable type	Variable	Obs. range	Units	Source	Description
Response	WILDSEV	20.2–42.2	–	Landsat 5	Pre- to post-wildfire, Landsat derived change in normalized burn ratio, transformed as: $(700+\text{dNBR})^{0.5}$
Pixel-level predictor	RXSEV	20.1–36.9	–	Landsat 5	Pre- to post-prescribed fire, Landsat derived change in normalized burn ratio, transformed as: $(700+\text{dNBR})^{0.5}$
	ELEV	1106–2467	meters	DEM	Mean elevation of the pixel
	SLOPE	0–360	degrees	DEM	Mean slope of the pixel
	ASPECT	0–73	degrees	DEM	Aspect of the pixel
	HEATLOAD	0–1	–	DEM	Transformed ASPECT such that 0 = coolest and 1 = warmest slopes
	TRMI	1–27	–	Calculated	Expected relative moisture content based on topography, 1 = most xeric, 27 = most mesic. Based on Manis et al. (2001).
	VEGTYPE	–	Categorical	LANDFIRE	LANDFIRE SAF Existing Vegetation Type
	VEGCOV	5–95	percent	LANDFIRE	Calculated using mid-points of LANDFIRE Existing Vegetation Cover classes
	VEGHT	0.25–37.5	meters	LANDFIRE	Calculated using mid-points of LANDFIRE Existing Vegetation Height classes
	VEGVOL	$10–32 \times 10^3$	m^3	LANDFIRE	Calculated as: pixel area (900 m^2) x VEGCOV x VEGHT
Spatial predictor	EASTING	596,580–620,010	meters	GIS	Easting coordinates measured in WGS_84_UTM_zone_11 N
	NORTHING	49,77,360–49,86,930	meters	GIS	Northing coordinates measured in WGS_84_UTM_zone_11 N
Patch-level predictor	RXPERIMDIST	−1000–+1247	meters	Calculated	Number of meters outside (negative), or inside (positive) the nearest edge of a treatment perimeter
	RXPATCHDIST	−1312 to +510	meters	Calculated	Number of meters outside (negative), or inside (positive) nearest edge of a contiguous treatment patch with RxSev > 27
	HIVOLDIST	−379 to +362	meters	Calculated	Number of meters outside (negative), or inside (positive) nearest edge of a contiguous patch where VEGVOL > 10×10^3 m^3
	LOVOLDIST	−999 to +241	meters	Calculated	Number of meters outside (negative), or inside (positive) nearest edge of a contiguous patch where VEGVOL < 2×10^3 m^3

that these areas would have likely burned had there been no pre-wildfire treatment.

To address each research question, we used nonparametric multiplicative regression (NPMR; HyperNiche 2.16; McCune and Mefford, 2009), which allowed us to determine how treatment, topographic, vegetation, and landscape context variables combine in non-linear, multiplicative ways to influence wildfire severity at a given site (McCune, 2006; McCune, 2009). In each NPMR analysis, we used the local linear model with Gaussian weighting functions to conduct a free search of combinations of predictor variables and tolerances (tolerance = SD of Gaussian weighting function for each predictor) that maximized model fit (assessed by cross-validated R^2, or xR^2) and minimized over-fitting (assessed by a minimum average neighborhood size, a minimum data-to-predictor ratio, and an improvement criterion). The best fitting model for each analysis was the model with a given number of predictor variables that resulted in a $\geqslant$3% increase in xR^2 over the competing model with one fewer predictor variables. We report xR^2, the average neighborhood size (N^*; mean number of sample units contributing to the estimate of the response variable at each point on the modeled surface), and for quantitative predictor variables, tolerance and sensitivity values. High tolerance values (relative to the range of the predictor variable) indicate that data points with a greater distance (in predictor space) from the point targeted for estimation, contribute to the estimate of the response variable's value at the target point. Sensitivity, which ranges from 0 to 1, indicates the relative importance of each predictor in the model. Predictors with sensitivity values of 1 have the maximum influence possible, whereas a value of zero indicates that the variable has no influence on the response variable.

2.3.1. Prescribed fire effectiveness

We addressed question 1 using two different approaches. First, we performed a matched pairs *t*-Test (SAS 9.2, SAS Institute Inc., Cary, NC, USA) on the observed mean wildfire severity of pixels in treated (n = 3 treated areas) and untreated (n = 3 treatment buffers) areas to determine if treated pixels had a significantly lower wildfire severity than pixels in surrounding areas. Second, we developed a model predicting wildfire severity only in the buffer around each treatment using pre-fire vegetation, topographic, and vegetation patch variables ("Wildfire Potential Model"). We applied the model to all pixels (both to buffer pixels used to develop the model and to treated pixels which were not used in model development) to estimate wildfire severity. The results of this model provide an estimate of potential burn severity within treated areas, had prescribed fires not been conducted. They can also show that treated areas are not inherently less susceptible to wildfire than surrounding areas. We used these model outputs to calculate the mean proportion of pixels in each of four burn severity classes for each treated area (n = 3) and for each untreated buffer area (n = 3). We also performed a matched pairs t-Test on the observed mean wildfire severity of pixels in treated areas (n = 3) and the potential (based on Wildfire Potential Model predictions) mean wildfire severity of pixels in the same treated areas (n = 3).

2.3.2. Within-pixel predictors of wildfire severity

To evaluate question 2, we developed a NPMR model for each site, using only potential predictor variables that described the characteristics (prescribed fire severity, topography, and vegetation) within pixels ("Pixel-level Model"). This model indicates the relative importance of these predictors at the same spatial scale at which wildfire severity is being assessed.

2.3.3. Landscape-context predictors of wildfire severity

To evaluate question 3, we developed a NPMR model ("Patch-level Model") for each prescribed fire, using only patch-scale potential predictor variables that describe the landscape context of each pixel (e.g. RXPERIMDIST, RXPATCHDIST, HIVOLDIST, LOVOLDIST). This model assesses the importance of the landscape context of pixels in the absence of any information about the treatment, topographic, or vegetative conditions within the pixel itself. We also developed a "Pixel+Patch Model" using potential predictor variables that describe both within-pixel conditions and the landscape context of each pixel. This model indicates the relative importance of variables at both spatial scales.

We developed a "Spatial Model" using only UTM coordinates, which when modeled together multiplicatively, indicate the amount of variability in wildfire severity that can be attributed to the geographic location of the pixel alone (i.e. a high xR^2 indicates high spatial autocorrelation). The variables and tolerances fitted in the Spatial Model were added to each of the best Pixel-level, Patch-level, and Pixel+Patch Models to assess the change in model fit when geographic information is added. These models do not remove the effects of spatial autocorrelation as is often the goal of autoregression-type analyses, but instead include spatial effects, allowing for comparisons of the relative contribution and overlap of information represented by variables in the combined models. Although spatial autocorrelation can bias hypothesis tests, it does not necessarily bias model estimates (Hawkins et al., 2007). It is these estimates of the predictive ability of independent variables, and not formal hypothesis tests, that are the focus of our approach.

2.3.4. Differences between prescribed fire and wildfire

We addressed question 4 by separately modeling the relationship between two topographic variables, HEATLOAD and TRMI, and wildfire severity in untreated pixels. We then compared these relationships to those between HEATLOAD, TRMI, and prescribed fire severity in treated pixels, focusing on how wildfire and prescribed fire differ with regards to burn severity magnitude and the location of peak burn severity along gradients of the two topographic predictors.

3. Results

3.1. Prescribed fire effectiveness

Observed wildfire severity (WILDSEV) was heterogeneous and patchy at all three sites (Fig. 2). Mean observed WILDSEV was significantly lower in treated areas than in untreated buffers ($n = 3$ paired treated and untreated areas, mean difference = 3.61 WILDSEV units, SE = 0.44, $t = 8.11$, $p = 0.015$; Supplemental Fig. 3). The highest mean WILDSEV was in the untreated buffer around the

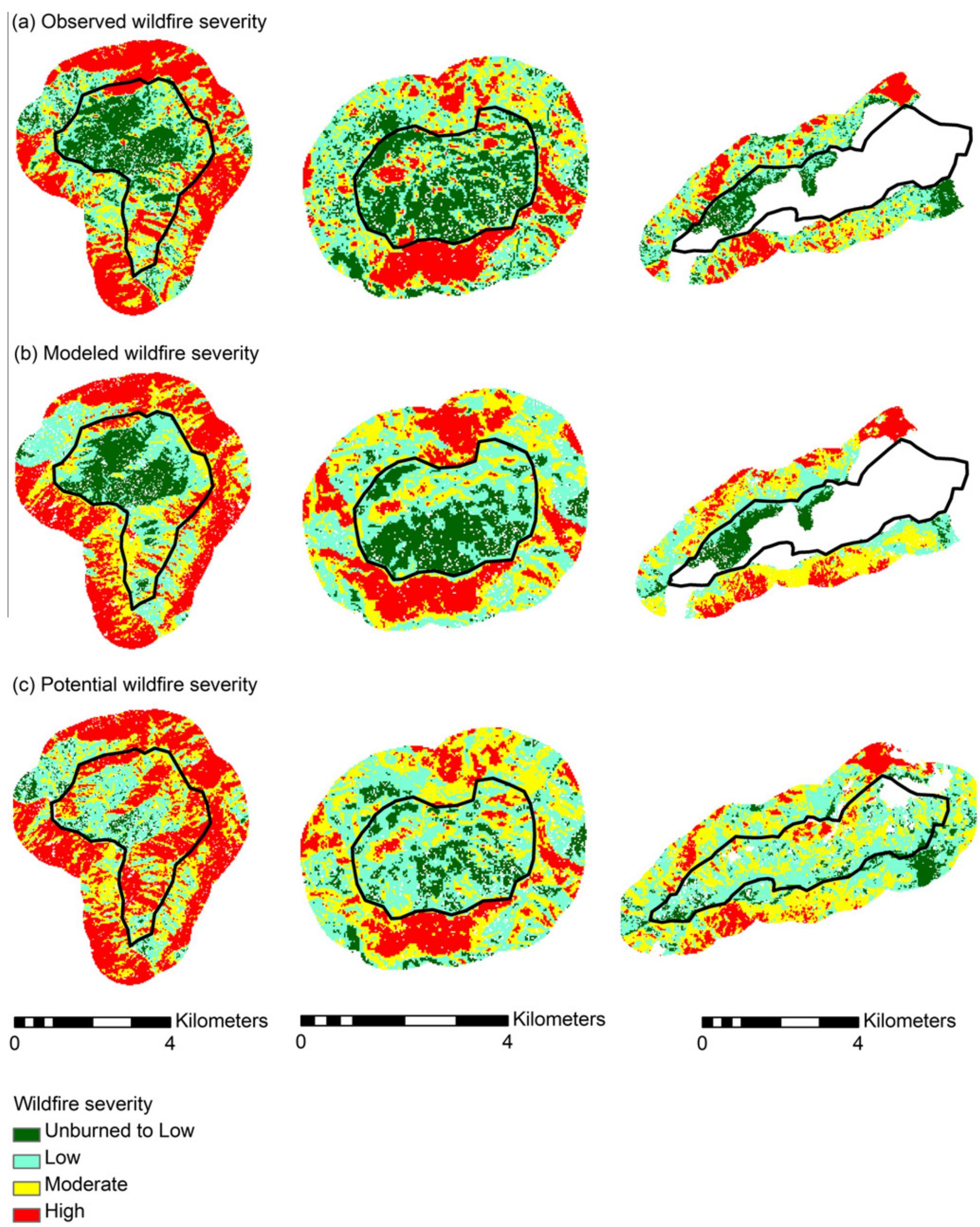

Fig. 2. For Williams, Fitsum, and Parks sites (left to right), (a) observed wildfire severity (based on dNBR calculated from Landsat 5 imagery), (b) modeled burn severity (based on predictions from NPMR Pixel+Patch Models), and (c) potential wildfire severity had treatments not been conducted (based on predictions from NPMR Wildfire Potential Models). Black lines indicate treatment perimeters. All data clipped to within 1 km of a treatment perimeter.

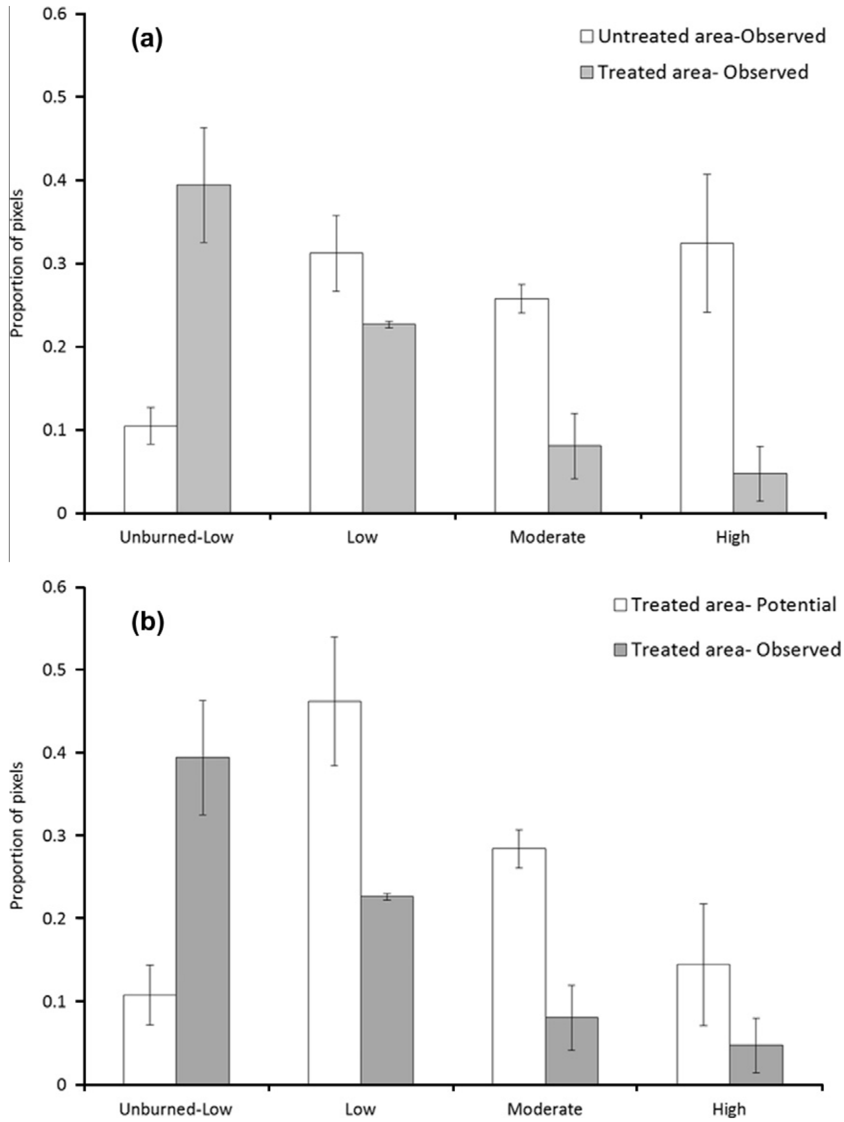

Fig. 3. (a) Observed mean wildfire severity distribution for pixels in untreated (unshaded bars) and prescribed fire treated (shaded bars) areas. (b) For pixels located within treatment perimeters only, the potential wildfire severity (unshaded bars; based on Wildfire Potential Models) had no treatments occurred and the observed (shaded bars) wildfire severity. Values indicate the average (±1 SE) proportion of pixels in each burn severity class at $n = 3$ sites.

Williams prescribed fire, whereas the lowest mean WILDSEV was within the Parks prescribed fire treatment, the oldest of the three treatments. Mean severity within the Parks treatment area would have been lower if calculations included areas that were unburned by the wildfire. The largest difference between a treated area and the corresponding untreated area was at the Williams site. The proportion of pixels (i.e. area) in each burn severity class was consistent across sites for both treated and untreated areas, with untreated buffers having substantially more area in the higher burn classes (Fig. 3a).

The three Wildfire Potential Models explained 60–66% of the variation in WILDSEV of untreated pixels (Table 3). When we applied and mapped these model estimates to treated areas (i.e. to predict potential wildfire severity had these areas not been treated), we found that the proportion of pixels in low, moderate, and high severity classes was substantially reduced by the three prescribed fire treatments relative to potential WILDSEV values for these areas (Fig. 2a versus 2c). Based on estimates from the Wildfire Potential Models, the proportion of pixels in the unburned-low class was about 4-fold greater because of treatment (Fig. 3b). Mean observed WILDSEV was significantly lower in treated areas than mean potential WILDSEV in treated areas ($n = 3$ paired observed and potential values, mean difference = 3.03 WILDSEV units, SE = 0.61, $t = 4.90$, $p = 0.039$; Supplemental Fig. 4).

3.2. Within-pixel predictors of wildfire severity

Pixel-level Model fit was strong for each of the prescribed fires, with xR^2 ranging from 0.46–0.58 (Table 3). Three within-pixel variables were consistently important predictors of wildfire severity: HEATLOAD, RXSEV, and VEGVOL (Supplemental Table 2). For each of the three sites, VEGVOL was the most influential variable, followed by RXSEV, then HEATLOAD. TRMI and ELEVATION were included in one model each. The inclusion of ELEVATION in the Parks prescribed fire model was driven by an increase in WILDSEV with ELEVATION in the untreated buffer, not within treated pixels. TRMI was likely included in the Williams model because at this site there was a greater range of xeric to mesic values that did not correlate as strongly with HEATLOAD. SLOPE was not an important predictor of wildfire severity for any of the three sites, nor were VEGTYPE, VEGCOV, or VEGHT, likely because of correlations with VEGVOL, the strongest predictor of WILDSEV.

Table 3
NPMR results for four different models predicting wildfire severity at three different sites in and around prescribed fire treatments. Different model types include different combinations of potential predictor variables and different subsets of input data.

Site	Model	xR^2	%ΔxR^2	N^*
Williams	Wildfire Potential	0.62	3.8	110.9
	Pixel-level	0.58	5.2	229.7
	Patch-level	0.66	5.4	141.5
	Pixel+Patch	0.69	3.2	75.0
Fitsum	Wildfire Potential	0.60	7.9	76.0
	Pixel-level	0.50	11.0	415.0
	Patch-level	0.55	5.0	99.2
	Pixel+Patch	0.63	3.0	53.9
Parks	Wildfire Potential	0.66	3.9	39.9
	Pixel-level	0.46	5.1	156.2
	Patch-level	0.56	3.2	66.0
	Pixel+Patch	0.59	3.4	82.1

xR^2 is the cross validated R^2 value calculated using a leave-one-out approach, which provides an estimate of model fit where the error rate in the training data approximates that of the prediction data.
%ΔxR^2 is the percent change in model fit (xR^2) when the final variable is added to develop the best model. This value must be ⩾3 to justify including the final variable in the model.
N^* is the average number of data points contributing to estimates of each point on the model surface. Higher values indicate that on average estimates of the response variable are well supported throughout the predictor space.

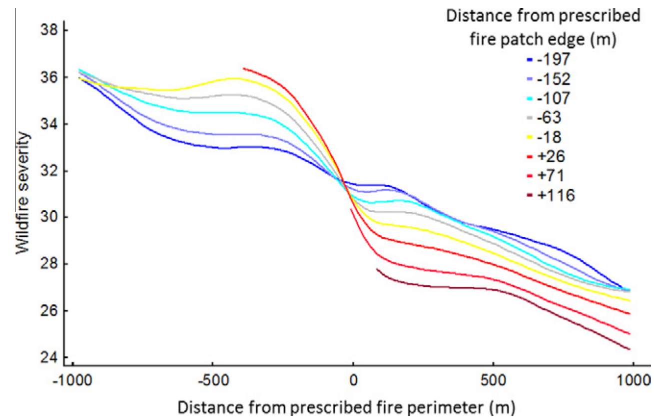

Fig. 4. NPMR modeled relationship between wildfire severity (WILDSEV) and variables describing the spatial location of pixels relative to the treatment perimeter (*x*-axis) and treatment patches (color coded line series). Negative values indicate pixels outside and positive values indicate pixels inside of the treatment perimeter (RXPERIMDIST) or a treatment patch edge (RXPATCHDIST). Warmer (red) line colors indicate pixels further inside of prescribed fire treatment patches, and cooler (blue) colors indicate pixels further outside of treatment patches. Pixels outside of the treatment perimeter, yet inside of a "treatment patch" are pixels that exhibited spectral changes analogous to those of prescribed fire treatment, but likely represent some other disturbance type.

WILDSEV increased with VEGVOL, but across the VEGVOL gradient, WILDSEV was substantially lower in areas treated with higher severity prescribed fire (see Supplemental Fig. 5a–c for relationships described in this section). This mediating effect of RXSEV on the relationship between VEGVOL and WILDSEV was greatest when VEGVOL was between 5 and 10×10^3 m^3, subsequently RXSEV became gradually less important as VEGVOL approached 17×10^3 m^3. Similarly, the effect of RXSEV on the relationship between TRMI and WILDSEV was greatest at low (dry) values of TRMI, and diminished in more mesic areas (TRMI = ca. 22). HEATLOAD was negatively related to WILDSEV; however over the HEATLOAD gradient, WILDSEV was reduced where prescribed fire severity was higher. The effect of RXSEV on the HEATLOAD–WILDSEV relationship was greatest in hotter areas, whereas RXSEV had little effect in cooler locations. The lack of an effect of RXSEV at the respective ends of the gradients described above, is at least partially due to a lack of treated pixels in those regions (i.e. few treated pixels in cool, mesic locations).

3.3. Landscape-context predictors of wildfire severity

Landscape context variables were stronger predictors of WILDSEV (xR^2 = 0.55–0.66) than were variables representing within-pixel conditions, as Patch-level Model fit was better than Pixel-level Model fit for each of the three sites (Table 3). Continuity between models was good, with all three Patch-level Models containing the same four variables (Supplemental Table 2). RXPATCHDIST was the most or second most influential variable in all three models. RXPERIMDIST was less influential than RXPATCHDIST in all three models, but provided additional predictive ability. HIVOLDIST was more important than LOVOLDIST in 2 of 3 models, and was the most influential predictor of WILDSEV in one of the Patch-level models.

WILDSEV was highest in pixels located farther inside patches of high vegetation volume (or farther outside patches of low vegetation volume) that were well outside of treated areas. Within treatment perimeters (RXPERIMDIST > 0), WILDSEV dropped continuously towards the interior of the prescribed fire boundary (Fig. 4, general trend of all line series), with the largest decrease in WILDSEV observed in pixels located further inside patches of high vegetation volume. However, prescribed fire severity was not uniform within treatment perimeters, and pixels located in patches of higher severity prescribed fire (RXPATCHDIST > 0) had substantially lower WILDSEV than those located outside of prescribed fire patches (RXPATCHDIST < 0) but still within the treatment perimeter (Fig. 4, difference between line series). But even those pixels about 200 m outside of prescribed fire patches, but still within the prescribed fire perimeter, had reduced WILDSEV (relative to untreated pixels) if located closer to the treatment center (Fig. 4, dark blue line). Outside of the treatment perimeter (RXPERIMDIST < 0), pixels in patches that were mapped (erroneously) as prescribed fire patches had the highest WILDSEV (Fig. 4, red line), which decreased with distance from these patches of non-treatment vegetation change. These patches were caused by a non-treatment disturbance, but exhibited spectral changes analogous to those of the prescribed fire. In addition to the edge effects observed inside of the treatment boundary (i.e. for pixels outside of prescribed fire patches, WILDSEV decreased with decreasing distance to prescribed fire patches) there appeared to be a slight edge effect near the prescribed fire boundary, as WILDSEV decreased in pixels that were less than 200 m outside of the treatment boundary.

3.4. Within-pixel and landscape-context predictors of wildfire severity

Combining variables representing within-pixel conditions with those representing the landscape-context of pixels (Pixel+Patch Models) resulted in the overall best fitting models predicting WILDSEV (xR^2 = 0.59–0.69; Table 3). Continuity between models was high, as all three Pixel+Patch Models shared four variables (Supplemental Table 2). Only one variable, ELEVATION, was not shared by all three models. Within-pixel VEGVOL was the most influential variable in all three Pixel+Patch Models. The landscape-context variable RXPERIMDIST was the second best predictor of WILDSEV. LOVOLDIST and HEATLOAD were both included in each model. Models containing variables not listed above (i.e. TRMI, RXPATCHDIST, RXSEV, and HIVOLDIST) were quite competitive with the best fitting Pixel+Patch Model, and the absence of these variables from the final Pixel+Patch Model is likely due to their containing shared information with selected variables, and not to a lack of importance or predictive capability. Overall, the relationships between

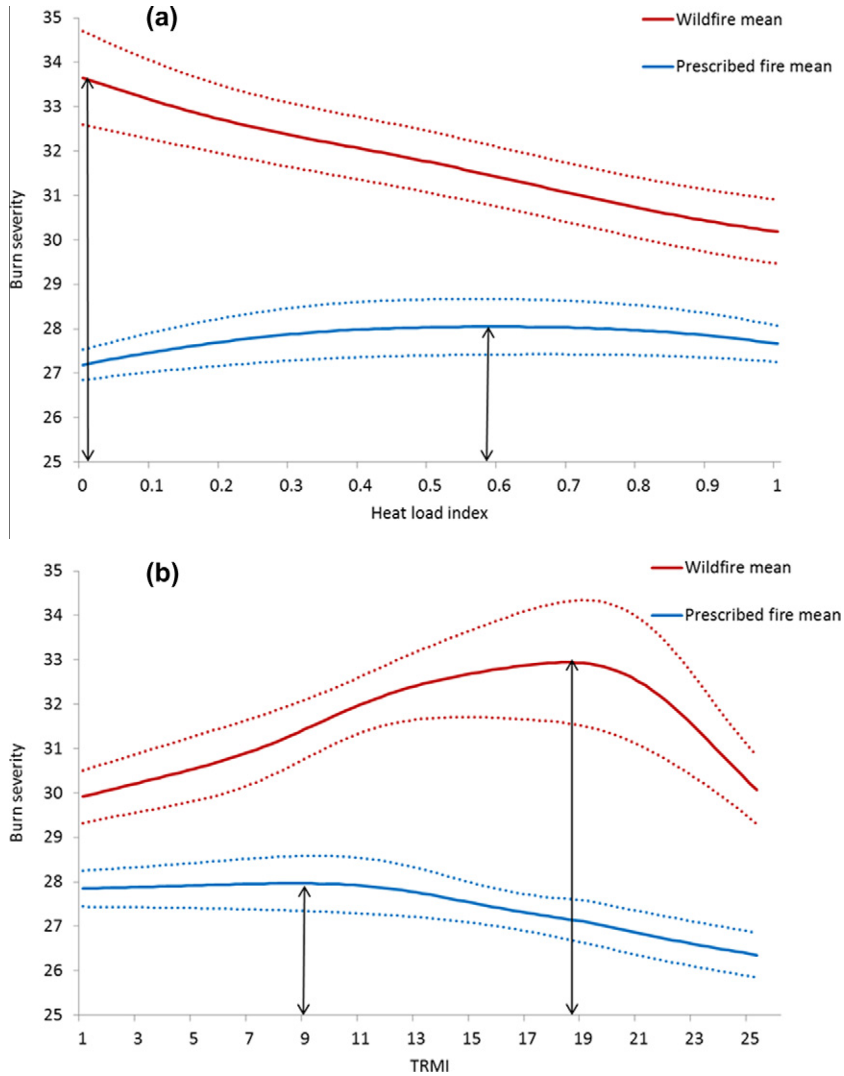

Fig. 5. NPMR modeled effects of (a) heat load and (b) topographic relative moisture index on wildfire severity (in untreated areas) and prescribed fire severity (in treated areas). Solid lines are mean values of estimates generated from separate models developed at $n = 3$ sites. Dashed lines indicate ±1 SE. Arrow locations along x-axis indicate peaks in burn severity along the two environmental gradients. Arrow length indicates the magnitude of peak burn severity.

predictor variables and WILDSEV in the Pixel+Patch Models were similar to those observed in the Pixel Models and in the Patch Models.

Predicting and mapping WILDSEV from the best-fitting Pixel+Patch Models to all pixels (i.e. those used to develop the models and those not used in model development) at each site illustrated the strong spatial agreement with the observed burn severity patterns at all three sites (Fig. 2). This continuity between observed and modeled WILDSEV indicates that models, derived from only pre-fire GIS variables, can generate spatially realistic burn severity predictions.

3.5. Spatial models

The Spatial Model explained 49–57% of the observed variation in WILDSEV at a given site, an amount comparable to that explained by each site's best Pixel-level Model (Supplemental Table 3). Adding the spatial terms to each site's best Pixel-level Model (Pixel+Spatial Model; Supplemental Table 2) resulted in model fits of 52–83%. However, adding information about the geographic location of the pixels in these models did little to help predict observed WILDSEV when patch-level predictors were already included because adding the spatial terms to each site's best Patch-level Model, or to each site's best Pixel+Patch Model, tended to result in very small increases, or in decreases in resulting model fits.

3.6. Differences between prescribed fire and wildfire

Not only did prescribed fires burn at lower severity than wildfires, but wildfires and prescribed fires tended to burn different locations on the landscape (Fig. 5). WILDSEV peaked at HEATLOAD values of 0 (i.e. the coolest aspects) and TRMI values of about 19, relatively mesic locations. In contrast, prescribed fire severity peaked at HEATLOAD values of about 0.6 and TRMI values about 9, in warm, dry locations. Although these trends were similar for all three prescribed fires, the magnitude of RXSEV at these peaks was higher in the Parks treatment (RXSEV = 29) than in the Williams and Fitsum treatments (RXSEV = 27).

4. Discussion

4.1. Do prescribed fires reduce subsequent wildfire severity relative to potential wildfire severity?

Prescribed fires are commonly used by forest managers to reduce the likelihood of severe wildfires by lowering fuel loads in fire-adapted forests, yet few empirical data are available to support this application. Most of the available information has come from plot-based studies that cover relatively small portions of treated landscapes and use ocular indices or categorical measures of burn severity. These studies have found that prescribed fires do successfully alter wildfire severity relative to untreated areas (Pollet and Omi, 2002; Lezberg et al., 2008; Symons et al., 2008; Safford et al., 2009; Prichard et al., 2010), but inference is often limited by small sample sizes that may not capture the full range of environmental conditions and gradients across treated landscapes. We know of only two studies that have compared wildfire severity of treated areas with similar untreated surroundings using a landscape scale remote sensing-based approach (Finney et al., 2005; Wimberly et al., 2009). Only one of the prescribed fires examined in those studies was conducted in the northern Rocky Mountains and the site was mechanically thinned prior to prescribed fire treatment. Despite differences in study regions and treatment characteristics, our results are consistent with those of Finney et al. (2005) and Wimberly et al. (2009), who also found sizable reductions in wildfire severity within areas treated with prescribed fire.

The congruence among landscape-scale and plot-based studies supports the use of prescribed fires as an effective means of reducing future wildfire severity in dry coniferous forest types. Prescribed fires in these studies were particularly effective when implemented shortly before wildfires, when large in size, and when repeated in the same locations (Finney et al., 2005), or when they were combined with thinning treatments (Wimberly et al., 2009). Others have found similar decreases in subsequent wildfire severity when thinning and prescribed fire treatments were combined (Pollet and Omi, 2002; Symons et al., 2008; Prichard et al., 2010). No thinning occurred prior to the prescribed fires in our study area and we did not examine the effects of prescribed fire age because two of three fires were conducted one year prior to the wildfires. Of the three prescribed fires examined, Parks was the most effective. The majority of the Parks treatment area did not burn in the wildfire, whereas the two other treatment areas burned throughout and at somewhat higher severity. We suspect this difference was caused by the higher severity and burn continuity of the prescribed fire at the Parks site. Our results suggest that these factors could be more important than treatment age, at least within the first few years following treatment, but further investigation is needed.

Our study is the first to compare observed burn severity within treated areas to potential burn severity (based on predictive modeling) had those areas not been treated. We found that the treated areas were susceptible to wildfire, which provides further evidence that the prescribed fire treatments effectively lowered the wildfire severity. Our findings suggest that this approach may provide a more accurate means of assessing treatment effectiveness in the future. It could also be used as a management tool to predict potential wildfire severity across unburned landscapes and prioritize fuel reduction activities.

4.2. How do vegetation, topography, and prescribed fire severity influence prescribed fire effectiveness?

At the pixel-level, pre-treatment vegetation volume, heat load, and prescribed fire burn severity were consistently strong predictors of wildfire severity, while TRMI and elevation were important at one site each. There were complex interactions between these variables, which reveal that not only were specific combinations of these factors important predictors at the local scale, but also that certain locations on the landscape benefited more from prescribed fire treatment than others. For example, pixels treated with higher severity prescribed fire were much more effective at reducing wildfire severity, but this effect was much greater in relatively warm, dry locations than in cool, mesic locations. Paradoxically, it is the cooler, more mesic locations that tended to have higher vegetation volumes and tended to burn more severely during wildfire. We attribute the lower effectiveness of prescribed fire in these locations to the moist early season conditions (relative to those of typical summer wildfires) present during the prescribed fire treatments. Prescribed fire burned at higher severity in warmer, drier locations because these areas contained fuels dry enough to carry an early season prescribed fire. Similar results were reported for a fire in northwestern Montana, where fuel loads, heat load, and canopy cover were found to be important predictors of wildfire severity in a treated landscape (treatments included thinned, thinned and prescribed burned, and untreated areas), while elevation and slope were relatively unimportant (Camp 32 Fire, ordinary least-squares models in Wimberly et al. 2009).

Others have shown the importance of topographic variables in predicting wildfire severity in untreated landscapes (e.g. Lentile et al., 2006; Dillon et al., 2011). Although these or related variables (i.e. vegetation volume, heat load, TRMI, elevation) have been found to be important predictors of wildfire severity in several studies, the magnitude and even the directionality of their effects on wildfire severity may be highly context dependent. Context dependence of wildfire burn patterns may be due to differences in regional climates during wildfire season, or to regional differences in forest stand profiles (i.e. tree species, sizes, densities, and ladder fuels). For example, in northern California and adjacent areas of Oregon, studies have shown that wildfire severity is lower in cooler, north-facing, old growth forests, where biomass was greatest, and that wildfire severity was greater on warmer, south or west facing slopes with lower biomass (Weatherspoon and Skinner, 1995; Alexander et al., 2006; Skinner et al., 2006). This is opposite the pattern we observed in central Idaho. We suspect that this difference may be driven by regional climate; that is, the northern California and Oregon sites may receive enough summer precipitation, or may retain enough spring fuel moisture, that the locations with the highest biomass are too moist to have a high probability of burning at high severity. The forest biomass and fuel moisture on south-facing slopes at the California and Oregon sites may be more analogous to the conditions of north-facing slopes at our Idaho sites (i.e. moderately high biomass and relatively low summer fuel moisture).

4.3. How does landscape context combine with local conditions to influence wildfire severity?

The landscape context, or position of pixels within vegetation patches, treatment patches, and treatment boundaries, had a strong influence on wildfire severity in and around treated areas. Wildfire severity was lower further inside contiguous prescribed fire patches, and was lower still when those patches were located further inside the prescribed fire boundary. Outside of the treatment perimeter, areas where non-treatment disturbances were detected had the highest wildfire severities, which diminished with increasing distance from these disturbances. These areas may represent locations where tree disease, beetle infestation, or blow-down events caused highly flammable fuel conditions (i.e. brown needles) and the associated spectral changes observed in satellite imagery (Wulder et al., 2006; Vogelmann et al., 2009). Both inside and outside of treatment perimeters, wildfire severity was highest further inside continuous patches of high vegetation volume and lowest in areas that were far from these patches (i.e. usually in contiguous patches of low vegetation volume). We did not find evidence that the treatments influenced wildfire severity more than 200 m outside of the treatment perimeter; previous studies had suggested that prescribed fires had altered fire spread on the leeward side of the fire (Finney et al., 2005; Wimberly et al., 2009).

Wildfire severity was determined by factors operating at multiple spatial scales. As expected, we found that wildfire severity in and around treated areas was best explained by a combination of local (within-pixel) and landscape-context variables. Fit for the Pixel+Patch Models was quite high, as was the continuity between models, with all three Pixel+Patch Models sharing four variables: two pixel-level variables (vegetation volume and heat load) and two landscape-context variables (distance to prescribed fire edge and distance to the edge of a patch of low vegetation volume). The pixel-level portion of our findings is consistent with Lentile et al. (2006) who found that topography and pre-fire tree density were important predictors of wildfire severity in a ponderosa pine forest of South Dakota, U.S.A.

Our results also suggest that prescribed fire size, shape, and burn continuity may be more important in reducing wildfire severity than achieving high prescribed fire severity. We provide the first evidence that the severity and continuity of prescribed fires influences subsequent wildfire severity, but similar to our study, Finney et al. (2005) found that pixels located in larger treatments, or further in the interior of treatments, had lower wildfire severities. After approximately four years elapsed between treatment and a subsequent wildfire, they found that the importance of distance from the treatment edge diminished, whereas the beneficial effects of large treatments persisted. Similarly, Ritchie et al. (2007) suggested that high tree mortality is likely in small treated areas (e.g. 0.5 ha) because of edge effects from intense fire in neighboring untreated areas; hence, treatment size should be considered during planning.

4.4. Do prescribed fires treat locations most at risk of high severity wildfires?

We found that in addition to burning at much lower severities than wildfires, early season prescribed fires tend to burn in locations that are warmer and more xeric than the relatively cool, mesic locations which are most at risk of high severity summer wildfire. These findings conflict with those of a study conducted in the southern Sierra Nevada Mountains of California which found that at fine spatial scales, prescribed fires and managed wildfires had similar burn severities, heterogeneity patterns, and effects on survivorship of small trees (Nesmith et al. 2011). However, as previously stated, early season prescribed fires in the northern Rocky Mountains are typically ignited shortly after snowmelt and thus the locations most likely to burn are on south-facing aspects where fuels have dried sufficiently. Wildfires in this region burn more severely where vegetation biomass is greater, particularly during drought conditions when these fuels are dry. These results agree with our observation that the most effective of the three prescribed fire treatments (Parks site) was successful because of an early spring and drier fuels. Fire managers involved in these treatments reported drier fuel conditions in May 2004 than May 2006, especially on the cooler, more mesic aspects. It is likely this difference that caused the increased treatment severity, continuity, and ultimately effectiveness of the Parks burn.

Although the three treatments examined here were quite effective at reducing subsequent wildfire severity, our results beg the question of whether prescribed fires would be even more effective if conducted when fuel characteristics are more similar to those of wildfire, perhaps later in the fall when drier conditions facilitate increased fuel consumption by prescribed fire (Knapp et al., 2005). There are obvious challenges in managing potentially higher severity fall prescribed fires and it is unknown if these challenges are worth the effort and risk, especially when evidence supports the efficacy of current treatment practices.

4.5. Conclusions

Overall, these findings have important implications for prescribed fire programs in dry coniferous forests. First, even patchy, low severity prescribed fires can be effective at reducing wildfire severity, at least within a few years post-treatment. Second, the size, shape, and continuity of prescribed fires may be more important than prescribed fire severity at reducing the severity of subsequent wildfires (e.g. larger prescribed fires that maximize interior area and have higher burn continuity may be more effective). Third, prescribed fires and wildfires may burn in fundamentally different ways, likely because of differences in seasonal fuel conditions, but this does not appear to reduce the effectiveness of prescribed fire. Fourth, accurate prediction of wildfire severity in areas considered for prescribed fire treatments may be possible and could reveal where on the landscape prescribed fires would be most or least effective.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2012.04.002.

References

Agee, J.K., 1998. The landscape ecology of western forest fire regimes. Northwest Sci. 72, 24–34.

Agee, J.K., Skinner, C.N., 2005. Basic principles of forest fuel reduction treatments. For. Ecol. Manage. 211, 83–96.

Alexander, J.D., Seavy, N.E., Ralph, C.J., Hogoboom, B., 2006. Vegetation and topographical correlates of fire severity from two fires in the Klamath-Siskiyou region of Oregon and California. Int. J. Wildland Fire 15, 237–245.

Arkle, R.S., Pilliod, D.S., 2010. Prescribed fires as ecological surrogates for wildfires: a stream and riparian perspective. For. Ecol. Manage. 259, 893–903.

Barrett, S., 2000. Fire history and fire regimes south fork Salmon River drainage, central Idaho. In: USDA Forest Service Unpublished Report 43–0256-9-0651. Payette and Boise National Forests, ID, USA.

Battaglia, M.A., Smith, F.W., Shepperd, W.D., 2008. Can prescribed fire be used to maintain fuel treatment effectiveness over time in Black Hills ponderosa pine forests? For. Ecol. Manage. 256, 2029–2038.

Dillon, G.K., Holden, Z.A., Morgan, P., Crimmins, M.A., Heyerdahl, E.K., Luce, C.H., 2011. Both topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006. Ecosphere 2 (12), 130. http://dx.doi.org/10.1890/ES11-00271.1.

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

Fernandes, P.M., Botelho, H.S., 2003. A review of prescribed burning effectiveness in fire hazard reduction. Int. J. Wildland Fire 12, 117–128.

Finney, M.A., McHugh, C.W., Grenfell, I.C., 2005. Stand- and landscape-level effects of prescribed burning on two Arizona wildfires. Can. J. For. Res. 35, 1714–1722.

Fulé, P.Z., Crouse, J.E., Roccaforte, J.P., Kalies, E.L., 2012. Do thinning and/or burning treatments in western USA ponderosa or Jeffrey pine-dominated forests help restore natural fire behavior? Forest Ecol. Manage. 269, 68–81.

Graham, R.T., McCaffrey, S., Jain, T.B., 2004. Science basis for changing forest structure to modify wildfire behavior and severity. In: USDA Forest Service General Technical Report RMRS-GTR-120. Rocky Mountain Research Station, Fort Collins, CO, USA, p. 43.

Hawkins, B.A., Diniz-Filho, J.A.F., Mauricio Bini, L., De Marco, P., Blackburn, T.M., 2007. Red herrings revisited: spatial autocorrelation and parameter estimation in geographical ecology. Ecography 30, 375–384.

Holden, Z.A., Morgan, P., Smith, A.M.S., Vierling, L., 2010. Beyond Landsat: a comparison of four satellite sensors for detecting burn severity in ponderosa pine forests of the Gila Wilderness, NM, USA. Int. J. Wildland Fire 19, 449–458.

Hunter, M.E., Shepperd, W.D., Lentile, L.B., Lundquist, J.E., Andreu, M.G., Butler, J.L., Smith, F.W., 2007. A comprehensive guide to fuels treatment practices for ponderosa pine in the Black Hills, Colorado Front Range, and Southwest. In: USDA Forest Service General Technical Report RMRS-GTR-198. Rocky Mountain Research Station, Fort Collins, CO, USA, p. 99.

Jain, T.B., Graham, R.T., 2007. The relation between tree burn severity and forest structure in the Rocky Mountains. In: USDA Forest Service General Technical Report PSW-GTR-203. Rocky Mountain Research Station, Missoula, MT, USA, p. 38.

Kilgore, B.M., Sando, R.W., 1975. Crown-fire potential in a Sequoia forest after prescribed burning. Forest Sci. 21, 83–87.

Knapp, E.E., Keeley, J.E., 2006. Heterogeneity in fire severity within early season and late season prescribed burns in a mixed-conifer forest. Int. J. Wildland Fire 15, 37–45.

Knapp, E.E., Keeley, J.E., Ballenger, E.A., Brennan, T.J., 2005. Fuel reduction and coarse woody debris dynamics with early season and late season prescribed fire in a Sierra Nevada mixed conifer forest. For. Ecol. Manage. 208, 383–397.

Knapp, E.E., Schwilk, D.W., Kane, J.M., Keeley, J.E., 2007. Role of burning season on initial understory vegetation response to prescribed fire in a mixed conifer forest. Can. J. For. Res. 37, 11–22.

Lentile, L.B., Smith, F.W., Shepperd, W.D., 2006. Influence of topography and forest structure on patterns of mixed severity fire in ponderosa pine forests of the South Dakota Black Hills, USA. Int. J. Wildland Fire 15, 557–566.

Lezberg, A.L., Battaglia, M.A., Shepperd, W.D., Schoettle, A.W., 2008. Decades-old silvicultural treatments influence surface wildfire severity and post-fire nitrogen availability in a ponderosa pine forest. For. Ecol. Manage. 255, 49–61.

Manis, G., Lowry, J., Ramset, R.D., 2001. Preclassification: an ecologically predictive landform model. In: USDI Geological Survey GAP Analysis Program Bulletin 10, Moscow, ID, USA.

McCune, B., Grace, J.B., 2002. Analysis of Ecological Communities. MjM Software Design, Gleneden Beach, OR.

McCune, B., 2006. Non-parametric habitat models with automatic interactions. J. Veg. Sci. 17, 819–830.

McCune, B., Mefford, M.J., 2009. HyperNiche. Nonparametric Multiplicative Habitat Modeling. Version 2.16. MjM Software, Gleneden Beach, Oregon, USA.

McCune, B., 2009. Nonparametric Multiplicative Regression for Habitat Modeling. <http://www.pcord.com/NPMRintro.pdf> (accessed 15.03.2012).

Nesmith, J.C.B., Caprio, A.C., Pfaff, A.H., McGinnis, T.W., Keeley, J.E., 2011. A comparison of effects from prescribed fires and wildfires managed for resource objectives in Sequoia and Kings Canyon National Parks. Forest Ecol. Manage. 261, 1275–1282.

Peterson, D.L., Johnson, M.C., Agee, J.K., Jain, T.B., McKenzie, D., Reinhardt, E.D., 2005. Forest structure and fire hazard in dry forests of the western United States. In: USDA Forest Service General Technical Report PNWGTR-628. Pacific Norhwest Research Station, Portland, OR, USA, p. 38.

Pierce, J.L., Meyer, G.A., Jull, A.J.T., 2004. Fire-induced erosion and mellennial-scale climate change in northern ponderosa pine forests. Nature 432, 87–90.

Pollet, J., Omi, P.N., 2002. Effect of thinning and prescribed burning on crown fire severity in ponderosa pine forests. Int. J. Wildland Fire 11, 1–10.

Prichard, S.J., Peterson, D.L., Jacobson, K., 2010. Fuel treatments reduce the severity of wildfire effects in dry mixed conifer forest, Washington, USA. Can. J. For. Res. 40, 1615–1626.

Pyne, S.J., Andrews, P.L., Laven, R.D., 1996. Introduction to Wildland Fire, second ed. John Wiley & Sons, New York, NY, USA.

Reinhardt, E.D., Keane, R.E., Calkin, D.E., Cohen, J.D., 2008. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. For. Ecol. Manage. 256, 1997–2006.

Ritchie, M.W., Skinner, C.N., Hamilton, T.A., 2007. Probability of tree survival after wildfire in an interior pine forest of northern California: effects of thinning and prescribed fire. For. Ecol. Manage. 247, 200–208.

Rollins, M.G., Frame, C.K., 2006. The LANDFIRE Prototype Project: nationally consistent and locally relevant geospatial data for wildland fire management. In: USDA Forest Service General Technical Report RMRS-GTR-175. Rocky Mountain Research Station, Fort Collins, CO, USA, p. 416.

Safford, H.D., Schmidt, D.A., Carlson, C.H., 2009. Effects of fuel treatments on fire severity in an area of wildland-urban interface, Angora Fire, Lake Tahoe Basin, California. For. Ecol. Manage. 258, 773–787.

Scott, J.H., Reinhardt, E.D., 2001. Assessing crown fire potential by linking models of surface and crown fire behavior. In: USDA Forest Service Research Paper RMRS-RP-29. Rocky Mountain Research Station, Fort Collins, CO, USA, p. 59.

Skinner, C.N. 2005. Reintroducing fire into the Blacks Mountain Research Natural Area: effects on fire hazard. In: Ritchie, M. W., Maguire, D.A., Youngblood, A. (Eds.), Proceedings of the Symposium on ponderosa pine: Issues, trends, and management. 2004 October 18–21; Klamath Falls, OR. General Technical Report PSW-GTR-198. Pacific Southwest Research Station, Forest Service, U.S. Department of Agriculture, Albany, CA, pp. 245–257.

Skinner, C.N., Taylor, A.H., Agee, J.K., 2006. Klamath Mountains bioregion. In: Sugihara, N.S., van Wagtendonk, J.W., Fites-Kaufmann, J., Shaffer, K., Thode, A. (Eds.), Fire in California Ecosystems. University of California Press, Berkeley, pp. 170–194.

Stephens, S.L., Moghaddas, J.J., 2005. Experimental fuel treatment impacts on forest structure, potential fire behavior, and predicted tree mortality in a California mixed conifer forest. For. Ecol. Manage. 215, 21–36.

Stephens, S.L., Moghaddas, J.J., Edminster, C., Fiedler, C.E., Haase, S., Harrington, M., Keeley, J.E., Knapp, E.E., McIver, J.D., Metlen, K., Skinner, C.N., Youngblood, A., 2009. Fire treatment effects on vegetation structure, fuels, and potential fire severity in western US forests. Ecol. Appl. 19, 305–320.

Symons, J.N., Fairbanks, D.H.K., Skinner, C., 2008. Influences of stand structure and fuel treatments on wildfire severity at Blacks Mountain experimaental forest. Calif. Geographer 48, 1–23.

Vogelmann, J.E., Tolk, B., Zhu, Z., 2009. Monitoring forest changes in the southwestern United States using multitemporal Landsat data. Remote Sens. Environ. 113, 1739–1748.

Weatherspoon, C.P., Skinner, C.N., 1995. An assessment of factors associated with damage to tree crowns from the 1987 wildfires in northern California. Forest Sci. 41, 430–451.

Wimberly, M.C., Cochrane, M.A., Baer, A.D., Pabst, K., 2009. Assessing fuel treatment effectiveness using satellite imagery and spatial statistics. Ecol. Appl. 19, 1377–1384.

Wulder, M.A., Dymond, C.C., White, J.C., Leckie, D.G., Carroll, A.L., 2006. Surveying mountain pine beetle damage of forests: a review of remote sensing opportunities. For. Ecol. Manage. 221, 27–41.