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Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event

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Abstract. Under a rapidly warming climate, a critical management issue in semiarid forests of western North America is how to increase forest resilience to wildfire. We evaluated relationships between fuel reduction treatments and burn severity in the 2006 Tripod Complex fires, which burned over 70 000 ha of mixed-conifer forests in the North Cascades range of Washington State and involved 387 past harvest and fuel treatment units. A secondary objective was to investigate other drivers of burn severity including landform, weather, vegetation characteristics, and a recent mountain pine beetle outbreak. We used sequential autoregression (SAR) to evaluate drivers of burn severity, represented by the relative differenced Normalized Burn Ratio index, in two study areas that are centered on early progressions of the wildfire complex. Significant predictor variables include treatment type, landform (elevation), fire weather (minimum relative humidity and maximum temperature), and vegetation characteristics, including canopy closure, cover type, and mountain pine beetle attack. Recent mountain pine beetle damage was a statistically significant predictor variable with red and mixed classes of beetle attack associated with higher burn severity. Treatment age and size were only weakly correlated with burn severity and may be partly explained by the lack of treatments older than 30 years and the low rates of fuel succession in these semiarid forests. Even during extreme weather, fuel conditions and landform strongly influenced patterns of burn severity. Fuel treatments that included recent prescribed burning of surface fuels were particularly effective at mitigating burn severity. Although surface and canopy fuel treatments are unlikely to substantially reduce the area burned in regional fire years, recent research, including this study, suggests that they can be an effective management strategy for increasing forest landscape resilience to wildfires.

Key words: burn severity; mixed-conifer forests; mountain pine beetle; prescribed fire; spatial autoregression; wildfire.

Introduction

Wildfire activity in western North America is expected to intensify under global warming scenarios (McKenzie et al. 2004, Flannigan et al. 2005, Littell et al. 2010). In recent decades, warmer-than-normal summers and periods of prolonged drought have been common, and the extent and incidence of wildfires have increased (Gillett et al. 2004, Westerling et al. 2006, Morgan et al. 2008, Miller and Safford 2012). Of the total area burned in western North America, most wildfires occur during regional fire years in which climatic events dominate fire behavior and lead to synchronous, regional wildfires. Under a warming climate, longer fire seasons with more prolonged summer drought will likely result in the higher probability of extreme fire weather and regional fire events.

Concurrent with a changing climate, fire exclusion and timber management practices have reduced the complexity of many forested landscapes by homogenizing spatial fuel and age structures and increasing their susceptibility to insect outbreaks and high-severity fire events (Hessburg et al. 2005, Bentz et al. 2010). Managers of semiarid forests are faced with a combined challenge of restoring forest ecosystems so as to be more resilient to future climatic change and to be less vulnerable to wildfires, insects, and pathogens (Reinhardt et al. 2008, Stephens et al. 2012*a*). Existing studies of fuel treatments generally agree that mechanical thinning followed by prescribed burning is effective at reducing surface and ladder fuels and increasing forest resilience to wildfire (Fernandes and Botelho 2003, Agee and Skinner 2005, Finney et al. 2005, Strom and Fulé 2007, Reinhardt et al. 2008, Prichard et al. 2010, Lyons-Tinsley and Peterson 2012, Safford et al. 2012). However, little is known about the duration of treatment effectiveness and whether treatments can remain effective in extreme fire events.

The relative influence between top-down climatic controls and bottom-up influences of fuels and topography on fire behavior and effects is not well understood. Lessons from the 1988 Yellowstone fires (Turner and Romme 1994) suggest that under extreme antecedent climatic (drought) and fire weather conditions, a

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wide range of stand ages, vegetation, and fuels were available to burn and that fuel breaks (e.g., riparian corridors, moist vegetation types, and young forests) were not effective. Similar conclusions have been made for chaparral ecosystems of southern California (Moritz 2003) and boreal wildfires (Bessie and Johnson 1995). Under average or mild weather conditions, differences in fuel loads, vegetation types, and topographic roughness can reduce wildfire behavior and create barriers to fire spread (Boer et al. 2009, Moritz et al. 2011). Recent large wildfire events that have burned over past fuel treatments provide an opportunity to evaluate whether fuel treatments are capable of mitigating burn severity even under extreme fire weather events and under what conditions they remain effective (Finney et al. 2005, Prichard et al. 2010, Lyons-Tinsley and Peterson 2012, Safford et al. 2012).

A promising approach to evaluating fuel-treatment effectiveness at broad spatial scales is retrospective analysis of burn severity. Burn severity mapping has become standard for large fire events, and it is available in the United States from the Monitoring Trends in Burn Severity (MTBS) program (Eidenshink et al. 2007). The most common image differencing technique, and the one adopted by MTBS, is the differenced Normalized Burn Ratio index (dNBR). The dNBR index is calculated from pre- and post-burn Landsat Thematic Mapper (TM) images and is responsive to changes in vegetation and ground reflectance (Miller and Yool 2002, Key 2006). The relative difference Normalized Burn Ratio (RdNBR) index was developed to compensate for prefire variability in biomass and cover (Miller and Thode 2007, Miller et al. 2009). Comparisons of dNBR and RdNBR have shown that RdNBR may be more accurate in sparsely vegetated areas or in heterogeneous vegetation (Zhu et al. 2006, Miller and Thode 2007), whereas the indices have similar accuracy in dense forests (Zhu et al. 2006, Soverel et al. 2010, Cansler and McKenzie 2012). Fire progression, local weather, landform, vegetation, and fuel layers makes it possible to explore the key drivers of burn severity and to evaluate the effect of fuel treatments in the context of other potential covariates.

Several studies have presented approaches for modeling drivers of burn severity across forested landscapes. Bigler et al. (2005) employed ordinal logistic regression to evaluate the effect of past fires; an old, mountain pine beetle (MPB, *Dendroctonous ponderosae*) outbreak; forest cover type; stand structure; and landform on burn severity in a 2002 Colorado wildfire. Finney et al. (2005) used conditional spatial autoregression analysis to evaluate the effectiveness of prescribed burning, time since treatment, unit size, and burn frequency in mitigating burn severity in the 2002 Rodeo-Chedeski fires of Arizona. Collins et al. (2007) performed a regression tree analysis on burn severity in two recent fires in Yosemite National Park and examined landform, vegetation, and weather as predictor variables. Kulakowski and Veblen (2007) also used regression tree analysis to evaluate the effect of prior disturbances, including bark beetle outbreaks, blowdowns, and salvage logging, on burn severity in a 2002 Colorado wildfire. Wimberly et al. (2009) evaluated fuel treatment effectiveness on burn severity for three recent California wildfires using ordinary least squared regression (OLS) and sequential autoregression (SAR).

In this study, we use SAR modeling to evaluate the effects of fuel treatments and other biophysical variables on burn severity within the 2006 Tripod Complex fires, which burned over 70 000 ha of semiarid, mixed-conifer forest. SAR improves on standard regression analysis by leveraging the inherent spatial autocorrelation in burn severity data to provide a proxy for missing variables, such as local fire weather and fuel conditions, and by creating more robust inferences than do models such as OLS that do not account for spatial autocorrelation (Wimberly et al. 2009). The main objective of this study was to determine the effect of fuel treatments on burn severity across the treated portions of the Tripod Complex landscape. A number of other factors likely influenced the extent and severity of the wildfires, including fire weather, vegetation, landform, and past disturbances. A secondary objective was to evaluate these other potential drivers of burn severity, including a widespread MPB outbreak on the prefire landscape. Because the Tripod Complex was such a large event, much of the fire spanned untreated landscapes in which forest and fuels management had little or no influence on fire spread and severity.

Materials and Methods

Study area

The Tripod Complex fire area is located in the Okanogan-Wenatchee National Forest, north-central Washington State (Fig. 1; see Plate 1). Winters are cold, and summers are warm and dry with prolonged seasonal drought. Based on 1971–2001 annual weather data, mean annual temperature is 7.4°C, ranging from −10.8°C (January annual average minimum) to 29.9°C (August annual average maximum; Western Regional Climate Center, Winthrop, Washington, USA; data *available online*).[2] Mean annual precipitation is 382 mm with 70% of precipitation falling predominantly as snow between October and March. Topography is highly dissected with steep slopes and numerous subdrainages (Barksdale 1975). The study area spans a range of elevations, forest types, and fire regimes. At low elevations, forests are dominated by ponderosa pine (*Pinus ponderosa*) and Douglas fir (*Pseudotsuga menziesii*). These lowland forests historically supported high-frequency, low-intensity fire and have been most affected by fire exclusion (e.g., fire suppression and cessation of aboriginal burning), with substantial

[2] http://www.wrcc.dri.edu

increases in stand densities and surface-fuel accumulations over the past century (Agee 1993, Hessburg et al. 2005). Mid-elevation sites (800–1300 m) are mixed-conifer forests of ponderosa pine, Douglas fir, lodgepole pine (*Pinus contorta* var. *latifolia*), western larch (*Larix occidentalis*) and Engelmann spruce (*Picea engelmannii*). High-elevation forests (>1300 m) are dominated by lodgepole pine, subalpine fir (*Abies lasiocarpa*), Engelmann spruce, subalpine larch (*L. lyallii*), and whitebark pine (*P. albicaulis*). The fire regime at mid elevations is characterized as mixed severity, with wildfires of varying size, patch mosaics, and severity. High elevation lodgepole pine, Engelmann spruce, and subalpine fir forests have a high-severity fire regime (Agee 1993).

The 2006 Tripod Complex fires were the largest wildfire event in Washington State in over 50 years. They were preceded by an early spring snowmelt and ongoing MPB and spruce beetle (*Dendroctonus rufipennis*) outbreaks in mid- to high-elevation forests. The fires began as two separate lightning strikes. The Spur fire ignited on 4 July 2006 and was fully contained by 12 July. The Tripod fire started on 24 July. Under strong gusty winds and extreme fire weather, the Spur fire jumped containment lines, and both fires spread rapidly as a mixture of crown fire and high-intensity surface fire. The fires converged in mid-August and were extinguished in late October following a season-ending snowfall. Based on an existing MTBS Burned Area Reflectance Classification (BARC, Eidenshink et al. 2007), much of the fire area burned in lodgepole pine and Engelmann spruce forests at high severity (45%) and moderate severity (28%). The fires also burned 387 harvest and prescribed burn units dating back to the early 1970s. Past harvests included clearcuts, shelterwood cuts, and commercial thins, located mostly in low- to mid-elevation forests. Harvests that occurred before the mid 1990s generally were conducted for reasons other than treating hazardous fuel (e.g., extracting merchantable timber and forest type conversion), but many units were broadcast burned or underburned following harvest to reduce logging slash.

Data

The dNBR and RdNBR images used in this analysis were calculated based on virtually cloud-free, pre- and post-burn Landsat TM images taken one year prior to and one year following the 2006 Tripod Complex fires (Eidenshink et al. 2007). Burn severity was divided into four classes: unchanged, low, moderate, and high severity in a BARC, which was used to stratify field validation sampling of burn severity images.

Composite burn index (CBI) data were collected to determine the relative accuracy of the two indices (Key 2006). Plots were sampled across a range of severity classes, obtained from an existing BARC, during the summers of 2007 and 2009. A total of 44 CBI plots were collected in the summer of 2007 as part of a study by Newcomer et al. (2009). We supplemented this dataset with an additional 55 CBI plots in the summer of 2009 to ensure adequate representation in each BARC class. Needles on scorched trees were still present in 2009 and allowed for comparable CBI observations. To assess the accuracy of dNBR and RdNBR images, simple regression models were constructed to predict each severity index from field-based CBI.

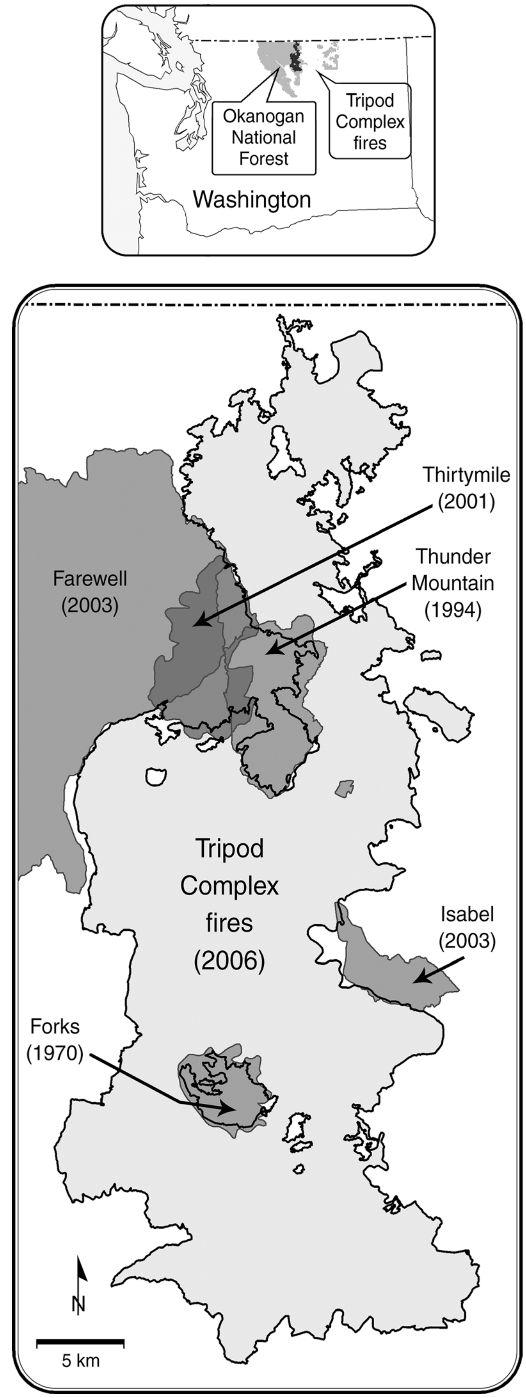

FIG. 1. Tripod Complex fire location map with previous wildfire areas.

TABLE 1. Summary of fuel treatments located within the Tripod Complex perimeter including total number in each treatment type (n), mean years since harvest, mean years since burn, and mean unit size.

Treatment	n	Years since harvest	Years since burn	Size (ha)
CC	89	20 (2–32)	na	53 (7–473)
CCBB	145	17 (10–31)	13 (1–17)	41 (5–146)
LB	3	na	7 (6–8)	2726 (2240–3211)
Thin	57	14 (2–44)	na	188 (7–1423)
ThinBB	54	17 (8–39)	10 (0–16)	98 (17–1314)
ThinSan	15	5 (2–8)	na	68 (20–161)
WF	17	na	21 (3–36)	112 (28–316)

Notes: Minimum and maximum values are included in parentheses. Treatments include clearcut only (CC), clearcut and broadcast burn (CCBB), landscape burns (LB), thin only (Thin), thin and broadcast burn (ThinBB), Thin and sanitation cut (ThinSan), and past wildfires (WF). Years since harvest do not apply to LB and WF treatments, and years since burn to not apply to CC, Thin, and ThinSan treatments and are therefore indicated by "na" for "not applicable."

A geospatial treatment layer, including harvest type and date and prescribed burn type and date, was compiled within the Tripod Complex perimeter (Table 1) and verified with hard-copy records. Several fuel treatments were visible in the 2 July 2006 National Agriculture Imagery Program (NAIP) image but were not captured by the available geospatial fuel treatment layer. These were field verified (Tom Leuschen; *personal observation*) and added to the fuel treatment layer. The NAIP image was coregistered with GPS control points at major road intersections. Treatment polygons were redigitized where perimeters did not match NAIP imagery. The final raster treatment layer includes recent thinning and shelterwood harvest units with (ThinBB) and without broadcast burning (Thin), thin units with sanitation cuts in which small trees were harvested and left on site (ThinSan), clearcut harvest units with broadcast burning (CCBB) and without (CC), landscape burns in which prescribed underburns were conducted on large burn units (>2000 ha) with no recent harvest activity (LB), and recent wildfires (WF; since 1980). The majority of fuel treatments and harvest units were conducted after 1990. Older units exist in the study area but are not contained in the treatment layer.

Fire perimeters were obtained from the National Interagency Fire Center and used to compile a progression layer with weather data summarized and assigned by progression interval (Appendix A). Daily fire progression intervals are available for the first 13 days of the Tripod Complex, but as the fires converged and dense smoke prevented daily overflights, perimeters become less reliable. In some cases, intervals between documented progressions span several days. Where possible, available infrared (IR) imagery and Landsat TM images captured during the fires were used to verify and correct fire perimeters. Daily weather records were obtained from the First Butte Remote Area Weather Station (48° N, 120.128° W; elevation, 1674 m), located near the fire perimeter (Fig. 2). The following weather variables were summarized for each fire interval: minimum relative humidity (minRH, %), maximum temperature (maxTemp, °C), total precipitation (cm), average temperature (°C), and average wind speed (AvgWind; km/h) and maximum wind speed (MaxWind; km/h).

Landform variables were derived from a 30-m digital elevation model and include elevation, slope angle (slope, °), and aspect. Aspect was converted into a continuous Beers heat load index (HeatLoad; Beers et al. 1966). Existing vegetation type (CoverType) and canopy cover (%) layers were obtained from LANDFIRE (*available online*).[3] Cover types were reclassified into major cover type classes: alpine; avalanche; dry, mixed conifer; Engelmann spruce–subalpine fir; grass; lodgepole pine; nonvegetated; ponderosa pine; shrub; and subalpine.

Data analysis

Forests in unattacked, mixed, and red-needle stages following MPB attack were classified from Landsat 5 TM imagery from 18 August 2003 to 8 August 2005 using a calculated enhanced wetness difference index (EWDI; Wulder et al. 2006). The EWDI is well suited for detecting areas of MPB red attack because it captures changes in vegetation wetness between reference images (Skakun et al. 2003, Wulder et al. 2006). High EWDI values correspond to areas of dry vegetation relative to the pre-disturbance image and tend to be strongly correlated with recently dead vegetation. We considered using aerial survey program polygons of MPB attack as has been done in other published studies of bark beetles and burn severity or fire extent (Lynch et al. 2006, Kulakowski and Veblen 2007). However, preliminary comparison of the aerial survey program layers against a July 2006 National Agricultural Imagery Program (NAIP) image revealed many spatial inaccuracies (e.g., beetle polygons in unvegetated areas or regenerating forests). Our classification followed procedures from Wulder et al. (2006), which employs a tasseled cap transformation (Cohen et al. 1995) of bands 1, 2, 3, 4, 5, and 7 in each compared image. A wetness index is calculated as

[3] http://landfire.cr.usgs.gov/viewer/

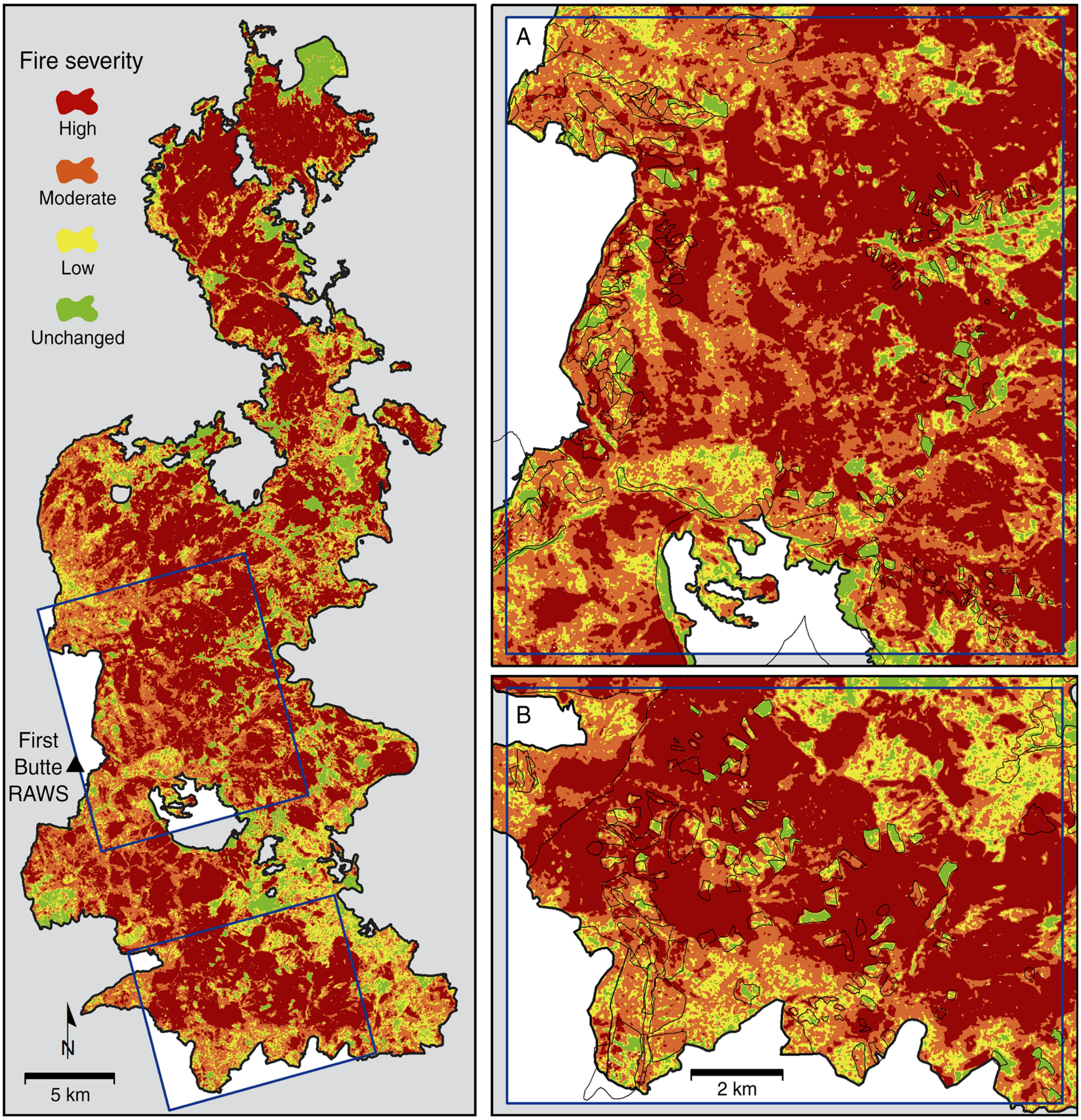

FIG. 2. Burned area reflectance classification image of the Tripod Complex fires with the Spur (north) and Tripod (south) sampling areas. (A) Spur and (B) Tripod study areas are displayed on the right with fuel treatments outlined in black. The First Butte Remote Area Weather Station (RAWS) was the source of hourly weather information for the study.

$$\mathrm{WI} = 0.262\mathrm{b}_1 + .2141\mathrm{b}_2 + 0.0926\mathrm{b}_3 + 0.0656\mathrm{b}_4 - 0.7629\mathrm{b}_5 - 0.5388\mathrm{b}_7$$

where WI represents TCT wetness indices and b_i represents the top of atmosphere reflectance of band i, for i values of 1, 2, 3, 4, 5, and 7.

EWDI is calculated as

$$\mathrm{EWDI} = \mathrm{WI}(2005) - \mathrm{WI}(2003).$$

We classified the continuous EWDI into the following categories: regeneration including old clearcut blocks (regen, <-7), healthy (green, -7–2), healthy to red attack (mixed, 2–7), red attack (red, 7–18), and red attack with foliage loss (red-gray, >18; Wulder et al. 2006). The last class, new cut blocks (EWDI > 23), was not assigned because no EWDI values fell into that category. Because few pixels ($n = 28$) were classified as red-gray, they were reclassified as red for data analysis. Classification accuracy was assessed at 50 random points per MPB category using the 2 July 2006 NAIP image.

SAR and OLS models were constructed in the R programming language (Wimberly et al. 2009, R

TABLE 2. Predictor variables used in sequential autoregression (SAR) regression modeling for the Spur and Tripod sampling areas of the Tripod Complex fires.

Variable	Definition
Fuel treatment	
Age (yr)	years since harvest date, prescribed burn, or wildfire
Size (ha)	treatment area
Treatment	no treatment (NT); clearcut only (CC); clearcut and broadcast burn (BB); landscape burn (LB); thin only (Thin); thin and broadcast burn (ThinBB); past wildfire (WF)
Landform	
Elev (m)	elevation
Slope (°)	slope gradient
HeatLoad	beers heat load index used as a proxy for aspect
Weather	
MaxTemp (°C)	maximum temperature over each fire progression interval
MinRH (%)	minimum relative humidity each fire progression interval
MaxWind (kph)	maximum recorded wind gust over each fire progression interval
AvgWind (kph)	average wind speed over each fire progression interval
Vegetation	
CanCov (%)	percent canopy cover of vegetation (LANDFIRE)
Cover type	existing vegetation type (LANDFIRE)
EWDI	enhanced wetness difference index
MPBclass	mountain pine beetle class, including regeneration (regen); healthy, green (green); green and red (mixed); red attack (red)

Development Core Team 2011) to predict dNBR and RdNBR based on the following layers: fuel treatment category, order of fire progression intervals (progression order); landform, including Elev, Slope, and HeatLoad; weather, including MaxTemp, minRH, AvgWind, and MaxWind; and vegetation, including CoverType, CanCov, EWDI, and MPB classification (Table 2). Because weather variables were assigned by progression interval, they were not included in the same model as progression order. Progression intervals generally included day and nighttime burning periods, and temperature, humidity and wind extremes were selected in preference to daily average values. Treatment contrasts were assigned to all categorical variables within regression models, including fuel treatment (base represents no treatment), cover type (base represents dry, mixed conifer), and MPB classification (base represents green). To identify potential predictor variables, box and whisker plots were used to examine relationships between predictor variables and burn severity. Because field validation demonstrated a similar accuracy between dNBR and RdNBR indices, SAR models were constructed to predict both indices. Models were compared using Akaike's Information Criterion (AIC; Akaike 1974), and final models were selected to include only significant covariates ($P < 0.05$) and the lowest AIC values. For the SAR analysis, we selected two subareas of the Tripod Complex fires that contain the majority of fuel treatments and represent the early stages of the wildfires when the Spur and Tripod fires were separate fire events (Fig. 2). To avoid edge effects (e.g., suppression activities at fire edge and potentially milder fire behavior along the perimeter), study areas were buffered to exclude the area within 500 m of the fire perimeter. The two study areas allow comparison of model predictions in co-occurring fires burning in similar vegetation types but with a different set of fuel treatments and landscape configuration (Fig. 3). We used the error version of SAR, which is written as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \lambda\mathbf{W}(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}) + \boldsymbol{\varepsilon} \quad (1)$$

(Cressie 1993:441) where $\mathbf{Y}$ is the dependent variable (vector), $\mathbf{X}$ is the design matrix of explanatory variables, $\boldsymbol{\beta}$ is the vector of coefficients, λ is an autoregressive coefficient, $\mathbf{W}$ is a matrix of spatial weights, and $\boldsymbol{\varepsilon}$ is the uncorrelated error term. Neighborhoods define the $\mathbf{W}$ matrix such that a weight of zero is assigned to all pixels outside of the specified neighborhood relative to the focus pixel, and weights equal to the inverse of the distance to the focus pixel are assigned within the neighborhood. The weights are row-standardized so they sum to 1. A sparse $N \times N$ matrix defines the variance/covariance structure ($\boldsymbol{\Sigma}$)

$$\boldsymbol{\Sigma} = \sigma^2(\mathbf{I} - \lambda\mathbf{W})^{-1}(\mathbf{I} - \lambda\mathbf{W})^{-1} \quad (2)$$

(Haining 1990) where σ^2 is a constant variance term and $\mathbf{I}$ is the identity matrix.

Due to computational limitations, Wimberly et al. (2009) subsampled their data for the SAR analysis. However, Beale et al. (2010) strongly advocate using the full data set whenever possible for spatially explicit regression, and they explicitly warn against subsampling data. With our computational resources, we were able to conduct the SAR analysis on the full 30-m resolution data set, so we followed the recommendation of Beale et al. (2010). To select our neighborhood distance for the SAR model (the distance at which pixels were allowed to be included as nonzero weights in the autocorrelation portion of the model), we followed the recommendation

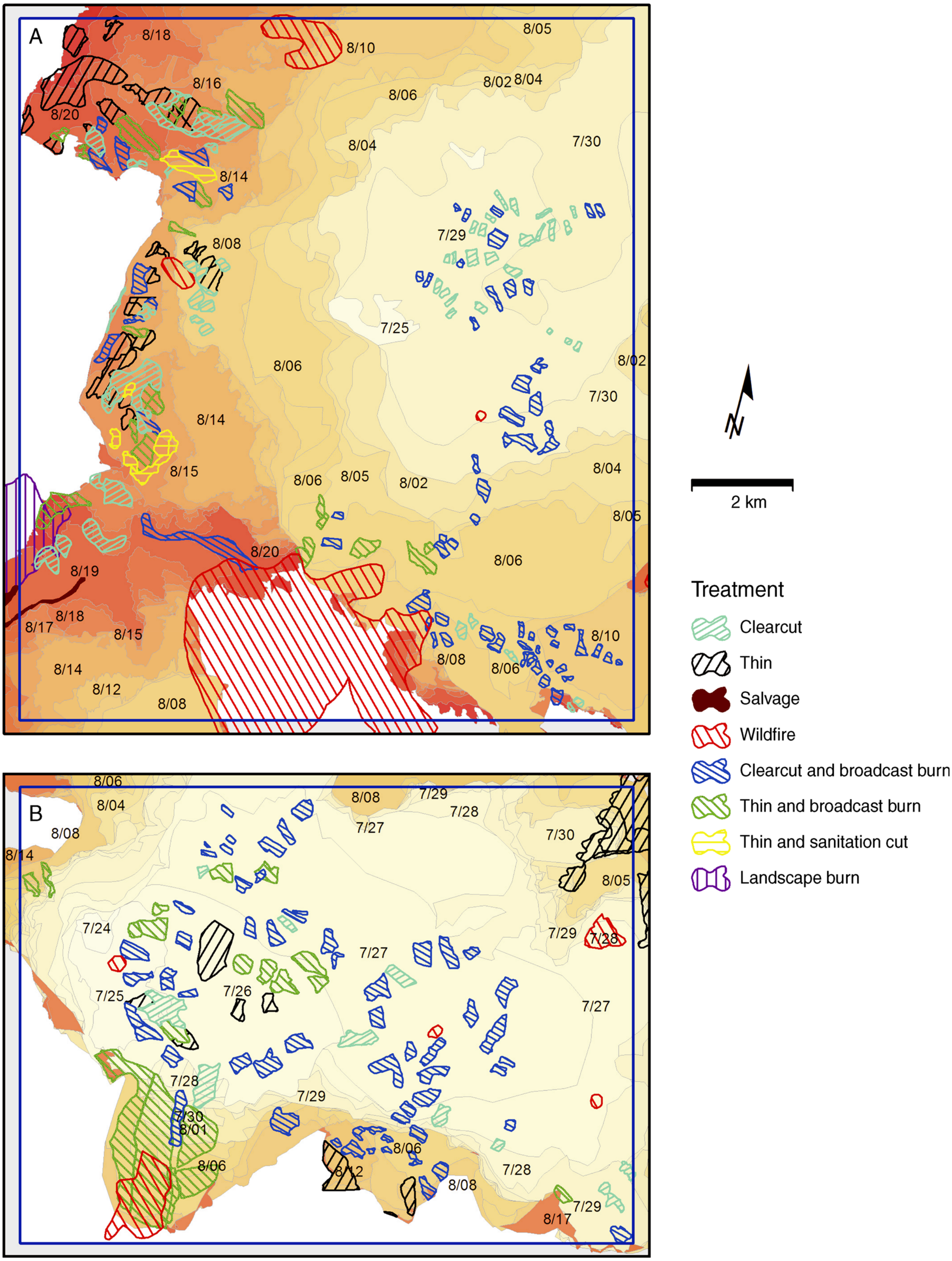

FIG. 3. Fire progression intervals and treatment polygons in the (A) Spur and (B) Tripod study areas. The interior border represents the actual sampling areas. Progression interval dates are displayed in month/day format.

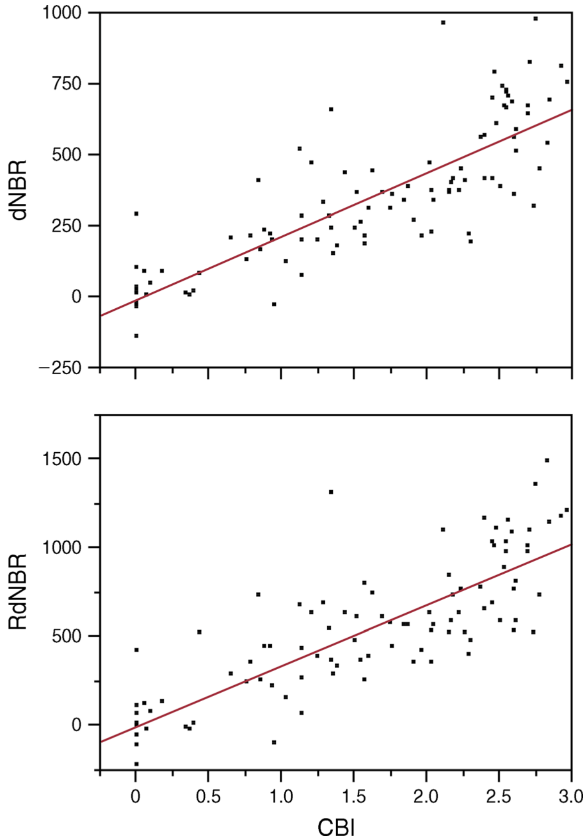

FIG. 4. Linear relationships between composite burn index (CBI) and fire severity indices for differenced Normalized Burn Ratio (dNBR) values ($R^2 = 0.6951$, $P < 0.0001$) and relative differenced Normalized Burn Ratio (RdNBR) values ($R^2 = 0.7103$, $P < 0.0001$).

of Kissling and Carl (2008) of choosing the neighborhood that minimizes both AIC and residual spatial autocorrelation (de Knegt et al. 2010). This required fitting the SAR model and calculating both the AIC and the Moran's I statistic for increasing neighborhood distance, using the moran.test function in the spdep package (Bivard 2013). We found that the nearest neighborhood distance (≤30 m) minimized both AIC and Moran's I, with both increasing with increasing neighborhood distance. We therefore fit all models using the nearest neighbor (≤30 m) distance to define the SAR neighborhood weight matrix, which is consistent with other SAR applications (Kissling and Carl 2008).

Because untreated pixels had no assignment of time since treatment or treatment area, a separate modeling approach was necessary to evaluate the effects of treatment age and size. We confined our dataset to treated portions of the landscape and randomly sampled 1500 pixels by major treatment type (CC, CCBB, Thin, ThinBB, and WF). Random sampling of data points was performed to emulate a high-intensity field study and remove spatial autocorrelation, a necessary criterion of simple linear regression modeling. Treatment edges were excluded from the sample using a 60-m buffer within each treatment perimeter. Linear regression models were constructed by major treatment type to predict RdNBR based on time since treatment (age, years), size (ha), and continuous variables found to be important predictors in the SAR models including CanCov, Elev, Slope, EWDI, MaxTemp, and AvgWind. Models were compared using AIC, and final model selection was based on the significance ($\alpha = 0.05$) of predictor variables and the lowest AIC values.

RESULTS

Validation of the burn severity layer

Field-based CBI values are highly correlated with dNBR ($R^2 = 0.69$) and RdNBR values ($R^2 = 0.71$; Fig. 4). Model residuals are evenly distributed, with no particular bias toward under- or over-predicting burn severity indices across the compared range of values.

SAR models

Predicted burn severity indices using the SAR modeling approach have a strong correspondence to actual dNBR and RdNBR values; spatial patterns of low and high severity are visibly similar between actual and predicted values (Fig. 5). Models of dNBR and RdNBR are almost identical in terms of predictive variables and explanatory power. Results from RdNBR models are presented because the relative index is more appropriate for comparing burn severity in heterogeneous vegetation, including old and young forests (Table 3; Miller and Thode 2007). Significant predictors in the final models, based on lowest AIC values, are similar between both study areas and include treatment category, canopy cover, elevation, maximum temperature, minimum relative humidity, and MPB class (Table 4). Other predictor variables, including cover type, slope, AvgWind, minRH, and progression order, are significant predictors of RdNBR but were not included in the final selected models, based on lowest AIC values. Variables tested that are not significant predictors in any model include heat load index and maximum wind speed. Progression order does not reduce AIC values in SAR models. Appendix B and C include simple RdNBR models based on categorical predictor variables, including treatment type, cover type, and MPB class, to demonstrate the relative influence of categories.

Fuel treatments

Inclusion of treatment categories reduces model AIC values, and most treatments are significantly different than no treatment (NoTrt), assigned as the base contrast in the regression models (Table 4). In both study areas, the CCBB treatment has the greatest difference from NoTrt, and prescribed burn treatments have lower RdNBR values than do treatments without prescribed fire. ThinSan units, in which small trees were cut and piled or lopped and scattered (Spur study area only), have higher severity than do Thin units (Fig. 6). Past

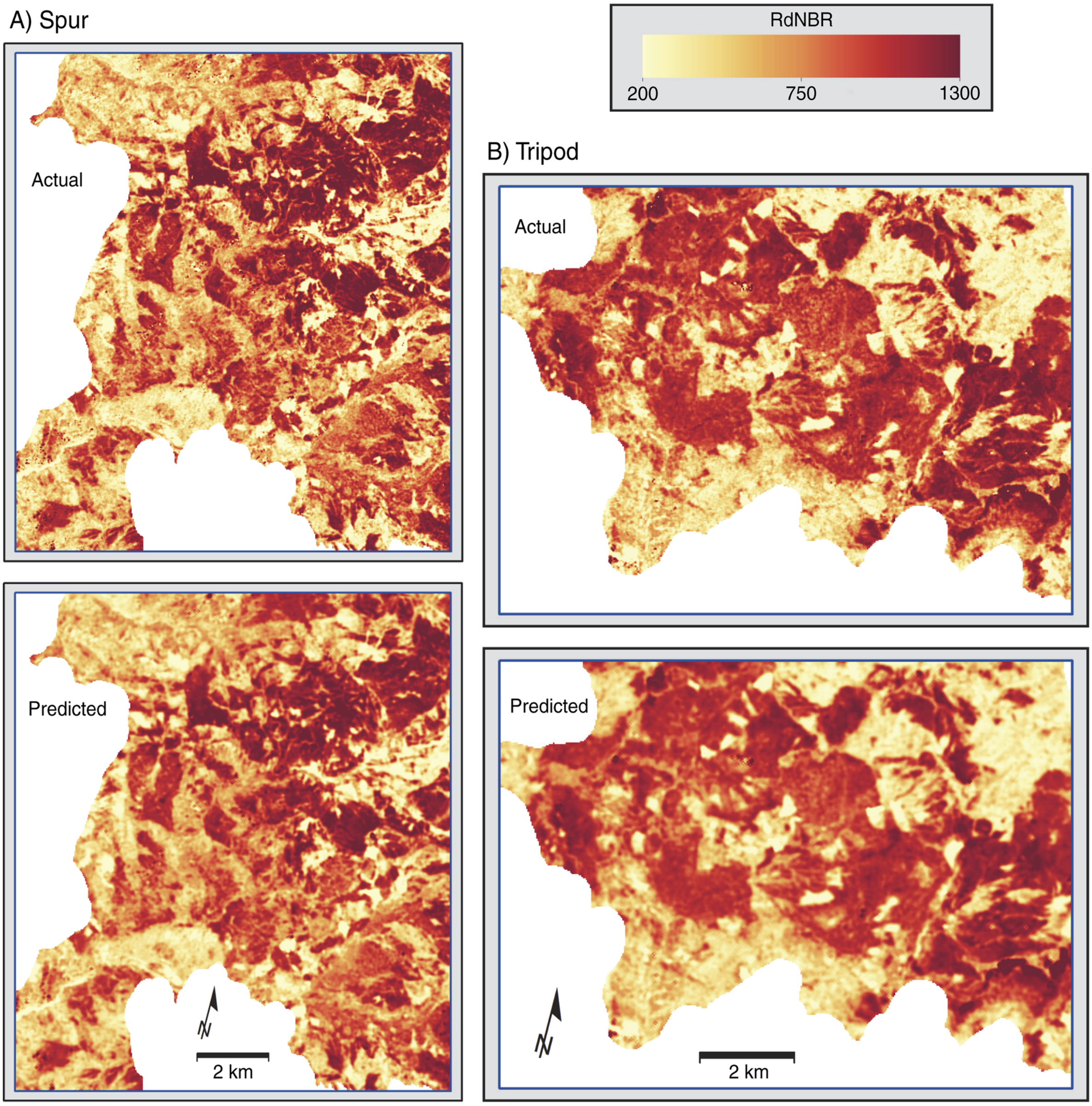

FIG. 5. Actual RdNBR values vs. predicted RdNBR values from the SAR model with fire progression for (A) Spur study area and (B) Tripod study area.

TABLE 3. Regression models of relative differenced Normalized Burn Ratio (RdNBR) for the Spur and Tripod study areas of the Tripod Complex fires.

Model	Predictor variables	N	R^2	AIC
Spur_SAR1	CC, elev, EWDI, treatment	40 506	0.7619	1 908 098
Spur_SAR2	CC, elev, MPBclass, treatment		0.7619	1 908 139
Tripod_SAR1	CC, elev, EWDI, MaxTemp, treatment	25 267	0.9289	1 037 660
Tripod_SAR2	CC, elev, MaxTemp, MPBclass, treatment		0.9289	1 037 655

Notes: Predictor variables include canopy cover (CC), elevation (elev), EWDI (Enhanced Wetness Difference Index), maximum temperature (MaxTemp), mountain pine beetle class (MPBclass), and fuel treatment (treatment). Two models (SAR1 and SAR2) are presented for each study area to compare differences in using EWDI and MPBclass. The alpha level of all models is 0.05. N represents number of pixels.

TABLE 4. Predictor variables, coefficients, standard error (SE), and *P* values in SAR models of RdNBR in the Spur and Tripod study areas of the Tripod Complex fires.

Variables	Spur			Tripod		
	Estimate	SE	*P*	Estimate	SE	*P*
Intercept	134.5248	31.6364	<0.0001	140.3350	60.5774	0.0205
Treatment_CC	−14.6520	5.7478	<0.0001	−9.1560	5.8762	0.1192
Treatment_CCBB	−50.3033	5.3016	<0.0001	−20.1587	2.9625	<0.0001
Treatment_LB	−33.4332	27.0702	0.2168	na	na	na
Treatment_Thin	1.3795	7.5584	0.8552	−16.6085	6.3538	0.0089
Treatment_ThinBB	−20.2424	8.4827	0.0170	−19.2083	5.2416	0.0002
Treatment_ThinSan	−3.3010	14.8581	0.8242	na	na	na
Treatment_WF	−4.0009	11.7872	0.7343	5.6809	10.5690	0.5909
Canopy cover (%)	0.2343	0.0250	<0.0001	0.1105	0.0206	<0.0001
Elevation (m)	0.3692	0.0186	<0.0001	0.2079	0.0359	<0.0001
Maximum temperature (°C)	na	na	na	0.7089	0.2900	0.0145
MPB_mixed	5.3987	0.7775	<0.0001	1.7344	0.5644	0.0021
MPB_red	8.3398	1.4884	<0.0001	2.4234	1.5619	0.1208
MPB_regen	−21.2406	2.5956	<0.0001	−3.7288	2.2555	0.0983

Notes: Treatments include clearcut only (CC), clearcut and broadcast burn (CCBB), landscape burn (LB), thin only (Thin), thin and broadcast burn (ThinBB), thin and sanitation cut (ThinSan), and past wildfires (WF). Mountain pine beetle classes (MPBclass) include mixed, red, and regeneration. Positive treatment coefficients imply greater fire severity and negative coefficients imply lower fire severity compared to baseline contrasts (Treatment, no treatment; MPBclass, green). Unused predictor variables are indicated by "na."

wildfires (WF) are not significant predictors of RdNBR in either study area. Clearcut and Thin units have significantly lower burn severity than do no treatment areas, but effects are inconsistent between study areas. In the Spur study area, ThinRx units are much less effective at reducing burn severity than are Thin units, and ThinSan units are not significantly different than untreated pixels (Table 4, Appendix B). In the Tripod study area, Thin units have significantly lower burn severity than do unmanaged pixels, but CC units do not (Table 4, Appendix C).

Landform

Elevation is a significant predictor variable of RdNBR and its inclusion reduces model AIC values (Table 4). RdNBR values are highest between elevations of 1600 and 2100 m, with a pronounced drop at 2100 m in the Spur study area and 2000 m in the Tripod study area (Fig. 7). Correlations between slope and RdNBR are weak, with slightly higher RdNBR values at gradual slopes and slightly lower values on steep slope gradients. Heat load index is not a significant predictor of RdNBR in any model.

Weather

Of the weather variables assigned by progression interval, the most important predictors of RdNBR are MaxTemp and MinRH (Table 4). Because temperature and relative humidity are highly inversely correlated, only MaxTemp, the stronger of the two predictors, is included in the Tripod study area final model. MaxTemp and AvgWind are weakly correlated with RdNBR in the Spur fire and are not included in the final model. Relationships are more pronounced within the Tripod study area, with clearly higher RdNBR values above 27°C as well as at higher average wind speeds (>7 km/h; Fig. 7).

Vegetation

Canopy cover is positively correlated with RdNBR and substantially reduces AIC values in all models (Fig. 7). Cover type is a significant predictor but only slightly reduces AIC values. Mean RdNBR values are generally highest in dry, mixed conifer; Engelmann spruce–subalpine fir; lodgepole pine; and subalpine vegetation and lowest in grass, riparian, and shrub cover types (Appendix B, C).

MPB classification accuracy ranges from 84% correct for green vegetation (16% misclassified as mixed), 66% correct for mixed attack (10% misclassified as red attack and 24% misclassified as green) and 44% correct for red attack (54% misclassified as mixed and 2% misclassified as green). The MPB classification is a significant predictor of RdNBR in all models. In simple models using only MPB class as a predictor variable (Appendices B and C), RdNBR in the mixed and red MPB classes is significantly higher than in green vegetation (base contrast), and regeneration areas are significantly lower than green vegetation. Red attack areas have somewhat higher RdNBR values than do mixed attack, particularly in the Spur study area. Results are consistent with models of EWDI in which unclassified EWDI values are positively correlated with RdNBR in both study areas.

Treatment age and size

Treatment age and size are weak predictors of RdNBR and contribute only slightly to some predictive models of RdNBR, based on lower AIC values and higher coefficients of determination, than do models that do not include treatment age and size (Table 5).

Treatment age is weakly correlated with RdNBR in CC, Thin, ThinBB, and WF treatments but is not a significant predictor in the CCBB treatment. Although model coefficients of determination are extremely low ($R^2 < 0.06$), RdNBR values decline over time in CC and Thin units and increase over time in ThinBB and WF treatments. Treatment size is a weak but significant predictor of RdNBR. Again, model coefficients of determination are low (<0.08), but RdNBR decreases with size in CC, Thin, and WF treatments and increases with size in CCBB and ThinBB units.

Discussion

The Tripod Complex was one of many regional fire events in 2006. The 2006 fire season represents the largest area burned since 1984 in the northern Cascades (Cansler 2011) and second largest recorded area burned since 1980 across the broader eastern Cascade region (Littell and Gwozdz 2011). Regional fire years generally correspond to higher than average spring and summer temperatures and drier than average summers (Gedalof et al. 2005, Morgan et al. 2008, Littell et al. 2009). In the Pacific Northwest, the majority of the fire area tends to burn at mid to high elevations (Heyerdahl et al. 2008) and is generally characterized by top-down climatic controls (e.g., frontal systems accompanied by high temperatures, low relative humidity, and strong winds [Gedalof et al. 2005, Littell and Gwozdz 2011]). A common interpretation of weather-driven fire events is that bottom-up controls, including fuels and topography, are superseded by climatic factors and are relatively unimportant (Turner and Romme 1994, Bessie and Johnson 1995).

Even under extreme fire weather, landform, vegetation, and fuels influenced patterns of burn severity and fire spread in the Tripod Complex fires. For example, past wildfires strongly influenced patterns of fire spread across the landscape, likely due to a lack of available surface fuels for fire spread. Recent fires, including the 1994 Thunder Mountain fire, 2001 Thirty-mile fire, and 2003 Farewell and Isabel fires, constrained fire spread (Fig. 1); the Tripod Complex fires wrapped around the edges of these regenerating landscapes with little overlap in area burned. A somewhat surprising fire break was the 1700-ha 1970 Forks fire, composed of regenerating, 40-year-old, lodgepole pine forest with sparse surface fuels. However, the effect of past wildfires was not uniform. Smaller WF treatments within the Spur and Tripod study areas (Fig. 3) were not significant predictors of burn severity. This may be explained in part by low sample size and also that the majority of these small wildfires were 20–30 years old.

Across both study areas, prescribed burn fuel treatments (i.e., CCBB and ThinBB) experienced lower burn severity than did unmanaged areas and other treatments. Clearcut and Thin treatments also reduced burn severity, suggesting that treatments without surface fuel reduction modified crown fire behavior and resulted

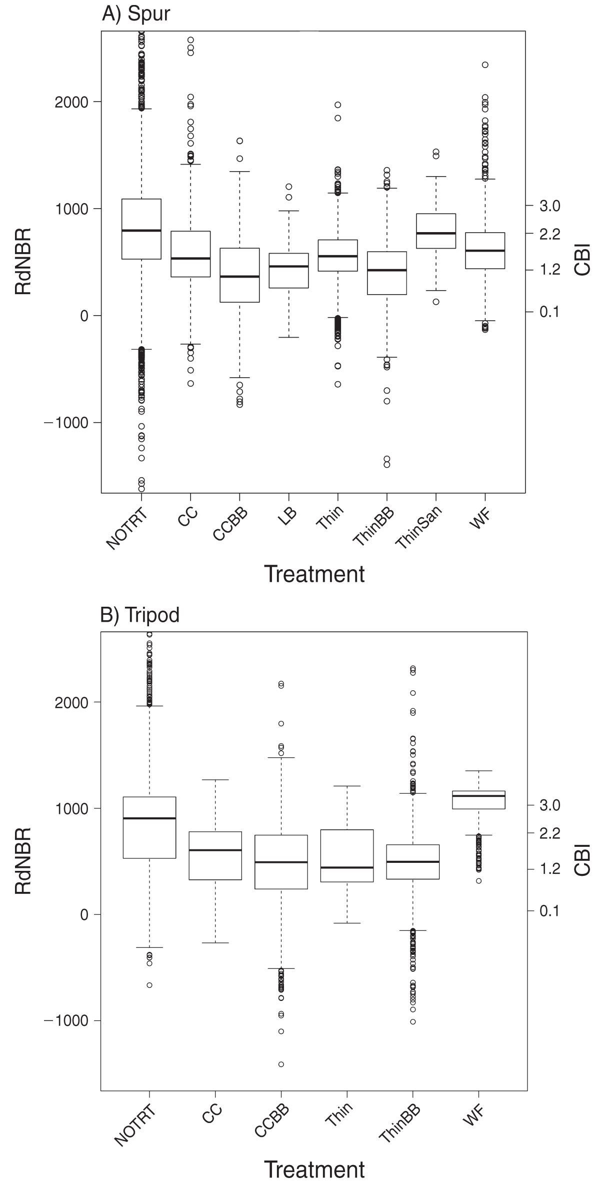

Fig. 6. Box and whisker plots of RdNBR by treatment category in the (A) Spur and (B) Tripod study area. Box plots represent the lower quartile (25th percentile), second quartile (median), and upper quartile (75th percentile); whiskers represent the 100th percentile, and open circles represent outliers. Right-hand y-axes display corresponding CBI values, binned in a standard burn severity classification (unchanged, <0.1; low, 0.1–1.24; moderate, 1.25–2.24; and high, ≥ 2.25 [Miller and Thode 2007]). Treatments include clearcut (CC), clearcut and broadcast burn (CCBB), landscape burn (LB), no treatment (NOTRT), salvage (SALV), thin only (Thin), thin and broadcast burn (ThinBB), thin and sanitation cut (ThinSan), and wildfire (WF).

in less stand replacement. Many past fuel treatments now comprise islands of mature and regenerating trees in a landscape otherwise highly modified by stand-replacing fire (Fig. 2). Comparison of corresponding CBI values indicates that the majority of RdNBR values

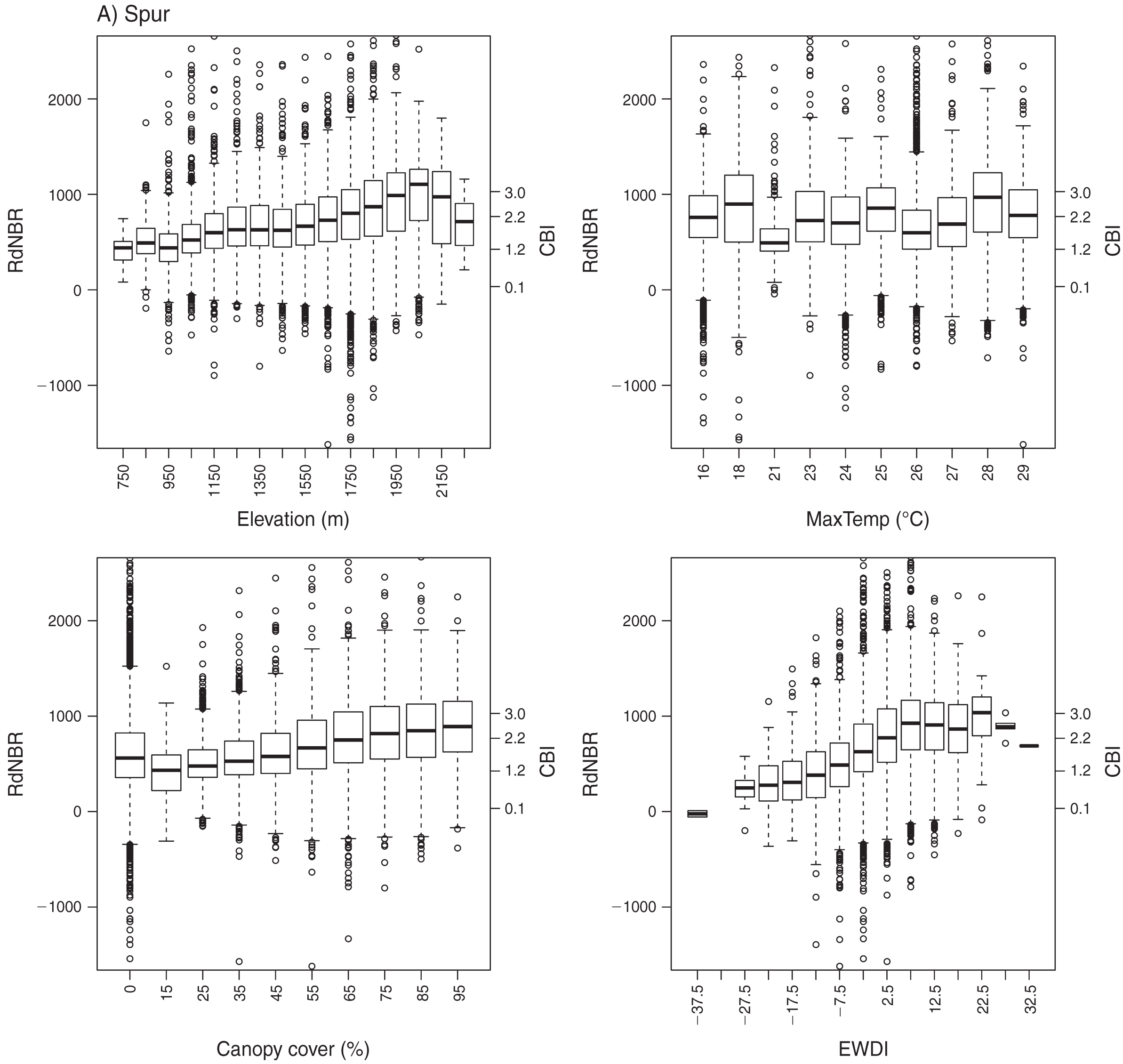

FIG. 7. Box and whisker plots between RdNBR and four predictor variables (elevation [m], maximum temperature [MaxTemp, °C], canopy cover [%] and enhanced wetness difference index [EWDI]) in the (A) Spur study area and (B) Tripod study area. Individual box plots summarize RdNBR values for binned values of each predictor variable. Box plots represent the lower quartile (25th percentile), second quartile (median), and upper quartile (75th percentile); whiskers represent the 100th percentile, and open circles represent outliers. Right-hand *y*-axes display corresponding CBI values, binned in a standard burn severity classification (unchanged, <0.1; low, 0.1–1.24; moderate, 1.25–2.24; and high, ≥2.25; Miller and Thode 2007).

within each treatment were within the range of measurable burn severity. Using a standard, four-class classification of burn severity (Miller and Thode 2007), mean differences between treatments do not generally translate to differences in severity class. The means of most treatments fall in the moderate severity class, likely due to the lack of resolution in the four-class system and inherent variability of RdNBR within each treatment type, particularly in small treatment units in which edge pixels may have influenced the moderate severity classification.

Although the Tripod Complex wildfires burned over four months, initiating on 4 July and finally ending with a snowfall in late October, substantial portions of the landscape burned under extreme fire weather. The Tripod study area offers particularly compelling evidence; most treatments burned during the first few days of the wildfire, completely undefended, and under strong, gusty, southwesterly winds, low relative humidity values (MinRH 11–15; MeanRH 21–25), and high temperatures (MaxTemp 27–33°C; MeanTemp 20–30°C). Our findings are corroborated by two previous

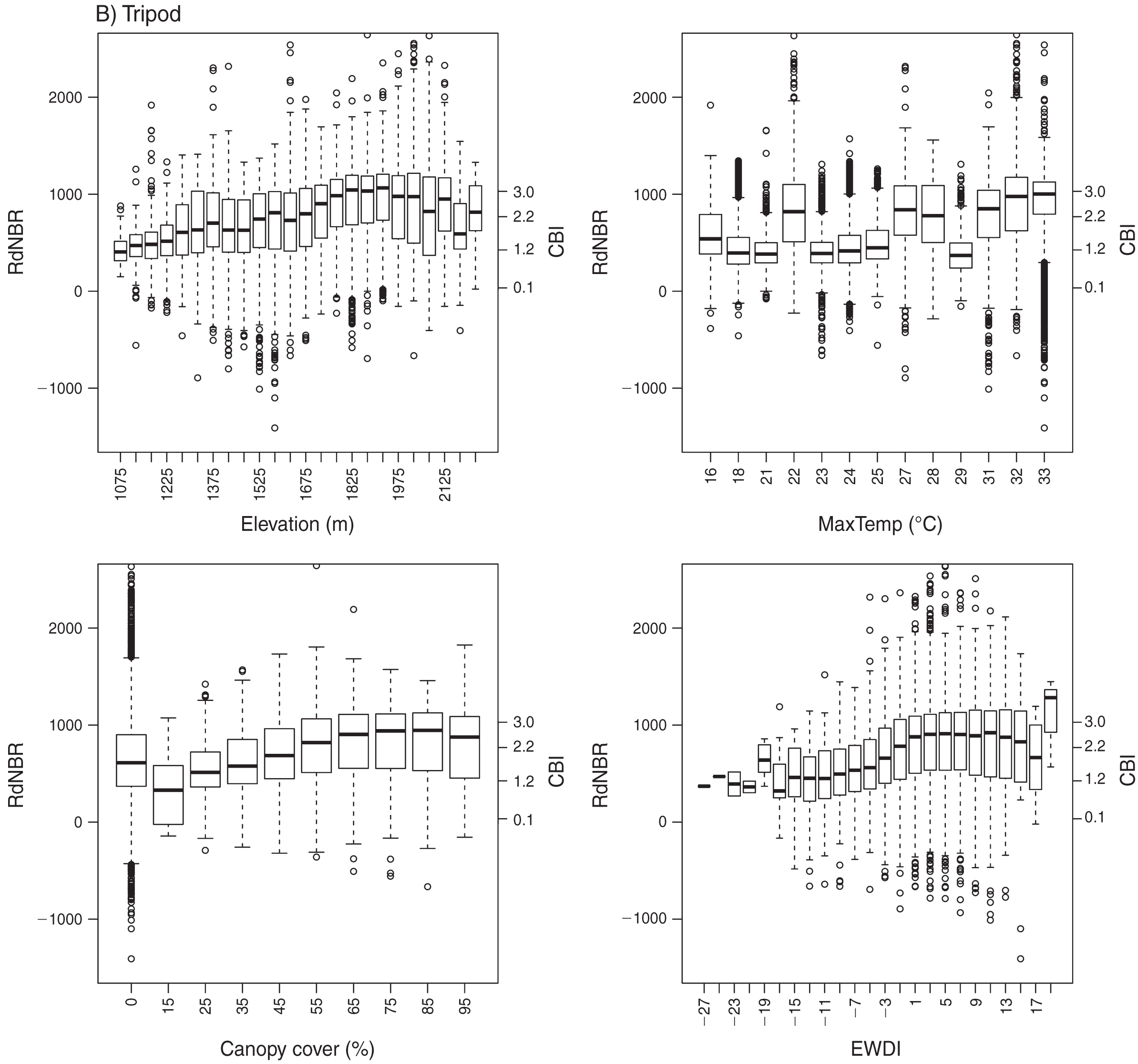

FIG. 7. Continued.

field studies in the Tripod Complex conducted in thin and prescribed burn units (Prichard et al. 2010) and young regenerating forests (Lyons-Tinsley and Peterson 2012). Both field studies demonstrate that units that were prescribed burned prior to the wildfires had significantly lower tree mortality and other fire severity measures (e.g., crown scorch and bole char height) than did thin- or clearcut-only treatments.

Previous studies have proposed that fuel reduction treatments may influence fire behavior and fire spread to neighboring pixels (Finney 2005, Finney et al. 2005). Because fuel treatments were not placed strategically on the prefire landscape, it is not surprising that treatment effects were localized. However, we did not observe any evidence that treatments protected leeward, neighboring pixels as described by Finney et al. (2005) in the 2002 Rodeo-Chedeski fires. As the wildfires burned through the treated portion of the landscape, observed fire behavior included spotting distances of 0.5–1 km (Matt Castle, *personal observation*), and the wildfires often burned at high severity within the unmanaged matrix surrounding treatment blocks.

Our ability to predict burn severity is limited by a number of missing variables that are generally unavailable for large fire events (Finney et al. 2005, Collins et al. 2007, Wimberly et al. 2009). These include vegetation structure; surface fuel loads and moistures; local fire weather, including wind speed, wind direction, temperature, and relative humidity; and fine-scale interactions between landform, fuels, wind, and fire. We approached the missing variable problem by assigning summarized weather from a nearby weather station to progression intervals and the SAR modeling approach. The SAR models offer a substantial refinement to traditional

TABLE 5. Age and size regression models of relative differenced Normalized Burn Ratio (RdNBR) by treatment type including clearcut only (CC), clearcut and broadcast burn (CCBB), thin only (Thin), thin and broadcast burn (ThinBB), and past wildfires (WF).

Model	Intercept	Slope	P	R^2	AIC
CC					
RdNBR ~ Age	676.2020	−7.5620	<0.0001	0.0240	21 125
RdNBR ~ Size	550.2484	−1.1897	0.0012	0.0070	21 151
RdNBR ~ Age + Elev + Slope + MaxTemp			<0.0001	0.0399	21 106
CCBB					
RdNBR ~ Age	446.733	−5.1800	0.1506	0.0014	21 824
RdNBR ~ Size	336.622	3.5220	0.0442	0.0027	21 822
RdNBR ~ CanCov + Elev + MaxTemp			<0.0001	0.0944	21 627
Thin					
RdNBR ~ Age	685.7463	−8.6548	<0.0001	0.0514	21 167
RdNBR ~ Size	604.0906	−1.4665	<0.0001	0.0749	21 129
RdNBR ~ Size + CanCov + Elev + MaxTemp + AvgWind			<0.0001	0.2124	20 899
ThinBB					
RdNBR ~ Age	347.534	5.380	0.0002	0.0093	21 171
RdNBR ~ Size	294.2907	4.0820	<0.0001	0.0719	21 073
RdNBR ~ Age + Size + CanCov + Slope + MaxTemp + AvgWind			<0.0001	0.1595	20 941
WF					
RdNBR ~ Age	429.9594	4.1332	<0.0001	0.0186	22 500
RdNBR ~ Size	563.0788	−0.0293	0.0200	0.0036	22 523
RdNBR ~ CC + Elev + MaxTemp + AvgWind			<0.0001	0.1503	22 290

Notes: Predictor variables include treatment age, treatment size (ha), elevation (Elev, m), slope (%), maximum temperature (MaxTemp, °C), and average wind (AvgWind, km/h). Slope and intercept values are included for models with only one predictor variable. Interaction terms are included only where they are significant and result in a substantial reduction in model Akaike information criterion (AIC) values. Best multiple regression models, based on lowest AIC values, are presented for each treatment type.

regression models by using the inherent spatial autocorrelation of pixels as a proxy for the missing variables (Wimberly et al. 2009). The autoregressive term is particularly robust in predicting areas of high severity, likely reflecting the fact that high-severity crown fire events spread as a contagious process, with neighboring unburned areas more likely to burn if adjacent cells have burned at high severity (Peterson 2002).

Selection of a particular burn severity index can be important to classification accuracy and model development in some regions (e.g., Miller and Thode 2007), but we found that RdNBR and dNBR indices were both suitable for our study. Our findings are corroborated by Cansler and McKenzie (2012), who concluded that both indices are suitable for use in the Cascade Range but that RdNBR had somewhat higher classification accuracy. Tripod CBI plots were used in the Cansler and McKenzie (2012) study, so our similar findings would be expected.

The following sections address the relative contributions of landform, weather variables, and vegetation and fuels to severity predictions. Modeling burn severity in two study areas that burned around the same time period allowed us to determine if our results are broadly applicable to similar forest types or whether some results might be an artifact of our particular sampling area.

Landform

Burn severity was highest at elevations between 1600 and 2100 m in both study areas (Fig. 7) and decreased in severity at elevations greater than 2100 m. The relationship between elevation and burn severity is understandable given that low elevations tend to support more fire-resistant species such as Douglas fir and ponderosa pine, and mid to high elevations tend to have dense, mixed-conifer forests (e.g., Douglas fir, ponderosa pine, Engelmann spruce, and subalpine fir) with thin-barked species that are more susceptible to fire (Agee 1993). At the highest elevations, vegetation consists of subalpine parklands of subalpine fir and Engelmann spruce and alpine grasslands, which generally remained unburned or burned at low severity.

Our results are consistent with other studies that examine the influence of landform on burn severity (Bigler et al. 2005, Lee et al. 2009, Wimberly et al. 2009). Because vegetation is strongly associated with landform, they are generally covariates in models of burn severity. For example, Bigler et al. (2005) and our present study found that burn severity was highest at mid elevations with a pronounced drop at higher elevations containing subalpine and alpine vegetation. Slope gradient is a predictor variable in some studies, but with mixed effects. Collins et al. (2007) and Lentile et al. (2006) found that burn severity was positively correlated with slopes, while Lee et al. (2009) reported a negative correlation. Although fire behavior increases with slope gradient (Rothermel 1972), at higher elevations, steep slope gradients can be associated with discontinuous vegetation, ridgelines, and other landscape features that can act as fire breaks and can result in decreased burn

Plate 1. Postfire photograph of the Tripod Complex (Okanogan-Wenatchee National Forest, Washington, USA) landscape including the landscape burn scar of the 1970 Forks Fire, composed of young regenerating trees that did not burn in the 2006 wildfires. Photo credit: S. J. Prichard.

severity (Haire and McGarigal 2010, Moritz et al. 2011). Heat load index was positively correlated with burn severity in Wimberly et al. (2009) and Arkle et al. (2012), but it is not a significant predictor in this study.

Weather

Because we assigned weather variables (MaxTemp, MinRH, AvgWind, and MaxWind) by progression interval from a single RAWS station, we anticipated that relationships with burn severity would be weak. However, weather variables, including MaxTemp and MinRH, are important predictors in Tripod study area models, suggesting that broadly summarized weather by progression interval is able to represent some of the finer-scale, fire-weather relationships. Regional weather patterns likely influenced the temporal variability of temperature and humidity at the scale of fire progression layers. Collins et al. (2007) also reported significant relationships between weather assigned by progression layers and burn severity, and Wimberly et al. (2009) relied on progression interval as a proxy for fire weather in predictive models of burn severity. The accuracy and consistency of progression intervals are important to this analysis. The Tripod study area contains fewer progressions than does the Spur study area and has ample infrared imagery to validate each progression interval. The Spur study area spans the initial early July progressions along with later July and August progressions in common with the Tripod fire. Because fire perimeters are numerous and complex in the Spur fire, it is not surprising that weather variables assigned by progression intervals are not strong predictor variables.

Vegetation

Vegetation cover and type are both significant predictors of burn severity. Canopy cover is strongly correlated with RdNBR, with higher severity at higher canopy cover values. Burn severity was also highest in mixed-conifer forests (e.g., Engelmann spruce–subalpine fir, lodgepole pine, mixed conifer, and subalpine forests), which tend to grow densely with multilayered canopies and are structurally more predisposed to stand-replacing fire (Agee 1993). Non-forest vegetation (e.g., no vegetation, grass, and shrubs) generally have low RdNBR values and are not strong predictors of burn severity. Postfire vegetation was slow to recover across the study area, and little sprouting or pioneering vegetation was observable one year following the wildfire event. Because this study used an image captured one year post fire, it is therefore unlikely that recovering vegetation obscured measures of burn severity in non-forest vegetation such as grasses, shrublands, and regenerating clearcuts.

Structure and composition of vegetation is an important factor in most studies of burn severity. High burn severity is generally associated with dense, multi-canopied forests (Bigler et al. 2005, Lentile et al. 2006) and specific forest types including mixed-conifer forests (this study), Engelmann spruce-subalpine fir (Bigler et al. 2005), lodgepole pine (Collins et al. 2007), and Japanese red pine (*Pinus densiflora*; Lee et al. 2009). Across study locations, forest types share common characteristics, including high density and cover and multilayered canopies that can act as canopy ladder fuels and facilitate crown fire development during wildfire events. Shrublands burn at high severity in many ecosystems (e.g., Moritz 2003, Collins and Stephens 2010), but shrubs were uncommon in the prefire Tripod landscape and mostly consisted of deciduous species such as slide alder (*Alnus viridis* ssp. *sinuata*) and regenerating quaking aspen (*Populus tremuloides*).

Mountain pine beetles

A key question regarding MPB-affected forests is whether tree mortality following MPB outbreaks predisposes landscapes to high-severity crown fire, particularly during the red attack phase when dead needles dominate canopy fuels (Hicke et al. 2012). The relationship between wildfire events and MPB outbreaks is still unclear in the published literature, and many uncertainties remain regarding fuel succession and fire hazard following MPB outbreaks (Kulakowski and Jarvis 2011, Simard et al. 2011, Hicke et al. 2012, Hoffman et al. 2012, Jolly et al. 2012). A recent MPB outbreak was widespread across the mid to high elevation forests of the prefire Tripod landscape. We found MPB-affected forest vegetation, represented by mixed and red classes or more coarsely by high values of EWDI, to be a significant predictor of burn severity. Relationships between MPB and RdNBR are consistent between the two study areas, but the predicted difference between burn severity in green and red classes is much higher in the Spur study area, and only the mixed class was a significant predictor in the Tripod study area (Table 4). Burn severity was also higher in the red attack than the mixed class, suggesting that red attack areas indeed burned more intensively than do areas that were not attacked by MPB or had mixed levels of attack. In both study areas, the regen class has significantly lower RdNBR values than does the green classification, suggesting that areas that were wetter in August 2005 than in August 2003 burned at lower severity than did unchanged vegetation. The majority of the area classified as regen was either young, regenerating forest or subalpine meadows that appear to have been wetter in the 2005 image than in the 2003 image.

Although these results are compelling, they may be biased because burn severity was also greater in lodgepole pine forests. A potential test of this bias would have been to evaluate differences in burn severity between unattacked vs. mixed and red attack lodgepole pine forests. This was not possible because MPB attack was widespread across the prefire landscape, and there were no available sampling areas of unattacked vs. attacked forests. Field-based studies that include pre- and postfire fuel characterization are likely necessary to address how recent MPB activity may influence fire behavior and effects (Hicke et al. 2012).

Time since treatment and treatment size

Because surface fuels are critical for wildland fire ignition and spread, prescribed and wildland fires can act as temporary fire breaks and mitigate future wildfire behavior (Peterson et al. 2005, Boer et al. 2009, Stephens et al. 2012*b*). The longevity of this effect depends on how quickly surface fuels accumulate following the fire event (Collins et al. 2007, Miller et al. 2012). For example, Finney et al. (2005) reported that prescribed burns within nine years of the Rodeo-Chedeski fires in Arizona were effective at mitigating burn severity, whereas 20-year-old prescribed burns in this study generally remained effective. In a broadscale study of recent wildfires in northern California, Miller et al. (2012) reported that the incidence of high severity of fire was lower in areas that burned within 30 years of a previous wildfire. Similarly, Boer et al. (2009) found recent prescribed burns (<6 years old) reduced the incidence and extent of wildfires in eucalypt (*Eucalyptus* spp.) forests of southwestern Australia.

Across treatment categories in this study, the weak influence of treatment age on burn severity may be partly explained by the lack of treatments older than 30 years and the low primary productivity of vegetation in this semiarid landscape. For example, reported mean site index (i.e., height at 50 years) for low- to mid-elevation Douglas fir and ponderosa pine forests are 15.6 and 24.8 m, respectively (Lillybridge et al. 1995). Fuel succession is slow, and prescribed burn treatments that were up to 20 to 30 years old still appeared effective at mitigating burn severity. Models of burn severity by treatment category suggest that treatment age and size are only weakly significant predictors of burn severity. When combined with other predictor variables, including CanCov, Elev, Slope, MaxTemp, and AvgWind, they result in only slightly lower AIC model values. In ThinBB units, treatment age is positively but weakly correlated to RdNBR, suggesting that burn severity increases with time since prescribed fire and would result in a higher severity classification in 20 to 30 years. Clearcut and broadcast burn treatments were the most effective treatment in mitigating burn severity and appear to have been effective regardless of treatment area or time since treatment.

Size of treatment area has also been demonstrated to influence burn severity. Because larger treatments have more interior space and less edge, they are more effective at mitigating burn severity than are small treatments (Finney et al. 2005, Arkle et al. 2012, Safford et al. 2012). In this study, we found that treatment size is negatively correlated to burn severity for CC, Thin, and WF treatment categories, suggesting that larger treatments (>200 ha) indeed burn at lower severity than do small units.

Sampling area

Comparison of two co-occurring fires allowed us to evaluate drivers of burn severity in two study areas and also some of the potential artifacts of sampling area. Overall, the resulting models and relationships between predictor variables and RdNBR are strikingly similar between the two study areas. Canopy cover, fuel treatment, elevation, and MPB classification are the strongest predictors of RdNBR in both study areas. There are two main differences in the Spur and Tripod sampling areas. First, burn severity in CC treatments does not significantly differ from untreated pixels in the Tripod study area, but it is significantly different in the Spur area. This may be due to sample size: there were only 14 CC units in the Tripod area compared to 57 in the Spur study area. Slope coefficients are similar, suggesting a similar but nonsignificant effect in the Tripod study area. Second, the straightforward and well-validated fire progressions in the Tripod fire likely explain why weather variables, assigned by progression interval, are significant predictors of RdNBR. In contrast, the Spur progressions are more convoluted and numerous, and relationships between assigned weather variables and fire severity are weak. Combined, these differences in the two study areas suggest that caution must be used in interpreting drivers of burn severity due to potential differences in the type, sample size, configuration, and data quality of predictor variables between wildfire events.

Management implications

This study corroborates previous research on fuel treatments and further demonstrates that some timber harvest and fuel reduction treatments are effective at mitigating wildfire effects in these semiarid forests. Even during extreme fire weather in which forest landscapes burned at moderate to high severity, fuels and vegetation strongly influenced patterns of burn severity. Fuel treatments that included recent prescribed burning of surface fuels were particularly effective at mitigating burn severity. In contrast, units that were mechanically thinned from below and those with sanitation cuts, in which small trees were cut and piled, burned at higher severity than did prescribed burn treatments.

The management context for mitigating future wildfire severity depends on vegetation type and fire regime. In forests with a historical low-severity fire regime, reintroducing frequent, low-severity fire through mechanical thinning and prescribed fire and/or landscape underburns without prior thinning are promising approaches to mitigating fire severity in future wildfires (Fernandes and Botelho 2003, Agee and Skinner 2005, Peterson et al. 2005, Boer et al. 2009, Fulé et al. 2012). The effects of past fire exclusion may not be readily apparent in forested landscapes with mixed- to high-severity fire regimes (Perry et al. 2011). Because few species in forests with high-severity fire regimes (e.g., lodgepole pine and Engelmann spruce) are adapted to frequent fire, fuel reduction treatments such as thinning and prescribed burning are not deemed appropriate or effective (Agee and Skinner 2005, Reinhardt et al. 2008). However, managing future wildfires to increase landscape heterogeneity and resilience to future extreme fire events are promising strategies in forests with mixed- to high-severity fire regimes (Keane et al. 2008). Operational crown fires are also being employed in some parks and wilderness areas of the Canadian Rockies to create fire breaks and reintroduce landscape heterogeneity (Kubian et al. 2009). Although clearcut harvests were effective at mitigating fire severity in this study, they have markedly different biological legacies than wildfires. Clearcut, or regeneration harvests, generally lack the diversity of stand structures left by wildfires, including live trees, snags, and downed logs (Franklin et al. 2002). Over time, stand and landscape heterogeneity of forests may be key factors in promoting forest resilience to future extreme fire events and other disturbances such as insects and pathogens (Churchill et al. 2013).

Regional climate is also an important consideration for implementing fuel treatments. In the semiarid climate of the Tripod Complex, many fuel treatments that were even two to three decades old still appeared to be effective at mitigating burn severity. In contrast, treatments may need to be repeated frequently (2–10 years) in more productive ecosystems with flammable shrub and/or understory tree layers that could be released by thinning and prescribed burn treatments (Finney et al. 2005, Battaglia et al. 2008, Stephens et al. 2012*a*). Differences in understory plant assemblages may also explain why fuel treatments remained effective in the Tripod complex fires but might not mitigate burn severity in other ecosystems (Thompson and Spies 2009). Understory shrub and herbaceous vegetation layers are conspicuously sparse and discontinuous in the dry forests of our study area and generally did not contribute to fire spread into treatment units.

This study provides evidence that bottom-up controls, including fuels and landform, remained important in a large, climatically driven wildfire event. Under climatic change scenarios, semiarid forests will experience a greater likelihood of extreme wildfire events, and it is reasonable to expect that no amount of fuel treatment will prevent large areas from burning during regional fire years (Gedalof et al. 2005, Littell et al. 2009). However, research on fires during extreme fire weather (Finney et al. 2005, Boer et al. 2009, Prichard et al. 2010, Lyons-Tinsley and Peterson 2012, Safford et al. 2012) indicates that fuel treatments can remain effective and are a plausible management strategy for increasing forest landscape resilience to wildfires.

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Supplemental Material

Appendix A

Fire progression intervals and summarized RAWS station weather for the (a) Spur and (b) Tripod study areas (*Ecological Archives* A024-034-A1).

Appendix B

Spur area sequential autoregression (SAR) regression models of categorical predictor variables including (a) treatment type, (b) mountain pine beetle (MPB) classification, and (c) cover type (*Ecological Archives* A024-034-A2).

Appendix C

Tripod area SAR regression models of categorical predictor variables including (a) treatment type, (b) MPB classification, and (c) cover type (*Ecological Archives* A024-034-A3).