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Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires

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Abstract. Large wildfires (>50,000 ha) are becoming increasingly common in semiarid landscapes of the western United States. Although fuel reduction treatments are used to mitigate potential wildfire effects, they can be overwhelmed in wind-driven wildfire events with extreme fire behavior. We evaluated drivers of fire severity and fuel treatment effectiveness in the 2014 Carlton Complex, a record-setting complex of wildfires in north-central Washington State. Across varied topography, vegetation, and distinct fire progressions, we used a combination of simultaneous autoregression (SAR) and random forest (RF) approaches to model drivers of fire severity and evaluated how fuel treatments mitigated fire severity. Predictor variables included fuel treatment type, time since treatment, topographic indices, vegetation and fuels, and weather summarized by progression interval. We found that the two spatial regression methods are generally complementary and are instructive as a combined approach for landscape analyses of fire severity. Simultaneous autoregression improves upon traditional linear models by incorporating information about neighboring pixel burn severity, which avoids type I errors in coefficient estimates and incorrect inferences. Random forest modeling provides a flexible modeling environment capable of capturing complex interactions and nonlinearities while still accounting for spatial autocorrelation through the use of spatially explicit predictor variables. All treatment areas burned with higher proportions of moderate and high-severity fire during early fire progressions, but thin and underburn, underburn only, and past wildfires were more effective than thin-only and thin and pile burn treatments. Treatment units had much greater percentages of unburned and low severity area in later progressions that burned under milder fire weather conditions, and differences between treatments were less pronounced. Our results provide evidence that strategic placement of fuels reduction treatments can effectively reduce localized fire spread and severity even under severe fire weather. During wind-driven fire spread progressions, fuel treatments that were located on leeward slopes tended to have lower fire severity than treatments located on windward slopes. As fire and fuels managers evaluate options for increasing landscape resilience to future climate change and wildfires, strategic placement of fuel treatments may be guided by retrospective studies of past large wildfire events.

Key words: climate change; fire severity; fuel treatments; landscape restoration; prescribed burning; random forest; simultaneous autoregression; Washington; wildfires.

Introduction

With a warming climate combined with a legacy of fire exclusion, large wind-driven wildfire events are becoming more common in semiarid landscapes of the western United States (Miller et al. 2012, Stephens et al. 2014, Abatzoglou and Williams 2016). In forested areas that burn mostly as stand-replacing wildfires, an additional concern is that large (>50,000 ha), high-severity fires can accelerate vegetation responses to climate change (Stavros et al. 2014, Coop et al. 2016, Crausbey et al. 2017, Tepley et al. 2018). Landscape restoration treatments are often used to mitigate the impacts of future wildfires by implementing treatments focused on reducing surface and canopy fuel loads through mechanical removal of live and dead trees and by using prescribed fire to mimic the influence of wildfires under controlled weather

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conditions (Agee and Skinner 2005, Stephens et al. 2014). Planning and implementing landscape restoration treatments requires considerable investment and, over the past few decades, the footprint of treated areas has been dwarfed by wildfire area burned in western North America (Barnett et al. 2016, Schoennagel et al. 2017). Research is needed to characterize the ability of different treatments to reduce wildfire spread and severity, the weather and biophysical conditions under which they are expected to be most effective, and the longevity of treatment effectiveness. Such information is essential for prioritizing landscapes to maximize the ecological and economic benefits of treatment.

Over the past decade, numerous post-fire studies have evaluated the effectiveness of fuel reduction treatments at mitigating fire behavior and post-fire tree mortality and other fire effects in fire-prone forests (Stephens et al. 2012, Hessburg et al. 2015, Prichard et al. 2017). A common finding is that past fires generally act as a short-term barrier to fire spread (Teske et al. 2012, Parks et al. 2015, Stevens-Rumann et al. 2016) but that duration of treatment effectiveness depends on site productivity and the rate of accumulation of flammable live and dead surface fuels. Once post-fire live and dead fuels reach levels that support fire spread, treatments still can mitigate the severity of subsequent wildfires for up to 20 yr (Prichard et al. 2017).

However, both treatment effectiveness and longevity can vary by treatment type. Mechanical thinning of forests generally reduces the potential for crown fire, but where surface fuels support intense surface fire, post-fire tree mortality can be comparable to untreated forests (Safford et al. 2009, Prichard et al. 2010, Fulé et al. 2012). Pile burning is commonly used to reduce post-harvest surface fuels, and studies have reported a reduction in subsequent wildfire severity following this treatment relative to unmanaged forests (Strom and Fulé 2007, Safford et al. 2009). Chipping and mastication are alternative treatments to fire, but results from field experiments suggest that these treatments can promote long-duration smoldering fires with substantial soil heating, which can lead to high tree mortality and impact understory vegetation recovery (see Kreye et al. 2014 for a review).

Furthermore, studies have shown that treatment effectiveness is contingent on fire weather, landscape positioning relative to wind and fire spread direction, and plume dynamics, which can drive fire growth and behavior independently of local weather conditions. For example, Graham (2003) found that past prescribed burns and wildfires did not alter fire spread or behavior during a 24,000-ha single-day run of the 2002 Hayman Fire. Similarly, Turner and Romme (1994) found that, under extreme fire weather days in the 1988 Yellowstone fires, the fire was driven by top-down climatic variables with little evidence of bottom-up influences of topography or fuels. Similar results were found for the 2013 Rim Fire in the Sierra Nevada where plume-dominated fire weather led to high-severity fire regardless of vegetation type and pre-burn surface fuel loads (Lydersen et al. 2014). During the 2011 Wallow Fire in Arizona, severity of wildland–urban interface fuel treatments was dependent on neighboring forest conditions and resultant fire severity delivered to fuels treatments (Johnson and Kennedy 2019).

Results from these studies suggest that, while fuel reduction treatments are an effective tool for mitigating future fire severity, their ultimate effectiveness is context specific and related to treatment type, the surrounding forest mosaic, their biophysical setting, and fire weather. Such complexity creates difficulties in predicting future treatment success and landscape prioritizations for identifying locations of future treatments on the landscape. To this end, plot-level evaluations provide a standardized method for evaluating treatment effectiveness while attempting to control for variability in fire behavior related to fire weather, topography, and biophysical environments (e.g., Prichard et al. 2010, Lydersen et al. 2014). However, field data are limited in their inference space given their low sample size. As a complement to field studies, retrospective landscape analyses of remotely sensed fire severity evaluate data on fire extent and severity across large contiguous landscapes. Such data are capable of quantifying both the average effect of a given treatment over the course of a fire or multiple fires, as well as the variability in treatment effectiveness over a range of biophysical settings and fire progressions. These analyses develop statistical relationships between fire severity and a variety of bottom-up variables (i.e., topographic position, vegetation patterns, and fuel treatments) and top-down variables (i.e., fire weather and climate) to interpret main drivers of observed severity patterns and help predict future behavior.

Empirical models have the dual goal of describing the complex relationships between fire severity and its drivers as well as controlling for spatial autocorrelation (SA) that is inherent to all contagious processes. Spatial autocorrelation present in regression model residuals violates the assumption that they are independent and identically distributed and has been shown to result in biased coefficient estimates and inflate model significance (Dormann et al. 2007). Methods generally employed to account for SA are to (1) use a spatially explicit model, (2) establish a minimum allowable distance between sample points to exclude fine-scaled SA from analyses a priori, and (3) apply spatial eigenvector mapping, which develops a series of multi-scaled spatial covariates (Dray et al. 2006). Simultaneous autoregression modeling (SAR) has been used in several past studies of fuel treatment effectiveness and other drivers of fire severity in large fire events, which incorporates SA directly into a linear model through a spatially explicit error term, which improves coefficient estimates, reduces Type I error rates in assessing variable significance, and improves model inference where the SA component is large (Prichard and Kennedy 2014, Stevens-Rumann et al. 2016, Kennedy and Prichard 2017). However, these models are inherently linear in functional form and nonlinear relationships and interactions among predictor variables must be stated explicitly. Other recent studies have attempted to model these complex relationships using machine learning algorithms such as random forest (RF) or boosted regression trees to evaluate the drivers of fire severity, including past forest and fire management, and the relative importance of these predictor variables (Coppoletta et al. 2016, Zald and Dunn 2018; Povak et al., 2020). Spatial autocorrelation in these models is often removed a priori using a minimum distance between sample points. These two modeling approaches, SAR and machine learning, both appear to be promising paths to improving our understanding of the main drivers of fire severity patterns, but no formal comparisons among these methods exist in the fire severity modeling literature to our knowledge. Zald et al. (2016) made comparisons between SAR and RF models in estimating forest carbon density within a watershed in the Cascades Mountains of Oregon, USA. The authors found that RF models excelled in identifying important predictor variables and modeling key nonlinear relationships not captured by SAR, but SAR allowed for more traditional statistical inference and significance testing.

In this study, we evaluated landscape patterns of fire severity using past fuel treatment records and fire severity imagery for the 2014 Carlton Complex fires using both SAR and RF methods as complementary modeling frameworks. The Carlton Complex was the largest wildfire event in Washington state history, and much of the fire progressions burned under extreme weather conditions with strong sustained winds and explosive fire growth. Because the Carlton Complex burned over many recent fuel treatments in forested areas and varied terrain, it offered an opportunity to evaluate how fuel treatments may have mitigated fire severity under exceptional weather conditions across a wide range of biophysical settings. In a previous study, Prichard and Kennedy (2014) evaluated landscape fuel treatment effectiveness in the 2006 Tripod Fires, which are located just north of the Carlton Complex, and reported that thinning and burning or burning alone generally either acted as complete barriers or mitigated fire severity even under the largest fire growth days. However, preliminary assessments of fuel treatment effectiveness in the 2014 Carlton Complex fires indicated that many past fuel treatments had substantial tree mortality and were less effective overall than in the 2006 Tripod Complex (Trebon and Johnson 2014). Several notable differences between the 2006 and 2014 large fire events suggest that fuel treatments were particularly challenged in the 2014 Carlton Complex fires. Specifically, of the 103,000 ha burned, over 67,000 ha burned within a single burn period on 17 July 2014; fire spread was associated with wind gusts over 15 m/s, column-driven fire behavior, and mass ignitions in advance of the flaming fire front. In contrast, the 2006 Tripod Complex burned over 70,000 ha over a 2-month period with episodic fire growth over longer periods and less severe wildfire conditions. Additionally, <40% of the 2014 Carlton Complex fire area was forested; the majority of the vegetation burned was semiarid grassland and shrub steppe. The Carlton Complex provided an ideal landscape to assess fuel reduction treatment effectiveness as it (1) represented a typical east Cascade landscape matrix of forest and rangeland vegetation, which are tightly controlled by topographic position and elevation, (2) spanned a large area across diverse climate, topography, and vegetation conditions, (3) burned under both benign and extreme fire weather conditions, which allowed us to identify potential threshold conditions under which treatments became ineffective, and (4) included a range of fuel treatment types.

The main objective of this study was to evaluate the effectiveness of previous fuel treatments and other drivers of fire severity within forested areas in mitigating fire effects within the context of other biophysical drivers of fire severity. The 2014 Carlton Complex was a clear outlier relative to historical fires in the region due to its extreme fire behavior and size (Cansler and McKenzie 2014, Hessburg et al. 2016). As such, it provides an opportunity to learn from both treatment successes and failures and to provide guidance for the type, size, and landscape configuration of fuel treatments that may be most effective under increasingly severe wildfire events under climate change. Because fuel treatment effectiveness cannot be isolated from other factors driving fire severity, we used two complementary methods of landscape analysis that examined the spatial drivers of fire severity while accounting for SA. Following the methods of Povak et al. (2020), we further extend the RF modeling framework to explore spatial variability in predictor variable importance across the study area to help identify local instances of treatment effectiveness and to quantify model variance explained that is both shared and unique to a variety of bottom-up and top-down predictors of fire severity.

Methods

Study area

The 2014 Carlton Complex fire burned over 100,000 ha of semiarid grasslands and forests of north-central Washington State. Of the burned area, 56% is classified as grassland, 37% forestland, 4% sparse or unvegetated, and 3% developed (LANDFIRE 2012). Climate is semiarid with cold winters and warm, dry summers. Mean annual temperatures range from a low of −0.1°C in January to a mean annual high of 31.1°C in August. Total annual average precipitation is 32 cm with the majority falling as snow. Treatment areas are confined to dry forest types, ranging from ponderosa pine at low elevations (500–700 m) to mixed conifer forests dominated by ponderosa pine, Douglas-fir, western larch, and lodgepole pine at mid-elevations (700–

1,200 m) and Engelmann spruce, subalpine fir, and lodgepole pine at high elevations (>1,200 m).

The burned area was partitioned into two study areas (north and south, Fig. 1) to focus on forested areas with past fuel treatments and to create more manageable inputs for SAR and RF analyses, which are both computationally intensive (Kennedy and Prichard 2017). The north study area was also dominated by severe, wind-driven fire progressions whereas the south study area had more complex progressions and burned under a range of fire weather conditions. Vegetation types within the two study areas were comparable, with mosaics of closed-canopy mixed conifer forests and grasslands, but the north study area had a greater proportion of continuous montane mixed conifer forest than the south study area.

Data layers

Three fire severity indices were evaluated as response variables including the difference normalized fire severity index (dNBR), relative difference normalized fire severity index (RdNBR; Miller and Thode 2007) and the relativized burn ratio (RBR), which also offers a relative index of change to soil and vegetation reflectance but corrects known issues with high or low outlier values resulting from a square root transformation in the

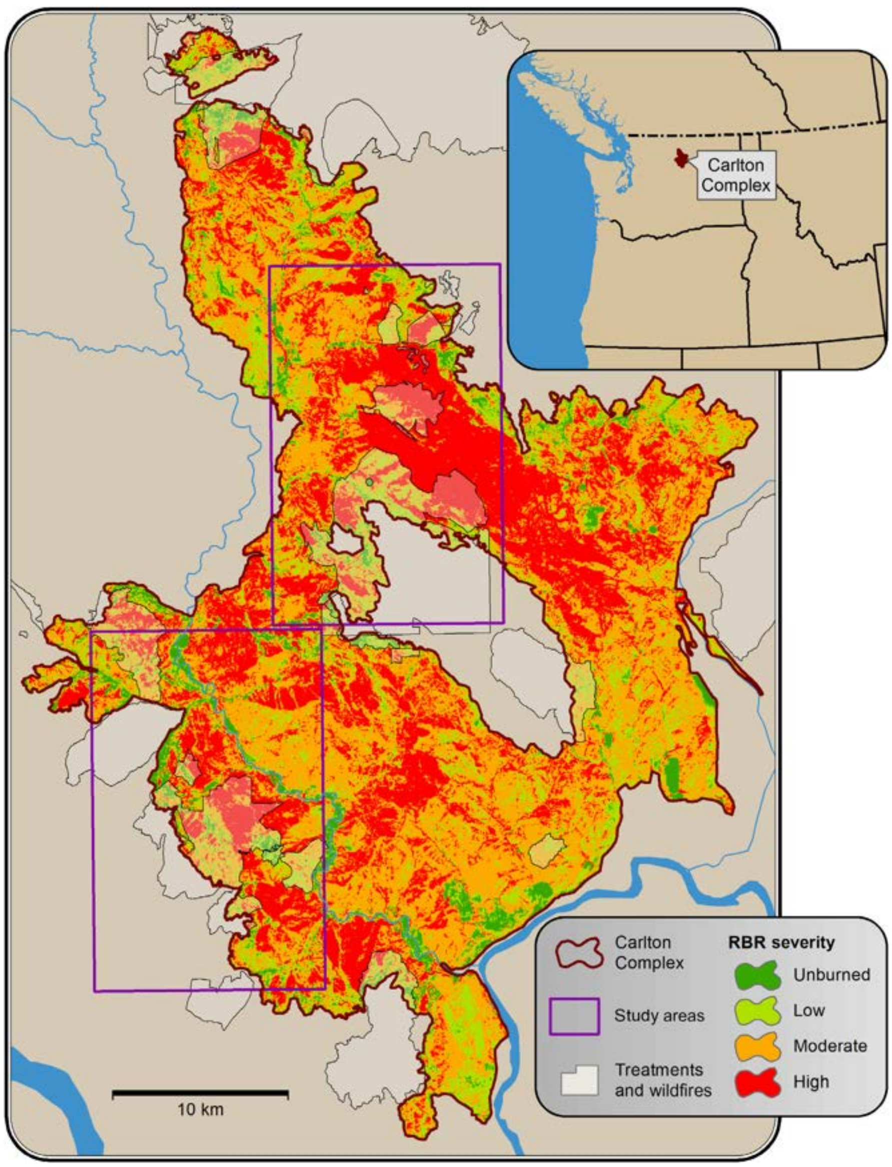

FIG. 1. Carlton Complex final burn perimeter with a burned area reflectance classification of the north and south study areas and location within north-central Washington State, USA. RBR, relativized burn ratio.

RdNBR denominator term (Parks et al. 2014*a*). Source images were taken from cloud-free pre- and post-burn Landsat images (Monitoring Trends in Burn Severity https://www.mtbs.gov). During the summer of 2015, we conducted composite burn index surveys on 170 post-burn monitoring plots. These were used to validate fire severity classifications and determine which fire severity index had the highest correlation with assessed plot severity. Fire severity classifications of unburned, low, moderate, and high severity from RBR values followed Parks et al. (2014*a*) for the 2006 Tripod Fire (Spur Peak) area.

Fuel treatment records were obtained from the Methow Valley Ranger District from 1995 to 2014. Most records were in the Forest Service Activity Tracking System (FACTS), but additional landscape prescribed burns and older treatments were compiled from secondary layers obtained from fire and fuels managers at the ranger district. Fuel treatment perimeters were overlaid on a pre-burn National Agriculture Information Program (NAIP) image (2011), and perimeters were edited to more closely correspond to treatment boundaries. We also used paper records to attribute older treatments (pre 2000) with treatment type, description, harvest dates, and prescribed burn dates (T. Leuschen, *personal communication*). Final fuel treatment fields included treatment type (Type), harvest date, time since fire (applicable to prescribed fires and wildfires), number of fires (in the case of multiple past prescribed burns or wildfires had burned a pixel), distance from treatment edge (calculated as the distance from treatment edges for each treated pixel) and treatment size (ha; Table 1). Treatments were grouped into general categories including clear-cut (CC), clear-cut and broadcast burn (CCBB), thin-only harvest (Thin), thin and understory prescribed burn (ThinUB), thin and pile burn (ThinPB), prescribed underburn (UB), past wildfire (WF), and no treatment (None). Forested areas that had no record of treatment were either harvested prior to 1995 or prescribed burned before 2000 were categorized as having no treatment.

TABLE 1. Predictor variables for simultaneous autoregression models.

Data set and variable	Description
Treatment	
Edge	distance from past treatment edge, m (prescribed burns and past wildfires only)
Number of fires	number of past fires
TSF	time since fire, yr (prescribed burns and past wildfires only)
Type	clear-cut (CC), clear-cut and broadcast burn (CCUB), thin-only harvest (Thin), thin and broadcast prescribed burn (ThinUB), thin and pile burn (ThinPB), landscape burn (UB), past wildfire (WF), no treatment contrast (None).
Size	treatment size (ha)
Topographic variables	
Elev	elevation, m
Slope	slope gradient, %
TPI_{100}, TPI_{600}, TPI_{1200}	topographic position indices calculated for 100, 600, and 1,200 m neighborhoods
$Ridge_{100}$, $Ridge_{600}$, $Ridge_{1200}$	ridge-like classifications of TPI at the three neighborhood scales
$Valley_{100}$, $Valley_{600}$, $Valley_{1200}$	valley-like classifications of TPI at the three neighborhood scales
SRad	average annual solar radiation, W/m^2
SRadMax	summer solar radiation, W/m^2 (July average)
Vegetation and fuels	
CanCov	canopy cover, % (LANDFIRE 2012)
CBH	canopy base height, m (LANDFIRE 2012)
CH	canopy height, m (LANDFIRE 2012) (m)
FM40	standard fire behavior fuel models (Scott and Bergen 2005)
Vegetation type	broad classification based on existing vegetation type (LANDFIRE 2012). developed (Dev), dry mixed conifer (DMC), Engelmann spruce–subalpine fir and lodgepole pine (ESSF), grassland (Grass), moist mixed conifer (MMC), ponderosa pine (PP), riparian vegetation (Rip), shrubland (Shrub)
Weather variables (summarized by progression interval)	weather summarized by Douglas-Ingram RAWS hourly data for each progression interval
Wind	average wind, m/s
MaxGust	maximum wind gust, m/s
WNSpeed	average wind, m/s, predicted by progression interval in Wind Ninja.
Temp	average temperature, °C
MaxTemp	maximum temperature, °C
RH	average relative humidity, %
MinRH	minimum relative humidity, %

Topographic indices were calculated from digital elevation models and included elevation (Elev, m), slope (degrees), and solar radiation (SolRad [average annual] and SolRadMax [July maximum], W/m^2). Topographic position indices (TPI) were calculated within 100-, 600-, and 1,200-m neighborhoods of each pixel using methods developed by Weiss (2001). This method compares the elevation of each DEM pixel with the mean elevation within the nearest neighborhood of each pixel. Valley positions are classified as negative TPI (−2 to 0), and ridge positions are classified as positive TPI values (0 to 2).

Fire progression layers were compiled from operational firefighting records from the Carlton Complex Fire Box, obtained from the Okanogan-Wenatchee supervisor's office (Wenatchee, Washington, USA; Appendix S1: Fig. S1). Progressions were validated with IR imagery and corrected for overlaps and other digitization errors. Hourly fire weather data were taken from the Douglas Ingram Ridge Remote Area Weather Station, located above Alta Lake State Park, Pateros, Washington, USA (48.0333° N, 119.9667° W). Hourly RAWS data were summarized by progression interval (Appendix S1: Table S1). For example, minimum relative humidity and maximum temperature and wind gusts were averaged for the hours represented by each interval. Because wind fields are mediated by terrain and the potential limitations of using a single RAWS station for wind, we also calculated wind grids in Wind Ninja (Forthofer et al. 2014*a*, *b*) using weather summarized by progression interval for the three nearest RAWS stations, including Douglas-Ingram, First Butte, and North Cascades Smoke Jumpers Base. Wind Ninja surfaces were processed by progression interval to interpolate between weather stations and predict local wind fields across the varied topography of our study areas.

Existing vegetation type and canopy fuels layers were obtained from the LANDFIRE 2012 refresh to represent pre-fire fuels and vegetation for each 30-m pixel (data *available online*).[6] Vegetation was reclassified to broader vegetation categories including developed (Dev), dry mixed conifer (DMC), Engelmann spruce–subalpine fir and lodgepole pine (ESSF), grassland (Grass), moist mixed conifer (MMC), ponderosa pine (PP), riparian vegetation (Rip) and shrubland (Shrub).

Statistical analyses

Based on relationships with CBI, RBR was selected as the response variable for all subsequent analyses. Relationships between fire severity indices and CBI (n = 170) were strong with coefficients of determination ranging from 0.8140 for dNBR, 0.8199 for RBR and 0.8455 for RdNBR. Although classification accuracies were comparable, RBR had the highest overall classification accuracy and relatively even classification errors in low and moderate categories (Table 2). Across all three severity indices, classifications were accurate (>90%) for high and unburned categories of severity but with mixed accuracy for low and moderate severity. However, 38 of the 40 classification errors were adjacent categories (e.g., moderate but measured as low or low but measured as moderate). Of the 15 moderate severity classification errors using the RBR index, 5 were moderate and 10 were low based on CBI values; of the 19 low severity classification errors, 1 was high, 13 were moderate and 5 were low. Based on field verification, sites with unburned and low classifications were associated with <20% tree mortality with only two unburned plots and on low severity plot having mortality higher than 20%.

Table 2. Classification accuracy of dNBR, RNBR, and RBR classifications of fire severity.

Burn severity classification	N	dNBR (%)	RdNBR (%)	RBR (%)
High	52	94	90	90
Moderate	29	62	55	48
Low	35	31	23	46
UB	54	93	96	96
Total	170	75	72	76

Notes: Fire severity indices are difference normalized fire severity index (dNBR), relative difference normalized fire severity index (RdNBR), and the relativized burn ratio (RBR). Classification bins for dNBR and RdNBR were used from Miller and Thode (2007); location-specific bins were used for the Spur peak area, which is within 30 km of the Carlton Complex perimeter (Parks et al. 2014a).

We first evaluated treatment effectiveness using pixel summaries of RBR for treated areas only. Fuel treatments are generally designed for multiple objectives, including thinning from below to improve forest health and reduce crown fire potential, salvage harvesting following insect and disease outbreaks, restoring dry forest habitat, and prescribed burning to reduce accumulated surface fuels (Agee and Skinner 2005, Stephens et al. 2012). We considered past harvests and fuel reduction treatments as "treatment types" within this study.

We first classified RBR within treated areas to evaluate patterns of fire severity classes across different treatment types, time since fire, and days of the Carlton Complex fire. For each treatment unit, we quantified the percent area in four fire severity classes including unburned (≤42), low (>42 to ≤158), moderate (>158 to ≤304), and high severity (> 304). Based on these classifications, we summarized percent of unburned, low, moderate, and high severity pixels within treatment units across early (15–18 July) and late (19 July–10 August) progression intervals. The number of units within each treatment type varied widely with low representation of ThinPB in both early and late progression data sets (n = 6 and 11, respectively) and ThinUB in the early progression data set (n = 10). An exploratory analysis of variance was conducted to examine statistical differences of the percentage of treatment area that was either unburned or low severity among treatment types.

[6] https://www.landfire.gov

We then used a pair of correlative modeling techniques across a portion of the Carlton Complex extent to identify key biophysical drivers of fire severity patterns and to determine the relative effect of treatments on mitigating fire severity. Simultaneous autoregression models were evaluated using the R programming language (R Development Core Team 2012), to predict fire severity indices by fuel treatment, topography, vegetation and fuels, and weather variables across the north and south study areas, including untreated pixels (Table 1). These models include a linear combination of predictor variables as well as spatially autocorrelated errors

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

In our simultaneous autoregression model, Y is RBR and $\boldsymbol{\beta}$ is the vector of coefficients estimated for the design matrix of explanatory variables (X). The λ coefficient is an estimate of the strength of autocorrelation and $\mathbf{W}$ is the neighborhood weighting matrix. The autocorrelated error term ($\lambda\mathbf{W}[Y - \boldsymbol{\beta}X]$) accounts for both intrinsic autocorrelation and any potential missing autocorrelated explanatory variables. These are combined with the explanatory variables to predict Y. The value ε is the remaining unexplained variability in Y.

For categorical variables, base contrasts (i.e., the category to which others were statistically compared within the model) were no treatment (none) for treatment type, and grass for vegetation type. Following Kennedy and Prichard (2017), we performed an analysis of the effect of neighborhood size on model inference and found that the 30-m neighborhood yielded the minimum Akaike Information Criterion (AIC) value, and thereby was used to define the weight matrix of the SAR neighborhood (Beale et al. 2010, Kennedy and Prichard 2017). Models of fire severity were compared using AIC (Akaike 1974), and final models were selected to include significant covariates ($P < 0.05$) that contributed to the lowest AIC values. All models were estimated using the spautolm function in the spdep package v1.0.2 in R (Bivand and Piras 2015). To further assess the contribution of spatial autocorrelation to predictions, we estimated an intercept-only model (no explanatory variables, only the spatially autocorrelated error terms). We also calculated the correlation between the intercept-only model predictions and the final SAR model predictions with the lowest model AIC. A high correlation would imply little contribution of the explanatory variables to model predictions and that the spatial autocorrelation term explained most of the variability in RBR.

Random forest (Breiman 2001) is an ensemble regression tree model in which hundreds to thousands of regression trees (De'ath and Fabricus 2000) are developed with iterative subsets of the data and predictions are averaged across trees. For this application, we set the number of trees to 2,500, which increased stability in local importance estimation. Model performance was evaluated using out-of-bag variance explained (R^2_{oob}). Variable importance measures were calculated using conditional forests with the cforest function in the party v1.3.3 package in R (Strobl et al. 2008), which provided unbiased estimates of importance. Variable importance was assessed globally across all sample points, and locally for individual sample points. Importance values were calculated for each predictor variable as the difference in out-of-bag mean squared error of the original data compared to when the values are randomly permuted. Differences are then averaged across individual regression trees to calculate local importance values for each sample point and then averaged across sample points to calculate global importance values for each variable. Importance values are unbounded; values <0 indicate unimportant variables, while large positive values indicate highly important variables. Global values were calculated using the varimp function in the party v1.3.3 package, while local importance was calculated using the generateFeatureImportanceData function within the mlr package v2.13 in R (Bischl et al. 2016). Importance values are unbounded; values <0 indicate unimportant variables, while large positive values indicate highly important variables. Local importance was scaled where all values <0 were excluded (i.e., converted to NA) and remaining values were scaled between 0 (lowest) and 100 (highest) using a linear transformation. Scaled local importance values were subsequently mapped for further inspection.

Consistent with the SAR modeling, RF models were developed separately for the north and south using the same global set of predictors as the SAR models. Variable reduction was conducted for each model to balance model complexity with model performance. Multicollinearity was assessed prior to variable reduction using $r < |0.7|$. Among correlated variables, those with the highest correlation with RBR were retained. The remaining variables were sequentially reduced using backward elimination until R^2_{oob} fell below 10% of the maximum R^2_{oob} for the full model. With few exceptions, final predictor variable sets were similar among north and south models following backward elimination. Missing variables from one model were then added to the other model to create a matching set, which aided in inter-model comparisons. Final models were run using the randomForestSRC v2.8.0 package (Ishwaran and Kogalur 2018), which provided lower error rates compared to conditional forests.

Spatial autocorrelation was accounted for in RF modeling using a combination of subsampling and spatial eigenvector mapping. To reduce the spatial dependency among sample points and the computational burden, the data set was sampled at 270-m spacing, which is comparable to the methods of Kane et al. (2015) and Zald and Dunn (2018). Greater spacing than 270-m resulted in insufficient data to develop relationships between predictor variables and fire severity. We then used principal components of neighborhood matrices (PCNM), a special case of spatial eigenvector maps,

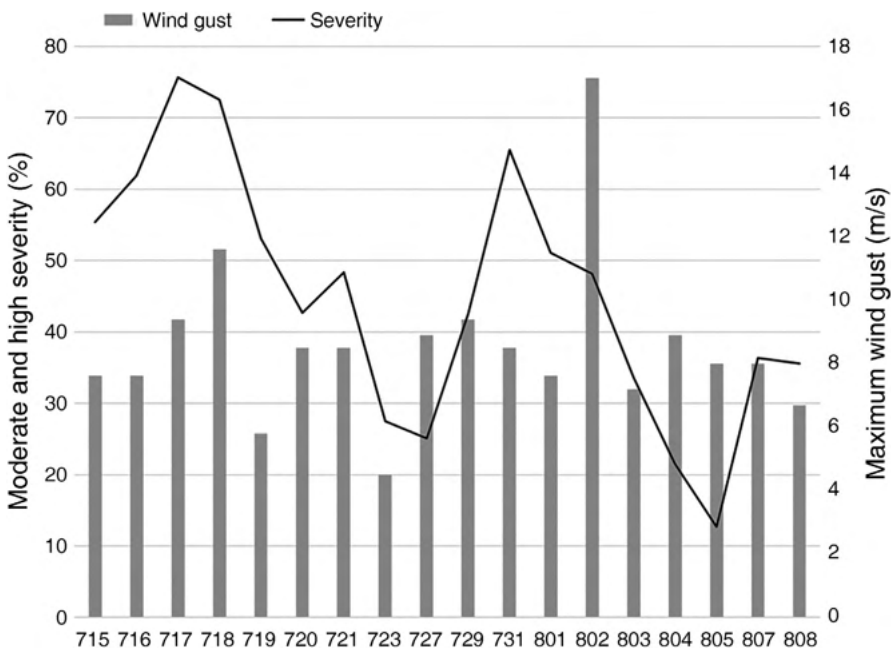

Fig. 2. Percentage of fuel treatment areas classified as having burned at moderate to high severity, by fire date (e.g., 715 = 15 July 2014). Maximum wind gust (m/s) is displayed on the secondary *y*-axis.

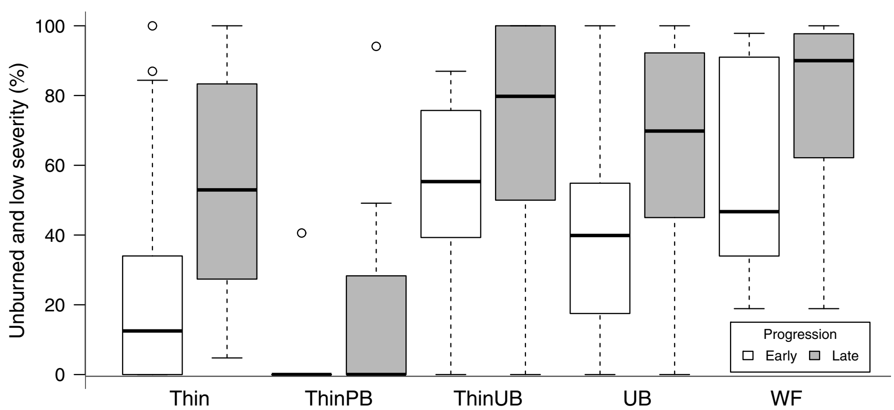

Fig. 3. Box plots of the percentage of pixels in treatment units categorized as unburned and low severity by treatment type for early progression dates ranging from 15 July to 18 July and later progression dates ranging from 19 July to 10 August. Treatments include thin only (thin), thin and pile burn (ThinPB), and thin and prescribed underburn (ThinUB), prescribed underburn only (UB) and past wildfire (WF). Clear-cut and broadcast burn (CCBB) was not included in this comparison because this treatment type was only present in the north study area. Box plot components are mid line (median), lower box edge (25th percentile), upper box edge (75th percentile), open circles (max values).

which incorporates spatial predictor variables into the RF analysis (Borcard and Legendre 2002, Dray et al. 2006). Principal components of neighborhood matrices also allowed for an examination of the dominant scales at which spatial autocorrelation was most influential to severity patterns. Principal components of neighborhood matrices create a truncated Euclidean distance matrix for all data points within a predefined distance and perform a principal coordinates analysis on the resultant distance matrix. The truncation distance was set at 10,000-m for both study areas based on Moran's I correlograms calculated for the RBR response, which assesses the level of spatial dependence across a series of inter-point distances. From the resultant truncated distance matrix, a series of positive eigenvectors (PCNM axes) were calculated and used as predictor variables in the RF models. Backward elimination was conducted separately on the PCNM axes, which were then appended to the final set of predictors (Appendix S1: Figs. S2, S3). Low-order PCNM axes retained following backward elimination (e.g., PCNM axes 1, 2, or 3) represented large-scale (5–10 km) spatial autocorrelation,

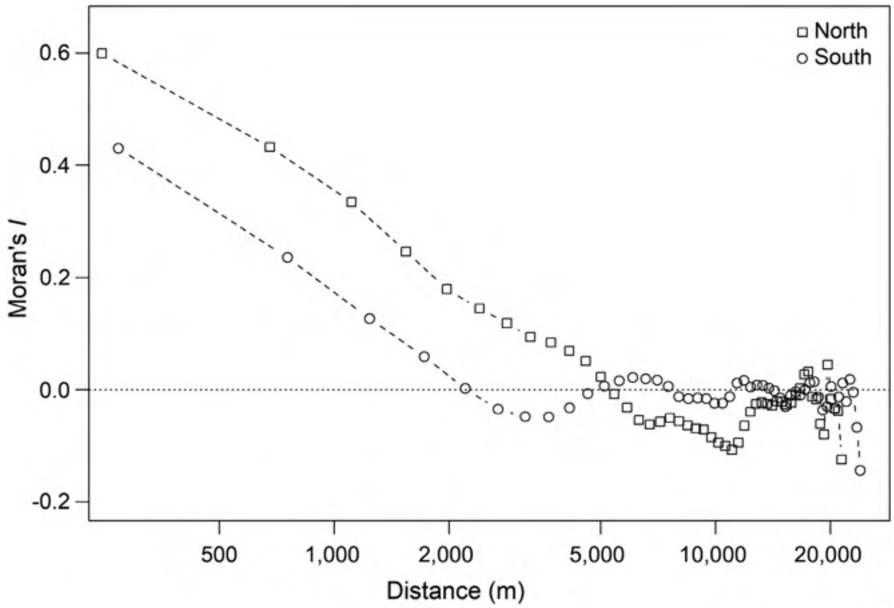

Fig. 4. Spatial autocorrelation of fire severity (RBR), represented by Moran's *I*, across distances from 0 to 20 km in the south and north study areas of the 2014 Carlton Complex. Note log scale.

while higher-order axes (e.g., PCNM axes 5, 7, 11) represented meso-scale (2–3 km) spatial autocorrelation (Appendix S1: Fig. S4). Once final models were developed, variance decomposition (Borcard et al. 1992) was used to quantify both the unique and shared variance explained by several predictor variable groups representing top-down down controls (i.e., climate, fire weather), bottom-up controls (i.e., topography, fuels, and past management), and spatial autocorrelation (represented by PNCM axes). Residual variance is defined as the remaining variance not explained by the models.

Results

Burned area reflectance classification of treated areas

Overall, the percentage of unburned area and low severity fires within treatments was much higher in later progressions than early progressions. The majority of area burned in our two study areas was between 15 July and 18 July and is associated with reduced treatment effectiveness within fuel treatment areas (Figs. 2, 3). The period of 17–18 July in which 68,421 ha burned in <24 h with maximum wind gusts >8 m/s, corresponding with a peak in the percentage of treated areas that burned at moderate and high severity (Fig. 2, Appendix S1: Fig. S5). Higher severity within treated areas was also observed between 29 July and 2 August. Treatments that involved fire (ThinUB, UB and WF) had significantly higher areas of unburned and low severity than Thin and ThinPB units did even during early progression days (Fig 3, Appendix S1: Table S2). However, disparate samples sizes existed among treatment units, with particularly low representation in ThinPB and ThinUB units.

Spatial autocorrelation in fire severity

Moran's *I* analysis of SA reflected broad-scale spatial patterning in fire severity with high SA ($I > 0.2$) in RBR for both study areas for distances up to 0.8 (south) to 1.8 (north) km and lower levels of SA were detectable up to 2 km in the south and 5 km in the north (Fig. 4). Accordingly, λ parameters for the SAR models, which determine the amount of weight given to SA in the

Table 3. Simultaneous autoregression (SAR) model results.

Model	λ	R^2	AIC
North			
RBR ~ CanCov + Elev + SRadMax + Treatment + WNSpeed	0.9716	0.9539	2,463,861
South			
RBR ~ CanCov + CovType + MaxTemp + Treatment + Valley1200	0.9684	0.9378	2,118,000

Notes: Predictor variables are listed in alphabetical order. The λ coefficient is an estimate of the strength of autocorrelation. AIC, Akaike information criterion.

model, were >0.96 for both study areas, close to the maximum of 1.0 for that parameter (Table 3). The correlation between the intercept-only SAR model predictions and the final SAR model predictions was >0.90, implying that most of the variability in severity was explained by the spatial structure.

For RF models, PCNM axes selected in backward elimination were low-ordered axes that represented meso- to broad-scale patterns of SA for both study areas (2–10 km, Appendix S1: Figs. S2–S4); these were PCNM1 in the south (second-leading RF importance), and, in the north, PCNM2 and PCNM3 variables (first and second leading RF importance). Principal components of neighborhood matrices variables exhibited higher overall importance in the north compared to the south study area. All other PCNM axes included in the model had low importance.

Simultaneous autoregression models

Final SAR models for both study areas were selected to contain significant predictor variables that contributed to lowest model AIC values (Table 3, Fig. 5). Final models for north and south study areas contained a combination of fire weather variables (wind and ambient temperature) and biophysical variables including vegetation, fuels, and landform. Of the three response variables, RBR severity index exhibited the lowest model AIC and was used in final models. In the north study area, fire severity was positively correlated with modeled wind speed (WNSpeed), elevation and forest canopy cover. Fire severity was negatively correlated with solar radiation. In the south study area, wind and elevation were not included in final models. Fire severity was positively correlated with maximum temperature but negatively associated with forest canopy cover as well as valleys. Cover type was also a significant predictor in the south with negative correlations with fire severity in nonforest types and riparian forests.

Fuel treatments were important variables in SAR models of fire severity for both study areas (Table 4). With the exception of ThinPB treatments in the north, all fuel treatments were negatively correlated with fire severity. However, Thin and underburn (ThinUB) treatments were associated with lower RBR than other treatments. Other treatments that involved past fires including UB and WF, were more comparable with Thin treatments. Time since fire was a significant predictor but did not contribute to lower model AIC and was not included in the final SAR model of either study area.

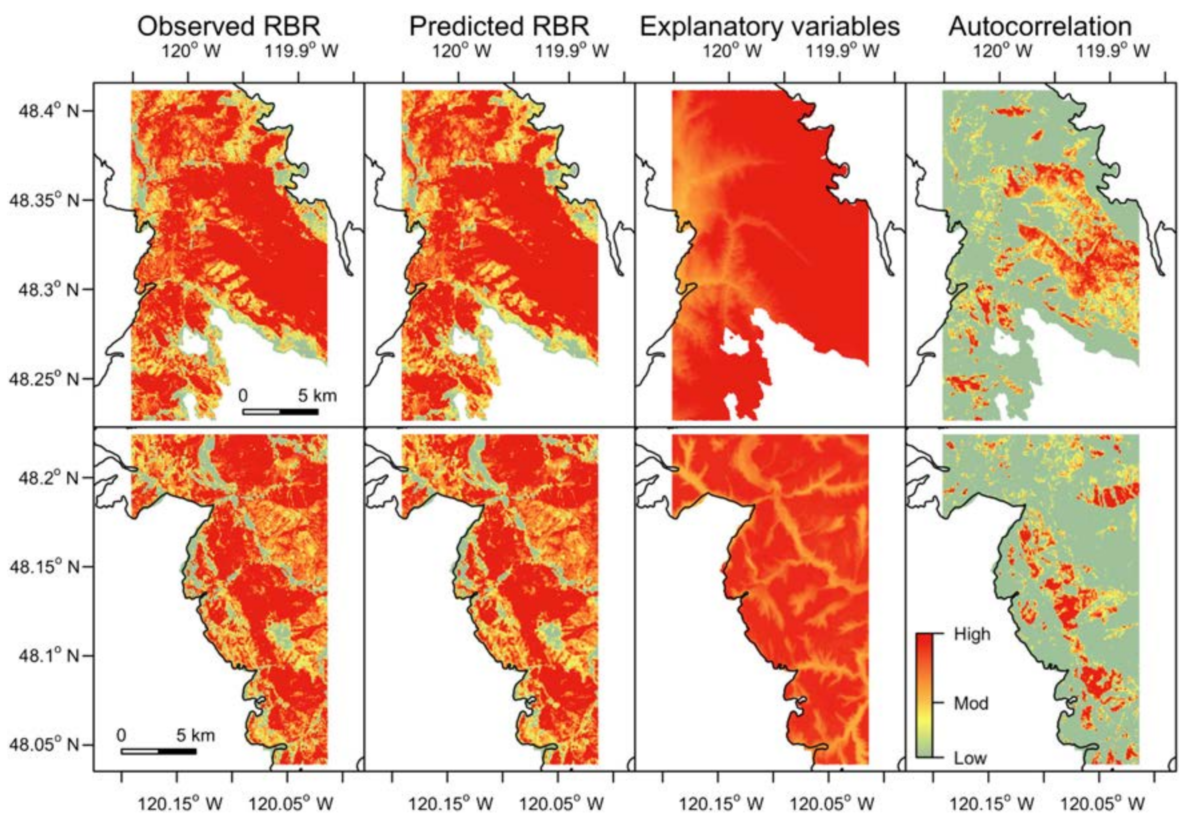

Fig. 5. Observed and predicted fire severity patterns from simultaneous autoregression (SAR) models for the 2014 Carlton Complex in central Washington State. Models were developed for the north (top row) and south (bottom row) study areas separately. Predictions were broken down to the non-spatial (column 3) and spatial (column 4) components of the fitted values. Therefore, predictions in column 3 + column 4 = column 2.

TABLE 4. Estimates, standard error, and *P* values of simultaneous autoregression models (SAR) of fire severity by study area.

	Carlton North			Carlton South		
Variable	Estimate	SE	*P*	Estimate	SE	*P*
Intercept	152.56	16.52	**<0.0001**	272.47	7.45	**<0.0001**
Treatment						
CCBB	−2.92	2.38	0.2204			
Thin	−5.64	1.64	**0.0006**	−6.94	3.43	**0.0428**
ThinPB	1.97	1.97	0.3174	−0.30	4.12	0.9419
ThinUB	−9.36	2.11	**<0.0001**	−16.26	4.48	**0.0003**
UB	−5.65	1.64	**0.0006**	−1.10	2.25	0.6251
WF	−2.66	2.43	0.2737	−5.95	1.64	**0.0003**
CanCov	0.28	0.01	**<0.0001**	−0.06	0.01	**<0.0001**
Cover type						
Bare	–	–	–	−8.03	0.56	**<0.0001**
Dev	–	–	–	−8.18	0.98	**<0.0001**
DMC	–	–	–	−0.20	0.88	0.8224
MMC	–	–	–	1.08	0.73	0.1384
PP	–	–	–	1.60	0.87	0.0674
Rip	–	–	–	−3.03	1.53	**0.0473**
Shrub	–	–	–	−1.83	0.38	**<0.0001**
Elev	0.29	0.01	**<0.0001**	–	–	–
Valley1200	–	–	–	−1.02	0.07	**<0.0001**
MaxTemp	–	–	–	0.47	0.21	**0.0231**
SolRadMax	−0.03	0.00	**<0.0001**	–	–	–
WNSpeed	0.74	0.11	**<0.0001**	–	–	–

Notes: Treatment types include clear-cut and broadcast burn (CCBB), thin only (thin), thin and pile burn (ThinPB), thin and prescribed underburn (ThinUB), underburn (UB) and past wildfire (WF). CanCov, canopy cover; cover types include bare ground (Bare), developed/roads (dev), dry mixed conifer forest (DMC), moist mixed conifer forest (MMC), ponderosa pine forests (PP), riparian vegetation (Rip), and shrublands (Shrub). –, Not applicable.

Bold values are significant at ($P < 0.05$).

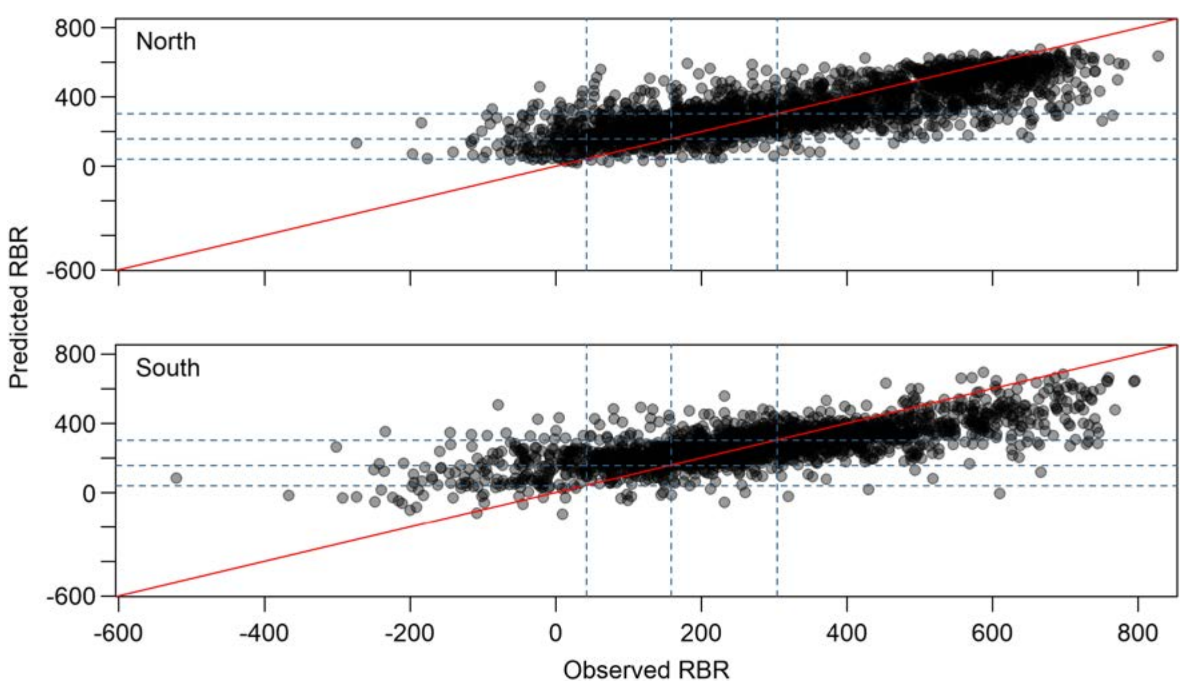

FIG. 6. Predicted RBR vs. observed RBR for the north and south study areas using random forest modeling. Blue dashed lines represent low-, moderate-, and high-severity thresholds on *x*- and *y*-axes.

Of the landform variables we evaluated, elevation was the most important predictor of fire severity in the north study area, and maximum solar radiation was associated with lower fire severity. In the south, fire severity had a weak but significant positive relationship with elevation and was significantly lower in valley bottoms. Based on plotted comparisons of elevation and RBR across both study areas, fire severity increased with elevation but then declined at the highest elevations (i.e., over 1,400 m in the north and 1,200 m in the south).

Vegetation cover and type also influenced fire severity in both study areas. Forest canopy cover was positively correlated with fire severity in the north but was negatively correlated with severity in the south. Among the fuels and vegetation predictors, cover type was an important variable in the south with significantly lower fire severity in riparian forests, shrublands, and non-vegetated areas and significantly higher fire severity in ponderosa pine forests. Canopy cover was an important predictor in both models and had a positive relationship with fire severity in the north and a slightly negative relationship in the south.

Random forest models

Random forest modeling allowed for an explicit examination of the role of spatial autocorrelation in model prediction and included the ability to model nonlinear relationships and interactions among predictors and fire severity by virtue of the regression tree model structure. Model performance was higher for the north ($R^2_{oob} = 0.628$) compared to the south ($R^2_{oob} = 0.519$) study area. Models generally predicted high and moderate severity well but tended to over predict low and unburned pixels (Fig. 6).

Similar to SAR models, wind variables were important in the north but less so for the south (Fig. 7). Max Gust was the leading variable in the north, and severity increased nonlinearly with increasing gust speeds, with large increases in severity between 8 and 12 m/s. Maximum temperature was the leading variable for the south, which had a positive linear relationship with fire severity. Severity increased with increasing canopy cover in both study areas, in contrast to SAR models in which a strong positive relationship was found for the north and weak negative relationship was found in the south.

The fuel treatment variable was moderately predictive of fire severity for both study areas, and similar to SAR, Thin, ThinUB, and UB exhibited the largest reductions in severity across treatments. However, partial plots showed comparatively little variation in severity response to treatment across treatment types (Fig. 8). Time since last fire was not a leading variable for either study area.

Landform variables were generally more predictive of fire severity patterns in the south than the north. Valley bottom topography was a strong predictor in the south but not the north, and severity generally declined as topographic setting converged toward valley bottom settings. Fire severity decreased with increasing solar radiation for both study areas, but this variable had higher importance in the south. Slope was generally a weak predictor of severity, and higher severities were found on moderate slopes for both study areas. Elevation showed an asymptotic pattern where severity increased with increasing elevation until a point and then severities leveled off (~1,000 m north, ~500 m south).

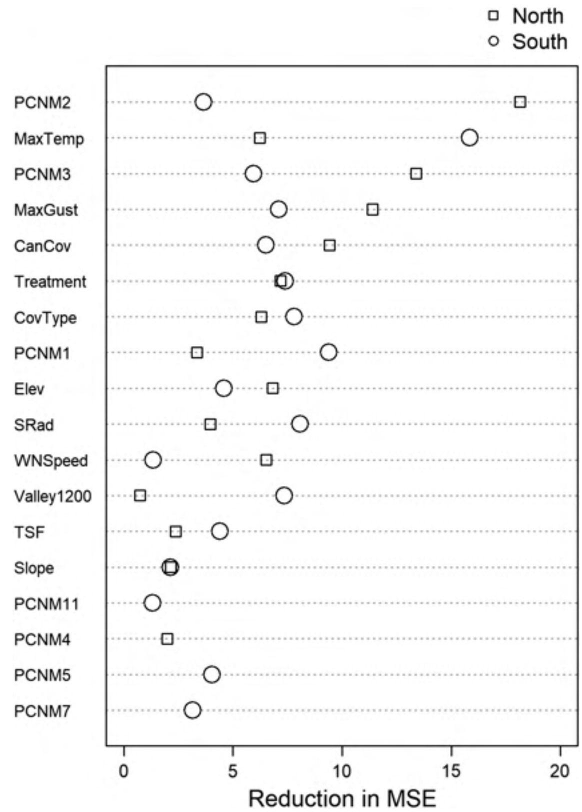

FIG. 7. Variable importance (reduction in mean squared error) for the north and south study areas of the Carlton Complex, ranked by mean predictor variable importance for both sites. Predictor variables other than PCNM axes are defined in Table 1. PCNM (1-3), Low-order Principal Components of Neighborhood Matrices representing large-scale (5-10 km) spatial autocorrelation, PCNM (5, 7, 11) higher-order axes representing meso-scale (2 – 3 km) spatial autocorrelation.

Local importance revealed that the strength of predictor variable groups varied considerably across the two study areas (Fig. 9). For the north study area, fuel and vegetation variables were strongest in the west and south (i.e., earlier in the fire progression) and SA was strongest in the eastern portion. Spatial autocorrelation was most prominent in the north where the fire burned with very high severity on the 17–18 July fire progression days. This also corroborated results from the SAR model, where large positive autocorrelated residuals (implying higher severity relative to the explanatory variables) were predicted in this region as well. In the south, weather

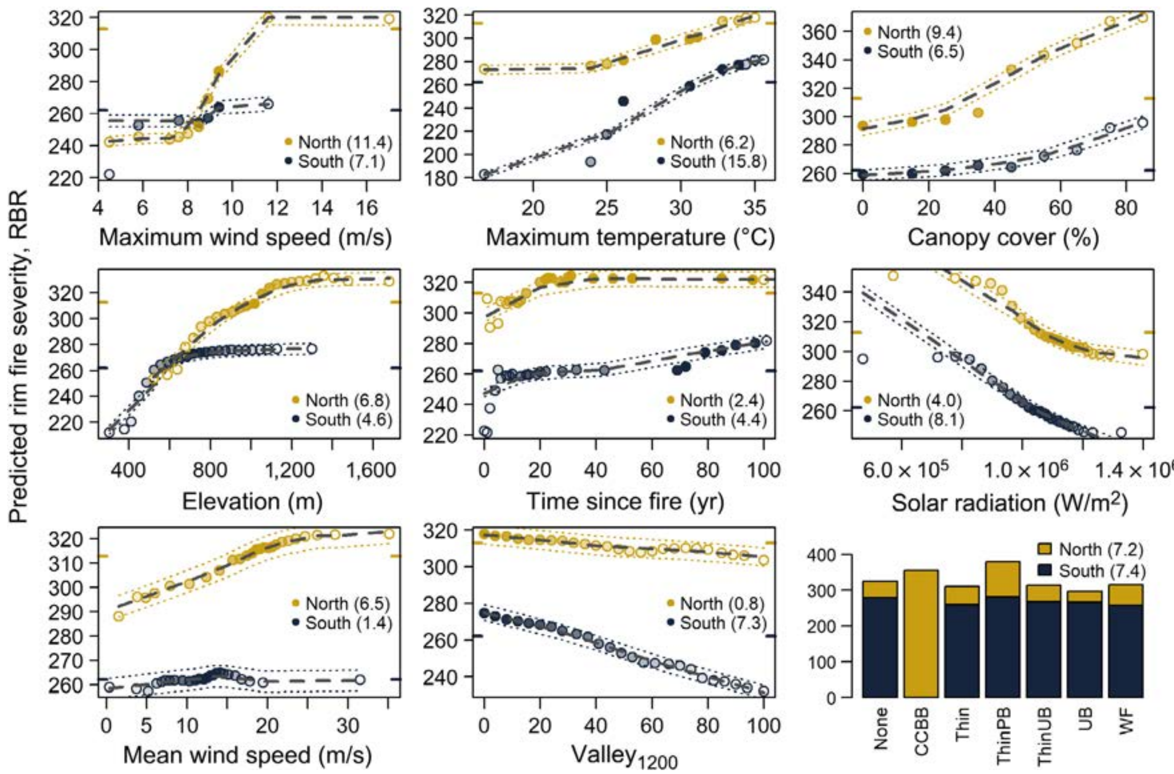

Fig. 8. Partial dependence plots for the top nine predictor variables identified by random forest models used to explain fire severity patterns for the 2014 Carlton Complex in central Washington State. Models were developed for the north and south study areas separately. Values in parentheses indicate relative variable importance. Plots depict the marginal effect of a predictor variable on predicted severity. Points represent severity predictions made for 25 values across the range of each predictor variable. Dashed gray lines are lowess (locally weighted scatterplot smoothing) smoothed trend lines, and colored dashed lines are 2 × SE of the lowess estimate. The opacity of each point was determined by the empirical density function of the predictor variable with darker hues representing higher densities and lighter hues representing sparse data. An overlaid bar chart is used to represent predicted fire severity by fuel treatment type for the north study area with consistently higher severity values than the south study areas. See Table 1 for predictor variable descriptions.

variable importance was high overall and high importance generally corresponded with high-severity patches, with the exception of the western edge where high importance was associated with low-moderate severity pixels that burned during benign fire growth days. Despite having low overall importance in the RF models, topography importance was high in isolated patches, corresponding with lower fire severity in valley bottoms and low gradient slopes of both study areas.

Local importance for treatments varied across treatment type and early vs. late progression days. Sample points corresponding with high treatment importance (importance > 0.75) generally had lower RBR compared to those with low importance (importance ≤ 0.25; Fig. 10, Appendix S1: Fig. S6). Differences among observed RBR between low and high importance sample points were greater for early progression days (more extreme weather) compared to later progression days and indicated that treatments were capable of reducing burn severity under extreme weather condition, although the incidence of treatment effectiveness was lower under these extreme conditions. Prescribed underburn (UB) and wildfire (WF) treatments in particular led to the greatest disparities in observed RBR between low and high importance (Appendix S1: Fig. S6).

Variance decomposition (Fig. 11) revealed high shared variance across variable groups, particularly with PCNM axes, suggesting a high level of broad-scale spatial structure in covariates and the fire severity response. Pure variance explained by any one variable group contributed between 0 and 5% of the total variability in fire severity. The largest contribution to variance explained was shared between fuels, weather, and SA models in the north (17.2%), and weather and SA models in the south (13.6%).

Discussion

Past research suggests that under extreme fire weather conditions, thresholds to fire spread and severity are effectively reduced, and the influence of terrain, vegetation, and biophysical setting are less important than under milder weather conditions. As such, there is no way to guarantee a given fuel reduction treatment or

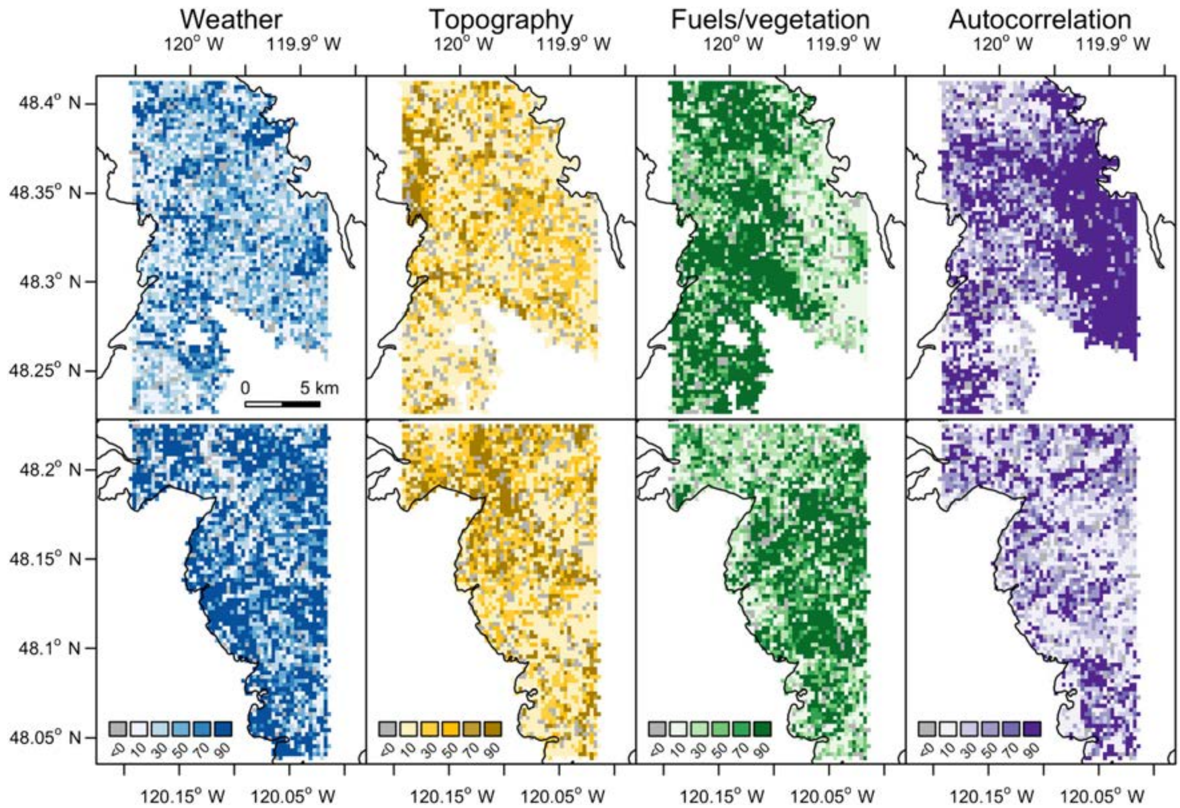

FIG. 9. Local importance of predictor variable groups for random forest models used to model spatial patterns of fire severity for the 2014 Carlton Complex in central Washington State. Models were developed separately for the north (top row) and south (bottom row) study areas. Importance values range from 0 to 100, with larger values indicating higher relative importance. Predictor variables included in each group are described in Table 1.

past wildfire will be effective at mitigating wildfire spread and effects. Studies of fuel treatment effectiveness within the 2006 Tripod Complex demonstrated that fuel reduction treatments, particularly those that involved past prescribed or wildfires, were effective even under the most severe fire weather days (Prichard et al. 2010, Lyons-Tinsley and Peterson 2012, Prichard and Kennedy 2014). The 2014 Carlton Complex, which burned adjacent to the 2006 Tripod Complex, provided an opportunity to evaluate treatment effectiveness in close spatial and temporal proximity across both treated and untreated landscapes and across a range of fire weather and under an exceptional wind-driven fire event. Preliminary fire effects monitoring (Trebon and Johnson 2014) for the Carlton Complex suggested that fuel treatments did not fare as well as in the Tripod Complex and supported more active fire spread through treatment units and higher tree mortality. Through spatial modeling of landscape fuel treatment effectiveness under varied biophysical conditions and fire weather in the Carlton Complex, we found that fuel reduction treatments reduced severity even under severe fire weather and that strategic placement of treatments may be an effective strategy to mitigate wildfire effects.

Across semiarid forested landscapes, there is growing evidence that fine- to meso-scale vegetation patchworks are more resilient to fire than large patches of continuous forest cover because not all of the mosaic is generally available to burn or modify fire behavior and effects (Collins et al. 2007, Holden et al. 2010, Parks et al. 2015). Hessburg et al. (2005) used historical reference data sets from photo interpreted (1930s–1950s) aerial photography in the interior Columbia River Basin area and found higher proportions of grassland and shrubland vegetation than modern reference landscapes. These patterns were perpetuated by frequent low-intensity fire events and likely contributed to lower levels of contagion for insects, disease, and fire compared to modern landscapes. Historical reference data sets offer important context for guiding restoration of native fire regimes and resilient landscapes (Hessburg et al. 2016). After decades of fire exclusion and a gradual infilling of forest landscapes, recent wildfires within the past three decades have burned with large patches of high severity (Cansler and McKenzie 2014, Reilly et al. 2017). Fuel reduction treatments that thin canopy fuels and reduce surface fuels appear to be effective strategies for restoring landscape patterns that are more resilient to large wildfire events.

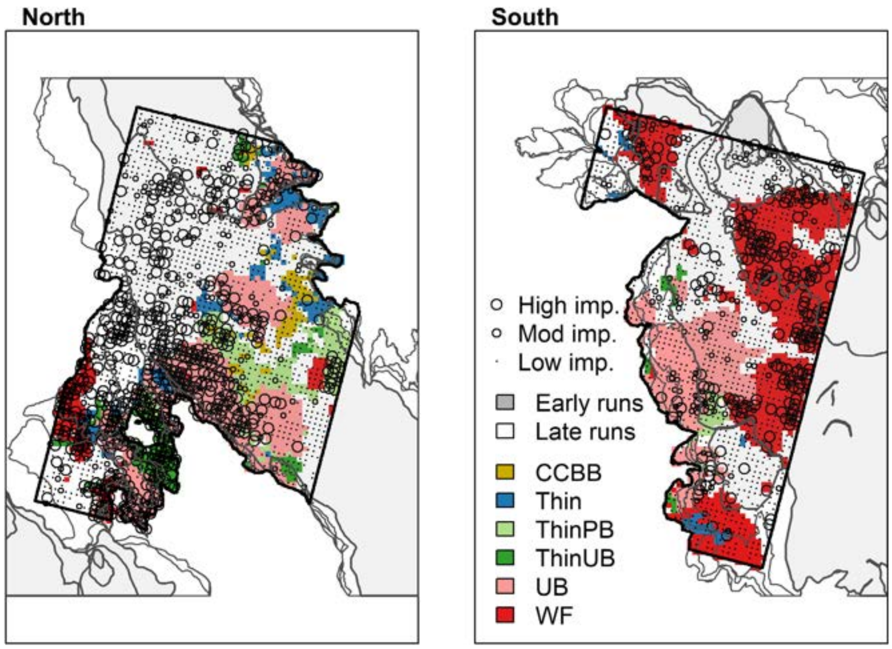

FIG. 10. Map of local variable importance (imp.) for the treatment predictor variable from random forest modeling. Local importance values range between 0 and 1 and classes are high (0.75–1.0), moderate (0.5–0.74), and low importance (0–0.49). Treatments are clear cut and broadcast burn (CCBB); thin-only (Thin); thin and pile burn (ThinPB), thin and prescribed underburn (ThinUB), prescribed underburn only (UB) and past wildfire (WF). Early runs include area burned by the Carlton Fire between 15 and 18 July under extreme weather conditions, while later runs occurred between 19 July and 7 August under milder weather conditions.

Fuel treatment effectiveness was reduced but not eliminated on extreme fire weather days

Treatments tended to reduce fire severity overall but were much less effective under extreme weather (Figs. 3, 10, Appendix S1: Fig. S2). However, our study showed that while the incidence of local controls provided by fuel reduction treatments was lower under extreme weather conditions, where treatments were effective (i.e., had high local variable importance) they tended to exhibit a strong mitigating effect (Fig. 10, Appendix S1: Fig. S6). This was particularly true for burning treatments (ThinUB, UB, WF). Similar results were found for the 2013 Rim Fire in California, which similarly experience periods of extreme (i.e., plume-dominated) and mild weather conditions (Povak et al., 2020). Previous studies have found that fuel treatments involving broadcast burning of surface fuels (e.g., past wildfires, prescribed burns and thinning or clear-cutting with prescribed understory or broadcast burns) are generally more effective than thin-only or thin and pile burn treatments (see Fulé et al. 2012, Stephens et al. 2012 for reviews). Our results corroborate these studies but offer a rare evaluation of how treatments fared on wind-driven progressions compared to those that burned under milder weather conditions. All treatment areas burned with lower proportions of unburned and low severity fire during early fire progressions (i.e., extreme weather; Fig. 3). Simultaneous autoregression analysis shows that ThinUB treatments were the most effective, followed by Thin and UB treatments. All treatment types were more effective in later progressions under milder fire weather conditions, and differences between treatments were less pronounced (Appendix S1: Fig. S6). Some treatment types such as clear-cut and broadcast burn and thin and pile burn were not significantly related to fire severity, which is likely due to low sample size, but treatment type could have also contributed to the lack of significance.

Random forest analyses showed that high modeled local importance was generally associated with lower fire severity providing further evidence of local controls provided by past treatments across burn periods. The RF analysis revealed more differentiation among treatments in the north (Fig. 9), largely related to higher predicted severities for ThinPB treatments. Overall, Thin, ThinUB, and UB treatments, along with past wildfire (WF), appeared to be the most effective at mitigating fire severity. High local importance for fuel treatments in the RF models was identified in the north, even during burn periods with large fire growth (Fig. 10). Effective treatments in the north corresponded roughly with leeward south and southwest-facing aspects that may have been partially sheltered from the strong prevailing winds coming from the north and northwest (Appendix S1: Fig. S1). This finding provides some evidence that lower fire severity was associated with treatments situated on leeward slopes in relation to the predominant wind direction during wind-driven fire progressions. Leeward

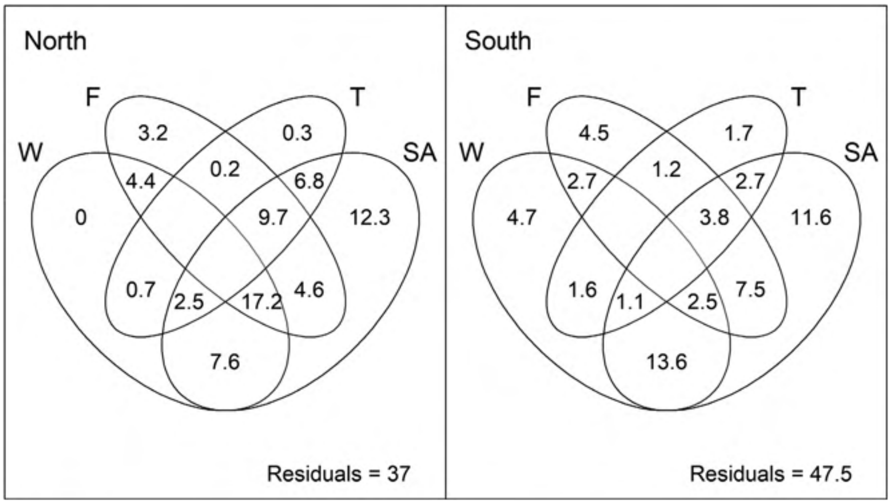

FIG. 11. Variance decomposition plot depicting the percentage of the out-of-bag variance explained by random forest models for individual predictor variable groups (non-overlapping regions) and shared among predictor variable groups (overlapping regions). Residuals are the remaining variance left unexplained by each model and are equal to 100 − R^2. Variable groups are weather (W), fuels/vegetation (F), topography (T), and spatial autocorrelation (SA). Predictor variables included in each group are described in Table 1.

treatments may have slowed fire growth during this period but did not appear to be absolute barriers to fire spread. However, there is evidence that a set of fuel treatments, located along a leeward ridge in the southeastern section of the north study area, mitigated fire severity and contributed to a large unburned island between the north and south study areas. More research is warranted in identifying treatment effectiveness as a function of terrain positioning in relation to the prevailing winds during fire spread. Interestingly, in the north study area, the RF methods identified high local importance for the treatment variable where no treatment occurred (Fig. 10). This possibly indicated that the lack of treatment led to higher severities than would have otherwise been predicted if the area had been treated and may provide support for directing future fuel treatments.

With longer wildfire seasons and a growing incidence of extreme fire weather events, planning for wind-driven fire growth in drought-impacted forests is increasingly necessary. As fire and fuels managers evaluate options for increasing landscape resilience and resistance to future climate change and wildfires, strategic placement of fuel treatments may be guided by retrospective studies of past large wildfire events. Our results suggest that during strong wind-driven fire spread, fuel treatments that were located on leeward slopes to prevailing winds during fire progression tended to have lower fire severity. The wind-driven progression on 17–18 July during the Carlton fire originated from a weather system that moved from the Pacific Coast to interior Washington State and was funneled through the Methow Valley, leading to strong, directional winds. These winds, as well as the wind patterns observed during the 2006 Tripod Complex, and large fires of 2015 in north-central Washington State, were typical of summer wildfire weather. This suggests that modeling of predominant summer wind characteristics can be a useful tool in strategic planning of landscape treatment prioritizations (Hessburg et al. 2015).

Although treatment type was a significant variable in SAR and RF models, some of the other variables of interest, such as treatment size, distance to treatment edge, and time since fire, were also significant predictors of fire severity but based on their low importance, were not included in final SAR and RF models. Size of treatments may be an important factor in treatment effectiveness because larger units contain more interior area. Previous studies have demonstrated gradients in fire severity from the edge of treatments to more interior areas (Safford et al. 2009, Kennedy and Johnson 2014; Povak et al., 2020). Similarly, time since fire was a significant predictor of fire severity but was not included in final SAR models and exhibited low variable importance in RF models (Fig. 7). A potential reason for the lack of inclusion of the time since fire variable in SAR analyses is the generic assignment of 100 yr for pixels that did not have any record of recent treatment. Treatment size and distance to edge may have had low predictive power because treated areas represented a low percentage of the overall study areas. Furthermore, treatments tended to be clustered in certain areas, thereby creating a mediating effect of neighboring treatments that reduced the effect of treatment size in the models. For the RF models, partial plots for the south revealed steep increases in severity for reburns between 0 and 5 yr old and severities gradually increased for older reburn patches. For the north, the time-since-fire mosaic played less of a role even within recent reburns and effect of past fires leveled off for reburns >20 yr old. Parks et al. (2015) found that previous wildfire reduced subsequent fire severity up to

6–18 yr after fire. Parks et al. (2014*b*) also found that past wildfires reduced subsequent fire severity for up to 22 yr within wilderness areas in Idaho and New Mexico. Prichard and Kennedy (2014) found that treatment age and size were weak but significant predictors of fire severity in the 2006 Tripod Complex fire with lower severity with greater time-since-fire and small treatment units. However, they noted that several past wildfires and thin and prescribed burn units had low fire severity even 20 yr or more post-treatment. In this study, time since fire may not have been significant due to a limitation in record length (i.e., few treatments were included in the study that were older than 20 yr).

Landform and vegetation influenced fire severity

Final SAR models of the north and south areas demonstrated strong correlations between fire weather variables (i.e., wind and maximum temperature) and fire severity but also some topographical constraints. The influence of landform and vegetation/fuels on fire severity revealed some differences between the north and south study areas. In particular, fire severity was positively correlated with both canopy cover and elevation in the north study area, likely reflecting the higher severity fire effects in montane, mixed conifer forests. The negative correlation with maximum solar radiation also suggests that burn severity tended to be lower in more open, low elevation forest types in the north study area. In contrast, canopy cover is negatively correlated with fire severity in the south study area, and elevation is only weakly but positively correlated with severity. Low elevation ponderosa pine forests are more common in the south study area, and the more xeric ponderosa pine forests located in valleys had low canopy cover and were likely less prone to high-severity fire.

The variance decomposition results from RF indicated a high degree of shared variance explained across the variable groups, suggesting that controls on fire severity patterns are not independent of one another but rather are highly interactive (Fig. 11). Largest sources of shared variance were between weather, fuels/vegetation and spatial autocorrelation for the north study area and weather and spatial autocorrelation in the south. In the north, results corroborate the previous findings that the fire was driven largely by strong winds, leading to a high level of contagion (spatial autocorrelation). However, it also suggests that continuous fuels may have also contributed to the high spatial contagion in this region. In the south, higher levels of pure variance explained by the weather, fuels, and topography and the lower relative influence of spatial autocorrelation suggest a higher level of local control on fire severity patterns.

SAR and RF methods are complementary

Although SAR and RF model approaches have both been used to evaluate fuel treatment effectiveness, this is the first study to offer comparative analyses using the same fire severity data set. We found that the approaches are complimentary and highly instructive as a combined approach for landscape analyses of fire severity. Simultaneous autoregression makes use of a full neighborhood of pixels without subsampling and is the recommended approach to ensure that models avoid type I errors and incorrect inferences (Ver Hoef et al. 2017). Although RF used subsampled data sets, model inference was nearly identical to that of SAR, and the combination of approaches ensures that correct inferences were made in both approaches.

The SAR models presented here show a high level of SA ($\lambda > 0.96$), which is illustrated in the map of predicted severity where the majority of the spatial variation in severity occurs via the SA error component (Fig. 6). The environmental predictors and SA error patterns modeled by SAR provide accurate representations of observed severity. Simultaneous autoregression modeling integrates SA directly into a linear modeling framework by incorporating severity information from neighboring cells into the model directly and scales their level of influence through a parameter (i.e., λ in Table 3). Spatial autocorrelation thus tends to be the most important predictor in SAR models and appears to somewhat mask the spatial importance of other predictor variables when compared to the RF model results, which reveal a larger contribution of environmental and fuel treatment variables in explaining severity patterns. Furthermore, the RF modeling explicitly modeled the non-stationarity in the strength of environmental and spatial autocorrelation predictors, which showed considerable variation in the relative roles of each. The high correlation between intercept-only SAR model and the final SAR model predictions was >0.9, suggesting a minor contribution of the explanatory variables to the predicted values. Similarly, the magnitude of the coefficients in the fitted SAR models was relatively low compared to the RBR scale, suggesting that severity was relatively insensitive to the spatial covariates, including the treatment variable (Table 4). This result appears to be corroborated by the RF modeling, which showed low variability in treatment effectiveness across treatment types relative to the untreated pixels (Fig. 9).

The RF modeling approach offers a refinement to SAR in that it can incorporate nonlinear effects and interactions among predictor variables without a priori knowledge, include SA predictor variables, and evaluate local importance measures including fuel treatment effectiveness. Approaches such as SAR use global measures of variable importance or global coefficients (i.e., average effect size and significance) to represent empirical relationships between fire severity and environmental covariates, which are known to be highly variable and interactive across landscapes. This is particularly problematic for categorical variables such as fuel treatment type that are spatially discontinuous and often dominated by untreated pixels. Our results suggest that local measures of importance from RF analyses can reveal patterns that otherwise may be obfuscated by global assessments of variable importance that most other models provide.

In our assessment, fuel treatments were grouped with other fuel/vegetation variables in the RF local importance and variance decomposition analyses. Because of this association, it was difficult to separate vegetation effects (i.e., canopy cover) from the effectiveness of fuels reduction treatments in our models. Local importance values from RF modeling showed some spatial correspondence between high treatment variable importance on southern aspects, but results were not definitive. Variance decomposition results showed shared variance was slightly higher between topography and fuels compared to topography and weather, suggesting that the topographically entrained variability in fuels (accounting for SA) was slightly more important to fire severity than terrain routing of fire weather (Fig. 11). The difficulty in disentangling the effects of vegetation, topography, weather, and fuel treatments on fire severity cannot be understated and is not necessarily a deficiency of the modeling approach. The main effect of fuel treatments is to reduce tree density, remove ladder fuels, lower surface fuel continuity and biomass, and, in turn, reduce subsequent fire severity. Within the Carlton Complex landscape, our finding that treatments were most effective on south-facing, leeward slopes, may be a product of treatment and also may be driven by the higher rates of incident solar radiation (i.e., a function of topography) leading to more open forested conditions on southern aspects (i.e., a function of vegetation). Furthermore, wind speeds generally are reduced on leeward compared to windward slopes, which also could have contributed to lower severities (i.e., a function of weather).

To date, both SAR and RF modeling are useful tools for retrospective evaluation of the landscape drivers of fire severity. More research is needed to identify methods to determine tradeoffs in empirical models used to explain fire severity patterns and how to make results generalizable across wildfires in other environments. However, without better understanding of how to resolve the effect of spatial autocorrelation in a modeling environment, retrospective models cannot effectively forecast the severity of future wildfire events. Paired wildfire simulation modeling has been shown to assist in evaluation of drivers of fire spread and severity (e.g., Coen et al. 2018) and offers a promising approach for future studies.

Random forest modeling has been used extensively in fire severity modeling, but controlling for SA in RF models has generally been restricted to minimum spacing among samples. In this study, we incorporated spatially explicit covariates into the RF model via spatial eigenvector mapping (i.e., PCNM). The RF models identified broad-scale SA patterns via the low-order PCNM axes included in the models. These variables were highly interactive with weather, vegetation, and topography variables (Fig. 11), suggesting that relationships among predictors and fire severity varied over space and across burn periods (i.e., exhibiting non-stationarity). Principal components of neighborhood matrices axes were more influential in the north, and high variable importance for PCNM axes corresponded with areas where the fire burned under extreme weather conditions resulting in large high-severity patches (Fig. 1). The local importance maps for SA (Fig. 10) generally were in agreement with the SAR predictions related to the spatial component (Fig. 5, right column). Given the premise that large high-severity patches in the early progression days were driven by extreme weather conditions, it was surprising that weather variables were not more strongly influential. The high importance of PCNM axes likely relates to the fact that (1) the contagion of the fire itself overwhelmed all other environmental control, (2) they exhibited shared variance with weather and fuels/vegetation variables indicating that interactions among these variables in this region likely contributed to high severity, and (3) other fire weather variables not included such as those incorporating fuel moisture or more localized wind speed and direction could potentially contribute to the variance explained by weather variables (e.g., Coen et al. 2018).

Management implications

As the incidence and area burned of large wildfires increases across fire-prone landscapes of the western United States (Stavros et al. 2014, Abatzoglou and Williams 2016, Westerling 2016), the impact of wildfires is often outpacing that of other fuel reduction treatments such as thinning and prescribed burning or managed natural ignitions (Calkin et al. 2015, Vaillant and Reinhardt 2017), at times with markedly different patterns of fire severity. Although trends in fire severity are not always toward greater stand replacement (Doerr and Santin 2016, Reilly et al. 2017), recent summer wildfires in north-central Washington State have been dominated by large, severe events particularly large patches of stand replacement during large fire growth days (Cansler and McKenzie 2014, Reilly et al. 2017). Of forestland area that burned within the Carlton Complex, 24% percent burned as moderate and 49% as high severity. Considering this wildfire event as a type of fuel reduction treatment, the Carlton Complex resulted in high tree mortality and as a large-scale change agent. Given future climatic change scenarios, many of the drier sites dominated by ponderosa pine may not return to forested conditions (Stevens-Rumann et al. 2017, Kemp et al. 2019). In addition, as dead trees decay and fall following post-fire mortality, accumulated fine and coarse wood may lead to reburn events and further challenge forest regeneration (Peterson et al. 2015, Prichard et al. 2017). On some landscapes, fire-vegetation interactions may be restoring patchwork mosaics of grasslands and shrublands (Hessburg et al. 2019) but given rapid changes in climate could also be contributing to accelerated rates of forest conversion across dry mixed conifer forests (Parks et al. 2019). Past fuel treatments and small wildfire events mitigated fire severity, even under the most severe fire spread days. This finding provides evidence supporting the utility of fuel treatments in increasing landscape resilience to large, summer wildfire events and resistance to vegetation type changes. Our findings also suggest that we need a better understanding of the strategic placement of treatments to maximize the likelihood of them remaining effective during wind-driven fire spread periods.

A number of approaches are being used to restore more resilient forest structure and landscape mosaics to semiarid forests across western north America. These include managing unplanned ignitions for resource benefit, prescribed burning, and mechanical thinning to remove understory and midstory trees that can act as ladder fuels and contribute to more severe wildfire effects. Although thinning alone can be somewhat effective at mitigating wildfires (e.g., Safford et al. 2009, Fulé et al. 2012, Prichard and Kennedy 2014), it can also contribute to surface fuel biomass accumulation and more severe wildfire effects. Of these approaches, fire, either from planned or unplanned ignitions, is generally the most effective at reducing surface fuels and increasing the resilience of forests to subsequent fire events.

In this study, we found that a range of fuel treatments, including Thin and ThinUB, effectively reduced fire severity relative to untreated pixels during milder fire weather days. Wind-driven fire weather put all treatments to the test and suggest that ThinUB treatments were most effective at mitigating fire severity during these events. Wildland fire burns as a contagious process, and fire weather, associated with antecedent drought, high temperatures, low relative humidity and strong winds driving fire spread reduces thresholds to burning. Our results suggest that thinning on its own can mitigate fire severity but is much less effective during extreme fire weather. Higher fire severity and reduced treatment effectiveness in the north study area provides strong evidence of this and the importance of recent fuel reduction treatments that involved prescribed burning.

Landscape mosaics of past fires and fuel reduction treatments can be integral in providing sources of natural regeneration to accelerate forest recovery in neighboring high-severity patches and contribute to habitat and overall landscape heterogeneity. Some of the most promising examples of using unplanned ignitions to restore landscape resiliency to fire come from wilderness areas where fire has returned as an ecological process since the 1970 “let it burn” policy was adopted. For example, in New Mexico’s Gila Aldo Leopold Wilderness, there is evidence that past fires either act as temporary barriers to subsequent fire spread or alter fire severity (Holden et al. 2010, Parks et al. 2014*b*). Additionally, resilient forest structure, including dominance of large-diameter, fire resistant trees such as ponderosa pine or western larch, are perpetuated by repeat wildfires (Holden et al. 2007). Grand Canyon and Yosemite National Parks have both used unplanned ignitions in remote areas of the parks and strategically allowed fires to increase their ecological footprints over the decades of fire management (Collins et al. 2007, Boisramé et al. 2017, van Wagdentonk et al. 2012, Coppelleta et al. 2016). Outside of wilderness areas and national parks, many regions of the western United States, including that of the 2014 Carlton Complex, have a growing impact on the wildland-urban interface. Use of unplanned ignitions is challenging in these areas due to risk and smoke management concerns. As an alternative, a combination of mechanical thinning and prescribed burning treatments are used, but require favorable burn windows to reduce smoke impacts to neighboring communities. However, costs, available resources, and sufficient burn windows often limit the amount of area treated (Ryan et al. 2013).

Although much has been learned about the type and duration of fuel treatment effectiveness, less in known about how to strategically place treatments on landscapes and how they may interact with fires during large fire growth days. For example, fuel treatments were generally more effective on leeward slopes in our study, which may suggest a strategy for increasing overall landscape resilience to future wildfire events may be to evaluate wind probabilities during peak summer wildfire seasons. Wind modeling can be used to develop probability grids of wind speed and direction to help strategically allocate fuel treatments on topographic positions that may be protected from severe winds. These data could then be used to determine where fuel treatments might be strategically placed to help slow fire spread and mitigate wildfire severity. Such information can also be used in larger planning efforts to optimize the value of treatments across landscapes or larger planning areas.

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Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.2104/full

Data Availability

Data are available from the USDA Forest Service Research Data Archive: https://doi.org/10.2737/RDS-2020-0003