Ecological Applications, 0(0), 2018, pp. 1–13

Severe fire weather and intensive forest management increase fire severity in a multi-ownership landscape

Harold S. J. Zald[1,3] and Christopher J. Dunn[2]

[1]*Department of Forestry and Wildland Resources, Humboldt State University, 1 Harpst Street, Arcata, California 95521 USA*
[2]*Department of Forest Engineering, Resources, and Management, Oregon State University, 280 Peavy Hall, Corvallis, Oregon 97331 USA*

Abstract. Many studies have examined how fuels, topography, climate, and fire weather influence fire severity. Less is known about how different forest management practices influence fire severity in multi-owner landscapes, despite costly and controversial suppression of wildfires that do not acknowledge ownership boundaries. In 2013, the Douglas Complex burned over 19,000 ha of Oregon & California Railroad (O&C) lands in Southwestern Oregon, USA. O&C lands are composed of a checkerboard of private industrial and federal forestland (Bureau of Land Management, BLM) with contrasting management objectives, providing a unique experimental landscape to understand how different management practices influence wildfire severity. Leveraging Landsat based estimates of fire severity (Relative differenced Normalized Burn Ratio, RdNBR) and geospatial data on fire progression, weather, topography, pre-fire forest conditions, and land ownership, we asked (1) what is the relative importance of different variables driving fire severity, and (2) is intensive plantation forestry associated with higher fire severity? Using Random Forest ensemble machine learning, we found daily fire weather was the most important predictor of fire severity, followed by stand age and ownership, followed by topographic features. Estimates of pre-fire forest biomass were not an important predictor of fire severity. Adjusting for all other predictor variables in a general least squares model incorporating spatial autocorrelation, mean predicted RdNBR was higher on private industrial forests (RdNBR 521.85 ± 18.67 [mean ± SE]) vs. BLM forests (398.87 ± 18.23) with a much greater proportion of older forests. Our findings suggest intensive plantation forestry characterized by young forests and spatially homogenized fuels, rather than pre-fire biomass, were significant drivers of wildfire severity. This has implications for perceptions of wildfire risk, shared fire management responsibilities, and developing fire resilience for multiple objectives in multi-owner landscapes.

Key words: fire severity; forest management; Landsat; multi-owner landscape; Oregon; plantation forestry; RdNBR.

Introduction

The wildfire environment has become increasingly complicated, due to the unanticipated consequences of historical forest management and fire exclusion (Weaver 1943, Hessburg et al. 2005, Fulé et al. 2009, Naficy et al. 2010, Merschel et al. 2014), an increasingly populated wildland urban interface (Haas et al. 2013), and a rapidly changing climate (Westerling and Bryant 2008, Littell et al. 2009, Jolly et al. 2015). These factors are resulting in more intense fire behavior and increasingly negative ecological and social consequences (Williams 2013, Stephens et al. 2014). Fuels reduction via mechanical thinning and prescribed burning have been the dominant land management response for mitigating these conditions (Agee and Skinner 2005, Stephens et al. 2012), although there is an increasing recognition of the need to manage wildfires more holistically to meet social and ecological objectives. (North et al. 2015a, b). However, overcoming these challenges is inhibited by numerous disagreements in the scientific literature regarding historical fire regimes and appropriate policies and management of contemporary fire-prone forests (Hurteau et al. 2008, Hanson et al. 2009, Spies et al. 2010, Campbell et al. 2012, Odion et al. 2014, Collins et al. 2015, Stevens et al. 2016). These factors and others have resulted in a nearly intractable socioecological problem (Fischer et al. 2016); one that is compounded by the fact that many fire-prone landscapes consist of multiple owners and administrative jurisdictions with varying and often conflicting land management objectives.

Developing and prioritizing landscape fire management activities (i.e., thinning, prescribed fire, wildland fire use, and fire suppression) across jurisdictional and ownership boundaries requires landscape-scale assessments of the factors driving fire severity (i.e., the fire behavior triangle of fuels, topography, and weather). Researchers have focused on the influence of bottom-up drivers such as topography (Dillon et al. 2011, Prichard and Kennedy 2014, Birch et al. 2015), and fuels via fuel reduction effects (Agee and Skinner 2005, Raymond and Peterson 2005, Safford et al. 2009, Prichard and Kennedy 2014, Ziegler et al. 2017), as well as the top-down influence of weather on fire severity (Birch et al. 2015, Estes et al. 2017). They have also focused more broadly on how fire severity varies with vegetation and forest type (Birch et al. 2015, Steel et al. 2015, Reilly et al. 2017) and climate (Miller et al. 2012, Abatzoglou et al. 2017). While there is substantial value in further describing how components of the fire behavior triangle influence fire severity, we believe there is a need to account for these known influences on fire behavior and effects to understand

Manuscript received 23 August 2017; revised 14 December 2017; accepted 5 February 2018. Corresponding Editor: Bradford P. Wilcox.
[3] E-mail: hsz16@humboldt.edu

how different management regimes interact with these controlling factors, so appropriate landscape management strategies can be developed to support social-ecological resilience in fire-prone landscapes (Spies et al. 2014, Schoennagel et al. 2017).

Understanding the relationships between forest management regimes and fire severity is especially important in multi-owner landscapes, where wildfire governance systems concerned about short-term property loss and public safety can reinforce perceptions of wildfire risk and hazard, resulting in individual property owners being less likely to make management decisions that reduce long-term risk exposure (McCaffrey 2004, Fischer et al. 2016). This is particularly important in landscapes that include intensive plantation forestry, a common and rapidly expanding component of forest landscapes at regional, national, and global scales (Cohen et al. 1995, Landram 1996, Del Lungo et al. 2001, Rudel 2009, FAO 2010, Nahuelhual et al. 2012). Researchers have hypothesized that intensive forest management reduces fire behavior and effects (Hirsch et al. 2001, Rodríguez y Silva et al. 2014). However empirical results have been mixed, with evidence that intensive forest management can either reduce (Lyons-Tinsley and Peterson 2012, Prichard and Kennedy 2014) or increase fire severity (Odion et al. 2004, Thompson et al. 2007), and that reduced levels of forest legal protection (a proxy for more active management) have been associated with increased fire severity in the western U.S. (Bradley et al. 2016). These conflicting results further complicate the development of fire governance and management strategies for increasing social-ecological resilience in a rapidly changing fire environment.

The quality, spatial scale, and spatial correlation of explanatory data (i.e., weather, topography, and fuels) are major limitations to empirically understanding how forest management activities influence fire severity across landscapes. Regional studies of fire severity often rely on spatially coarse climatic data (Dillon et al. 2011, Miller et al. 2012, Cansler and McKenzie 2014, Kane et al. 2015, Harvey et al. 2016, Meigs et al. 2016, Reilly et al. 2017), rather than local fire weather that can be a significant driver of fire area and severity (Flannigan et al. 1988, Bradstock et al. 2010, Estes et al. 2017). This is in part because finer-scale fire weather variables are often incomplete across the large spatial and temporal domains of interest. Additionally, regional studies often occur in areas with large elevation relief resulting in strong climatic gradients, while more local studies often have less elevation relief and potentially weaker climatic gradients. Perhaps more importantly, the geographic distribution of different ownership types and management regimes can confound quantification of the drivers of fire severity. For example, high elevation forests in the Pacific Northwest region of the United States are largely unmanaged as National Parks and congressionally designated wilderness areas, compared to intensively managed forests at lower elevations, resulting in differences in topography, weather, climate, forest composition, productivity, and historical fire regimes between ownerships and management regimes. While landscape studies of fire severity and management activities have used a variety of statistical techniques to account for spatial correlation of both response and predictor variables (Thompson et al. 2007, Prichard and Kennedy 2014, Meigs et al. 2016), these techniques may not overcome fundamental differences in response and predictor variables between management and/or ownership types.

In this study, we examined the drivers of fire severity within one large (~20,000 ha) wildfire complex that burned within the Klamath Mountains, an ecoregion with a mild Mediterranean climate of hot dry summers and wet winters in southwestern Oregon, USA. The fire burned within a checkerboard landscape of federal and private industrial forestry ownership. This spatial pattern of contrasting ownership and management regimes provided a unique landscape experiment where we quantified the effects of management regimes after accounting for variation in well-known drivers of fire behavior and effects. Leveraging geospatial data on fire severity, fire progression, fire weather, topography, prefire forest conditions, and past management activities, we asked two questions: (1) What is the relative importance of different variables driving fire severity? And (2) is intensive plantation forestry associated with higher fire severity?

Methods

Study site

In the summer of 2013, the Douglas Complex burned 19,760 ha of forestland in southwestern Oregon, USA (Fig. 1). Starting from multiple lightning ignitions, individual small fires coalesced into two large fires (Dads Creek and Rabbit Mountain) managed as the Douglas Complex.

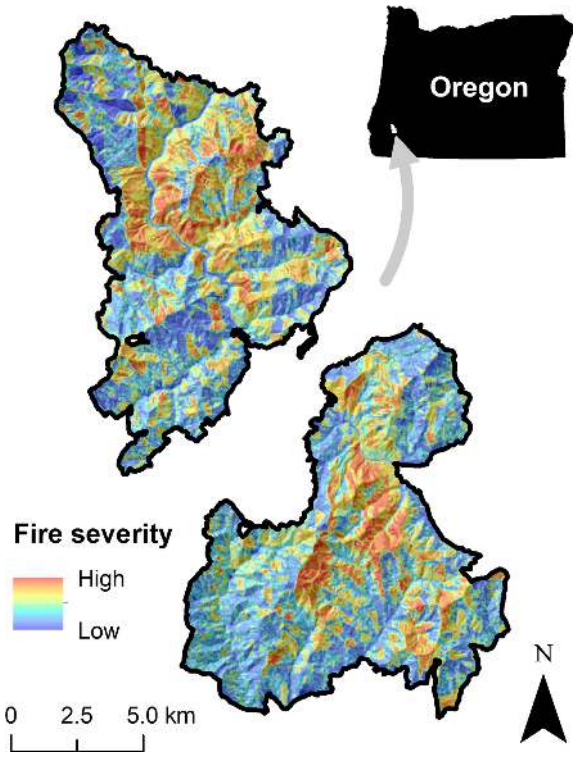

Fig. 1. Location of and fire severity within the Douglas Complex in Oregon, USA. Fire severity quantified using the Relative differenced Normalized Burn Ratio (RdNBR).

This fire burned within the Oregon and California Railroad Lands (hereafter O&C Lands). O&C Lands resulted from 19th century land grants that ceded every other square mile (259 ha) of federally held land to railroad companies along planned routes in Oregon and California to incentivize railroad development and homesteading settlement. The Oregon and California Railroad Company received a total of 1.5 million ha, but failing to meet contractual obligations, 1.1 million ha were transferred back to federal ownership under the Chamberlain-Ferris Revestment Act of 1916. The USDI Bureau of Land Management (BLM) is currently required to manage these lands for sustainable timber production, watershed protection, recreation, and wildlife habitat. Private industrial forestlands dominate the remaining O&C landscape, and are managed intensively as native tree plantations (primarily Douglas-fir, *Pseudotsuga menziesii* var. *menziesii*) for timber production typically on 30–50 yr harvest rotations. The Douglas Complex fires burned 10,201.64 ha of forests managed by the BLM, 9,429.66 ha of private industrial forests, and 129.33 ha managed by the Oregon Department of Forestry (ODF).

The Douglas Complex burned at elevations ranging from 213 to 1,188 m in mountainous terrain of the Klamath Mountains Ecoregion. Climate in the ecoregion is characterized by hot dry summers and wet winters, with greater winter precipitation at higher elevations and western portions of the ecoregion. Vegetation types within the region include oak woodlands and mixed hardwood/evergreen forests at low to mid elevations, transitioning into mixed-conifer forests at higher elevations (Franklin and Dyrness 1988). Forests within the Douglas Complex are dominated by Douglas-fir, ponderosa pine (*Pinus ponderosa*), and white fir (*Abies concolor*). Other conifer tree species present include incense cedar (*Calocedrus decurrens*), sugar pine (*Pinus lambertiana*), Jeffery pine (*Pinus jefferyi*), and knobcone pine (*Pinus attenuata*). Hardwood species include Oregon white oak (*Quercus garryana*), big-leaf maple (*Acer macrophyllum*), Pacific dogwood (*Cornus nuttallii*), Pacific madrone (*Arbutus menziesii*), canyon live oak (*Quercus chrysolepis*), California black oak (*Quercus kelloggii*), golden chinkapin (*Chrysolepis chrysophylla*), and tanoak (*Lithocarpus densiflourus*). Douglas-fir is the primary commercial timber species managed on private and public lands, while fire exclusion and historical management practices have expanded the density and dominance of Douglas-fir across much of the ecoregion (Franklin and Johnson 2012, Sensenig et al. 2013).

Data sources

We analyzed fire severity in relation to eight predictor variables representing topography, weather, forest ownership, forest age, and pre-fire forest biomass (Fig. 2). We quantified fire severity using the Relative differenced Normalized Burn Ratio (RdNBR), a satellite-imagery-based metric of pre- to post-fire change. Cloud-free pre-fire (3 July 2013) and post-fire (7 July 2014) images came from the Landsat 8 Operational Land Imager. Normalized Burn Ratio (NBR), which combines near-infrared and mid-infrared bands of Landsat imagery, was calculated for pre- and post-fire images. Differenced Normalized Burn Ratio (dNBR) was calculated by subtracting $NBR_{post\text{-}fire}$ from $NBR_{pre\text{-}fire}$ values, and RdNBR was then calculated following Miller et al. (2009), where:

$$\mathrm{RdNBR} = \frac{\mathrm{dNBR}}{\sqrt{\mathrm{Absolute\ Value}\,(\mathrm{NBR}_{\mathrm{pre-fire}}/1,000)}}. \quad (1)$$

We chose RdNBR over dNBR as our fire severity metric because RdNBR removes, at least in part, the biasing effect of pre-fire conditions, improving assessment of burn severity across heterogeneous vegetation and variable pre-fire disturbances (Miller and Thode 2007). We used the continuous RdNBR values as our response variable for fire severity at a 30-m resolution.

Elevation and other topographic variables were derived from the National Elevation Dataset 30 m digital elevation model (Gesch et al. 2002). We generated 30-m rasters of elevation (m), slope (%), topographic position index (TPI), and heat load ($MJ{\cdot}cm^{-2}{\cdot}yr^{-1}$). TPI was calculated as the difference between elevation in a given cell and mean elevation of cells within an annulus around that cell, calculated at fine and coarse scales (TPI fine and TPI coarse) with 150–300 m and 1,850–2,000 m annuli, respectively. We also originally considered TPI at a moderate spatial scale (850–1,000 m annuli), but rejected it as an predictor variable due to its high correlation to TPI fine ($r = 0.64$) and TPI course ($r = 0.84$). TPI course had strong linear correlations with elevation ($r = 0.83$) and TPI fine ($r = 0.46$), so it was also removed to avoid multi-collinearity in statistical analyses. Heat load was calculated by least-squares multiple regression using trigonometric functions of slope, aspect, and latitude following McCune and Keon (2002).

Rasters of daily fire weather conditions were generated by extrapolating weather station data to a daily fire progression map. We obtained hourly weather data for the duration of active fire spread (7 July–20 August 2013) from the Calvert Peak Remote Automatic Weather Station (NWS ID 352919; 42°46′40″ N 123°43′46″ W, 1,165 m), approximately 30 km west-southwest of the Douglas Complex. We then subset each 24-h period of weather data to the daily burn period (10:00 to 18:00) when fire behavior is typically most active. We then calculated the daily burn period minimum wind speed (km/h), maximum temperature (°C), and minimum relative humidity (%). For each daily burn period we also calculated the mean energy release component (ERC), spread component (SC), and burning index (BI) using FireFamilyPlus Version 4.1 (Bradshaw and McCormick 2000). ERC is an index of fuel dryness related to the maximum energy release at the flaming front of a fire, as measured from temperature, relative humidity, and moisture of 1–1,000 h dead fuels. SC is a rating of the forward rate of spread of a head fire, and is calculated from wind speed, slope, and moisture of live fine and woody fuels (Bradshaw et al. 1983). BI is proportional to the flame length at the head of a fire (Bradshaw et al. 1983), calculated using ERC and SC, thus incorporating wind speed and providing more information than ERC and SC individually. ERC, SC, and BI vary by broadly categorized fuel types. We calculated ERC, SC, and BI using the National Fire Danger Rating System Fuel Model G, which represents short-needled

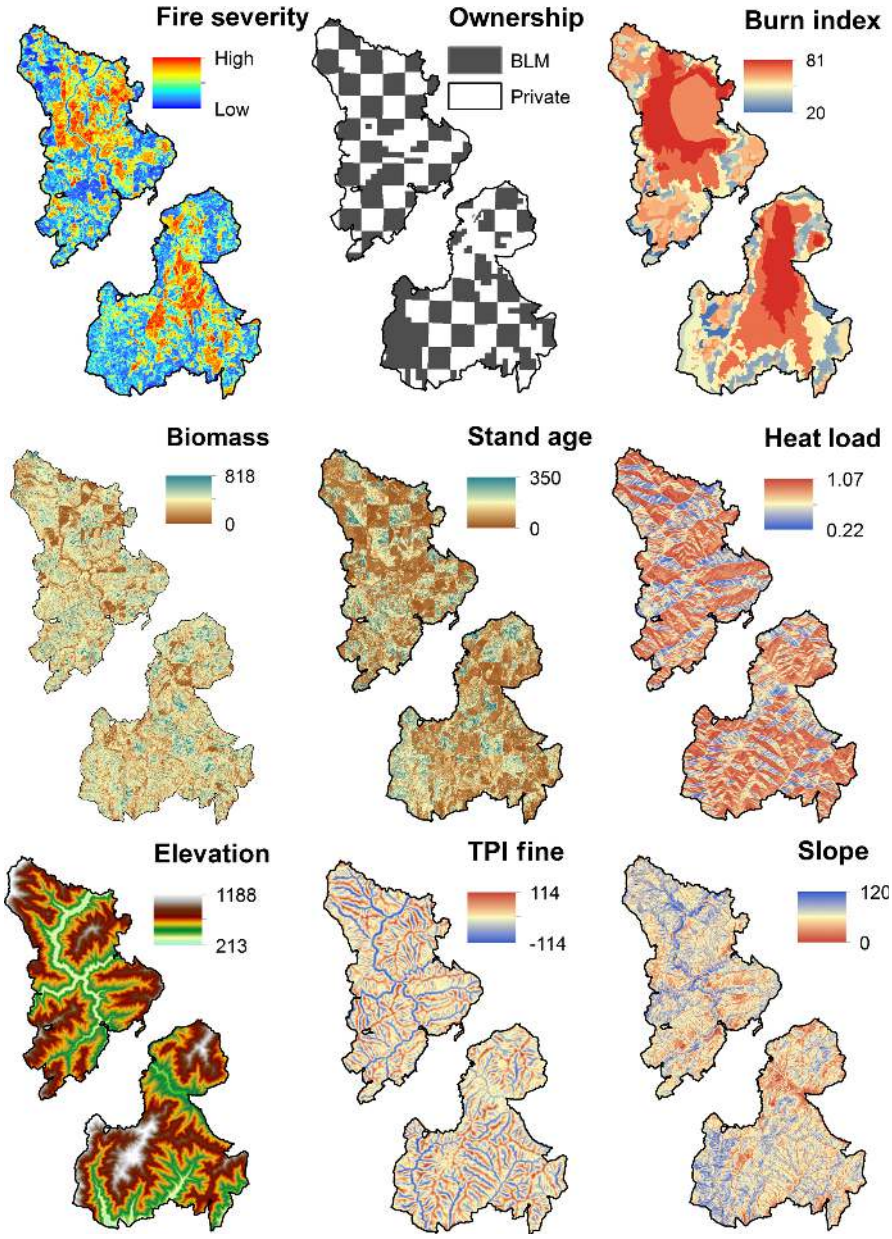

FIG. 2. Maps of response and predictor variables for Douglas Complex. TPI, topographic position index.

conifer stands with heavy dead fuel loads. Daily fire weather variables were then spatially extrapolated to the daily area burned based on daily fire progression geospatial data captured during the fire (GeoMAC 2013).

Forest ownership was derived from geospatial data representing fee land title and ownership in Oregon (Oregon Spatial Data Library 2015). We grouped ODF and BLM lands as a single ownership type, because ODF lands were a small component of the area burned and have management objectives closer to federal vs. private industrial forests (Spies et al. 2007). Pre-fire forest conditions were represented with 30-m rasters of live biomass (Mg/ha) and stand age, derived from a regional 2012 map of forest composition and structural attributes developed for the Northwest Forest Plan Monitoring Program (Ohmann et al. 2012, Davis et al. 2015). These maps were developed using the gradient nearest neighbor method (GNN), relating multivariate response variables of forest composition and structure attributes from approximately 17,000 federal forest inventory plots to gridded predictor variables (satellite imagery, topography, climate, etc.) using canonical correspondence analysis and nearest neighbor imputation (Ohmann and Gregory 2002). Biomass values are directly from the GNN maps, while we quantified forest age as a two-step process. First, we calculated pre-fire forest age in 2013 based on years since each pixel was disturbed in the Landsat time series (1985–2014) from a regional disturbance map generated for the Northwest Forest Plan Monitoring Program using the LandTrendr segmentation algorithm (Kennedy et al. 2010, Ohmann et al. 2012, Davis et al. 2015). Second, for pixels where no

disturbance had occurred within the Landsat time series, we amended forest age derived from the Landsat time series using dominant and codominant tree age from the GNN maps.

Statistical analyses

All statistical analyses were conducted in the R statistical environment version 3.3.3 (R Development Core Team 2017). We sampled the burned landscape using a spatially constrained stratified random design, from which response and predictor variables were extracted for analysis. Sample points had to be at least 200 m apart to minimize short distance spatial autocorrelation of response and predictor variables. Our choice of minimum inter-plot distance to reduce spatial autocorrelation was confounded by the dominance of long distance spatial autocorrelation driven by large ownership patches, which would have greatly reduced sample size and potentially eliminated finer scale variability in the sample. For these reasons we based our 200 m minimum inter-plot distance in part on prior research (Kane et al. 2015), that found residual spatial autocorrelation in Random Forest models of fire severity in the Rim Fire of 2013 in the California Sierra Nevada was greatly diminished when inter-plot distances were at least 180 m apart. Additionally, point locations had to be at least 100 m away from ownership boundaries to minimize inter-ownership edge effects. Within these spatial constraints, sample points were located in a stratified random design, with the number of points proportional to area of ownership within the fire perimeter, resulting in 571 and 519 points located in BLM and private industrial forests, respectively. Mean response and predictor variables were extracted within a 90 × 90 m plot (e.g., 3 × 3 pixels) centered on each sample point location to minimize the effects of potential georeferencing errors across data layers and maintain a plot size comparable to the original inventory plots used as source data in GNN maps as recommended by Bell et al. (2015).

We observed high correlation between fire weather variables (mean absolute $r = 0.59$), likely due to their temporal autocorrelation during the fire event, which could result in multi-collinearity in statistical analyses. Therefore, we evaluated the relationships between each fire weather variable and daily mean fire severity, selecting a single fire weather variable as a predictor variable in subsequent analyses. We based our variable selection on visual relationships to daily RdNBR, variance explained in regressions of RdNBR and fire weather variables, and Akaike information criterion (AIC) scores of regressions of RdNBR and fire weather variables following Burnham and Anderson (2002).

The study's strength rests in part on the implicit assumption that the checkerboard spatial allocation of ownership types is a landscape scale experiment, where predictor variables directly modified by management activities (e.g., prefire biomass and forest age) are different between ownership types, but fire weather and topographic variables are not. We assessed this assumption by visualizing data distributions between ownerships using boxplots and violin plots, and testing if variables were different between ownership types using Mann–Whitney–Wilcoxon Tests.

To assess the relative importance and relationships between predictor variables and RdNBR, we used Random Forest (RF) supervised machine learning algorithm with the randomForest package (Liaw and Wiener 2002). As applied in this study, RF selected 1,500 bootstrap samples, each containing two-thirds of the sampled cells. For each sample, RF generated a regression tree, then randomly selected only one-third of the predictor variables and chose the best partition from among those variables. To assess the relative importance and relationships of predictor variables on RdNBR across the entire study area and within different ownerships, separate RF models were developed for all 1,090 sample plots across the entire burned area, as well as separately for plots on BLM and private industrial lands. For each of the three RF models, we calculated variable importance values for each predictor variable as the percent increase in the mean squared error (MSE) in the predicted data when values for that predictor were permuted and all other predictors were left unaltered. In addition to variable importance values, we determined which predictor variables should be retained in each RF model using multi-stage variable selection procedures (Genuer et al. 2010). We applied two-stage variable selection for interpretation to each RF model using the VSURF package (Genuer et al. 2016). Final RF models were then run including only the selected variables. Predictive power of the final RF models were assessed by calculating the variance explained, which is equivalent to the coefficient of determination (R^2) used with linear regressions to assess statistical model fit for a given dataset. Last, we visualized the relationships of individual predictor variables on RdNBR in the final RF models using partial dependency plots (Hastie et al. 2001).

Importance values in RF models are not the same as quantifying the fixed effects of predictor variables, nor is RF well suited to explicitly test hypotheses or quantify effects of predictor variables while accounting for other variables in a model. To test if ownership type increased RdNBR, we developed a generalized least squares (GLS) regression model with an exponential spherical spatial correlation structure using the nlme package (Pinheiro et al. 2017). The GLS regression used the distance between sample locations and the form of the correlation structure to derive a variance–covariance matrix, which was then used to solve a weighted OLS regression (Dormann et al. 2007). Using the same response and predictor data as in the RF model for the entire Douglas Complex, and a binary predictor variable for ownership type, we developed a GLS model from which we calculated the fixed effect of ownership on RdNBR. We then predicted the mean and standard error of RdNBR by ownership after accounting for the other predictor variables in the GLS model using the AICcmodavg package (Mazerolle 2017).

Results

Fire weather variables

Regression models of fire weather variables (except maximum temperature) described a significant proportion of the variance in daily mean RdNBR (Table 1; Appendix S1: Fig. S1). SC described the most variance in daily RdNBR,

had the lowest AIC score, and was most likely to be the best model of those compared (w_i = 0.8250). However, BI described a comparable amount of the variance in daily RdNBR (R^2 = 0.5815), had a substantial level of empirical support (ΔAIC = 3.3816), was the second most likely model given the data (w_i = 0.1521), and contained additional metrics that influence fire behavior (influence of temperature, relative humidity, and drought on live and dead fuels) not incorporated in SC. For these reasons, we choose to use BI as the single fire weather variable in subsequent analyses, acknowledging that it may describe slightly less variation in RdNBR than SC.

Table 1. Regression models of daily mean Relative differenced Normalized Burn Ratio (RdNBR) in relation to daily burn period fire weather variables.

Models	R^2	AIC	ΔAIC	$L(g_i\|x)$	w_i
RdNBR = SC^2	0.6532	210.0324	0.0000	1.0000	0.8250
RdNBR = BI^2	0.5815	213.4140	3.3816	0.1844	0.1521
RdNBR = min wind speed^2	0.4542	218.1948	8.1624	0.0169	0.0139
RdNBR = log (min relative RH)	0.3800	220.4903	10.4579	0.0054	0.0044
RdNBR = ERC^2	0.3675	220.8497	10.8173	0.0045	0.0037
RdNBR = max wind speed^2	0.2179	224.6700	14.6376	0.0007	0.0005
RdNBR = max temperature^2	0.1069	227.0592	17.0268	0.0002	0.0002
RdNBR = null model	0.0000	228.1855	18.1531	0.0001	0.0001

Notes: R^2, adjusted R squared; AIC_c, Akaike information criterion corrected for sample size; ΔAIC_c, AIC_c differences; $L(g_i|x)$, likelihood of a model given the data; w_i, Akaike weights; SC, spread component; BI, burn index; RH, relative humidity; ERC, energy release component.

RdNBR and predictor variable differences by ownership

The majority of predictor variables were not statistically different by ownership, as expected given the spatial distribution of ownership. Based on Mann-Whitney-Wilcoxon tests, biomass and stand age were lower on private industrial vs. BLM managed lands (Table 2; Appendix S1: Fig. S2). TPI fine, heat load, slope, and BI were not different between ownership types. Elevation was different between ownership types, but only 44 m higher on BLM land across a range of 875 m for all sample plots. Mean RdNBR was higher (536.56 vs. 408.75) on private industrial vs. BLM lands.

Random forest variable importance values and partial dependency plots

Two-stage variable selection procedures retained seven, five, and six predictor variables in the final RF models for the entire Douglas Complex, BLM, and private forests, respectively (Fig. 3). Across the entire Douglas Complex, BI was the most important predictor variable of RdNBR (increasing MSE by 138.4%), while BI was also the most importance variable separately for BLM (105.4%) and private forests (83.2%). Age and ownership were the next most

Table 2. RdNBR (mean with SE in parentheses) and predictor variables on sampled plots for Bureau of Land Management (BLM) vs. private industrial (PI) ownership.

Variable	BLM	PI	*w*	*P*
RdNBR	408.75 (298.53)	536.56 (299.88)	111,124	<0.0001
Biomass (Mg/ha)	234.75 (87.24)	163.88 (74.47)	215,166	<0.0001
Age (yr)	108.81 (55.53)	52.18 (36.78)	236,021.5	<0.0001
BI (index)	62.99 (14.16)	63.64 (14.54)	142,575.5	0.2782
Elevation (m)	653.79 (153.48)	609.46 (161.62)	171,200	<0.0001
TPI fine	0.55 (32.51)	−1.08 (32.12)	152,275	0.4296
Heat load (MJ·cm^{-2}·yr^{-1})	0.77 (0.2)	0.77 (0.2)	150,363	0.6734
Slope (%)	48.4 (13.4)	47.05 (14.01)	156,435	0.1115

Notes: The *w* values and associated *P* values are from Mann–Whitney–Wilcoxon tests. TPI, topographic position index.

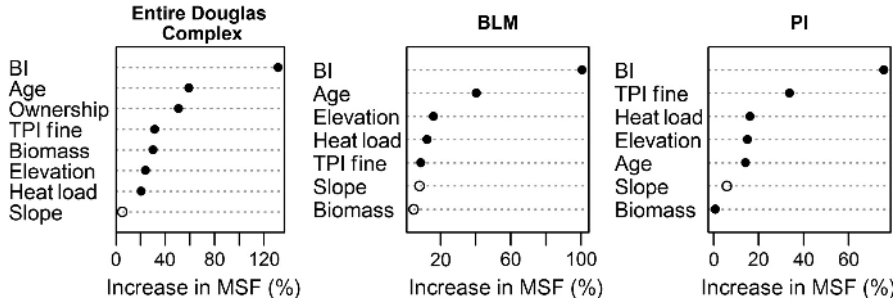

Fig. 3. Variable importance plots for predictor variables from Random Forest (RF) models of RdNBR for 1090 sample plots across the entire Douglas Complex (left panel), 571 plots on Bureau of Land Management (BLM) forests (middle), and 519 plots on private industrial (PI) forests (right). Solid circles denote variables retained in two-stage variable selection, open circles denote variables removed from the final RF models during variable selection. BI, burning index; MSE, Mean Squared Error.

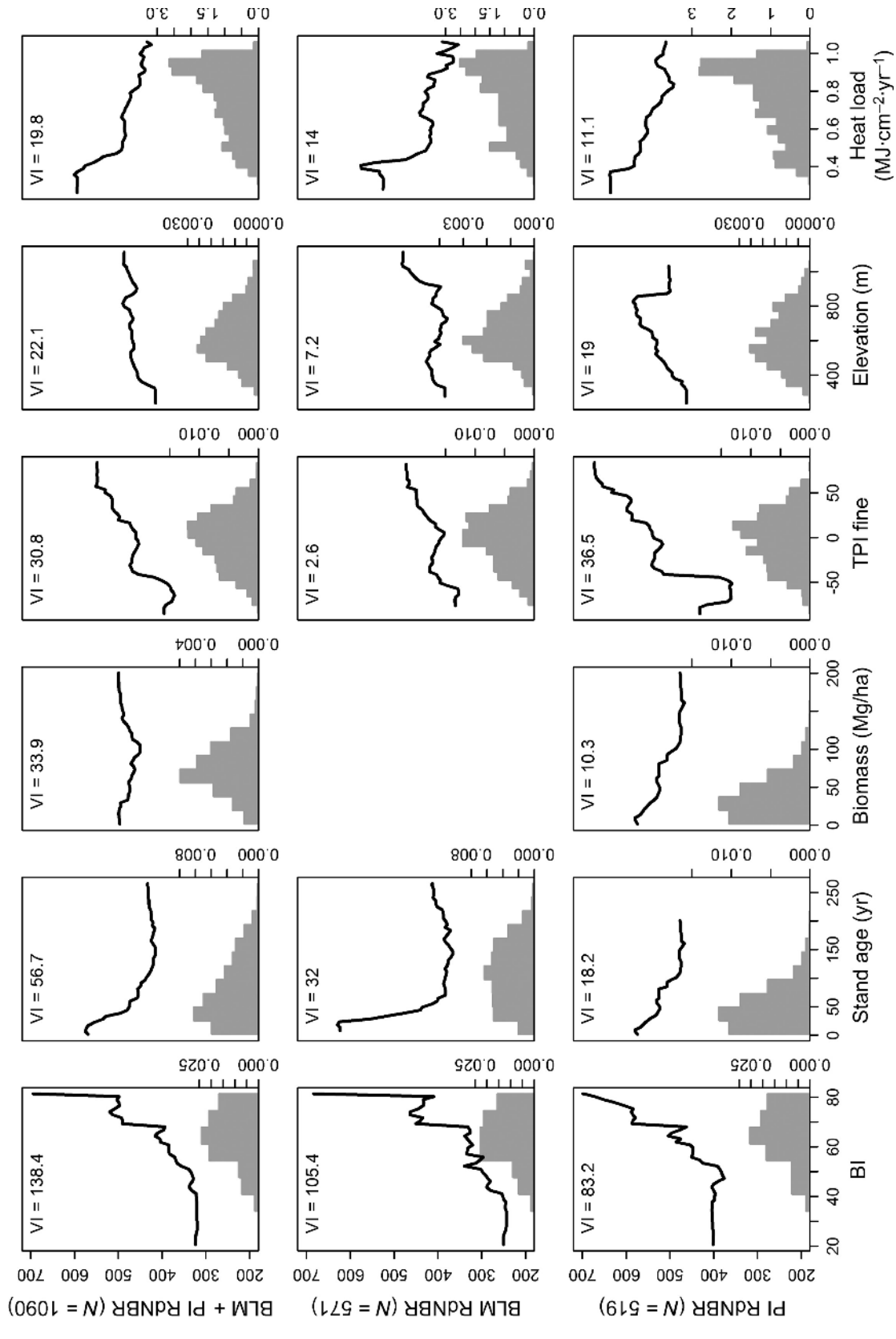

FIG. 4. Partial dependency plots showing relationships between each predictor variable and RdNBR in random forest models for all forests (BLM and PI, top panels), forests on Bureau of Land Management (BLM, middle panels), and private industrial land (PI, bottom panels). Number within each panel shows variable importance (VI; mean squared error increase [%]) of each predictor in the random forest model. Solid lines show trends in RdNBR in response to each predictor, histograms show the distributions of values for each predictor. Note there is no partial dependency plot for the relationship between RdNBR and biomass for BLM forests, as biomass was not a significant predictor variable for BLM forests based on two-stage variable selection procedures.

Table 3. Coefficients of predictor variables in generalized least squares model of RdNBR.

Variable	Parameter estimate	SE	*t*	*P*
Intercept	80.3321	90.4529	0.8881	0.3747
Age	−1.0544	0.2132	−4.9452	<0.0001
BI	6.1413	0.7618	8.0614	<0.0001
Ownership	76.3559	22.1111	3.4533	0.0006
Elevation	0.1179	0.0872	1.3512	0.1769
TPI fine	1.2839	0.2509	5.1169	<0.0001
Heat load	−150.0098	39.5750	−3.7905	0.0002
Slope	1.1321	0.5979	1.8933	0.0586
Biomass	0.1261	0.1194	1.0562	0.2911

important predictor variables, increasing MSE across the Douglas Complex by 56.7% and 53.2%, respectively. Age was the second most important variable in the final RF model for BLM forests (32%), but was the fourth most important variable for private forests (18.2%). Pre-fire biomass was the fourth most importance predictor variable in the RF model of the entire Douglas Complex (33.9%), but was not retained in the final RF model for BLM forests, and was the least important variable (10.3%) in the final RF model for private forests. Overall, topographic variables (TPI fine, heat load, and slope) were less important than BI, ownership, and age, increasing MSE across the Douglas Complex by 2.6–36.5%. RF models described 31%, 23%, and 25% of the variability in RdNBR across the entire burned area, BLM managed forests, and private forests, respectively.

Partial dependency plots displayed clear relationships between RdNBR and predictor variables (Fig. 4). RdNBR increased exponentially with BI across the entire Douglas Complex as well as for BLM and private forests separately, although RdNBR was shifted up by approximately 100 RdNBR on private forests vs. BLM forests for any given BI value. RdNBR was consistently higher in young forests on both ownerships. RdNBR declined rapidly on BLM forests between stand ages of 20 and 80 yr old, and remained roughly level in older forests. In contrast, RdNBR in private forests declined linearly with age across its range, although private lands had few forests greater than 100 yr old. RdNBR on both BLM and private forests increased with higher elevations, higher TPI fine, and steeper slope. Heat load was negatively correlated with RdNBR for all ownerships. Pre-fire biomass was not included in the final RF model for BLM lands, while, for the entire study and private lands, RdNBR appeared to decline slightly in forests with intermediate pre-fire biomass. However, the relationship between RdNBR and pre-fire biomass is more tenuous on private lands because they lacked forests with high pre-fire biomass.

Generalize least squares model

BI, age, ownership, TPI fine, and heat load were all significant predictors of RdNBR in the GLS model (Table 3). Slope had a suggestive relation with RdNBR ($P = 0.0586$), while elevation ($P = 0.1769$) and pre-fire biomass ($P = 0.2911$) were not a significant predictors. Relationships between predictors and RdNBR were consistent with partial dependency plots from RF models, with RdNBR increasing with BI and TPI fine and declining with age and heat load. Ownership had a fixed effect of increasing mean RdNBR by 76.36 ± 22.11 (mean ± SE) in private vs. BLM. Adjusting for all other predictor variables in the model, predicted mean RdNBR was higher on private (521.85 ± 18.67) vs. BLM forests (398.87 ± 18.23).

Discussion

Quantifying fire severity in the unique checkerboard landscape of the O&C Lands, this study disentangled the effects of forest management, weather, topography, and biomass on fire severity that are often spatially confounded. We found daily fire weather was the most important predictor of fire severity, but ownership, forest age, and topography were also important. After accounting for fire weather, topography, stand age, and pre-fire biomass, intensively managed private industrial forests burned at higher severity than older federal forests managed by the BLM. Below we discuss how the different variables in our analysis may influence fire severity, and argue that younger forests with spatially homogenized continuous fuel arrangements, rather than absolute biomass, was a significant driver of wildfire severity. The geospatial data available for our analyses was robust and comprehensive, covering two components of the fire behavior triangle (i.e., topography, weather), with pre-fire biomass and age serving as proxies for the third (fuel). However, we recognize there are limitations to our data and analyses and describe these below. We conclude by suggesting how our findings have important implications for forest and fire management in multi-owner landscapes, while posing important new questions that arise from our findings.

Fire weather was a strong top-down driver of fire severity, while bottom-up drivers such as topography and pre-fire biomass were less important. Across the western United States, evidence suggests bottom-up drivers such as topography and vegetation exert greater control on fire severity than weather, although the quality of weather representation confounds this conclusion (Dillon et al. 2011, Birch et al. 2015). At the same time, it is recognized that bottom-up drivers of fire severity can be overwhelmed by top-down climatic and weather conditions when fires burn during extreme weather conditions (Bradstock et al. 2010, Thompson and Spies 2010, Dillon et al. 2011). Daily burn period BI values were used in our analyses, but it is important to place fire weather conditions for any single fire within a larger historical context. We compared these daily BI values to the historical (1991–2017) summer (1 June–30 September) BI data we calculated from the Calvert RAWS data used in this study (3,296 total days). Within this historical record, mean burn period BI during the Douglas Complex for days with fire progression information was above average (79th percentile), but ranged considerably for any given day of the fire (15th–100th percentile). Fire severity was consistently higher on private lands across a range of fire weather conditions for the majority of days of active fire spread (Appendix S1: Fig. S3), leading us to conclude that while fire weather exerted top-down control on fire severity, local forest conditions that differed between ownerships remained important, even during extreme fire weather conditions.

Variation in pre-fire forest conditions across ownerships were clearly a significant driver of fire severity, and we believe they operated at multiple spatial scales. Private industrial forests were dominated by young trees, which have thinner bark and lower crown heights, both factors known to increase fire-induced tree mortality (Ryan and Reinhardt 1988, Dunn and Bailey 2016). At the stand scale, these plantations are high-density single cohorts often on harvest rotations between 30 and 50 yr, resulting in dense and relatively spatially homogenous fuel structure. In contrast, public forests were dominated by older forests that tend to have greater variability in both tree size and spatial pattern vs. plantations (Naficy et al. 2010), arising from variable natural regeneration (Donato et al. 2011), post-disturbance biological legacies (Seidl et al. 2014), and developmental processes in later stages of stand development (Franklin et al. 2002). Fine-scale spatial patterns of fuels can significantly alter fire behavior, and the effects of spatial patterns on fire behavior may increase with the spatial scale of heterogeneity (Parsons et al. 2017), which would likely be the case in O&C Lands due to the large scale checkerboard spatial pattern of ownership types.

Management-driven changes in fuel spatial patterns at tree and stand scales could also reconcile differences in prior studies that have found increases (Odion et al. 2004, Thompson et al. 2007) and decreases (Prichard and Kennedy 2014) in fire severity with intensive forest management. The two studies that observed an increase in fire severity with intensive forest management were conducted in the Klamath ecoregion of southwestern Oregon and northwestern California, the same ecoregion as this study. In contrast, Prichard and Kennedy (2014) examined the Tripod Complex in north-central Washington State, where harvests mostly occurred in low to mid elevation forests dominated by ponderosa pine, Douglas-fir, lodgepole pine (*Pinus contorta* var. *latifolia*), western larch (*Larix occidentalis*), and Engelmann spruce (*Picea engelmannii*). These forests have lower productivity compared to those studied in the Klamath ecoregion, with more open canopies and longer time periods to reach canopy closure after harvest, which likely results in more heterogeneous within stand fuel spatial patterns. Furthermore, forest clearcut units were relatively small in the Tripod Complex (mean 53 ha; Prichard and Kennedy 2014), and while these harvest units were spatially clustered, they were not large contiguous blocks as found in the O&C Lands. Last, it is unclear if the harvest units evaluated by Prichard and Kennedy (2014) experienced the full distribution of fire weather or topographic conditions compared to unharvested units, as our study does, which may confound their conclusions and our understanding of the relative importance of the factors driving fire behavior and effects.

Limitations

Our study examined a landscape uniquely suited to disentangling the drivers of wildfire severity and quantifying the effects of contrasting management activities. Additionally, we leveraged a robust collection of geospatial data to quantify the components of the fire behavior triangle. However, it is important to recognize the inherent limitations of our study. First, this study represents a single fire complex, instead of a regional collection of fires analyzed to elucidate broader system behaviors (sensu Dillon et al. 2011, Birch et al. 2015, Meigs et al. 2016). However, given the challenges of obtaining high quality fire weather information and accurate daily fire progression maps for fires that have occurred in landscapes with contrasting management regimes, we believe the landscape setting of our study provides key insights into the effects of management on fire severity that are not possible in large regional multi-fire studies. Second, while Landsat imagery is widely used to estimate forest conditions and fire severity, it has specific limitations. The GNN maps used in this study to derive pre-fire biomass and stand age are strongly driven by multi-spectral imagery from the Landsat family of sensors, whose imagery is known to saturate in forests with high leaf area indices and high biomass (Turner et al. 1999). Third, GNN maps of forest attributes used in this study were originally developed for large regional assessments, and as such have distinct limitations when used for analyses at spatial resolutions finer than the original source data (Bell et al. 2015), while application of GNN at fine spatial scales can underestimate GNN accuracy compared to larger areas commonly used by land managers (Ohmann et al. 2014). We addressed potential limitations of using GNN predictions at fine spatial scales in two ways. First, our sample plots are 90-m squares (3 × 3 30 m pixels) which more closely represents the area of the inventory plots used as GNN source data compared to pixel level analyses (Bell et al. 2015). Second, we visually assessed GNN predictions of live biomass and stand age within the Douglas Complex in relation to high resolution digital orthoimagery collected in 2011 by the USDA National Agriculture Imagery Program. From this qualitative assessment we concluded that GNN predictions characterize both between and within ownership variation in pre-fire biomass and age (Appendix S1: Fig. S4). Fourth and perhaps most fundamentally important, we relied on pre-fire biomass and stand age as proxies for fuel, in part because Landsat and other passive optical sensors have limited sensitivity to vertical and below-canopy vegetation structure (Lu 2006). Accurate and spatially complete quantitative information of forest surface and canopy fuels were not available for the Douglas Complex. More broadly, there are significant limitations to spatial predictions of forest structure and fuels using GNN and other methods that rely on passive optical imagery such as Landsat (Keane et al. 2001, Pierce et al. 2009, Zald et al. 2014), which is why we relied on the more accurately predicted age and pre-fire biomass variables as proxies. Surface and ladder fuels are the most important contributors to fire behavior in general (Agee and Skinner 2005), and surface fuels have been found to be positively correlated to fire severity in plantations within the geographic vicinity of the Douglas Complex (Weatherspoon and Skinner 1995). Yet correlations between biomass and fuel load can be highly variable due to site conditions and disturbance history (i.e., mature forests with frequent surface fires may have high live biomass but low surface fuel loads, while dense young forests that have regenerated after a stand replacing wildfire will have low live biomass but potentially high surface fuel loads as branches and snags fall). Therefore, GNN predicted pre-fire biomass may

represent the total fuel load, but not the available surface and ladder fuels that have the potential to burn during a specific fire, and this is supported by the low importance of pre-fire biomass as a predictor of fire severity in our study. Furthermore, it is important to recognize that in addition to total surface and ladder fuels, the spatial continuity of these fuels strongly influences fire behavior (Rothermel 1972, Pimont et al. 2011). Fifth, while private industrial and BLM forests in our study area had very different forest conditions due to contrasting management regimes, ownership alone misses management activities (e.g., site preparation, stocking density, competing vegetation control, partial thinning, etc.) that can influence fuels and fire behavior. Sixth, while our spatial extrapolation of fire weather correlated well with daily fire severity and area burned, it did not account for topographic mediation of weather that can influence fine scale fire behavior, nor did it examine the underlying weather patterns such as temperature inversions that are common to the region and may play a key role in moderating burning index (Estes et al. 2017). Finally, we were unable to discern the effects of fire suppression activities and whether they varied by ownership, since incident documentation of suppression activities are generally not collected or maintained in a manner consistent with quantitative or geospatial statistical analyses (Dunn et al. 2017).

Management Implications

Although only one fire complex, the contrasting forest conditions resulting from different ownerships within the Douglas Complex are consistent with many mixed-ownership or mixed-use landscapes, such that we believe our results have implications across a much broader geographic area. First, it brings into question the conventional view that fire exclusion in older forests is the dominant driver of fire severity across landscapes. There is strong scientific agreement that fire suppression has increased the probability of high severity fire in many fire-prone landscapes (Miller et al. 2009, Calkin et al. 2015, Reilly et al. 2017), and thinning as well as the reintroduction of fire as an ecosystem process are critical to reducing fire severity and promoting ecosystem resilience and adaptive capacity (Agee and Skinner 2005, Raymond and Peterson 2005, Earles et al. 2014, Krofcheck et al. 2017). However, in the landscape we studied, intensive plantation forestry appears to have a greater impact on fire severity than decades of fire exclusion. Second, higher fire severity in plantations potentially flips the perceived risk and hazard in multi-owner landscapes, because higher severity fire on intensively managed private lands implies they are the greater source of risk than older forests on federal lands. These older forests likely now experience higher fire severity than historically due to decades of fire exclusion, yet in comparison to intensively managed plantations, the effects of decades of fire exclusion in older forests appear to be less important than increased severity in young intensively managed plantations on private industrial lands.

Furthermore, our findings suggest challenges and opportunities for managing intensive plantations in ways that reduce potential fire severity. Increasing the age (and therefore size) of trees and promoting spatial heterogeneity of stands and fuels is a likely means to reducing fire severity, as are fuel reduction treatments in plantations (Crecente-Campo et al. 2009, Kobziar et al. 2009, Reiner et al. 2009). The extent and spatial arrangement of fuel reduction treatments can be an important consideration in their efficacy at reducing fire severity at landscape scales (Finney et al. 2007, Krofcheck et al. 2017). However, optimal extent and landscape patterns of fuels reduction treatments can be hampered by a wide range of ecological, economic, and administrative constraints (Collins et al. 2010, North et al. 2015a, Barros et al. 2017). In the past, pre-commercial and commercial thinning of plantations (a potential fuel treatment) in the Pacific Northwest were common, economically beneficial management activities that improved tree growth rates and size, but these practices have become less common with improved reforestation success, alternative vegetation control techniques, and shorter harvest rotations (Talbert and Marshall 2005). This suggests there may be strong economic limitations to increased rotation ages and non-commercial thinning in young intensive plantation forests. More broadly, the development of large-scale forest management and conservation strategies can face legal and equitability challenges in multi-owner landscapes given existing laws constraining planning among private organizations (Thompson et al. 2004, 2006).

We believe two major questions arise from our findings that are important to fire management in multi-owner landscapes, especially those with contrasting management objectives. Plantations burned at higher severity, and this implies they are a higher source of risk to adjacent forest ownerships. However, a more explicit quantification of fire severity and susceptibility is needed to understand how risk is spatially transmitted across ownership types under a variety of environmental conditions. Second, we suggest the need for alternative management strategies in plantations to reduce fire severity at stand and landscape scales. However, the economic viability of such alternative management regimes remains poorly understood. Optimization models integrating spatial allocation of fuel treatments and fire behavior with economic models of forest harvest and operations could be used to determine if alternative management activities in plantations are economically viable. If alternative management activities are not economically viable, but wildfire risk reduction is an important objective on lands adjacent to industrial forestlands, strategic land purchases or transfers between ownership types may be required to achieve landscape level goals. This may be particularly important given the previously stated legal and equitability challenges in multi-owner landscapes. Regardless of the landscape-level objectives and constraints, it is clear that cooperation among stakeholders will be necessary in multi-ownership landscapes if wildfire risk reduction, timber harvesting, and conservation objectives remain dominant yet sometimes conflicting objectives for these landscapes.

Acknowledgments

Funding for this research was in part provided by the USDI Bureau of Land Management (Cooperative Agreement no. L11AC20137/L01540). We thank Krissan Kosel at the USDI BLM Roseburg District for assistance providing Calvert Station RAWS weather data, as well as thoughtful review and discussions of prior versions of this manuscript. We also thank two reviewers for their helpful suggestions on earlier versions of this paper for their insightful and constructive comments.

Literature Cited

Abatzoglou, J. T., C. A. Kolden, A. P. Williams, J. A. Lutz, and A. M. S. Smith. 2017. Climatic influences on interannual variability in regional burn severity across western US forests. International Journal of Wildland Fire 26:269.

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Barros, A. M. G., et al. 2017. Spatiotemporal dynamics of simulated wildfire, forest management, and forest succession in central Oregon, USA. Ecology and Society 22:24.

Bell, D. M., M. J. Gregory, H. M. Roberts, R. J. David, and J. L. Ohmann. 2015. How sampling and scale limit accuracy assessment of vegetation maps: a comment on Loehle et al. (2015). Forest Ecology and Management 358:361–364.

Birch, D. S., P. Morgan, C. A. Kolden, J. T. Abatzoglou, G. K. Dillon, A. T. Hudak, and A. M. S. Smith. 2015. Vegetation, topography and daily weather influenced burn severity in central Idaho and western Montana forests. Ecosphere 6:art17.

Bradley, C. M., C. T. Hanson, and D. A. DellaSala. 2016. Does increased forest protection correspond to higher fire severity in frequent-fire forests of the western United States? Ecosphere 7: e01492.

Bradshaw, L., J. Deeming, R. Burgan, and J. Cohen. 1983. The 1978 national fire-danger rating system. General Technical Report INT-169. US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, Utah, USA.

Bradshaw, L., and E. McCormick. 2000. FireFamily Plus user's guide, version 2.0. Gen. Tech. Rep. RMRS-GTR-67WWW. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Ogden, Utah, USA.

Bradstock, R. A., K. A. Hammill, L. Collins, and O. Price. 2010. Effects of weather, fuel and terrain on fire severity in topographically diverse landscapes of south-eastern Australia. Landscape Ecology 25:607–619.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multi-model inference: a practical information-theoretic approach. Springer Verlag, New York, New York, USA.

Calkin, D. E., M. P. Thompson, and M. A. Finney. 2015. Negative consequences of positive feedbacks in US wildfire management. Forest Ecosystems 2:9.

Campbell, J. L., M. E. Harmon, and S. R. Mitchell. 2012. Can fuel-reduction treatments really increase forest carbon storage in the western US by reducing future fire emissions? Frontiers in Ecology and the Environment 10:83–90.

Cansler, C. A., and D. McKenzie. 2014. Climate, fire size, and biophysical setting control fire severity and spatial pattern in the northern Cascade Range, USA. Ecological Applications 24:1037–1056.

Cohen, W. B., T. A. Spies, and M. Fiorella. 1995. Estimating the age and structure of forests in a multi-ownership landscape of western Oregon, USA. International journal of Remote Sensing 16:721–746.

Collins, B. M., J. M. Lydersen, R. G. Everett, D. L. Fry, and S. L. Stephens. 2015. Novel characterization of landscape-level variability in historical vegetation structure. Ecological Applications 25:1167–1174.

Collins, B. M., S. L. Stephens, J. J. Moghaddas, and J. J. Battles. 2010. Challenges and approaches in planning fuel treatments across fire-excluded forested landscapes. Journal of Forestry 108:24–31.

Crecente-Campo, F., A. Pommerening, and R. Rodríguez-Soalleiro. 2009. Impacts of thinning on structure, growth and risk of crown fire in a *Pinus sylvestris* L. plantation in northern Spain. Forest Ecology and Management 257:1945–1954.

Davis, R. J., et al. 2015. Northwest Forest Plan–the first 20 years (1994–2013): status and trends of late-successional and old-growth forests. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA.

Del Lungo, L., P. Vourinen, and J. Carle. 2001. Preliminary analysis of global trends in forest plantation development, 1980–2000. FAO, Rome, Italy.

Dillon, G. K., Z. A. Holden, P. Morgan, M. A. Crimmins, E. K. Heyerdahl, and C. H. Luce. 2011. Both topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006. Ecosphere 2:art130.

Donato, D. C., J. L. Campbell, and J. F. Franklin. 2011. Multiple successional pathways and precocity in forest development: Can some forests be born complex? Journal of Vegetation Science 23:576–584.

Dormann, C., et al. 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography 30:609–628.

Dunn, C. J., and J. D. Bailey. 2016. Tree mortality and structural change following mixed-severity fire in Pseudotsuga forests of Oregon's western Cascades, USA. Forest Ecology and Management 365:107–118.

Dunn, C. J., D. E. Calkin, and M. P. Thompson. 2017. Towards enhanced risk management: planning, decision making and monitoring of US wildfire response. International Journal of Wildland Fire 26:551–556.

Earles, J. M., M. P. North, and M. D. Hurteau. 2014. Wildfire and drought dynamics destabilize carbon stores of fire-suppressed forests. Ecological Applications 24:732–740.

Estes, B. L., E. E. Knapp, C. N. Skinner, J. D. Miller, and H. K. Preisler. 2017. Factors influencing fire severity under moderate burning conditions in the Klamath Mountains, northern California, USA. Ecosphere 8:e01794.

Finney, M. A., R. C. Seli, C. W. McHugh, A. A. Ager, B. Bahro, and J. K. Agee. 2007. Simulation of long-term landscape-level fuel treatment effects on large wildfires. International Journal of Wildland Fire 16:712.

Fischer, A. P., et al. 2016. Wildfire risk as a socioecological pathology. Frontiers in Ecology and the Environment 14:276–284.

Flannigan, M. D., J. B. Harrington, M. D. Flannigan, and J. B. Harrington. 1988. A study of the relation of meteorological variables to monthly provincial area burned by wildfire in Canada (1953–80). Journal of Applied Meteorology 27:441–452.

Food and Agriculture Organization of the United Nations [FAO]. 2010. Global forest resource assessment. FAO, Rome, Italy.

Franklin, J. F., and C. T. Dyrness. 1988. Natural vegetation of Oregon and Washington. Oregon State University Press, Corvallis, Oregon, USA.

Franklin, J. F., and K. N. Johnson. 2012. A restoration framework for federal forests in the pacific northwest. Journal of Forestry 110:429–439.

Franklin, J. F., T. A. Spies, R. Van Pelt, A. B. Carey, D. A. Thornburgh, D. R. Berg, D. B. Lindenmayer, M. E. Harmon, W. S. Keeton, and D. C. Shaw. 2002. Disturbances and structural development of natural forest ecosystems with silvicultural implications, using Douglas-fir forests as an example. Forest Ecology and Management 155:399–423.

Fulé, P. Z., J. E. Korb, and R. Wu. 2009. Changes in forest structure of a mixed conifer forest, southwestern Colorado, USA. Forest Ecology and Management 258:1200–1210.

Genuer, R., J.-M. Poggi, and C. Tuleau-Malot. 2010. Variable selection using random forests. Pattern Recognition Letters 31:2225–2236.

Genuer, R., J.-M. Poggi, and C. Tuleau-Malot. 2016. VSURF: variable selection using random forests. R package version 1.0.3. https://cran.r-project.org/web/packages/VSURF/index.html

Geospatial Multi-Agency Coordination (GeoMAC). 2013. Douglas complex fire perimeters. https://rmgsc.cr.usgs.gov/outgoing/GeoMAC/2013_fire_data/Oregon/Douglas_Complex/

Gesch, D. B., M. J. Oimoen, S. K. Greenlee, C. A. Nelson, M. J. Steuck, and D. J. Tyler. 2002. The national elevation data set. Photogrammetric Engineering and Remote Sensing 68: 5–11.

Haas, J. R., D. E. Calkin, and M. P. Thompson. 2013. A national approach for integrating wildfire simulation modeling into

Wildland Urban Interface risk assessments within the United States. Landscape and Urban Planning 119:44–53.
Hanson, C. T., D. C. Odion, D. A. DelleaSala, and W. L. Baker. 2009. Overestimation of fire risk in the Northern Spotted Owl recovery plan. Conservation Biology 23:1314–1319.
Harvey, B. J., D. C. Donato, and M. G. Turner. 2016. Drivers and trends in landscape patterns of stand-replacing fire in forests of the US Northern Rocky Mountains (1984–2010). Landscape Ecology 31:2367–2383.
Hastie, T., R. Tibshirani, J. Friedman, and J. Franklin. 2001. The elements of statistical learning: data mining, inference, and prediction. Springer, New York, New York, USA.
Hessburg, P. F., J. K. Agee, and J. F. Franklin. 2005. Dry forests and wildland fires of the inland Northwest USA: contrasting the landscape ecology of the pre-settlement and modern eras. Forest Ecology and Management 211:117–139.
Hirsch, K., V. Kafka, C. Tymstra, R. McAlpine, B. Hawkes, H. Stegehuis, S. Quintilio, S. Gauthier, and K. Peck. 2001. Fire-smart forest management: a pragmatic approach to sustainable forest management in fire-dominated ecosystems. Forestry Chronicle 77:357–363.
Hurteau, M. D., G. W. Koch, and B. A. Hungate. 2008. Carbon protection and fire risk reduction: toward a full accounting of forest carbon offsets. Frontiers in Ecology and the Environment 6:493–498.
Jolly, W. M., M. A. Cochrane, P. H. Freeborn, Z. A. Holden, T. J. Brown, G. J. Williamson, and D. M. Bowman. 2015. Climate-induced variations in global wildfire danger from 1979 to 2013. Nature Communications 6:7537.
Kane, V. R., C. A. Cansler, N. A. Povak, J. T. Kane, R. J. McGaughey, J. A. Lutz, D. J. Churchill, and M. P. North. 2015. Mixed severity fire effects within the Rim fire: relative importance of local climate, fire weather, topography, and forest structure. Forest Ecology and Management 358:62–79.
Keane, R. E., R. Burgan, and J. van Wagtendonk. 2001. Mapping wildland fuels for fire management across multiple scales: integrating remote sensing, GIS, and biophysical modeling. International Journal of Wildland Fire 10:301–319.
Kennedy, R. E., Z. Yang, and W. B. Cohen. 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—temporal segmentation algorithms. Remote Sensing of Environment 114:2897–2910.
Kobziar, L. N., J. R. McBride, and S. L. Stephens. 2009. The efficacy of fire and fuels reduction treatments in a Sierra Nevada pine plantation. International Journal of Wildland Fire 18:791.
Krofcheck, D. J., M. D. Hurteau, R. M. Scheller, and E. L. Loudermilk. 2017. Prioritizing forest fuels treatments based on the probability if high-severity fire restores adaptive capacity in Sierran forests. Global Change Biology. https://doi.org/10.1111/gcb.13913
Landram, M. 1996. Status of reforestation on National Forest lands within the Sierra Nevada Ecosystem Project Study Area. Page Sierra Nevada Ecosystem Project: Final Report to Congress (Volume 3). University of California, Centers for Water and Wildland Resources, Davis, CA USA.
Liaw, A., and M. Wiener. 2002. Classification and regression by randomForest. R News 2:18–22.
Littell, J. S., D. McKenzie, D. L. Peterson, and A. L. Westerling. 2009. Climate and wildfire area burned in western US ecoprovinces, 1916–2003. Ecological Applications 19:1003–1021.
Lu, D. 2006. The potential and challenge of remote sensing-based biomass estimation. International Journal of Remote Sensing 27:1297–1328.
Lyons-Tinsley, C., and D. L. Peterson. 2012. Surface fuel treatments in young, regenerating stands affect wildfire severity in a mixed conifer forest, eastside Cascade Range, Washington, USA. Forest Ecology and Management 270:117–125.
Mazerolle, M. J. 2017. AICcmodavg: model selection and multimodel inference based on (Q) AIC (c). R package version, 2.1. https://cran.r-project.org/web/packages/AICcmodavg/index.html
McCaffrey, S. 2004. Thinking of wildfire as a natural hazard. Society and Natural Resources 17:509–516.
McCune, B., and D. Keon. 2002. Equations for potential annual direct incident radiation and heat load. Journal of Vegetation Science 13:603.
Meigs, G. W., H. S. Zald, J. L. Campbell, W. S. Keeton, and R. E. Kennedy. 2016. Do insect outbreaks reduce the severity of subsequent forest fires? Environmental Research Letters 11:045008.
Merschel, A. G., T. A. Spies, and E. K. Heyerdahl. 2014. Mixed-conifer forests of central Oregon: effects of logging and fire exclusion vary with environment. Ecological Applications 24: 1670–1688.
Miller, J. D., H. D. Safford, M. Crimmins, and A. E. Thode. 2009. Quantitative evidence for increasing forest fire severity in the Sierra Nevada and southern Cascade Mountains, California and Nevada, USA. Ecosystems 12:16–32.
Miller, J. D., C. N. Skinner, H. D. Safford, E. E. Knapp, and C. M. Ramirez. 2012. Trends and causes of severity, size, and number of fires in northwestern California, USA. Ecological Applications 22:184–203.
Miller, J. D., and A. E. Thode. 2007. Quantifying burn severity in a heterogeneous landscape with a relative version of the delta normalized burn ratio (dNBR). Remote Sensing of Environment 109:66–80.
Naficy, C., A. Sala, E. G. Keeling, J. Graham, and T. H. DeLuca. 2010. Interactive effects of historical logging and fire exclusion on ponderosa pine forest structure in the northern Rockies. Ecological Applications 20:1851–1864.
Nahuelhual, L., A. Carmona, A. Lara, C. Echeverría, and M. E. González. 2012. Land-cover change to forest plantations: proximate causes and implications for the landscape in south-central Chile. Landscape and Urban Planning 107:12–20.
North, M. P., S. L. Stephens, B. M. Collins, J. K. Agee, G. Aplet, J. F. Franklin, and P. Z. Fulé. 2015*a*. Reform forest fire management. Science 349:1280–1281.
North, M., A. Brough, J. Long, B. Collins, P. Bowden, D. Yasuda, J. Miller, and N. Sugihara. 2015*b*. Constraints on mechanized treatment significantly limit mechanical fuels reduction extent in the Sierra Nevada. Journal of Forestry 113:40–48.
Odion, D. C., E. J. Frost, J. R. Strittholt, H. Jiang, D. A. DellaSala, and M. A. Moritz. 2004. Patterns of fire severity and forest conditions in the western Klamath Mountains, California. Conservation Biology 18:927–936.
Odion, D. C., et al. 2014. Examining historical and current mixed-severity fire regimes in Ponderosa pine and mixed-conifer forests of western North America. PLoS ONE 9:e87852.
Ohmann, J. L., and M. J. Gregory. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation in coastal Oregon, USA. Canadian Journal of Forest Research 32:725–741.
Ohmann, J. L., M. J. Gregory, and H. M. Roberts. 2014. Scale considerations for integrating forest inventory plot data and satellite image data for regional forest mapping. Remote Sensing of Environment 151:3–15.
Ohmann, J. L., M. J. Gregory, H. M. Roberts, W. B. Cohen, R. E. Kennedy, and Z. Yang. 2012. Mapping change of older forest with nearest-neighbor imputation and Landsat time-series. Forest Ecology and Management 272:13–25.
Oregon Spatial Data Library. 2015. Oregon land management—2015. http://spatialdata.oregonexplorer.info/geoportal/catalog/search/resource/details.page?uuid=%7B9B644E0F-7A7D-4124-A50F-6B35C05626AE%7D
Parsons, R., R. Linn, F. Pimont, C. Hoffman, J. Sauer, J. Winterkamp, C. Sieg, and W. Jolly. 2017. Numerical investigation of aggregated fuel spatial pattern impacts on fire behavior. Land 6:43.
Pierce, K. B., J. L. Ohmann, M. C. Wimberly, M. J. Gregory, and J. S. Fried. 2009. Mapping wildland fuels and forest structure for land management: a comparison of nearest neighbor imputation

and other methods. Canadian Journal of Forest Research 39:1901–1916.
Pimont, F., J.-L. Dupuy, R. R. Linn, and S. Dupont. 2011. Impacts of tree canopy structure on wind flows and fire propagation simulated with FIRETEC. Annals of Forest Science 68:523–530.
Pinheiro, J., D. Bates, S. DebRoy, D. Sarkar, and R. C. Team. 2017. nlme: linear and nonlinear mixed effects models. https://cran.r-project.org/web/packages/nlme/index.html
Prichard, S. J., and M. C. Kennedy. 2014. Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event. Ecological Applications 24:571–590.
R Core Team. 2017. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
Raymond, C. L., and D. L. Peterson. 2005. Fuel treatments alter the effects of wildfire in a mixed-evergreen forest, Oregon, USA. Canadian Journal of Forest Research 35:2981–2995.
Reilly, M. J., C. J. Dunn, G. W. Meigs, T. A. Spies, R. E. Kennedy, J. D. Bailey, and K. Briggs. 2017. Contemporary patterns of fire extent and severity in forests of the Pacific Northwest, USA (1985–2010). Ecosphere 8:e01695.
Reiner, A. L., N. M. Vaillant, J. Fites-Kaufman, and S. N. Dailey. 2009. Mastication and prescribed fire impacts on fuels in a 25-year old ponderosa pine plantation, southern Sierra Nevada. Forest Ecology and Management 258:2365–2372.
Rodríguez y Silva, F., J. R. Molina Martínez, and A. González-Cabán. 2014. A methodology for determining operational priorities for prevention and suppression of wildland fires. International Journal of Wildland Fire 23:544.
Rothermel, R. 1972. A mathematical model for predicting fire spread in wildland fuels. Page 40. Research Paper INT-115, USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, Utah USA.
Rudel, T. K. 2009. Tree farms: driving forces and regional patterns in the global expansion of forest plantations. Land Use Policy 26:545–550.
Ryan, K. C., and E. D. Reinhardt. 1988. Predicting postfire mortality of seven western conifers. Canadian Journal of Forest Research 18:1291–1297.
Safford, H. D., D. A. Schmidt, and C. H. Carlson. 2009. Effects of fuel treatments on fire severity in an area of wildland–urban interface, Angora Fire, Lake Tahoe Basin, California. Forest Ecology and Management 258:773–787.
Schoennagel, T., et al. 2017. Adapt to more wildfire in western North American forests as climate changes. Proceedings of the National Academy of Sciences USA 114:4582–4590.
Seidl, R., W. Rammer, and T. A. Spies. 2014. Disturbance legacies increase the resilience of forest ecosystem structure, composition, and functioning. Ecological Applications 24:2063–2077.
Sensenig, T., J. D. Bailey, and J. C. Tappeiner. 2013. Stand development, fire and growth of old-growth and young forests in southwestern Oregon, USA. Forest Ecology and Management 291:96–109.
Spies, T. A., K. N. Johnson, K. M. Burnett, J. L. Ohmann, B. C. McComb, G. H. Reeves, P. Bettinger, J. D. Kline, and B. Garber-Yonts. 2007. Cumulative ecological and socioeconomic effects of forest policies in coastal Oregon. Ecological Applications 17:5–17.
Spies, T. A., et al. 2010. Underestimating risks to the Northern Spotted Owl in fire-prone forests: response to Hanson et al. Conservation Biology 24:330–333.
Spies, T., et al. 2014. Examining fire-prone forest landscapes as coupled human and natural systems. Ecology and Society 19:9. http://dx.doi.org/10.5751/ES-06584-190309
Steel, Z. L., H. D. Safford, and J. H. Viers. 2015. The fire frequency-severity relationship and the legacy of fire suppression in California forests. Ecosphere 6:1–23.
Stephens, S., R. Boerner, C. Fettig, J. Fontaine, B. Hartsough, P. Kennedy, and D. Schwilk. 2012. The effects of forest fuel-reduction treatments in the United States. BioScience 62:549–560.
Stephens, S. L., et al. 2014. Temperate and boreal forest mega-fires: characteristics and challenges. Frontiers in Ecology and the Environment 12:115–122.
Stevens, J. T., et al. 2016. Average stand age from forest inventory plots does not describe historical fire regimes in Ponderosa pine and mixed-conifer forests of western North America. PLoS ONE 11:e0147688.
Talbert, C., and D. Marshall. 2005. Plantation productivity in the Douglas-fir region under intensive silvicultural practices: results from research and operations. Journal of Forestry 103:65–70.
Thompson, J. R., M. D. Anderson, and K. N. Johnson. 2004. Ecosystem management across ownerships: the potential for collision with antitrust laws. Conservation Biology 18:1475–1481.
Thompson, J. R., K. N. Johnson, M. Lennette, T. A. Spies, and P. Bettinger. 2006. Historical disturbance regimes as a reference for forest policy in a multiowner province: a simulation experiment. Canadian Journal of Forest Research 36:401–417.
Thompson, J. R., and T. A. Spies. 2010. Factors associated with crown damage following recurring mixed-severity wildfires and post-fire management in southwestern Oregon. Landscape Ecology 25:775–789.
Thompson, J. R., T. A. Spies, and L. M. Ganio. 2007. Reburn severity in managed and unmanaged vegetation in a large wildfire. Proceedings of the National Academy of Sciences USA 104:10743–10748.
Turner, D. P., W. B. Cohen, R. E. Kennedy, K. S. Fassnacht, and J. M. Briggs. 1999. Relationships between leaf area index and Landsat TM spectral vegetation indices across three temperate zone sites. Remote Sensing of Environment 70:52–68.
Weatherspoon, C. P., and C. N. Skinner. 1995. An assessment of factors associated with damage to tree crowns from the 1987 wildfires in northern California. Forest Science 41:430–451.
Weaver, H. 1943. Fire as an ecological and silvicultural factor in the Ponderosa-pine region of the pacific Slope. Journal of Forestry 41:7–15.
Westerling, A., and B. Bryant. 2008. Climate change and wildfire in California. Climatic Change 87:231–249.
Williams, J. 2013. Exploring the onset of high-impact mega-fires through a forest land management prism. Forest Ecology and Management 294:4–10.
Zald, H. S. J., J. L. Ohmann, H. M. Roberts, M. J. Gregory, E. B. Henderson, R. J. McGaughey, and J. Braaten. 2014. Influence of lidar, Landsat imagery, disturbance history, plot location accuracy, and plot size on accuracy of imputation maps of forest composition and structure. Remote Sensing of Environment 143:26–38.
Ziegler, J. P., C. Hoffman, M. Battaglia, and W. Mell. 2017. Spatially explicit measurements of forest structure and fire behavior following restoration treatments in dry forests. Forest Ecology and Management 386:1–12.

Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.1710/full

Data Availability

Data available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.3gv5c78