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Biophysical Settings that Influenced Plantation Survival During the 2015 Wildfires in Northern Rocky Mountain Moist Mixed-Conifer Forests

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Abstract

Fire suppression and the loss of western white pine (WWP) have made northern Rocky Mountain moist mixed-conifer forests less disturbance resilient. Although managers are installing hundreds of plantations, most of these plantations have not experienced wildfire since establishment. In 2015, wildfires burned through 100 WWP plantations in this region, providing an opportunity to evaluate the effects of wildfires on sapling survival. A Weibull distribution approach was used to characterize the variation of fire severity pixels, as indicated by the differenced normalized burn ratio. The distribution parameters provided a method to identify the biophysical setting and plantation characteristics influencing fire severity and sapling survival. Plantations located on lower slope positions were more resistant to wildfires than plantations located midslope or close to the ridges. Snow water equivalent was positively correlated with wildfire resistance and resilience. Results will help focus reforestation efforts and identify locations where future plantations can potentially survive wildfires.

Study Implications: This study examined wildfire effects on western white pine plantations, with the intention to inform managers where to locate plantations that will be more resistant to wildfires and determine which plantations may require postfire reforestation. Plantations were more resilient and resistant to wildfires when they occurred on lower slopes, even when steep, indicating these places may be better suited for future plantations. Plantations located on upper slopes and ridges are vulnerable to wildfire even when located on moist habitat types and will likely need reforestation.

Keywords: mixed severity wildfire, dNBR, western white pine, fire severity, restoration, Weibull distribution

Species composition has shifted, and overall vegetative diversity has decreased, in the moist mixed-conifer forests of the northern Rocky Mountains. These changes occurred because of two decisive events: (1) the advent of extinguishing all types of fires, which removed the less lethal small fires that were abundant in the region (Arno 1980), and (2) the introduction of a nonnative disease, white pine blister rust (*Cronartium ribicola*), which resulted in the rapid decrease in western white pine (WWP; *Pinus monticola* Douglas ex D. Don) abundance (from 70% of the landscape to < 10% of the landscape) from mortality caused by the disease and timber salvage (Jain and Graham 2015). Prior to fire suppression and loss of WWP, these moist mixed-conifer forests experienced what Arno et al. (2000) called a variable and mixed-fire regime, which produced a complex mosaic of forest compositions and structures that contained vegetation that contributed to a diversity of ground, surface, ladder, and crown fuels and fuel moisture dynamics. As a result, these forests experienced highly variable fire intensities, severities, and return intervals ranging from 20 to 200 years (Arno et al. 2000). Without WWP and with fire suppression, today's northern Rocky Mountain forests do not have the species mix or forest structures reflective of the past, and may therefore have diminished fire resilience and a changed fire regime, favoring a higher proportion of the landscape being burned by stand-replacing wildfires (Jain and Graham 2015).

Managers working in moist mixed-conifer forests in the northern Rocky Mountains are investing resources to increase WWP abundance because it is resistant to most of the endemic disturbances (e.g., root disease, wind and ice damage, frost) that contribute to resilience in a mixed-severity fire regime. Genetic selection of blister-rust-resistant seed sources also has spurred interest in establishing plantations to increase WWP abundance across the region (Jain and Graham 2015). Since the 1970s, tens of thousands of acres of plantations have been planted with uniform spacing of WWP and western larch (*Larix occidentalis* Nutt.). Grand fir (*Abies grandis* [Douglas ex D. Don] Lindl.), western hemlock (*Tsuga heterophylla* [Raf.] Sarg.), western redcedar (*Thuja plicata* Donn ex D. Don), and blister-rust-vulnerable WWP trees also naturally regenerate within these plantations, creating dense stands with eight to 10 tree species. Often these plantations are cleaned and/or weeded (i.e., precommercially thinned) and the lower branches of the WWP trees are pruned to diminish blister rust inoculation (Hagle et al. 1989); however, some plantations have not been managed since establishment. In addition, plantations in moist mixed-conifer forests, due to their pattern (angular blocks), size (< 50 acres), and distribution (small patches on steep slopes), do not reflect the complex patch sizes and distribution created by a mixed fire regime (Arno 1980, Agee 2005). Therefore, we do not know how resistant these plantations are to wildfire.

To evaluate the resistance of WWP plantations to wildfire, we need to acknowledge that wildfire ignition and behavior are influenced by top-down and bottom-up drivers. Top-down drivers include regional climate and decadal, annual, and daily weather leading up to and during a wildfire event (Perry et al. 2011), including inversions that can trap smoke and dampen fire behavior (Estes et al. 2017). Bottom-up drivers consist of local-scale variables that affect fuel combustibility, which can include topographic complexity (e.g., Dillon et al. 2011), slope position, slope percent, and solar radiation (e.g., Kane et al. 2015, Estes et al. 2017). Local fuel moisture dynamics are partially influenced by forest composition and structure (e.g., Birch et al. 2015). Some shrubs such as *Ceanothus velutinus* Douglas ex Hook have volatile oils, which can also be considered a bottom-up driver (Countryman 1982). In the western United States and Canada, studies have tried to identify the bottom-up drivers associated with plantation survival after wildfire (Thompson et al. 2011, Lyons-Tinsley and Peterson 2012, Prichard and Kennedy 2014). Thompson et al. (2011) noted that younger stands, 15 to 25 years old, experienced more canopy damage compared with older plantations in the 2002 Biscuit wildfire in Oregon. Lyons-Tinsley and Peterson (2012) found that stands treated with some type of site preparation before planting tended to be more resistant to fire. Prichard and Kennedy (2014) noted that landform (topographic indicator) and sites that were recently prescribed-burned tended to burn less severely. We wanted to examine whether bottom-up drivers can be identified and applied to the postfire treatment and future placement of WWP plantations in moist mixed-conifer forests.

Over the last 50 years (since 1970), there has been a lack of large mixed severity wildfires (1 wildfire > 500 acres) in the moist forests (WWP/western redcedar/western hemlock forests) of the northern Rockies within the United States (Ruefenacht et al. 2008, Gibson et al. 2014) and therefore, the opportunity to examine plantation survival after fire is also rare. However, in 2015, there were five wildfires that burned within these forests in northern Idaho that contained WWP plantations, thus providing an opportunity to investigate and determine the resulting fire severities of plantations that existed within the fire perimeters. We seek to address the vulnerability and fire resistance of these plantations to tree mortality from fire by addressing three questions: (1) what is the distribution of fire severity within plantations, (2) what biophysical settings and characteristics are associated with the distribution of wildfires within plantations, and (3) how did the distribution of fire severity within plantations influence tree survival? Results can provide information to forest managers from two perspectives. In plantations that have biophysical characteristics that are identified as not being resistant to wildfire, this information can guide reforestation efforts after wildfire, as management actions are often limited because of organizational capabilities, access, costs, and other constraints. The distribution of fire severity within a stand in relation to biophysical conditions can also inform the resistance of plantations. This information can also guide future placement of plantations often intended to meet multiple objectives, one of which is wildfire resilience and resistance (DeRose and Long 2014).

To address these questions, we identified plantations within 2015 wildfire perimeters to determine what bottom-up drivers influenced postfire outcomes. Using USDA Forest Service databases, geospatial data, and field data collection, we identified one hundred plantations within the fire perimeters, the age of plantations (designated by planting year) when burned, and postfire severity. From these data, we selected a subset (48) of plantations to identify the bottom-up drivers that promoted wildfire-resistance. Although we only used a limited set of wildfires, we provide forest managers with insights that may inform reforestation efforts and future plantation investments. We selected a Weibull distribution to characterize the dispersion of fire severity within each plantation for several reasons. With some or all of the plantations being partially burned, using an average fire severity would eliminate our ability to emphasize the diversity of postfire outcomes. Fire severity in each plantation did not reflect a normal distribution, but rather the distribution of fire severity pixels was skewed to the left or the right (Appendix A); the Weibull distribution accounts for this attribute. Although the literature tends to depend on average fire severity or classes of fire severity, we asked local forest managers what they prefer; they indicated a distribution of fire severity would be more informative, particularly because most of the plantations contained a mixed fire severity outcome.

Methods

Study Area

This research was based on five wildfires that occurred on the Idaho Panhandle National Forests (IPNF) and Nez Perce–Clearwater National Forests (NP-CWNF) in northern Idaho in 2015 (Figure 1). The IPNF administers the Kaniksu, Coeur d'Alene, and St. Joe National Forests, whereas

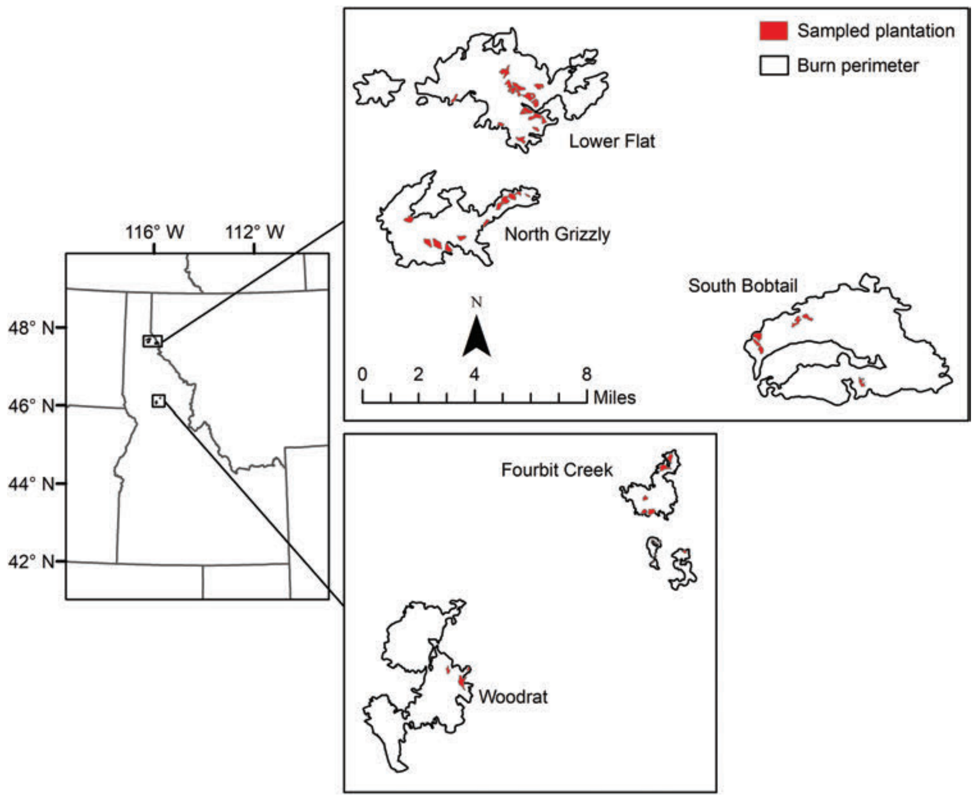

Figure 1. Location of 2015 wildfires (black perimeters) and sampled plantations (red polygons). Five wildfires were sampled: Lower Flat, North Grizzly, and South Bobtail fires burned on the Idaho Panhandle National Forests and the Woodrat and Fourbit Creek fires burned on the Nez Perce–Clearwater National Forests.

the NP-CWNF are located just south of the IPNF in north-central Idaho. These forests experience a maritime-influenced weather pattern despite being inland, with cold, wet winters and generally warm, dry summers. This weather pattern influences the dominant climax forest types, with western hemlock being more dominant in northernmost Idaho forests (on the IPNF) and western redcedar and grand fir more dominant to the south (on the NP-CWNF).

Study Design

We stratified all 100 burned plantations (≥ 5 acres) by age (year since planted) and fire severity. To obtain a list of plantations that occurred within the burn perimeters, we employed two data sources, the Monitoring Trends in Burn Severity (MTBS) (USDA Forest Service 2021b) and USDA Forest Service FACTS (Forest Service Activity Tracking System) databases (USDA Forest Service 2021a). The MTBS program uses Landsat satellite data to map fire severity for fires ≥1,000 acres across the western United States. Fire severity is estimated using the normalized burn ratio (NBR, Key and Benson 2006) and the differenced normalized burn ratio (dNBR). NBR and dNBR are defined as:

$$NBR = \frac{(NIR - SWIR)}{(NIR + SWIR)} \times 1000$$

$$dNBR = NBR_{pre} - NBR_{post}$$

where NIR is the near infrared Landsat band, SWIR is the shortwave infrared, and NBR_{pre} and NBR_{post} are pre- and post-fire NBR. Higher dNBR values indicate greater fire severity. Significant dNBR thresholds are then identified through analyst interpretation to create a fire severity class image.

MTBS data products for each fire were downloaded (https://www.mtbs.gov/) and dNBR and classified fire severity values (low, moderate, high) were extracted across plantation extents (Table 1). Within the NP-CWNF, some burned plantations fell within fires smaller than 1,000 acres that did not have MTBS data. To derive dNBR values for these plantations, we used the Google Earth Engine (GEE, Gorelick et al. 2017) script of Parks et al. (2018); dNBR values were classified as low, moderate, and high using the MTBS dNBR thresholds of downloaded products, which were nearly identical between products. For all the identified plantations, we obtained the year they were planted as the establishment date from the FACTS database. We created a sampling matrix of age class and fire severity (low, moderate, high) and assigned burned stands to each of the matrix cells. Stands within each cell were randomly ordered, and we prioritized the first four plantations in each cell for field sampling. In an ideal situation, we would have had an equal distribution of severity, but we had very few plantations in the high severity class, so we tried to get as many as possible. Therefore, if an age-fire severity class cell had fewer than four plantations, if time allowed, all plantations within cells were sampled. If a plantation wasn't accessible (i.e., required more than a one-hour hike) by the field crew or if the plantation didn't have WWP as a component of the planted species, it was not sampled but replaced by the next stand down the list within each cell (Table 1).

Field Data Collection

We located and measured a minimum of three plots in each selected burned plantation that were up to 12 acres in size; plantations larger than 12 acres had one plot added for every additional four acres (Table 1). Plots were established a minimum of 50 ft from any stand boundary to eliminate edge effect. To reduce sampling bias, a GIS-generated random starting point was used as the first plot and the remaining plots were located by selecting an azimuth that ensured the rest of the plots crossed the breadth and elevational gradient of the plantation. If stand size allowed, plots were spaced 200 feet apart, although in some cases, a shorter distance between plots was necessary due to stand shape, but all plots were at least 100 feet apart.

The field sampling plots were used to measure postfire survival of established trees. The plot was a circular 1/50 acre (16.7 foot radius) plot. All plot centers were geo-located using a Trimble global positioning system (GPS) unit logging approximately 150–200 positions. To measure postfire survival, we measured evidence of fire on the plot (Yes/No; Yes, if blackened soil and/or tree scorch). Slope, aspect, and elevation were obtained from the digital elevation model (DEM), using the GPS location as input. We counted the number of live and dead stems by species and DBH (diameter at breast height) class that were greater than or equal to breast height (4.5 feet above ground). We used 2 inch DBH classes until 15 inches DBH, then 5 inch classes until 30 inches, then all trees ≥ 30 inches DBH in the final upper class. Bark and crown architecture were used to identify the species for trees where needles were consumed by the fire. For WWP stems, we also noted if the tree had been pruned.

Table 1. Study sampling frame of the 48 plantations sampled. All plantations (100 total) within the wildfire parameters were binned by age class (establishment year planted) and fire severity (Monitoring Trends in Burn Severity [MTBS] classes based on differenced normalized burn ratio [dNBR] values). Number of plantations in each bin (*N*), selected plantation number in random order as selected, plantation size, plots in each plantation, silvicultural treatment (Group = group selection, CC/reserve = clearcut with reserves, Thin=commercial thin), and site preparation. Only the Idaho Panhandle (IP), and not the Nez Perce–Clearwater (NP-CW) National Forests, had high severity plantations.

Age class/fire severity	National Forests	*N*	Plantation number	Plantation size (acres)	Number of plots	Silvicultural treatment	Site preparation
1984–1989/Low	IP	12	42	33	8	Clearcut	Prescribed fire
			26	21	4	Clearcut	Prescribed fire
			22	26	8	Clearcut	Pile and burn
	NP-CW	10	112	28	7	Clearcut	Prescribed fire
			123	13	4	Clearcut	Prescribed fire
			118	43	10	Clearcut	Prescribed fire
			119	12	4	Clearcut	Pile and burn
			130	24	4	Clearcut	Pile/Prescribed fire
1984–1989/ Moderate	IP	10	38	17	4	Clearcut	Prescribed fire
			76	33	4	Salvage	Pile and burn
			41	27	8	Clearcut	Prescribed fire
1984–1989/High	IP	1	40	21	5	Clearcut	Prescribed fire
1990–1994/Low	IP	8	5	27	4	Clearcut	Pile and burn
			13	18	5	Clearcut	Prescribed fire
			77	39	10	Clearcut	Prescribed fire
			14	23	7	Clearcut	Prescribed fire
	NP-CW	3	132	16	5	Clearcut	Prescribed fire
1990–1994/ Moderate	IP	11	74	16	3	Clearcut	Pile and burn
			8	10	5	Clearcut	Mechanical
			12	27	10	Clearcut	Prescribed fire
			78	22	6	Clearcut	None
			71	39	10	Clearcut	Prescribed fire
	NP-CW	3	131	37	9	Clearcut	Pile/Prescribed fire
			117	34	9	Clearcut	Pile/Prescribed fire
1990–1994/High	IP	6	24	15	4	Clearcut	Prescribed fire
			73	41	10	Clearcut	Pile and burn
			15	13	3	Seedtree	Prescribed fire
1995–1999/Low	IP	8	59	23	6	Clearcut	Prescribed fire
			49	31	9	Clearcut	Prescribed fire
			56	40	10	Clearcut	Prescribed fire
			60	35	8	Clearcut	Prescribed fire
	NP-CW	3	105	11	4	CC/reserve	Prescribed fire
			113	30	8	CC/reserve	Prescribed fire
			106	22	7	Seedtree	Prescribed fire
1995–1999/ Moderate	IP	11	63	33	5	Clearcut	Prescribed fire
			75	137	3	Clearcut	Prescribed fire
			57	32	8	Clearcut	Prescribed fire
			6	28	10	Clearcut	Prescribed fire
	NP-CW	1	122	9	3	CC/reserve	Prescribed fire
2000–2014/Low	IP	7	46	6	3	Group	Prescribed fire
			82	11	7	Clearcut	Yard/Burn piles
			81	10	8	Seedtree	Yard/Burn piles
			70	29	7	Thin	Prescribed fire
	NP-CW	1	104	24	10	Thin	Yard/Burn piles

Table 1. Continued

Age class/fire severity	National Forests	*N*	Plantation number	Plantation size (acres)	Number of plots	Silvicultural treatment	Site preparation
2000–2014/ Moderate	IP	3	7	69	10	Group	Pile and burn
			45	7	3	Group	Prescribed fire
2000–2014/High	IP	2	44	6	3	Group	Prescribed fire
			9	34	8	Clearcut	Prescribed fire

Geospatial Data

In addition to the continuous dNBR and classified fire severity grids from MTBS and the GEE script of Parks et al. (2018), we acquired a 2014 aboveground forest biomass grid derived from lidar, Landsat, climate, and topographic data (Hudak et al. 2020). We extracted dNBR and aboveground forest biomass distributions within each plantation extent for statistical analysis.

We used site-specific climate-induced parameters that influence the bottom-up drivers of fire behavior, such as site-specific soil moisture parameters, snow-free days (SFD), and received solar radiation across plantation extents (Figure 2). We used the 30 m climate normal (30 year average) grids (1981–2010) that were adapted from 250 m climate normal grids developed as part of TOPOFIRE, a system for monitoring climate-induced soil and fuel moisture in complex terrain (Holden et al. 2019). These grids included snow water equivalent (SWE), soil water deficit (DEF), SFD, and solar radiation (SRAD) (Table 2). We extracted these variable distributions within each plantation extent for statistical analysis.

In addition to climate-induced variables, we produced several topographic variable grids to be used as explanatory variables in statistical analyses. DEMs (10 m spatial resolution) underlying the plantations were downloaded from the National Resources Conservation Service Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/). Slope (percent), topographic position index at 984 feet (TPI, Gallant and Wilson 2000), and transformed aspect (TRASP, Roberts and Cooper 1989) grids were derived from DEMs using the “raster” package in R (Hijmans 2016, R Core Team 2020) (Figure 2). TPI is defined as:

$$TPI = z_i - \bar{z}$$

where z_i is the elevation of pixel i and $\bar{z}$ is the mean elevation of surrounding pixels in a circle surrounding pixel i; in our case the radius of the surrounding circle was 984 feet. TPI describes slope position; positive values indicate ridge tops, values near zero indicate mid slope, and negative values indicate slope bottoms. TRASP is defined as:

$$TRASP = \frac{1 - (\cos(aspect - 30))}{2}$$

where *aspect* is in degrees. TRASP ranges from zero to one, where a value of zero indicates the coolest, wettest aspect at 30° and a value of one indicates the warmest, driest aspect at 210°. We extracted distributions of the DEM, slope, TPI, and TRASP grids within plantation extents for statistical analyses.

dNBR Pixel Distributions

To address our first question to understand the distribution of fire severity within plantations, instead of a single averaged value or a fire severity class as is the common approach, the distribution of dNBR pixels within a plantation were modeled for each stand using the two-parameter univariate Weibull distribution. Pixels of dNBR can often vary within a stand and across landscapes, especially in areas affected by mixed-severity fires. Averaging over all dNBR pixels within a stand or within a burn perimeter does not fully capture the variability in fire severity and thus potential tree survival. This uncertainty can complicate management decisions if areas within plantations need to be planted with tree seedlings following a wildfire. Using a Weibull distribution approach to model dNBR pixels could better characterize the diversity of fire-severity values within an area and better inform postfire management decisions. The Weibull distribution is a highly flexible functional form that can account for substantial variation such as that in a mixed-severity plantation. It is a unimodal distribution, so multiple peaks of dNBR values may not be fully accounted for by the distributions (Appendix A). Distribution parameters can be interpreted in terms of distribution magnitude (scale) and skewness (shape) (Figure 3). The two-parameter Weibull distribution probability density function has the following form:

$$p\,(X) = \frac{\beta X^{\beta-1} e^{-((X/\eta)^{\beta} - (\eta)^{\beta})}}{\eta^{\beta}}$$

where X is the dNBR pixel value, β is the shape parameter, and η is the scale parameter. We estimated the Weibull shape and scale parameters using the “fitdist”

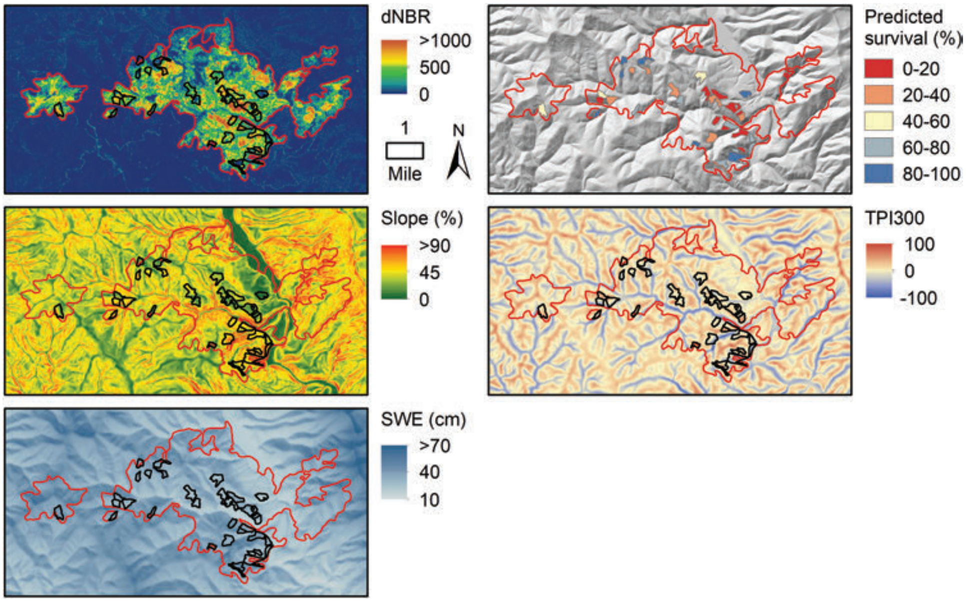

Figure 2. Panel illustrates a few attributes we used in the modeling within the perimeters of the Lower Flat wildfire. Attributes include differenced normalized burn ratio (dNBR), slope, snow water equivalent (SWE), topographic position index 984 ft pixel average (TPI; a value of 0 is midslope, negative value indicates lower slope, positive value indicates upper slope), and predicted survival using the models developed in this study.

Table 2. Mean and range of prefire, postfire, and biophysical characteristics of western white pine (WWP) plantations sampled. $N = 48$ plantations. How variables were calculated and defined are in the text.

Variable (units and definition)	Mean	Minimum	Maximum
Prefire characteristics			
Above ground biomass (AGB, tons ac^{-1})	131.2	57.4	239.3
Grand fir (trees ac^{-1})	455.4	0.0	1950.0
Western white pine (trees ac^{-1})	182.8	0.0	755.0
Postfire characteristics			
dNBR (unitless)	277.83	–23.3	729.6
Weibull shape	2.998	1.386	6.380
Weibull scale	489.5	123.3	986.3
Tree survival (%)	43.5	0.0	96.5
Biophysical characteristics			
Elevation (feet)	3890.0	2944.0	4979.0
TRASP (0 to 1)	0.363	0.027	0.897
Slope (%)	32.9	5.94	64.05
Snow water equivalent (SWE, inches)	12.9	6.1	20.2
Soil water deficit (DEF, inches)	14.1	9.6	21.5
Snow free days (SFD)	148	124	175
Soil radiation (SRAD, W m^{-2})	3575	3049	4040
Topographic index (984 ft pixel)	8.5	–22.6	40.2

function in the *fitdistrplus* package version 1.0-14 (Delignette-Muller and Dutang 2015) in R version 4.0.3. (R Core Team 2020). Because the Weibull distribution is only valid for positive values, all dNBR pixel values (included some negative values indicating vegetation growth in unburned pixels) were adjusted up by adding 100. Parametric bootstrap resampling was used to estimate the mean and 95% confidence intervals of the Weibull distribution parameters with 10,000 iterations for each plantation using the "bootdist" function in the *fitdistrplus* package (Delignette-Muller and Dutang 2015).

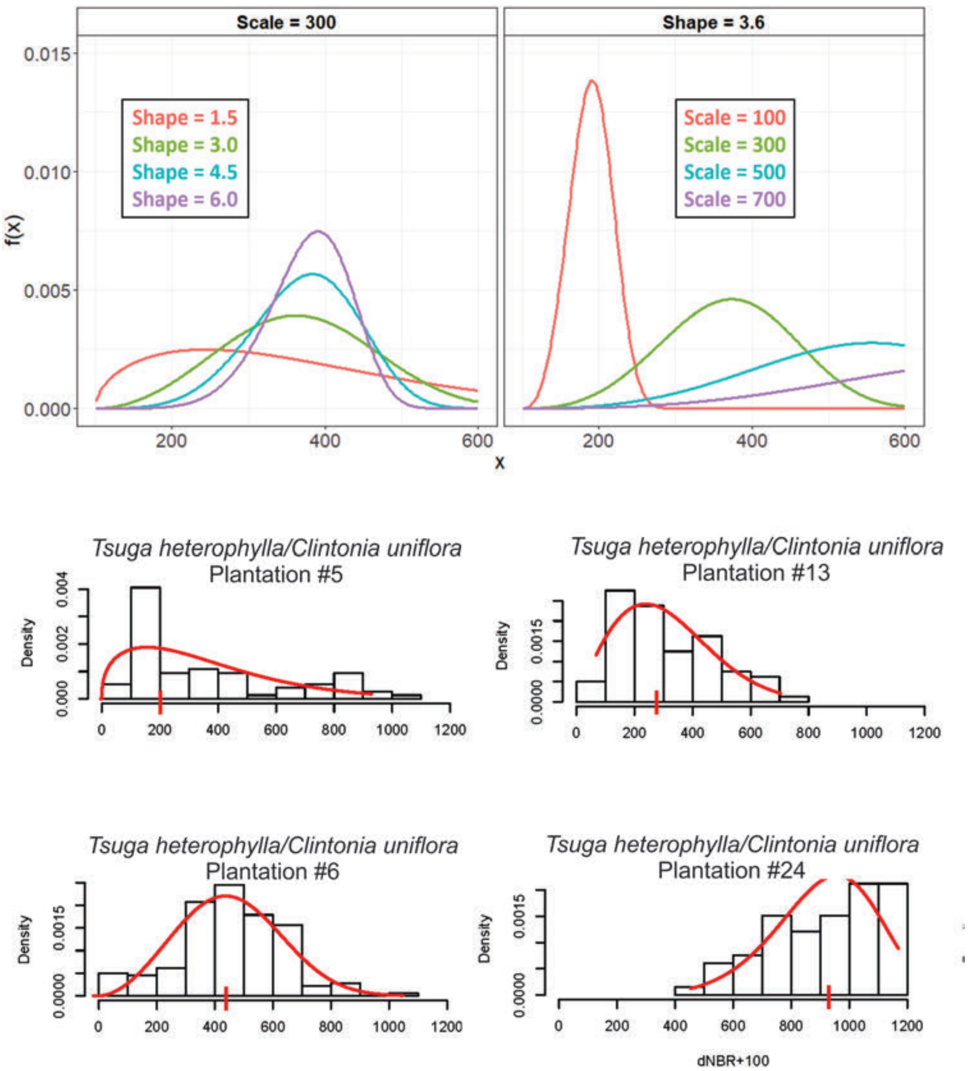

Figure 3. Illustration of different Weibull density distributions. The top figures show hypothetical Weibull distributions when the shape can vary at a scale of 300 and when the scale is allowed to vary at a shape of 3.6. The bottom four figures show histograms of differenced normalized burn ratio (dNBR) values and Weibull distribution fit to the data for a selection of western white pine (WWP) plantations. The small vertical red line indicates the median value of the Weibull distribution.

Statistical Analysis

The shape and scale parameters of the Weibull distribution can characterize the frequency of dNBR pixels in each plantation (Appendix A). For a fixed-scale parameter value, increasing shape parameter values shift the distribution to the right and increase the peak at the most frequent values (Figure 3). When the scale parameter increases for a fixed-shape parameter, the distribution shifts to the right, indicating a greater frequency of high fire-severity values. As both the shape and scale parameters describe the Weibull distribution, the parameters should be influenced by biophysical and prefire stand structural and compositional variables. Therefore, to address our second question of how biophysical settings and characteristics are associated with the distribution of wildfires within plantations, linear regression models were fit for the shape and scale parameters to identify the influence of biophysical and preburn plantation characteristics on the distribution of fire severity across stands. The biophysical variables screened for significance in linear regression models included elevation, slope, TRASP, TPI, SWE, DEF, SFD, and SRAD (Table 2). Correlation between variables were examined and if correlations were greater than 0.5, only one variable was tested in the full models of the shape and scale parameters. Nonsignificant variables ($P > 0.05$) were dropped sequentially, starting with the least significant variables, until the final model included only significant predictor variables with low correlation. Model residuals were evaluated to ensure assumptions of normality and heterogeneous variance. Dependent

Table 3. Parameter estimates (and standard errors) of linear regression models of differenced normalized burn ratio (dNBR) Weibull shape and scale parameters in relation to biophysical and stand structure variables. All variables were significant at $P < 0.05$. The root mean square error (RMSE) indicates how well the model fit the observed data, with lower values indicating a better model fit.

Weibull parameter	Intercept	Slope (%)	Topographic position index	Snow water equivalent (in)	Grand fir density (trees ac^{-1})	Western white pine density (trees ac^{-1})	R^2	RMSE
ln (shape)	1.3121 (0.1919)	0.0137 (0.0037)	0.0078 (0.0036)	−0.0055 (0.0016)	−0.0002 (0.0001)	—	0.424	0.3281
Variation explained (%)	--	3.2	8.6	24.5	6.6	—	—	—
ln (scale)	5.41421 (0.1643)	0.0125 (0.0042)	0.0101 (0.0049)	—	—	0.0009 (0.0003)	0.390	0.4292
Variation explained (%)	—	13.4	11.2	—	—	14.9	—	—

variables of both models were transformed with the natural logarithm to meet the assumption of the analysis. Because the shape and scale parameters are derived from the same distributions, they are inherently correlated. Therefore, the shape and scale regression models were fit simultaneously with seemingly unrelated regression (Zellner 1962), which accounts for the covariance structure of the residuals. This model was fit using the *systemfit* package in R (Henningsen and Hamann 2007). Model fit was evaluated using the generalized R^2.

Tree survival was calculated based on the field data collected in the main plots (trees ≥ 4.5 ft tall) by dividing the number of living trees by the sum of the living and dead trees after the fires. To address our third question of how the distribution of fire severity within plantations influenced tree survival and postfire vegetation responses, linear regression was used to examine the effects of the Weibull distribution shape and scale parameters, along with the biophysical variables, and stand structure variables on tree survival. For plantations that were not field sampled, we predicted survival of nonsampled plantations that were within the 2015 wildfire perimeters using the regression model we developed.

Results

Prefire, Postfire, and Biophysical Characteristics

Prior to the wildfires, average aboveground biomass estimated from the Hudak et al. (2020) rasters in the plantations ranged from 57.4 to 239.3 tons ac^{-1} (Table 2). The field data indicated that the plantations contained more grand fir per acre (455 trees ac^{-1}) than WWP per acre (182 trees ac^{-1}). Postfire dNBR ranged from –23.3 to 729.6 with a mean value of 277.8. Mean value of the Weibull distribution shape parameters was 2.998 and the scale parameters was 489.5, suggesting the fire-severity values were slightly skewed towards a greater number of pixels classified as high fire severity such as plantation #24 (Figure 3). Biophysical characteristics indicated that plantations occurred across a range of cooler and wetter sites (TRASP minimum of 0.027) to warmer and drier sites (TRASP maximum of 0.897). SWE ranged from 6.1 in to 20.2 in. TPI values indicate that many of the plantations tended to occur on lower (–22.6) to mid slopes (40.2).

Postfire dNBR in Relation to Biophysical Setting and Prefire Forest Composition

Weibull distributions were fit to the dNBR pixel values for each stand as we hypothesized that the distributions better captured the variability in pixel values within a plantation than a mean dNBR value or a fire severity class. When Weibull distributions were fit to dNBR pixels, it was clear the distributions did a good job approximating the variability in the dNBR values, although some plantations showed multiple peaks of dNBR values (Appendix A).

Results from the linear regressions, used to identify biophysical settings and characteristics influencing distribution of fire severity within plantations, found that both physical setting and prefire characteristics related to the distribution of dNBR pixels across plantations (Table 3). Slope and TPI were both significantly correlated with the Weibull shape and scale parameters. Predicted Weibull distributions across the

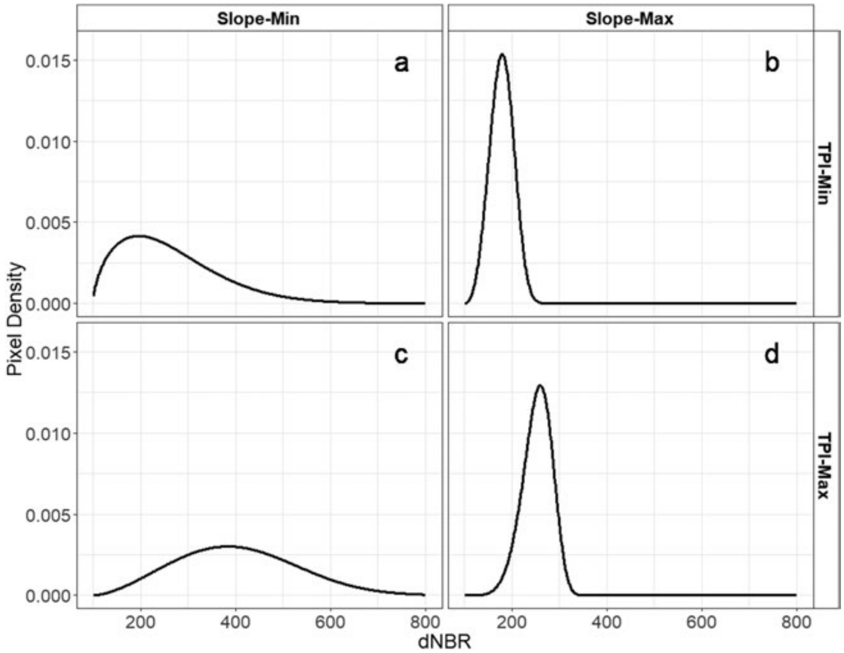

Figure 4. Relation of Weibull density distributions to differenced normalized burn ratio (dNBR) for minimum (5.9%) and maximum slope (64.0%) and minimum (−22.6) and maximum (40.251) topographic position index 984 ft pixel average (TPI). TPI value of 0 is midslope, negative values are lower slope and positive values are upper slope. As slope increased, the density of the dNBR pixels become more concentrated and lower slope dNBR pixel values spread across a broader range (a and b). As TPI increases, burn severity increased on the upper slopes closer to the ridges (c and d).

range of slope and TPI show that as slope increased, the density of dNBR pixel values became more concentrated around a single fire-severity value (Figure 4A & B). This suggests less variable fire severity at higher slope positions. As TPI increased, the density of dNBR values shifted to the right for both the minimum and maximum slope positions (Figure 4C and D). This suggests higher fire severity towards the top of ridges.

Climate variables and species composition also influenced the distribution of dNBR pixels across the stands affected by the wildfire. SWE was negatively correlated with the dNBR Weibull shape parameter, whereas the density of WWP trees was positively correlated with the Weibull scale parameter (Table 3). Therefore, as SWE increased (i.e., moister sites), the distribution of dNBR values became more variable. (Figure 5A and B). dNBR values also became more variable with a greater density of WWP (Figure 5C and D), suggesting more variation in postfire outcomes.

Postfire Survival

To compare whether our approach of using Weibull distributions to characterize fire severity is an improvement over the common approach of using the mean dNBR value, we compared the fit and explained variance between two regression models with tree survival as the dependent variable. The first model included the mean dNBR value for a plantation as the predictor variable, whereas the second model included the Weibull shape and scale as predictor variables. The tree survival model with the Weibull parameters explained 8.3% more of the total variation in the data than the regression model that only included the mean dNBR value for each stand (Table 4). The dNBR Weibull shape and scale parameters were negatively correlated with postfire survival. Because lower Weibull shape parameters result in a broader spread in dNBR values and lower scale values result in lower mean dNBR (Figure 3), the negative correlation of these parameters with survival suggests that wildfires with dNBR pixels spread over a broader range of values (i.e., mixed-severity) but concentrated at lower severity values resulted in greater survival. Interestingly, as the proportion of grand fir increased in the stand, postfire survival also increased.

Discussion

We sought to determine which topographic variables (as surrogates of moisture and temperature regimes) as well as prefire forest characteristics related to the distribution of dNBR pixels within stands. Percent slope, TPI, and SWE were the topographic and climate variables associated with the Weibull

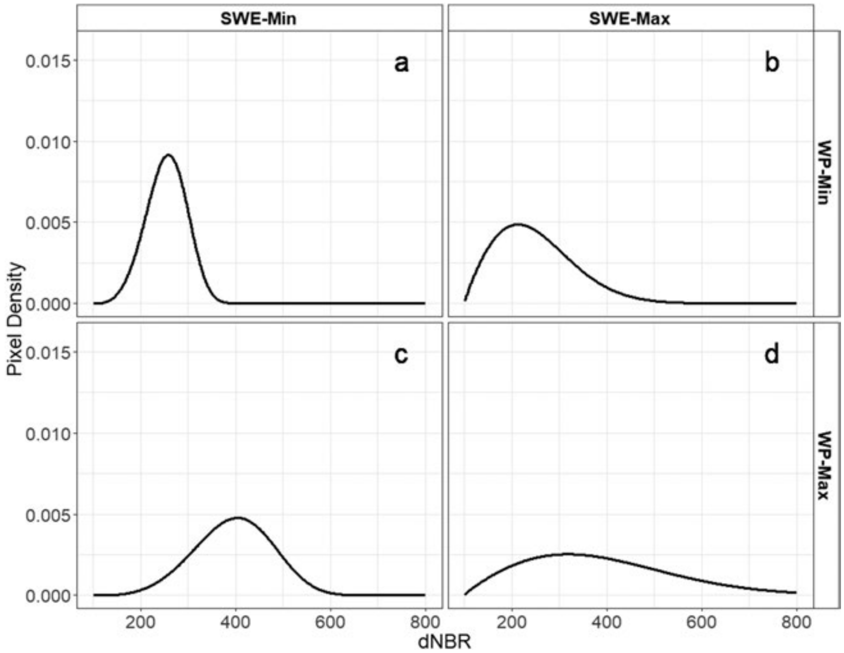

Figure 5. Relation of Weibull density distributions to differenced normalized burn ratio (dNBR) for minimum (6.1 in) and maximum snow water equivalent (SWE; 20.2 in) and minimum (182.8 trees ac^{-1}) and maximum (755.0 trees ac^{-1}) western white pine (WWP) tree density (trees ac^{-1}). With SWE maximum, the pixel density distributions of dNBR are much more variable (b and d). In contrast, when plantations had high amounts of WWP and minimum SWE, pixel distributions tended to move toward higher dNBR values (a and c).

Table 4. Two postfire regression results: postfire tree survival measured one year after the 2015 wildfires that was arcsine square root transformed with the mean differenced normalized burn ratio (dNBR) for a plantation as a predictor variable, and postfire tree survival measured one year after the 2015 wildfires that was arcsine square root transformed with the Weibull distribution shape and scale parameters as predictor variables. All variables were significant at $P < 0.05$.

Parameter	Parameter estimate (standard error)	Variation explained (%)
Postfire tree survival arcsine (sqrt (survival)) ($R^2 = 0.6707$)		
Intercept	0.9238 (0.0847)	
Mean dNBR	−0.0015 (0.0002)	54.1
Proportion of grand fir density	0.5748 (0.1394)	13.0
Total variation explained		67.1
Post-fire tree survival arcsine (sqrt (survival)) ($R^2 = 0.7547$)		
Intercept	1.3251 (0.1070)	
Weibull dNBR shape	−0.0809 (0.0300)	50.6
Weibull dNBR scale	−0.0010 (0.0001)	21.3
Proportion of grand fir density	0.3169 (0.1290)	3.5
Total variation explained		75.4

parameter regression models. Plantations that were located on the upper slopes (midslope to ridges) and greater than 30% slope tended to have greater fire severity. Within the context of fire behavior, slope percent and slope position have been noted to be bottom-up drivers (Kane et al. 2015, Estes et al. 2017). We found that SWE as a climate indicator of soil moisture provides additional insight in relation to postfire outcomes. Estes et al. (2017) found that slope position was an important topographic driver; mid- and upper-slope positions, where wind speeds are often greater, experienced higher fire severities than lower-slope positions. Wildfires usually burn upslope, preheating fuels, and the steeper the slope, the more rapidly the fire will burn upslope (e.g., Weise and Bigging 1996).

If the plantation occurred on lower topographic positions, the fire severity was low (dNBR 0 to 100); even on the steeper slopes (64% slope) at lower topographic positions, the dNBR was between 0 and 150. Also, these plantations had a higher SWE than mid or upper slopes and these locations tended to have higher postfire survival, even when slopes exceeded 30%. In contrast, when the topographic position was above midslope (TPI > 0), particularly on slopes greater than 30%, fire severity increased and the range in dNBR values decreased. On all slopes and slope positions, fire severity was not excessively high, as indicated by the range of dNBR. When we observe the dNBR Weibull shape model, there is more separation in fire-severity outcomes (Figures 4 and 5). When there were no WWP trees, places that tended to have a lower SWE had a higher frequency of consistent fire severities and dNBR values that ranged from 100 to as high as 300 (Figure 5). As SWE increased, WWP density did not highly influence dNBR, but when there was 750 trees ac^{-1} of WWP, the plantations tended to have more variation in dNBR.

We found that dNBR Weibull distributions, along with other variables, were effective predictors of postfire tree survival (R^2 = 0.76) in WWP plantations two years postfire. Like others (Dillon et al. 2011, Birch et al. 2015), we found that fire severity was related to topography and climate. Higher fire severity, as indicated by higher dNBR values, tended to occur on steeper slopes, on ridge tops (i.e., higher TPI values), and in drier areas, as indicated by lower SWE. In forest types that experience mixed-severity fires with a high level of variation in fire severity, dNBR Weibull distributions may be more informative than the classified or average dNBR values. dNBR varied considerably within the plantations sampled (Figure 2, Appendix A), and the Weibull distributions smoothed out this variability. However, the tree survival model with the dNBR Weibull parameters explained 8.3% more of the variation in the data than the regression model that only included the mean dNBR value for each stand.

One of the desired outcomes of this study was to infer how our results can be used to identify plantation locations that are more resistant to wildfire in the long-term, thus providing an opportunity for these plantations to grow to maturity and become a functional (e.g., seed production) contribution to the landscape. Results from this study indicated that mixed-severity outcomes (broader spread of dNBR values but concentrated around a lower mean dNBR within a plantation) with increasing proportion of grand fir favored higher tree survival. Plantations located in places with higher SWE and lower slopes may have deeper ash-cap soils and thus higher soil moisture; this leads to a topographic-driven decrease in fire intensity when compared with drier areas (Kimsey et al. 2007). With a shift in fire intensity, the influence of within-plantation variation of species composition and structure also influence surface fuel and live fuel moisture content. Green understory vegetation, because of its high foliar content compared with cured understory, may have a dampening effect on surface fire behavior (Agee et al 2002). However, fuel moisture content is a function of plant physiology and soil moisture conditions and thus more spatially variable (Pivovaroff et al 2019). Second, depending on the abundance of a particular species and its influence on shading the forest floor, there can be an effect on the variation in surface fuel loading and composition. Moreover, site preparation on most or all the plantations had prescribed fire, which has been related to a decrease in fire severity decreasing the surface fuel loads (Lyons-Tinsley and Peterson 2012) (Table 1). For future planning, more emphasis should be placed on locating plantations on lower slope positions, where, historically, WWP tended to dominate most stands.

Higher SWE was also a good indicator of plantation survival, which can be influenced by elevation and topography (Figure 2). Why was SWE a better indicator of fire severity than the other variables (Table 3)? Northern Idaho forest productivity is highly dependent on ash-cap soils, which play a critical role in water relations and nutrition. Kimsey et al. (2007) reported that thicker ash-cap mantles occur on north-facing aspects and on moist habitat types where SWE is greater. These tend to occur on the wettest sites (western hemlock potential vegetation) versus the drier south-facing aspects (grand fir and Douglas-fir potential vegetation), which were half the depth or less (Kimsey et al. 2007). Ash-cap horizons can have twice as much volumetric water-holding capacity as underlying horizons (Kimsey et al., 2007).

One shortcoming of this study was the limited years in which wildfires have burned through the moist mixed-conifer forests studied, where fire-return intervals vary widely (20 to 200 years); with the exception of 2015, many of these forests burned in the first thirty years of the 20th century (Arno et al. 2000). Fire suppression has drastically lengthened the fire-return interval (35 to 50 years) and future wildfires will likely continue to be extinguished given the extensive values at risk that need protection. Moist mixed-conifer forests have also changed substantially since the 1950s because of the loss of WWP, creating novel forest compositions and structures with little to no historical precedent. Thus, this study, although limited to one fire season and to a selection of WWP plantations in northern Idaho, does provide insight that can inform management strategies to create resilient forests and maximize reforestation efforts.

Unfortunately, we were unable to evaluate the effect of fire weather on our postfire outcomes for a variety of reasons, such as the lack of fire progression maps for all wildfires, the inability to know the particular day or time of day the wildfire burned in a specific plantation, the direction from which the wildfire entered the plantation, or whether fire suppression activities may have influenced how a plantation burned, all of which can influence the postfire outcome. However, we do acknowledge that having detailed fire weather at the specific time the plantation burned would likely identify a fire weather and topographic interaction as shown by Meigs et al. (2020), Povak et al. (2020), and Parks et al. (2018) and other similar investigations that describe the role of fire weather, topography, and fuel interactions in relation to fire behavior and effects. However, at one time under historical fire regimes, WWP dominated these forests, and the species does not reach moderate tolerance to fire until maturity (100+ years). Since 1970, we have suppressed more than 770 wildfires in these ecosystems (Gibson et al. 2014, Ruefenacht et al. 2008), so fire is uncommon. Therefore, there is a hypothesis we cannot test; that WWP-dominated forests combined with topography influenced fire outcomes by altering the local fire environment. It is important to recognize that this study does not include all factors that influence fire behavior and outcomes; only over time, as more fires occur within these moist mixed-conifer forests, can our findings be compared with future results.

Conclusion

This study provides managers with insight on plantation survival from wildfires in moist mixed-conifer forests in the northern Rocky Mountains. The study also gives evidence that the distribution of dNBR within plantations, and not just mean dNBR, provides additional insight on postfire condition within plantations, which may be particularly important for ecosystems that experience variable and mixed-fire regimes. Although this study only includes results from one fire season, it sets the foundation for learning and adapting management strategies to enhance plantation survival and reforestation strategies. The study also provides a basis for future monitoring of plantation survival after wildfires.

Supplementary Material

Supplementary material is available at *Journal of Forestry* online.

Appendix A. Weibull distribution of individual plantations that were field sampled. By applying the Weibull distribution, variation in dNBR pixels can be characterized and show the different shape and scale of each curve. Median is indicated with a red line on x-axis.

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Literature Cited

Agee, J.K. 2005. The complex nature of mixed severity fire regimes. P. 1–10 in *Mixed severity fire regimes: ecology and management*, Lagene L., J. Zelnik, S. Cadwallader and B. Hughes (eds.). Washington State University Cooperative Extention Service, Spokane, WA.

Agee, J.K., C.S. Wright, N. Williamson, and M.H. Huff. 2002. Foliar moisture content of Pacific Northwest vegetation and its relation to wildland fire behavior. *For. Ecol. Manage.* 167:57–66.

Arno, S.F. 1980. Forest fire history in the northern Rockies. *J. For.* 78:460–465.

Arno, S.F., D.J. Parsons, and R.E. Keane. 2000. Mixed-severity fire regimes in the northern Rocky Mountains: Consequences of fire exclusion and options for the future. P. 225–232 in *Wilderness science in a time of change conference*. USDA Forest Service RMRS-P-15-Vol-5, Rocky Mountain Research Station, Ogden, UT.

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(1):17.

Countryman, C.M. 1982. *Physical characteristics of some northern California brush fuels*. USDA Forest Service

Gen. Tech. Rep. PSW-61, Pacific Southwest Forest and Range Experiment Station, Berkeley, CA.

Delignette-Muller, M.L., and C. Dutang. 2015. Fitdistrplus: an R package for fitting distributions. *J. Stat. Software* 64(4):1–34.

DeRose, R.J., and J.N. Long. 2014. Resistance and resilience: a conceptual framework for silviculture. *For. Sci.* 60(6):1205–1212.

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(12):1–33.

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(5):e01794.

Gallant, J.C., and J.P. Wilson. 2000. Primary topographic attributes. P. 51–85 in *Terrain analysis: principles and applications*. Wilson, J.P. and J.C. Gallant (eds.). John Wiley & Sons, New York.

Gibson, C.E., P. Morgan, and A.M. Wilson. 2014. Atlas of digital polygon fire extents for Idaho and western Montana. 2nd Edition. Forest Service Research Data Archive, Fort Collins, CO. doi:10.2737/RDS-2009-0006-2

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore. 2017. Google Earth Engine: planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* 202:18–27.

Hagle, S.K., G.I. McDonald, and E.A. Norby. 1989. *White pine blister rust in northern Idaho and western Montana: alternatives for integrated management*. USDA Forest Service Gen. Tech. Rep. INT-261, Intermountain Research Station, Ogden, UT.

Henningsen, A., and J.D. Hamann. 2007. Systemfit: a package for estimating systems of simultaneous equations in R. *J. Stat. Software* 23(4):1–40.

Hijmans, R.J. 2016. *Raster: a geographic data analysis and modeling. R package version 2.5–8*. Available online at https://CRAN.R-project.org/package=raster; last accessed March 20, 2021.

Holden, Z.A., W.M. Jolly, A. Swanson, D.A. Warren, K. Jencso, M. Maneta, M. Burgard, et al. 2019. TOPOFIRE: a topographically resolved wildfire danger and drought monitoring system for the conterminous United States. *Bull. Am. Meteor. Soc.* 100(9):1607–1613.

Hudak, A.T., P.A. Fekety, V.R. Kane, R.E. Kennedy, S.K. Filippelli, M.J. Falkowski, W.T. Tinkham, et al. 2020. A carbon monitoring system for mapping regional, annual aboveground biomass across the northwestern USA. *Env. Res. Lett.* 15(9):095003.

Jain, T.B., and R.T. Graham. 2015. Restoring dry and moist forests of the inland northwestern United States. P. 467–493 in *Restoration of boreal and temperate forests*. Stanturf, J.A. (ed.) 2nd ed. CRC Press, New York.

Kane, V.R., C.A. Cansler, N.A. Povak, J.T. Kane, R.J. McGaughey, J.A. Lutz, D.J. Churchill, et al. 2015. Mixed severity fire effects within the Rim fire: relative importance of local climate, fire weather, topography, and forest structure. *For. Ecol. Manage.* 358:62–79.

Key, C.H., and N.C. Benson. 2006. Landscape assessment (LA): sampling and analysis methods. P. LA1-51 in *FIREMON: fire effects monitoring and inventory system*. USDA Forest Service Gen. Tech. Rep. RMRS-GTR-164-CD, Rocky Mountain Research Station, Fort Collins, CO.

Kimsey, M., B. Gardner, and A. Busacca. 2007. Ecological and topographic features of volcanic ash-influenced forest soils. P. 7–21 in *Volcanic-ash-derived forest soils of the inland Northwest: properties and implications for management and restoration*, Page-Dumroese, D., R. Miller, J. Mital, P. McDaniel, and D. Miller (eds.). USDA Forest Service RMRS-P-44, Rocky Mountain Research Station, Fort Collins, CO.

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. *For. Ecol. Manage.* 270:117–125.

Meigs, G.W., C.J. Dunn, S.A. Parks, and M.A. Krawchuk. 2020. Influence of topography and fuels on fire refugia probability under varying fire weather conditions in forests of the Pacific Northwest, USA. *Can. J. For. Res.* 50: 636–647.

Parks, S.A., L.M. Holsinger, M.A. Voss, R.A. Loehman, and N.P. Robinson. 2018. Mean composite fire severity metrics computed with Google Earth Engine offer improved accuracy and expanded mapping potential. *Remote Sens.* 10(6):879.

Perry, D.A., P.F. Hessburg, C.N. Skinner, T.A. Spies, S.L. Stephens, A.H. Taylor, J.F. Franklin, et al. 2011. The ecology of mixed severity fire regimes in Washington, Oregon, and northern California. *For. Ecol. Manage.* 262:703–717.

Pivovaroff, A.L., N. Emery, M.R. Sharifi, M. Witter, J.E. Keeley, and P.W. Rundel. 2019. The effect of ecophysiological traits on live fuel moisture content. *Fire* 2(2):28.

Povak, N.A., V.R. Kane, B.M. Collins, J.M. Lydersen, and J.T. Kane. 2020. Multi-scaled drivers of severity patterns vary across land ownerships for the 2013 Rim fire, California. *Landscape Ecol.* 35(2): 293–318.

Prichard, S.J., and M.C. Kennedy. 2014. Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event. *Ecol. Appl.* 24:571–590.

R Core Team. 2020. *R: a language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. Available online at https://www.r-project.org/; last accessed March 20, 2021.

Roberts, D.W., and S.V. Cooper. 1989. Concepts and techniques of vegetation mapping. P. 90–96 in *Proceedings—Land*

Classifications Based on Vegetation: Applications for Resource Management. USDA Forest Service Gen. Tech. Rep. INT-257, Intermountain Research Station, Ogden, UT.

Ruefenacht, B., M.V. Finco, M.D. Nelson, R. Czaplewski, E.H. Helmer, J.A. Blackard, et al. 2008. Conterminous U.S. and Alaska forest type mapping using forest inventory and analysis data. *Photogramm. Eng. Remote Sens*. 74(11):1379–1388.

Thompson, J.R., T.A. Spies, and K.A. Olsen. 2011. Canopy damage to conifer plantations within a large mixed-severity wildfire varies with stand age. *For. Ecol. Manage*. 262:355–360.

USDA Forest Service. 2021a. *FSGeodata clearinghouse*. Available online at https//data.fs.usda.gov/geodata/edw/datasets.php?xmlKeyword; last accessed March 22, 2021.

USDA Forest Service. 2021b. *Monitoring trends in burn severity.* Available online at https://www.mtbs.gov; last accessed March 22, 2021.

Weise, D.R., and G.S. Biging. 1996. Effects of wind velocity and slope on flame properties. *Can. J. For. Res*. 26(10):1849–1858.

Zellner, A. 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *J. Am. Stat. Assoc.* 57(298):348–368.