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Prescribed fire and fire suppression operations influence wildfire severity under severe weather in Lassen Volcanic National Park, California, USA

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Abstract. Fuels treatments and fire suppression operations during a fire are the two management influences on wildfire severity, yet their influence is rarely quantified in landscape-scale analyses. We leveraged a combination of datasets including custom canopy fuel layers and post-fire field data to analyse drivers of fire severity in a large wildfire in the southern Cascade Range, California, USA. We used a statistical model of tree basal area loss from the fire, factoring in weather, fuels and terrain to quantify the extent to which prescribed burning mitigated wildfire severity by simulating potential wildfire severity without prescribed fire and comparing that with modelled severity from areas burned with prescribed fire. Similarly, using a map of operations intensity, we calculated predicted fire severity under a scenario with no operations and used these predictions to quantify the influence of operations. We found that prescribed fires and operations reduced tree basal area loss from the wildfire by an average of 32% and 22% respectively, and that severity was reduced by 72% in areas with both prescribed fire and operations. Our approach could be applied to other wildfires and regions to better understand the effects of fuel treatments and fire suppression operations on wildfire severity.

Keywords: fire exclusion, fire management, fire severity, fire suppression, fuel treatments, prescribed fire management.

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Introduction

Increasing incidence of large, high-severity fires in western US forests over the past four decades has provoked concerns over fire-initiated forest loss and altered successional pathways (Westerling 2016; Liang *et al.* 2017; Coop *et al.* 2020). Climate change has accelerated this increase in fire activity, but fuel accumulation and increased tree density due to a century or more of fire exclusion have also played a role by increasing fire hazard (i.e. potential fire behaviour independent of weather, Hardy 2005) in lower to mid-montane forests of the western US (Brown *et al.* 2008; Scholl and Taylor 2010; Collins *et al.* 2011; Battaglia *et al.* 2018).

From a forest and fire management perspective, wildfire severity can be influenced in two primary ways. The first way is to reduce fuels through fuel treatments such as prescribed fire and thinning (Agee and Skinner 2005). A dampening effect of recent (within 10 years) fuel treatments, including prescribed fire, on subsequent wildfire severity has been well documented over limited extents in field-based studies (Fulé *et al.* 2012; Safford *et al.* 2012; Kalies and Yocom Kent 2016), and further supported by modelling of potential fire behaviour (van Wagtendonk 1996; Schmidt *et al.* 2008; Stephens *et al.* 2009). These field-based studies have demonstrated that fuel treatments can increase forest resilience to wildfire (Stevens *et al.* 2014). Furthermore, model simulations suggest that implementing fuel treatments over a portion of the landscape reduces landscape-scale risk of high-severity fire and therefore is vital to maintaining forest cover and carbon storage in forests adapted to frequent fire (Syphard *et al.* 2011; Liang *et al.* 2018; McCauley *et al.* 2019). Yet the degree to which fuel treatments reduce wildfire severity is a key uncertainty in these simulations and this effect is difficult to quantify over broader extents owing to confounding influences of weather and terrain that also influence fire severity. In addition, much of the literature on fuel treatment effectiveness has focused on dry pine and mixed-conifer forests whereas mid to upper-montane forest between the dry mixed-conifer and subalpine zones has received comparatively little attention (Schoennagel *et al.* 2004; Kalies and Yocom Kent 2016). However, studies of repeated wildfires that include mid to upper-montane forests have shown a dampening effect of past wildfires on reburn severity (Parks *et al.* 2014*a*; Harvey *et al.* 2016; Stevens-Rumann *et al.* 2016), suggesting that fuel treatments including wildfires managed for resource benefit would likely reduce wildfire severity in these forests. Because climate change and fire exclusion may be driving fire activity to increasingly higher elevations (Schwartz *et al.* 2015), evaluating fuel treatment effectiveness in these more mesic forest types is crucial.

One approach to assess the influence of fuel treatments is to build a statistical model of fire severity and to allow the strength and directionality of the fuel treatment effect to be assessed when other influences are taken into account (Finney *et al.* 2005; Wimberly *et al.* 2009; Harris and Taylor 2017; Lydersen *et al.* 2017; Prichard *et al.* 2020). However, this approach does not estimate the magnitude of the treatment effect on fire severity, only the strength of its influence in relation to other factors. Moreover, even if treatments have only low–moderate influence across an entire fire, they may have high influence on fire severity where treatments were conducted (Povak *et al.* 2020).

The second way in which wildfire severity can be influenced is through suppression operations during a wildfire. This includes any action used by fire crews *during* a fire to control spread, such as ground application of water or chemical retardants, fire line construction, backfiring and mopping up hot spots. Though effects of operations are a key uncertainty in analyses of wildfire severity, they are rarely accounted for owing to the difficulty of assessing the timing and extent of particular operations (Graham 2003; Birch *et al.* 2015; Estes *et al.* 2017). Prior work has stressed how firing operations (i.e. backfires or burn-outs) may increase fire severity, reduce the occurrence of low-severity forest patches that act as refugia, and therefore delay post-fire forest recovery (Backer *et al.* 2004; Driscoll *et al.* 2010; Stephens *et al.* 2013; Downing *et al.* 2019). However, operations could produce a wide range of fire effects depending on the conditions of fuels, terrain and weather when they are implemented. For example, Zhang *et al.* (2019) documented reduced risk of wildfire and increased growth in a ponderosa pine (*Pinus ponderosa*) plantation burned in a backfiring operation during a wildfire, suggesting operations increased forest resilience. The range of conditions under which fire suppression operations might increase or decrease fire severity relative to not conducting the operations is important to assess but has rarely been investigated. In addition, fuel treatments are known to facilitate suppression operations (Agee *et al.* 2000; Moghaddas and Craggs 2007), yet work quantifying their interactive effect on wildfire severity is again sparse.

In this study, we quantify and map the influence of prescribed fires and fire suppression operations on wildfire severity by developing a statistical model of wildfire severity, and then using the model to predict what fire severity would have been had prescribed fires and operations not occurred. Arkle *et al.* (2012) quantified prescribed fire effectiveness by developing a statistical model of wildfire severity outside treated areas and then using the model to predict wildfire severity within the treated areas, using a single set of vegetation and fuels variables. We extend this approach by modelling the severity of an entire wildfire, predicting fire severity using alternative sets of variables representing conditions in the absence of prescribed fires and operations, and then comparing the two sets of fire severity predictions. The statistical modelling framework that we use, in which the drivers of fire severity are evaluated at a pixel level using ensembles of classification or regression trees, is well established, spanning early efforts that highlighted the role of terrain (Holden *et al.* 2009; Dillon *et al.* 2011) to more recent studies that have considered a broader array of weather, fuel and other influences (Parks *et al.* 2018; Povak *et al.* 2020; Viedma *et al.* 2020). However, to our knowledge this statistical modelling approach has yet to be used to assess the influence of operations, or to quantify and map the influence of fuels treatments and operations on wildfire severity.

To develop a comprehensive statistical model of fire severity, we leveraged unusually rich fuels and vegetation datasets in a location that experienced a 11 465-ha wildfire (Reading Fire) in Lassen Volcanic National Park (LAVO) in the southern Cascade Range, California, USA. A century of fire exclusion had led to greater tree density and shifts towards fire-intolerant tree species in this area, which increased fire hazard and set the stage for high-severity wildfire (Fig. 1) (Taylor 2000; Bekker and Taylor 2010). However, the fire also burned over four recently conducted (<10 years prior) prescribed fires (Fig. 2). In addition, the fire was contained using widespread burn-out operations and other tactics (Lassen Volcanic National Park 2012).

Our two research questions were: (1) how did past prescribed fires influence wildfire severity, and what was the magnitude of this effect? We expected prescribed fires conducted in the 15 years before the wildfire to reduce fire severity, but that this effect might be somewhat dampened by the severe weather at the time of burning. (2) How did suppression operations during the fire influence fire severity? We hypothesised that operations might have moderated fire severity based on the generally lower severity observed near the margins of the fire where operations were reported to be more aggressive.

Methods

Study area

The 2012 Reading Fire burned 6946 ha within LAVO and the remainder of the fire burned in the adjacent Lassen National Forest. The fire was ignited by lightning on 23 July 2012, and initially grew minimally under moderate conditions (Lassen Volcanic National Park 2012). However, the fire spread rapidly under severe weather (i.e. >90th percentile) beginning with an increase in wind speed on 6 August (Fig. 2) before being contained on 22 August. The fire burned over four prescribed fires that had been conducted near the northern boundary of LAVO in 2003, 2005 and 2006 (Fig. 3), and it burned through these fuel treatments largely during >90th percentile weather (see further discussion in Supplementary material). Fortunately, Pierce *et al.* (2012) created custom canopy fuel layers for this area by surveying 223 field plots within LAVO in 2009–2010 and using statistical models to relate canopy fuel metrics to concurrent Landsat 5 imagery. The modelled relationships were then used by Pierce *et al.* (2012) to map canopy fuel using both 2003 and 2009 Landsat imagery, allowing us to characterise fuels both pre- and post-treatment. These canopy fuel layers were found to outperform fuel maps from the national LANDFIRE database (Rollins 2009) in predicting fire severity (Pierce *et al.* 2012). The Reading Fire also burned over the 1984 Badger wildfire and portions of 1920 and 2009 wildfires (Fig. 3), the latter of which facilitated management efforts to limit fire spread on the eastern flank (Lassen Volcanic National Park 2012). We restricted our analysis to an area for which custom fuels and vegetation layers

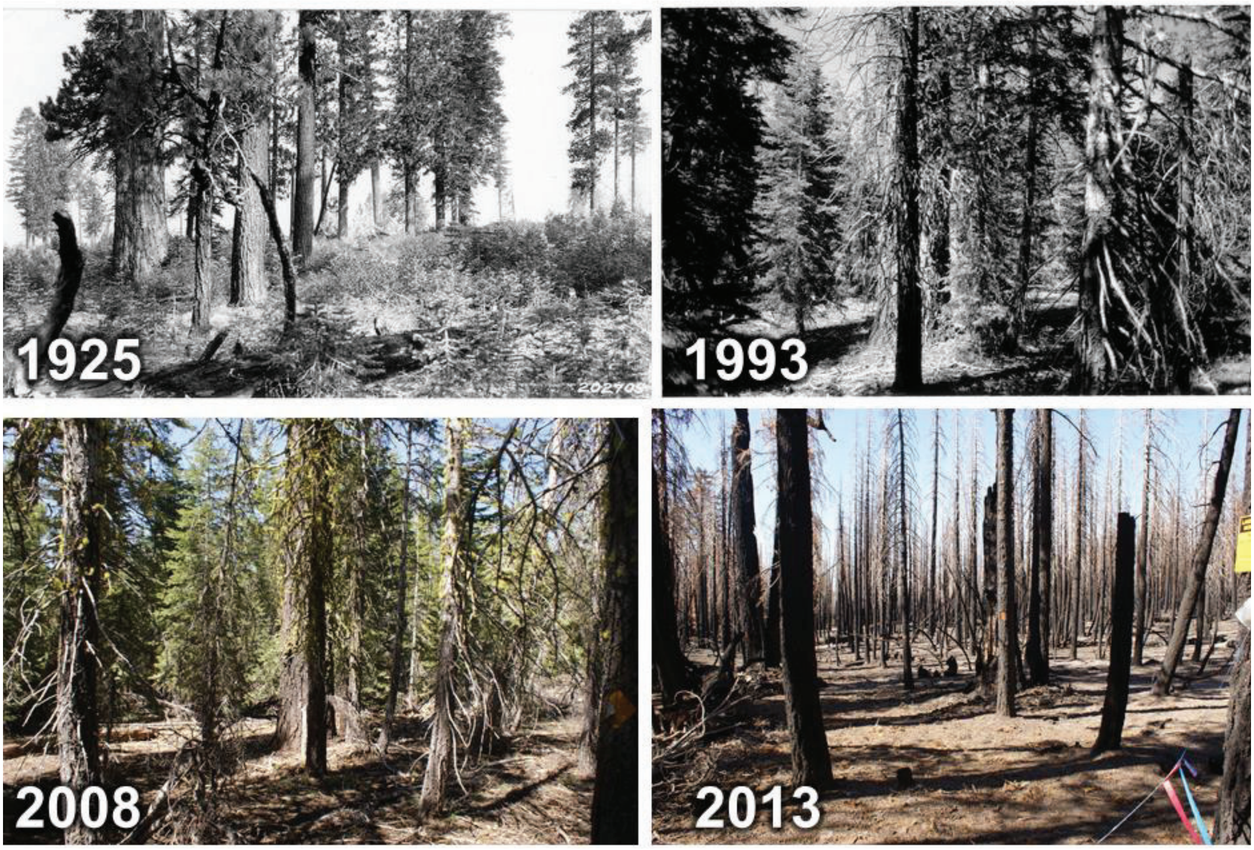

Fig. 1. Repeat photographs of the same location within the Reading Fire perimeter (year of photograph at lower left), illustrating 20th-century increases in tree density in a Jeffrey pine–white fir stand that burned at high severity in 2012.

were available, which included the entirety of the fire within LAVO as well as a small portion within the National Forest (7513 ha total, Fig. 3).

Within the study area, the fire burned at elevations between 1700 and 2300 m. The area has a Mediterranean climate and the winter snowpack commonly persists into May at middle elevations (Taylor 1990; Parker 1991). Mean daily temperatures at Manzanita Lake in LAVO (40.54°N, 121.57°W, 1783 m elevation) range from 0.0°C in December to 17.4°C in July and precipitation averages 1172 mm annually (based on 1998–2019 station data). Forest types within the fire perimeter included Jeffrey pine (*Pinus jeffreyi* Grev. & Balf.) and white fir (*Abies concolor* Gord. & Glend.) at lower elevations and xeric sites; red fir (*Abies magnifica* A. Murr.) in more mesic sites, commonly mixed with white fir at middle elevations and western white pine (*Pinus monticola* Dougl.) at higher elevations; and Sierra lodgepole pine (*Pinus contorta* var. *murrayana* [Grev. & Balf.] Engel.) in low-lying sites with cold air drainage or in disturbed areas (Parker 1991; Taylor 2000). The area within LAVO was never logged, and the portion of our study area on National Forest land had no recorded logging or fuel treatment history until the 2012 wildfire. Jeffrey pine and Jeffrey pine–white fir forests in the area burned frequently before Euro-American settlement (median point fire return intervals of 15–25 years), and 20th-century fire exclusion led to increased tree density and an accumulation of fuels in these forests (Taylor 2000; Bekker and Taylor 2010) (Fig. 1). Fir-dominated or lodgepole pine-dominated stands tended to burn less frequently historically (median point fire return intervals of 41–109 years) and consequently experienced less forest change due to fire exclusion though change was still evident in many stands (Taylor 2000; Taylor and Solem 2001).

Fire severity

We quantified the severity of the Reading Fire by calibrating a remote sensing index of fire severity, the Relative differenced Normalized Burn Ratio (RdNBR, Miller and Thode 2007) to the percentage mortality by tree basal area ('BA loss') from post-fire field data. This calibration to fire effects observed on the ground is important to give ecological meaning to spectral indices (Kolden *et al.* 2015), and we selected BA loss for our analyses because much of our study area was densely forested and therefore a field-based fire severity metric focusing on trees was appropriate. From 9 to 23 July 2013, we surveyed fire severity at 39 field plots within the Reading Fire (Fig. 3). A stratified random sampling approach by RdNBR fire severity class using the thresholds of Miller and Thode (2007) was used to select plot locations before fieldwork to ensure representation of a range of fire severities, and we restricted plot locations to $<$500 m from trails for ease of access. Within circular 707-m^2 plots, we measured the diameter at breast height (DBH) of all live trees, snags and logs $>$10 cm DBH within the plots. We

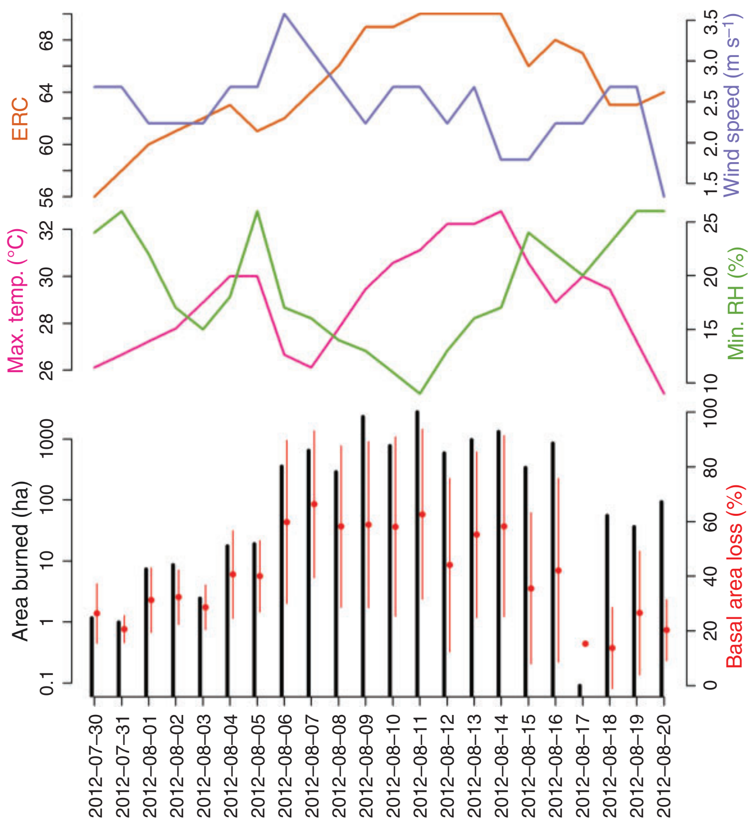

Fig. 2. Daily area burned, fire severity (mean ± s.d. of tree basal area loss) and weather during the Reading Fire including the Energy Release Component (ERC), average wind speed, maximum temperature and minimum relative humidity (RH) from the Manzanita Lake weather station.

used the tree diameters to calculate the proportion of tree basal area killed (BA loss) within the plots, excluding trees that appeared to have died before the fire. We developed linear regressions between Reading Fire RdNBR from the Monitoring Trends in Burn Severity program (MTBS, Eidenshink *et al.* 2007) and tree BA loss. Predictions for outlying RdNBR values were truncated to the range of possible BA loss values (0–100%). Based on linear regression models, we determined the following relationship:

$$\text{BA loss} = 9.43 + 0.101 \times \text{RdNBR} \left(R^2 = 0.72\right)$$

We also assessed the Composite Burn Index (CBI, Key and Benson 2006) in the same field plots and found that CBI and BA loss were strongly correlated ($r = 0.93$, Pearson correlation), and that our model of fire severity (see *Statistical modelling*) was highly similar when using the CBI in place of BA loss as the response variable (see Supplementary material).

Terrain

To assess the influence of terrain on fire severity, we derived four variables from a 30-m digital elevation model: elevation, slope steepness, aspect and the topographic position index (TPI). Aspect was cosine-transformed into a continuous variable ranging from 0 (south-west) to 2 (north-east) (Beers *et al.* 1966). The TPI (Weiss 2001) is the mean elevation difference between the focal cell and surrounding cells, and was calculated using a 600-m neighbourhood to identify mesoscale valley (negative values) and ridgeline (positive values) environments.

Fire history

Historical fire perimeters were downloaded from the California Department of Forestry and Fire Protection Fire and Resource Assessment Program (FRAP) (https://frap.fire.ca.gov/frap-projects/fire-perimeters/, version 18–1, accessed 13 Feb 20). In addition, we added a perimeter from one prescribed fire from 2003 (the Hole Fire) that was missing from the FRAP database (source: Lassen Volcanic National Park, see Fig. 2). BA loss was calculated for overlapping prior fires from 1984 to 2009 following the protocols used for the Reading Fire. Because no RdNBR layer was available from MTBS for the 2003 fire, we calculated RdNBR for this fire using Landsat 5 TM (Thematic Mapper) imagery from 23 July 2002 and 28 July 2004. A dNBR 'offset value' of –22 was used to account for differences between the two images as assessed in unburned areas adjacent to the fire (Key and Benson 2006). Based on historical fire perimeters and fire severity, we calculated two categorical fire history variables: years since last burn (0–14, 15–29, ≥30 years, no prior fire), and prior fire severity (<25% BA loss, low; 25–75%, moderate; >75%, high).

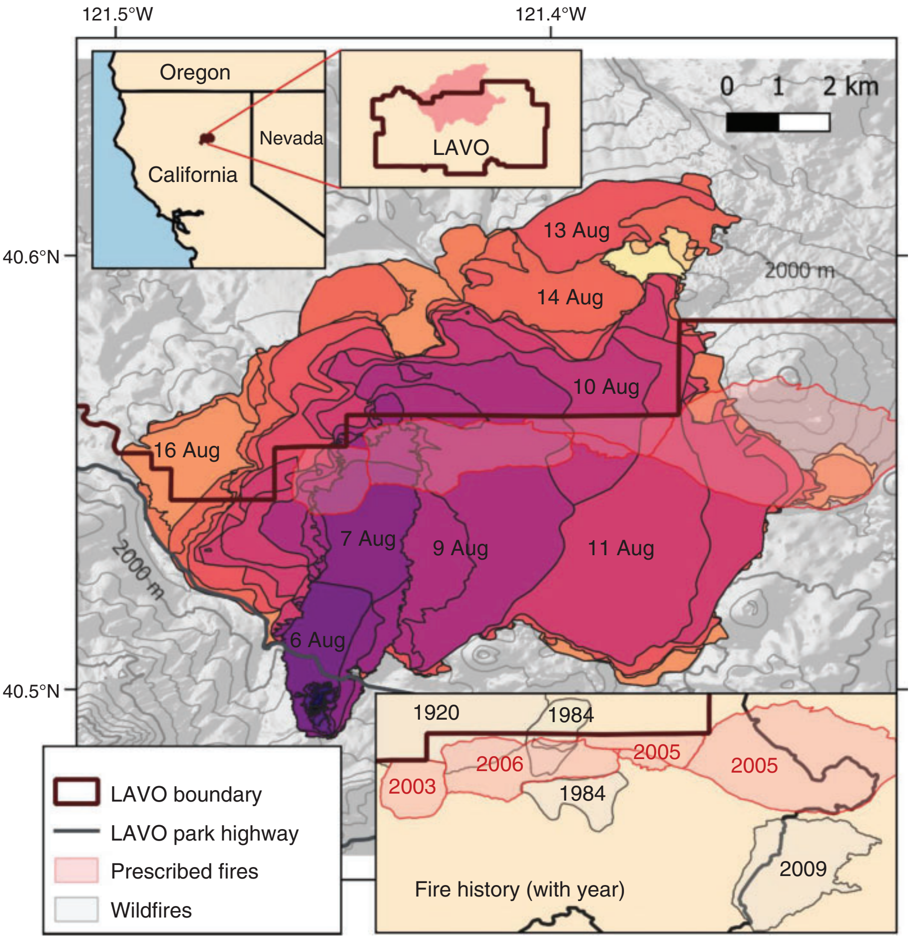

Fig. 3. Daily progression of the 2012 Reading Fire with key dates labelled. Perimeters and years of prior prescribed fires and wildfires are also shown. Insets at top show the location of Lassen Volcanic National Park (LAVO) within California and the location of the Reading Fire within LAVO. Elevation contour lines are at 100-m intervals.

Fire progression

A daily fire progression map for the Reading Fire (Fig. 2) was compiled from perimeters from the National Interagency Fire Center server (https://ftp.nifc.gov/public/incident_specific_data/, accessed 10 March 2020). Although knowing whether areas burned during the day or at night would have been useful for assessing fire weather influences, we mapped fire progression at daily resolution because only one fire perimeter map was available for most days. Perimeters from before noon were assigned to the previous day because such perimeters are likely to primarily represent area burned from the previous day (Parks 2014), unless a perimeter from after 2000 hours was available from the previous day to suggest otherwise as was the case for three perimeters dated 13, 14 and 18 August. This fire progression map was used to match daily weather with daily area burned.

Water balance

The California Basin Characterisation Model (Flint *et al.* 2013) was used to quantify actual evapotranspiration (AET) and climatic water deficit (CWD) for the 2012 water year (i.e. October 2011–September 2012). AET correlates with moisture availability for plants, which influences fuel productivity and therefore fire behaviour (Stephenson 1998; Littell and Gwozdz 2011; Parks *et al.* 2014*b*). CWD represents drought intensity, and may influence fire severity because high pre-fire water deficits make trees more susceptible to mortality from fire (van Mantgem *et al.* 2013*b*).

Fuels

To characterise canopy fuels, we considered four variables derived by Pierce *et al.* (2012): tree canopy cover; canopy bulk density (CBD), which measures the total quantity of canopy fuel available to a fire; canopy base height (CBH), or the distance from the forest floor to the lowest point on the crown; and canopy height. We subsequently removed CBD during the variable selection process because it was strongly correlated with canopy cover (Spearman rank correlation ≥ 0.75, see *Statistical modelling*). In addition, we made use of a map of surface fuel types for 2000 conditions used by Pierce *et al.* (2012) to represent spatial variation in surface fuels. The fuel

Table 1. Variables used in the statistical model of basal area loss from the 2012 wildfire

Type	Variable name	Definitions (range and mean or categories and number of samples)
Response	Tree basal area loss (%)	0–100 (57)
Fire history	Prior fire severity	No fire, 3920; low, 816; moderate, 361; high, 55
Fire history	Years since last burn	<15 years, 1155; 15–29 years, 186; 30–100 years, 231; no fire, 3580
Fuels	1935 vegetation type	Barren, 30; white pine, 350; herbaceous, 50; shrubland, 398; Jeffrey pine, 2627; white fir, 21; red fir, 585; lodgepole, 1076; riparian, 15
Fuels	2004 vegetation type	Barren, 96; riparian, 2; herbaceous, 67; shrubland, 87; Jeffrey pine, 236; white fir, 727; red fir, 2877; lodgepole pine, 1060
Fuels	Canopy cover (%)	9.4–75.8 (49.1)
Operations	Operations intensity	Low, 3749; moderate, 568; high, 835
Terrain	Transformed aspect (0, south-west; 2, north-east)	0.0–2.0 (1.1)
Terrain	Elevation (m)	1768–2338 (2012)
Terrain	Topographic position index (m)	–74–137 (0)
Water balance	Actual evaporation (mm)	280–622 (373)
Weather	Average wind speed (m s^{-1})	1.8–3.6 (2.6)
Weather	Energy release component	56–70 (68)

model maps include seven of the original fuel models of Anderson (1982) (numbered in Table 1), and three additional timber litter (TL) fuel models of Scott and Burgan (2005).

Although the surface fuel models serve as proxies for potential fire behaviour, particularly rate of spread, we also used vegetation type variables to indicate other aspects of fuel structure and flammability. To characterise vegetation types, we used data from the Vegetation Mapping Inventory Project of LAVO, in which vegetation types were manually interpreted from 2004 aerial photography (https://irma.nps.gov/Datastore/Reference/Profile/2244126). We condensed vegetation types from this map into the following classes: barren; herbaceous; shrublands; riparian; and forests dominated by: Jeffrey pine, white fir, red fir, aspen, lodgepole pine and western white pine. Non-vegetated areas (e.g. roads, developed areas, water, snow and ice) were excluded from the analysis. When available, maps of historical vegetation types may be useful in analyses of fire severity because they provide a more detailed picture of vegetation structure and composition (Harris and Taylor 2015). For example, a stand that was Jeffrey pine-dominated in the early 20th century but transitioned to fir-dominated by the end of the century is likely to have high fire hazard due to a high density of small-diameter firs. To characterise historical vegetation types, we used a 1935 vegetation type layer on file with LAVO and reclassified this layer to match the vegetation types used above (see Supplementary material for a comparison of these vegetation type layers). The 1935 map was generated using quantitative data in field plots and topographic maps to map vegetation cover types.

Operations

Fire suppression operations are often noted as a key uncertainty in analyses of fire severity, but their effects on fire severity are difficult to quantify because information on when and where certain tactics were used is not commonly available (Graham 2003; Birch *et al.* 2015; Estes *et al.* 2017). At the peak of the Reading Fire, resources assigned included more than 1200 personnel, consisting of 31 hand crews, 85 engines, 5 helicopters and support staff (Lassen Volcanic National Park 2012). Based on archival geospatial data and Incident Action Plans, we estimate that ~111 km of fire line was constructed, including 45 km of dozer lines, 42 km of existing roads and trails utilised (mostly unimproved dirt roads), and 14 km of hand line. We estimate that ~1100 ha of backfiring (National Wildfire Coordinating Group terminology, https://www.nwcg.gov/glossary/a-z) occurred to control or moderate fire spread and intensity along with 3310 ha of burn-out to consume fuels between fire lines and the edge of the fire (note that many of these firing operations were to the north of our study area). Aerial firefighting resources played a significant role in supporting ground crews and knocking down hot spots and spot fires, especially after 8 August, but it is impossible to estimate the exact numbers and locations of helicopter bucket drops and fixed-wing retardant drops from the available archival data. See Supplementary material for further description of suppression operations.

In this study, we used a combination of documentary information where available, and expert knowledge based on interviews with four fire operations specialists who worked on the Reading Fire (two Division Supervisors, an Operations Section Chief and a Decision Support Specialist), to classify polygons of fire operations intensity based on the aggregate of operational activities and their effectiveness in modifying fire activity in a given area. Documentary information included archival geospatial data from the National Interagency Fire Center (https://ftp.nifc.gov/public/incident_specific_data/), Incident Action Plans and the Reading Fire Review (Lassen Volcanic National Park 2012) as well as the interviews and additional photographs and notes. We produced a three-category map of operations intensity (Fig. 4) as follows:

Low: Fire suppression likely had minimal impacts on fire activity (e.g. rate of spread, time of burning, surface *v.* crown fire) in areas that burned (in some cases management may have prevented additional areas from burning).
Moderate: Fire suppression efforts likely had moderate to high impact on overall fire activity (i.e. fire activity would have likely been different in the absence of suppression).
High: Fire suppression was significant and was likely a strong influence on fire activity in most areas.

This map was generated independently of and before the analysis of fire severity, so that the classification and mapping of suppression operations would not be influenced by knowledge of observed patterns of fire severity or other inputs used in our analysis.

Weather

To determine how weather influenced fire severity, we obtained daily maximum temperature, minimum relative humidity and average wind speed at a height of 6.1 m from the Manzanita Lake weather station, which was <7 km west of the Reading Fire and was representative of conditions within the fire perimeter. We also calculated the Energy Release Component (ERC), a fire weather index that quantifies potential fire intensity based on large-fuel aridity (Bradshaw *et al.* 1983), using FireFamily Plus version 4.2 (Bradshaw and McCormick 2000).

Statistical modelling

To assess the relative influence of terrain, weather, fuels and fire history on fire severity, we created a random forest (RF) (Breiman 2001) model of BA loss. We built the RF model using the 'randomForest' *R* package using 2000 regression trees and the default value of $n/3$ variables considered at each node (Liaw and Wiener 2002). To quantify variable importance, we used the model improvement ratio (MIR), in which the most important variable is scaled to 1 and a variable with no effect on model accuracy is 0 (Murphy *et al.* 2010). Model accuracy was measured using the pseudo-r^2, which is analogous to r^2 but is calculated from the 'out-of-bag' sample, meaning the portion of the dataset withheld when building each tree (Breiman 2001).

Some of the variables considered were potentially redundant. To address this problem of redundancy, we iteratively ran RF models, identified the variable pair with the highest Spearman rank correlation (r_s), and removed the variable with lower variable importance. We continued this process until all pairs of predictors had $r_s < 0.75$, and in doing so removed CBD, which was correlated with canopy cover ($r_s = 0.95$), and minimum relative humidity, which was correlated with ERC ($r_s = -0.76$). Finally, we assessed the shape of relationships between the predictors and fire severity using partial dependence plots produced with the 'pdp' *R* package (Greenwell 2017). Based on the partial dependence plots, we removed maximum temperature from the model because it exhibited a negative relationship with BA loss, suggesting that temperature was serving as an indicator of some other influence on fire severity. We also removed CWD from the model because this variable had a nonsensical relationship with fire severity (i.e. jagged lines on the partial dependence plot; see Supplementary material), and instead included the other water balance component, AET. Finally, to further improve parsimony, we used steps one and two (thresholding and interpretation) of the variable selection procedure developed by Genuer *et al.* (2010) and implemented in the 'VSURF' *R* package (Genuer *et al.* 2015). Four variables were removed following this procedure (slope, surface fuel type, canopy height and CBH), resulting in 1% greater accuracy than if all 16 variables were included. The remaining 12 variables (Table 1) were used in final RF model.

Because spatial autocorrelation due to close spacing between samples can affect model results (Legendre and Fortin 1989), we sampled pixels on a grid and tested spacings from 120 to 390 m following the methodology of Kane *et al.* (2015*a*). After examining a correlogram of Moran's I values of model residuals (Moran 1950; Legendre and Fortin 1989), we selected the 120 m distance because it maximised sample size (n = 5056 pixels) relative to longer distances and had relatively small Moran's I values ($\leq$0.25). See Supplementary material for a full discussion of spatial autocorrelation.

Effect of prescribed fires and operations on wildfire severity

To evaluate potential fire severity had prescribed fires not been conducted, we used the RF model to predict fire severity using a second set of predictors that omitted these fires and their influence on fuels (hereafter the 'no prescribed fire' scenario). For the fire history variables, the prescribed fires were omitted from the time since fire and previous fire severity layers. Canopy fuel layers from Pierce *et al.* (2012) representing 2003 rather than 2009 conditions were used to create fuel maps as if the prescribed fires had not been conducted. We used the two sets of fire severity predictions (i.e. predictions from the 'prescribed fire' and 'no prescribed fire' scenarios) to quantify treatment effects on fire severity within the prescribed fire footprints. We then used a similar approach to assess the influence of operations by using the model to predict fire severity with all values for the operations variable set to 'low' and compared predicted fire severity values in areas with moderate–high operations intensity (referred to as the 'no operations' scenario). Finally, we predicted fire severity assuming neither prescribed fires nor operations to assess the interactive effect of fuel treatments and operations.

Results

Model of fire severity

The statistical model of BA loss had a pseudo-r^2 of 0.53, and maps of observed and predicted fire severity were visually similar except that the model predicted fewer very low (near 0% BA loss) and very high (near 100%) values (Fig. 5). The top three variables, which had similar importance to each other, were elevation, tree canopy cover and operations (Fig. 6). Fire severity responded negatively to elevation, positively to canopy cover and was lower in areas of moderate–high operations intensity.

A second group of eight variables had moderate importance (MIR 0.53–0.76, Fig. 6). Consistent with our expectations, BA loss was positively related to ERC (fourth important variable) and wind speed (11th). Areas of shrubland in 2004 tended to burn at the highest severity, followed by fir and lodgepole pine forest. Vegetation type in 1935 and 2004 had similar effects except that areas of Jeffrey pine in 2004 burned at lower severity whereas areas of Jeffrey pine in 1935 burned at higher severity (Fig. 6). Notably, 73% of Jeffrey pine forest in 1935 was identified as white or red fir-dominant in 2004. Ridgetops burned more severely than valleys (TPI, fifth), areas with high AET burned more severely (sixth), north-eastern aspects burned more severely than south-western aspects (ninth). Finally, areas that burned <15 years ago burned less severely (10th) although

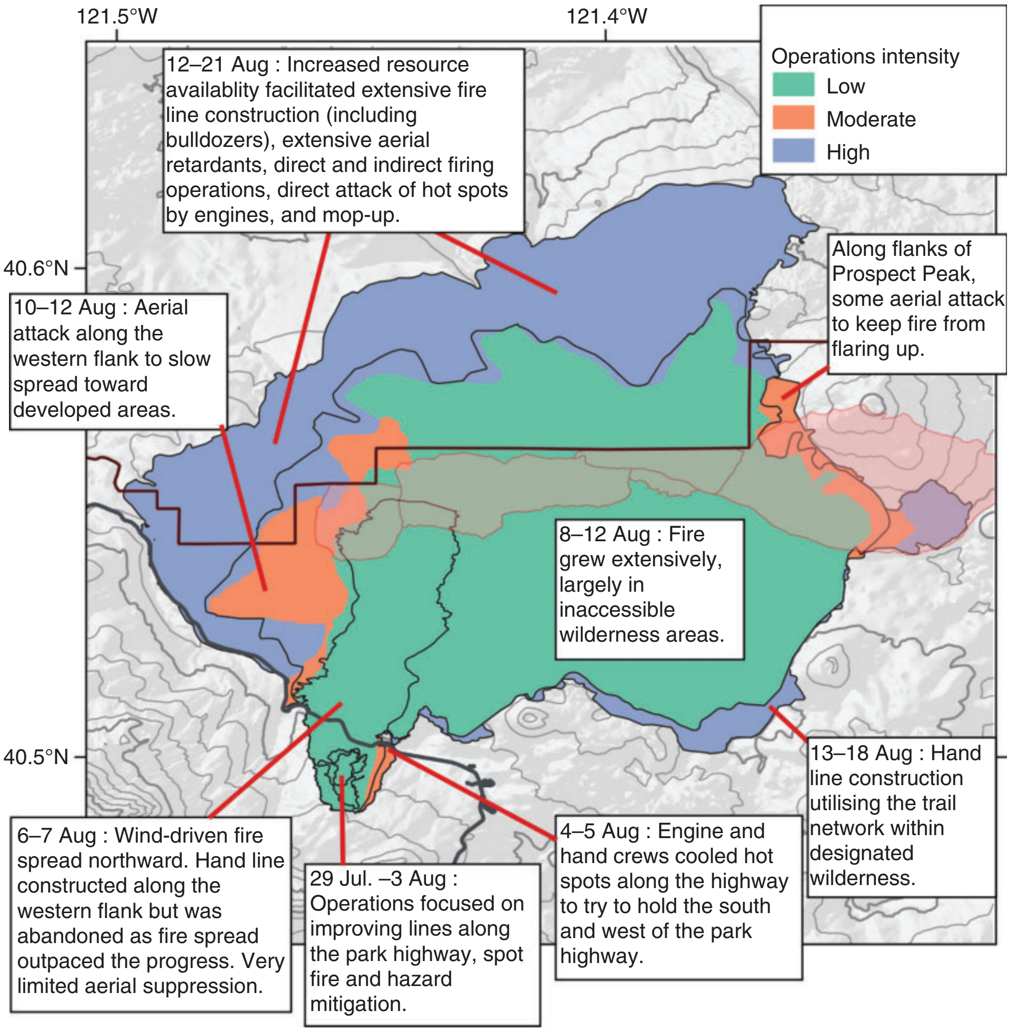

Fig. 4. Map of the intensity of fire suppression operations in the 2012 Reading Fire including descriptions of key time periods and operations. This map was generated based on interviews with four operations specialists on the Reading Fire and the personal experience of one of the authors (C. A. Farris). Past prescribed fires are shaded red, the brown line is the northern boundary of Lassen Volcanic National Park and the heavy grey line is the park highway.

areas burned >15 years prior had similar fire severity to those with no recorded fire (Fig. 6). Prior fire severity did not exert a strong influence (least important variable in the model). Notably, the prescribed fires had burned at predominantly low severity (79% of area had <25% BA loss) and therefore variability in prior fire severity was relatively low.

Influence of past fires and operations

Prescribed fire reduced BA loss by 32% on aggregate according to fire severity predictions in the 'no prescribed fire' scenario, although this effect was variable spatially and within vegetation types (Table 2, Fig. 5; see also Fig. S1, Supplementary material). Prescribed fire reduced predicted BA loss across all vegetation types although the effect was largest in Jeffrey pine forest (53% reduction) and smaller in fir and lodgepole pine forest (24–33% reduction, Table 2).

In areas with moderate–high operations intensity, operations reduced fire severity by 22% on aggregate according to fire severity predictions from the 'no operations' scenario (Table 3). As with prescribed fires, the effect of operations varied spatially and within vegetation types (Table 3, Fig. 5). On aggregate, operations reduced fire severity across all vegetation types (Table 3) but had a weak effect in white fir forest (6% reduction), a strong effect in Jeffrey pine forest (59% reduction) and intermediate effects in red fir and lodgepole pine forest. Fire severity was reduced by 72% in areas with both prescribed fires and moderate–high operations intensity (area of 410 ha), from $52 \pm 12\%$ to $14 \pm 9\%$ BA loss (Fig. 5).

Discussion

Influences on wildfire severity

Wildfires in the western US are increasingly burning under severe weather because fires burning under moderate conditions are typically contained or suppressed, because fuel aridity is increasing and because the occurrence of severe fire weather is becoming more likely with climate change (Skinner and Chang

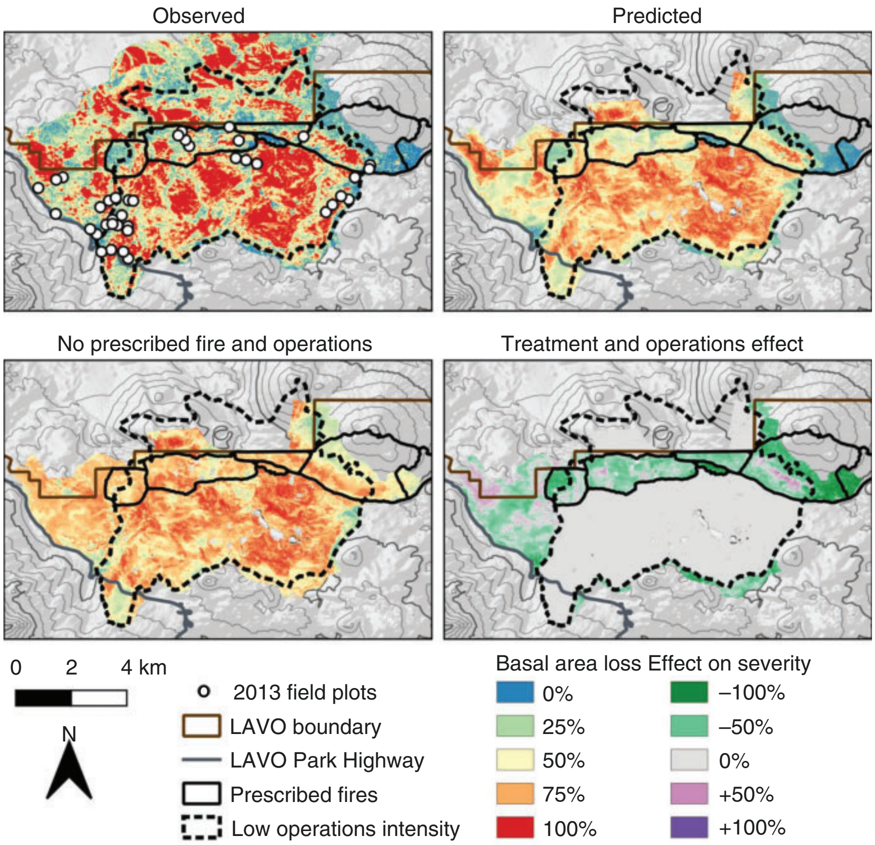

Fig. 5. Observed fire severity (tree basal area loss) from the Reading Fire, predicted fire severity under observed conditions and in the scenario assuming no prescribed fire or operations, and the percentage difference between the two predictions, i.e. the treatment and operations effect. Areas beyond (within) the black line experienced moderate–high (low) intensity of fire suppression operations. Locations of the field plots ($n = 39$) used to calibrate tree basal area loss are also shown.

1996; Agee and Skinner 2005; Collins 2014; North *et al.* 2015; Abatzoglou and Williams 2016). Weather was severe during much of the 2012 Reading Fire as evidenced by the >90th percentile ERC values after 8 August when much of the fire growth occurred. Productive forests with more abundant canopy fuel are structurally susceptible to high-severity fire, and combined with the drought conditions at the time of the Reading Fire, may explain the positive relationship that we found between canopy cover and fire severity. Povak *et al.* (2020) also found a positive relationship between tree cover and fire severity in California's Sierra Nevada, although research in California's Klamath Mountains has shown the opposite because low tree cover areas tended to have high shrub cover whereas areas of high tree cover had cooler understories with less ladder fuel (Odion *et al.* 2004; Grabinski *et al.* 2017). We also found fire severity was moderated in valley bottom locations (cooler, moister micro-climates) as evidenced by the lower severity we observed in herbaceous vegetation (largely wet meadows), riparian zones and areas of low TPI (i.e. valleys). These locations tend to have higher live fuel moistures than surrounding terrain (Van de Water and North 2010; Holden and Jolly 2011) and therefore lower fire severity (Bradstock *et al.* 2010; Harris and Taylor 2015; Kane *et al.* 2015*a*; Taylor *et al.* 2020), although reduced air flow in broad valleys could in some cases cause increased fire severity if fires burn more slowly. Different studies have found different relationships between elevation and fire severity depending on the region, elevation range and characteristic vegetation types (Weatherspoon and Skinner 1995; Parks *et al.* 2014*a*; Harris and Taylor 2017). In our case, a negative relationship between elevation and fire severity may be due to cooler and moister conditions at high elevations, or to the dominance of fire-intolerant lodgepole pine in low-lying basins (Harris *et al.* 2020).

We expected that Jeffrey pine would experience lower mortality from fire than firs or especially lodgepole pine owing to differences in bark thickness among species (Stevens *et al.* 2020), higher CBH and lower CBD in Jeffrey pine stands than fir or lodgepole pine stands (Pierce *et al.* 2012), and a positive effect of leaf length on fire severity via effects on litter density (Schwilk and Caprio 2011). Tree survival was indeed greater for more fire-resistant Jeffrey pine forest than for other forest types according to our statistical model, and our field data support this finding at the level of individual trees: considering all trees in the combined field plot data, Jeffrey pines experienced 31% BA loss whereas white fir, red fir and lodgepole pine experienced 57, 51 and 59% BA loss respectively. Although the influence of 1935

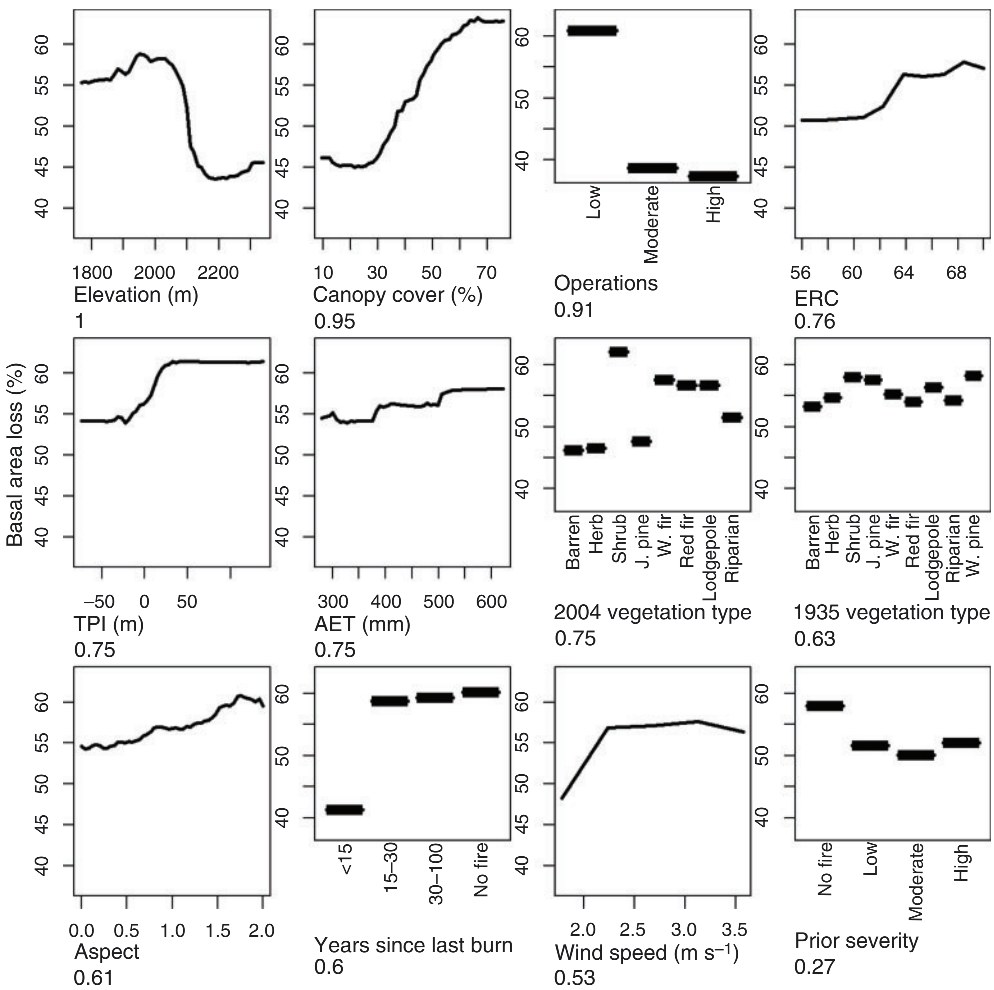

Fig. 6. Partial dependence plots showing the marginal effect of each predictor on tree basal area loss from the 2012 fire (model pseudo-r^2 0.53). Variable importance is shown below each variable name. See Table 1 for further details on variables and variable classes.

and 2004 vegetation types on fire severity was highly similar, there was one key difference: fire severity was low in areas of Jeffrey pine in 2004, but high in areas that were Jeffrey pine in 1935. Fire exclusion in yellow pine forests (i.e. Jeffrey pine and *Pinus ponderosa*) tends to favour ingrowth of shade-tolerant species with lower fire resistance, which increases fire hazard (Dolanc *et al.* 2014; Harris and Taylor 2015; Safford and Stevens 2017), and the vegetation type layers for the Reading Fire area suggest such a 20th-century shift towards shade-tolerant species. Therefore, areas of Jeffrey pine forest in 1935 were likely to contain small to medium-diameter firs, which likely led to increased fire severity, as illustrated in Fig. 1.

Influence of past fires

Prior fire severity was less important than time since last fire in our analysis, which makes sense given that most of the area with a recorded fire history had burned fewer than 10 years before the 2012 wildfire and that the prescribed fires had burned at predominantly low severity. According to prior work, a moderating effect of past fire on subsequent wildfire severity is likely to dominate if the interval between fires is less than 10 years as was the case for most of the prior fires in the Reading Fire footprint, but as the interval between fires increases, the relationship between prior and subsequent fire severity tends to strengthen such that a self-reinforcing effect of prior fire severity plays a greater role (Parks *et al.* 2014*a*; Harvey *et al.* 2016).

We found that prescribed fires conducted in the 10 years before the Reading Fire caused on average a 32% decrease in tree BA loss. Previous work suggests that recent fuel treatments (particularly within the past 10 years) are still effective at reducing fire severity under severe weather conditions, although much of that previous work focuses on stands that were mechanically thinned first rather than receiving only prescribed fire as was the case in our study area (Ritchie *et al.* 2007; Safford *et al.* 2012; Kalies and Yocom Kent 2016; Krofcheck *et al.* 2017; Lydersen *et al.* 2017). Modelling and remote sensing studies suggest that burn-only fuel treatments tend to reduce wildfire severity but not as strongly as thin and burn treatments (Finney *et al.* 2005; Stephens *et al.* 2009; Fulé *et al.* 2012; Yocom Kent *et al.* 2015). This is consistent with the fact that first-entry

Table 2. Effect of prescribed fires on wildfire severity
Fire severity (tree basal area loss ± s.d.) by vegetation type within prescribed fire perimeters, as predicted by the statistical model with and without prescribed fire

Type	With prior fire	Without fire	Treatment effect[A]	Area (ha)
Barren	25 ± 12%	31 ± 12%	−6 ± 7% (−19%)	29
Herbaceous	25 ± 11%	44 ± 7%	−19 ± 11% (−43%)	44
Jeffrey pine	17 ± 18%	36 ± 14%	−19 ± 9% (−53%)	212
White fir	49 ± 22%	65 ± 15%	−15 ± 19% (−24%)	303
Red fir	37 ± 18%	54 ± 21%	−18 ± 14% (−33%)	559
Lodgepole pine	45 ± 15%	66 ± 9%	−21 ± 16% (−32%)	427
Total[B]	38 ± 21%	56 ± 19%	−18 ± 15% (−32%)	1576

[A]Mean and s.d. of difference between model predictions without and with prescribed fire, with proportional change in parentheses.
[B]Total includes shrub and riparian types, not shown as separate rows because they covered only 1 ha each within footprints of prescribed fires.

Table 3. Effect of fire suppression operations on wildfire severity
Fire severity (tree basal area loss ± s.d.) by vegetation type within areas of moderate–high operations intensity, as predicted by the statistical model with and without operations

Type	Operations	No operations	Operations effect[A]	Area (ha)
Barren	24 ± 10%	37 ± 9%	−13 ± 7% (-36%)	54
Herbaceous	31 ± 11%	37 ± 8%	−6 ± 6% (-16%)	24
Shrub	61 ± 11%	70 ± 6%	−9 ± 10% (-12%)	25
Jeffrey pine	14 ± 13%	36 ± 12%	−21 ± 7% (-59%)	236
White fir	61 ± 21%	65 ± 11%	−4 ± 16% (-6%)	684
Red fir	39 ± 19%	54 ± 18%	−15 ± 12% (-28%)	930
Lodgepole pine	32 ± 12%	60 ± 13%	−28 ± 11% (-46%)	107
Total[B]	43 ± 24%	55 ± 18%	−12 ± 15% (-22%)	2064

[A]Proportional change in mean fire severity between the model predictions with and without operations.
[B]Total includes riparian areas, not shown as a separate row because they covered only 2 ha within areas of moderate–high operations intensity.

prescribed burns following a century of fire exclusion are often designed to be low intensity. We note, however, that from the limited field-based evidence available, recent burn-only treatments may reduce tree mortality from wildfire by 50% or more in dry pine or mixed-conifer forests (Wagle and Eakle 1979; Choromanska and DeLuca 2001; Fites *et al.* 2007), which is in line with the 51% reduction in BA loss we calculated within Jeffrey pine forest. The Reading Fire burned primarily in mid-montane forests dominated by red and white fir and lodgepole pine, which are less fire-resistant than Jeffrey pine or ponderosa pine, which are the forest dominants where many fuel treatments are implemented in the western US. Species with lower fire resistance may benefit less from treatment (Prichard *et al.* 2010; Safford *et al.* 2012), in part because reductions in stand density and ladder fuels may be insufficient to protect trees with thinner bark and lower CBHs from mortality during wildfires burning under severe conditions.

Influence of operations

Previous assessments of the effects of fire suppression operations on wildfire severity have tended to focus on the negative effects of high-intensity burn-outs (Backer *et al.* 2004; Driscoll *et al.* 2010; Stephens *et al.* 2013; Downing *et al.* 2019). However, using our approach of predicting fire severity under ‘operations’ and ‘no operations’ scenarios, we found that fire severity was reduced by 22% overall in areas of moderate–high operations intensity, with even higher reductions in fire-resistant forest types. BA loss was reduced by 72% in areas with both prescribed fires and moderate–high operations intensity, which is consistent with the idea that fuel treatments facilitate suppression operations (Agee *et al.* 2000; Moghaddas and Craggs 2007).

Operations had little dampening effect on fire severity in white fir forest even though operations reduced fire severity by 27% or more across the other forest types. Small white firs (<50 cm DBH) are more susceptible to mortality from fire than small yellow pines, owing to traits such as thinner bark (van Mantgem *et al.* 2013*a*). Twentieth-century fire exclusion is associated with white fir establishment leading to increased fire hazard in the southern Cascade Range (Bekker and Taylor 2010; Taylor and Solem 2001; Skinner and Taylor 2018). Field data from Pierce *et al.* (2012) in LAVO support this narrative, indicating that white fir forest had the highest CBD and the lowest CBH of any forest type. In addition, 76% of shrub fields in 1935 were classified as fir-dominated forest in 2004, suggesting 20th-century conversion of shrub fields to dense fir forest with high fire hazard, much of which may have been restored back to shrub fields by the Reading Fire. In summary, forest that was white fir-dominated before the Reading Fire may have been higher-density and more fuel-loaded than the other forest types and experienced less benefit from operations as a result because it was predisposed to burn at high severity under a wider range of conditions.

Operations could mitigate fire severity if they cause areas to burn outside peak burn periods. A key example is firing operations conducted at night when temperatures are lower and relative humidity is higher. Although reconstructing the exact timing and geography of particular operations is generally not feasible, anecdotally both of these scenarios occurred during the 2012 wildfire: fire spread was delayed to some fuel-rich areas until wind speeds were lower and relative humidity was higher, and firing operations near the margins of the fire appeared to reduce fire severity. In addition, both suppression operations and fuel treatments may reduce landscape-scale fire severity by influencing spatial patterns of fire spread, for example by breaking up the flaming front and increasing the area burned by flanking fire as opposed to heading fire (Finney 2001). Although our methodology does not directly account for these spatial dynamics, they are reflected in observed patterns of fire severity and therefore may contribute to our estimates of operations and fuel treatment influences. Our example with the Reading Fire illustrates that fire suppression tactics do not necessarily lead to higher-severity fire. In fact, our results suggest the opposite and demonstrate a need for more complete and quantitative analyses of the effects of operations on fire severity given variation in fuels, weather, terrain and tactics.

Limitations

Although our analysis offers the advantage of rich and detailed place-specific datasets, it has the drawback of being a single fire that burned a limited area. Given the small fire size and lack of replication in this study, further research is necessary to assess the extent to which our results apply outside our study area. Our statistical model predicted spatial patterns of fire severity reasonably well, but it could not account for a substantial portion of variability in fire severity (pseudo-r^2 0.53). Predicting pixel-level fire severity is notably challenging; our accuracy is higher than that of some comparable studies in western US forests that used a continuous response variable (e.g. BA loss or RdNBR) (Thompson and Spies 2009; Birch *et al.* 2015; Harris and Taylor 2015; Estes *et al.* 2017) but is lower than that of several others (Kane *et al.* 2015*a*, 2015*b*; Taylor *et al.* 2020). Viedma *et al.* (2020) achieved notably high model accuracy by combining sub-daily fire progression with hourly weather, suggesting that fire progression data may be a key limitation in our study and demonstrating the accuracy that might be achievable in the future if sub-daily fire progression data become more readily available. In particular, suppression operations may influence the time of day at which particular areas burn and therefore fire severity, yet we were only able to estimate this effect indirectly through our map of operations. Other weather influences that we were not able to capture in our model include terrain effects on wind (Sharples 2009) as well as plume-driven fire behaviour (Lydersen *et al.* 2014).

Our estimates of prescribed fire and operations effects on fire severity are subject to considerable uncertainty due to the limited extent of the study and the modest accuracy of our statistical model. The root-mean-square error from the RF model is 22% BA loss, which is greater than most of the effect sizes that we estimated for individual vegetation types (−4–28%), and unexplained variability in field-measured BA loss as predicted by RdNBR adds another layer of uncertainty. Ultimately, the accuracy of our estimates depends on the extent to which the statistical model captures the key drivers of fire severity, and improving the characterisation of fire severity drivers would result in more accurate estimates of prescribed fire and operations effects (e.g. improving the characterisation of weather as discussed above). Moreover, our methodology is spatially implicit rather than explicit and does not account for the influence of fuel treatments and operations on the direction and rate of fire spread, or the landscape-scale reduction in fire severity that may occur beyond treated areas due to modified fire behaviour (Syphard *et al.* 2011; Arkle *et al.* 2012; Cochrane *et al.* 2012).

Conclusion

Detailed case studies are an effective way to assess relative influences on fire severity, and particularly to evaluate the aspects of wildfire severity that may be influenced through management: fuels and fire history through prescribed fire, and timing and conditions of burning through fire suppression tactics. We found that past fires reduced wildfire severity but that their effect varied by forest type, which suggests a need to better quantify prescribed fire influence within more mesic mid-montane forest types that have been the subject of comparatively little fuel treatment research (Schoennagel *et al.* 2004; Kalies and Yocom Kent 2016). Our methodology of comparing fuel treatment effectiveness using a statistical model of wildfire severity and sets of ‘treatment’ and ‘no treatment’ vegetation and fuels variables could be applied to other fires and regions in different forest types and weather, which could help managers to prioritise fuel treatments. We also found that operations during the fire tended to reduce fire severity, and further assessments of the influence of operations are needed because quantitative information on their effects is sparse. Finally, we found that reductions in fire severity were particularly strong in areas with both fuel treatments and operations, suggesting the need for more quantitative work assessing the interaction between fuel treatments and fire suppression operations.

Conflicts of interest

The authors declare no conflicts of interest.

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