esa ECOSPHERE

Drivers of fire severity shift as landscapes transition to an active fire regime, Klamath Mountains, USA

ALAN H. TAYLOR,[1],† LUCAS B. HARRIS,[1] AND STACY A. DRURY[2]

[1]Department of Geography, Earth and Environmental Systems Institute, The Pennsylvania State University, University Park, Pennsylvania, USA
[2]Pacific Southwest Research Station, USDA Forest Service, Davis, California 95618 USA

Citation: Taylor, A. H., L. B. Harris, and S. A. Drury. 2021. Drivers of fire severity shift as landscapes transition to an active fire regime, Klamath Mountains, USA. Ecosphere 12(9):e03734. 10.1002/ecs2.3734

Abstract. Fire severity patterns are driven by interactions between fire, vegetation, and terrain, and they generate legacy effects that influence future fire severity. A century of fire exclusion and fuel buildup has eroded legacy effects, and contemporary fire severity patterns may diverge from historical patterns. In recent decades, area burned and area burned at high severity have increased and landscapes are transitioning back to an active fire regime where disturbance legacies will again play a strong role in determining fire severity. Understanding the drivers of fire severity is crucial for anticipating future fire severity patterns as active fire regimes are reestablished. We identified drivers of fire severity in the Klamath Mountains, a landscape with an active fire regime, using two machine learning statistical models: one model for non-reburns ($n = 92$) and one model for reburns ($n = 61$). Both models predicted low better than moderate or high-severity fire. Fire severity drivers contrasted sharply between non-reburns and reburns. Fire weather and fuels were dominant controls in non-reburns, while previous burn severity, fuel characteristics, and time since last fire were drivers for reburns. In reburns, areas initially burned at low (high) severity burned the same way again. This tendency was sufficiently strong that reburn fire severity could be predicted equally well with only severity of the previous fire in the model. Thus, reburn fire severity is more predictable than severity in non-reburns that are driven by the stochastic influences of fire weather. Reburn severity in aggregate was also higher than non-reburn severity suggesting a positive feedback effect that could contribute to an upward drift in fire severity as area burned increases. Terrain had low importance in both models. This indicates strong terrain controls in the past may not carry into the future. Low- and moderate-severity fire effects were prevalent in non-reburns under moderate fire weather and self-reinforcing behavior maintained these effects in reburns even under more extreme weather, particularly in reburns within 10 yr. Our findings suggest deliberate use of wildfire and prescribed fire under moderate conditions would increase fire resilience in landscapes transitioning to an active fire regime.

Key words: adaptation; climate change; ecological memory; fire exclusion; fire severity; legacy effects; resilience; topography; vegetation change; weather; wildland fire.

Received 17 February 2021; revised 16 April 2021; accepted 16 April 2021. Corresponding Editor: Franco Biondi.

† **E-mail:** aht1@psu.edu

INTRODUCTION

Fire is a natural disturbance process with lasting effects on vegetation patterns and landscape dynamics (Johnstone et al. 2016, Hessburg et al. 2019, Taylor et al. 2020). Prior to human-imposed fire suppression in the early 1900s CE, fire–vegetation interactions were strongly regulated by legacy effects generated by the fire regime. Fire exclusion has significantly altered historic fire–vegetation interactions in western U.S. forests, increasing the risk of uncharacteristically severe fire (Perry et al. 2011, Hessburg et al. 2019). However, as area burned continues to increase across western U.S. forests (Westerling 2016), landscapes are transitioning back to active fire regimes increasingly characterized by reburns (Buma et al. 2020) in which disturbance legacies again play a strong role. At the same time, concern is mounting over the potential for fire-initiated forest loss in the western North America as climate change alters fire–vegetation interactions (Coop et al. 2020). Therefore, it is crucial to understand the drivers of forest fire severity and how these drivers shift as active fire regimes are reestablished.

In frequent-fire forests, fire exclusion has increased forest cover, biomass, and density, and species composition has shifted toward fire-intolerant tree species (Knapp et al. 2013, Taylor et al. 2014). Similar forest changes are evident in forests that historically burned at longer intervals (50–100 yr), but the magnitude of change is lower since fewer fires have been skipped (Taylor 2000, Perry et al. 2011, Skinner and Taylor 2018, Hessburg et al. 2019). Vegetation changes, particularly in frequent-fire forests, have increased risk of severe canopy killing fire and along with a warming climate have driven increases in area burned and area burned at high severity in recent decades (Miller et al. 2012, Abatzoglou and Williams 2016).

In mountainous terrain, topographic-fire feedbacks historically perpetuated different vegetation types and fire regimes (Beaty and Taylor 2001, Taylor and Skinner 2003, Lydersen and North 2012), and this strong influence of terrain and fuels has been observed in non-reburn fires (i.e., burns after a long period of fire exclusion), when weather is primarily moderate (Harris and Taylor 2015, Kane et al. 2015, Taylor et al. 2020). However, during drought or extreme conditions such as high winds, a non-reburn fire can overwhelm bottom-up controls (Perry et al. 2011, Cansler and McKenzie 2014, Povak et al. 2020) leading to widespread high-severity fire regardless of terrain or fuel characteristics (Lydersen et al. 2014). Non-reburn fires may be particularly susceptible to an overriding effect of severe weather due to increased fire hazard from fire exclusion.

A key reason why non-reburn fires may initiate forest loss is that areas of high-severity fire will generally exhibit self-reinforcing fire–vegetation dynamics that could maintain a non-forest state such as shrublands (Coppoletta et al. 2016, Lauvaux et al. 2016, Tepley et al. 2017). In forests with a frequent (5–25 yr) low-severity fire regime, low-severity fire limits fuel buildup and promotes a canopy comprised of fire-resistant tree species, leading to further low-severity fire (Taylor and Skinner 2003, Scholl and Taylor 2010). In these same forests, areas that burn at higher severity due to fuel buildup tend to burn at high severity again if the fire initiates changes in plant species, vegetation structure, or local climate that are pyrogenic (Lauvaux et al. 2016, Harris and Taylor 2017). Such vegetation-disturbance feedbacks highlight the role of disturbance legacies in shaping vegetation patterns in disturbance-prone landscapes (Peterson 2002, Johnstone et al. 2016, Taylor et al. 2020) and suggest that reburn severity may be controlled by legacy effects of past fires. Severity patterns, however, are not simply regulated by self-organizing processes, and other factors such as terrain, weather, vegetation characteristics, and land use also influence fire severity (Taylor and Skinner 1998, Harris and Taylor 2017, Parks et al. 2018).

In the Klamath Mountains of northwestern California and southwestern Oregon, modeling of fire–vegetation dynamics suggests that wildfire and climate change will drive replacement of conifer forest by shrubs and hardwoods over the next century (Miller et al. 2018, Serra-Diaz et al. 2018). Yet, a region-wide empirical assessment of the influences on non-reburn and reburn wildfire severity is lacking. From 2002 to 2018, the cumulative equivalent of 41% of United States Forest Service (USFS) lands in the region burned, one-third of which had already experienced fire since 1984 (Fig. 1). Increased fuels from a century of fire exclusion (Taylor and Skinner 2003), high ignition density from regional lightning storms (Hayasaka and Skinner 2009, Skinner et al. 2018), a drying climate (Williams et al. 2019), and long duration fires due to limited suppression resources in years with high regional fire activity have all contributed to high area burned.

Recent work on fire patterns in the Klamath Mountains has found some evidence of self-

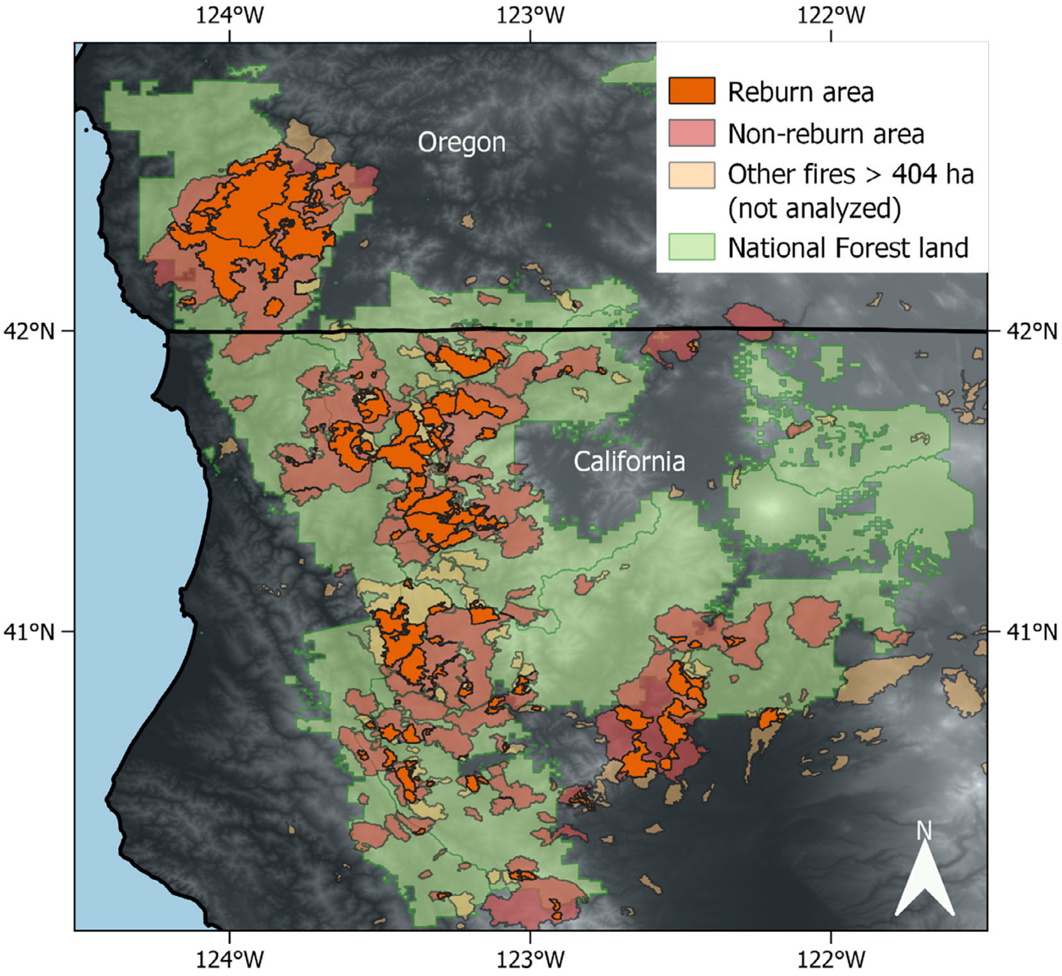

Fig. 1. Reburn and non-reburn portions of fires in our analysis plus perimeters from other fires >404 ha from 1984 to 2018. Lighter colors represent higher elevations (white is >2000 m). Fires were not analyzed if they occurred before 2002, did not overlap National Forest land, or lacked fire progression data, although they were included in calculations of fire history.

limiting and self-reinforcing behavior in reburns, related to vegetation type, monthly climate, and topography (Alexander et al. 2006, Thompson et al. 2007, Odion et al. 2010, Miller et al. 2012, Estes et al. 2017, Grabinski et al. 2017). While providing important insights on factors contributing to fire severity, these studies do not evaluate the full set of known influences on fire severity including fuel, topography, and daily weather (Agee 1993, Collins et al. 2007, Harris and Taylor 2017, Parks et al. 2018, Taylor et al. 2020). A study by Estes et al. (2017) is an exception, and they found topographic characteristic and vegetation type to be the most important variables controlling fire severity, with low influence by weather and fire history. Estes et al. (2017), however, evaluated only five fires in one year (2006), and they burned under moderate weather conditions. Grabinski et al. (2017) also analyzed reburn severity in the Klamath Mountains, yet they did not consider daily weather and also analyzed each fire separately rather than building a regional-scale model to investigate commonalities.

Here, we identify controls on fire severity in a large landscape with an active fire regime, the

Klamath Mountains, for two distinct cases. The first is for non-reburns or areas that had not burned since 1984, the first year for which data are available from the Monitoring Trends in Burn Severity (MTBS) program (http://www.mtbs.gov/). We refer to this case as "non-reburn" fire severity. Most (69%) of the non-reburn area had no prior record of fire according to historical fire perimeters from the California Department of Forestry and Fire Protection's Fire Resource and Assessment Program (FRAP, version 19-1, http://frap.fire.ca.gov), suggesting a history of fire exclusion dating back to the late 1800s or early 1900s. The second case is for fires burning after 1984 that burned over a previous fire with known fire severity, and we refer to this case as "reburn" fire severity. We sought answers to two questions: (1) "In forest landscapes that are transitioning to an active fire regime what are the critical controls of fire severity, and how do these controls change between non-reburns and reburns?" and (2) "When fire-excluded forests experience repeated burns, are severity patterns aligned more with topography or fire–vegetation interactions?". We expected fire severity controls for these two cases to be different because of diminished legacy effects from historical fires in the first case and strong self-reinforcing effects in the second case. Our analyses address broader questions on the controls of fire severity in landscapes transitioning to an active fire regime, and what this implies for future fire severity patterns and ecological fire management.

STUDY AREA

The Klamath Mountains bioregion comprises much of northwestern California and adjacent southwestern Oregon (Fig. 1). The terrain is very steep and complex and includes the most extensive exposure of ultramafic rocks in North America (Kruckeberg 1985, Sawyer 2006). Elevations range from 30 to 2755 m. The complexity of the geology and terrain strongly influences vegetation structure, composition, and productivity (Whittaker 1960, Sawyer 2006) and fire regimes. The climate of the Klamath Mountains is Mediterranean, with wet/cool winters and dry/warm summers but there are strong west–east moisture and temperature gradients caused by proximity to the Pacific Ocean. Average annual precipitation at Sawyers Bar (659 m) in the central Klamath Mountains is 117.6 cm, and average daily maximum temperatures range from 9.1°C in January to 32.9°C in July. Lightning-ignited fires account for most area burned in recent decades vs. human-ignited fires (Miller et al. 2012), and years with widespread and larger fires are usually dryer and warmer than the norm (Trouet et al. 2009, Skinner et al. 2018). Conifer forests and woodlands are found in all elevational zones. Three broad forest types are recognized and include as follows: (1) a diverse lower montane zone of mixed conifer (*Pseudotsuga menziesii* var. *menziesii*, *Pinus ponderosa*, *Calocedrus decurrens*, *Pinus lambertiana*, *Pinus jeffreyi*, *Abies concolor*) and evergreen (*Arbutus menziesii*, *Chrysolepis chrysophylla*, *Quercus chrysolepis*, *Lithocarpus densiflorus*) and deciduous (*Acer macrophyllum*, *Quercus kelloggii*, *Quercus garryana*, *Cornus nuttallii*) hardwoods that co-occur in various mixtures and share dominance in a stand, (2) a mid-upper montane zone where *A. concolor* is abundant and hardwoods are less important, and (3) a subalpine zone with *Abies magnifica* var *shastensis*, *Tsuga mertensiana*, *Pinus monticola*, *P. jeffreyii*, *Pinus albicaulis, Pinus contorta, Pinus balfouriana*, and *Cercocarpus ledifolius*.

Humans have affected fire regimes and land use in the Klamath Mountains in several ways. Prior to Euro-American colonization, native people in the Klamath Mountains used fire to promote production of acorns, berries, roots, and fiber and to improve hunting conditions (Lewis 1990, 1993, Lake and Christianson 2019). Euro-Americans entered the area in 1848, and fire frequency declined with extirpation of Native Americans (Fry and Stephens 2006). Fire frequency declined further with the implementation of a fire suppression policy in 1905 on newly established Forest Service lands (Shrader 1965). Since 1964, federal lands have also been designated as national recreation areas, wilderness, and northern spotted owl (*Strix occidentalis*) late-successional reserves (LSR). Fire management in lands with these designations influences fire management practices, which could influence fire regime characteristics compared with non-designated federal lands (Davis et al. 2016, Spies et al. 2018).

METHODS

Fires and fire severity

We analyzed fires occurring from 2002 to 2018 which had at least 50 ha overlap with each of the following National Forests: Klamath, Rogue River-Siskiyou, Six Rivers, and Shasta-Trinity (Fig. 1). The 50-ha threshold was used to ensure that fires burned within National Forest land and not just up to its boundary. Only fires within the United States Geological Survey's eight-digit watersheds (Seaber et al. 1987) overlapping or draining into California (i.e., the study area of Flint et al. 2013) were included. Fire perimeters and fire severity data were obtained from the MTBS program, which includes fires >404 ha since 1984 in the western United States (Eidenshink et al. 2007). Fires <404 ha were not included in this analysis because fire severity metrics were not readily available. For analysis purposes, we defined "reburn" as an area that had burned over a prior fire covered by MTBS, and the other areas that had not burned over MTBS fires were considered "non-reburns." Note that some "non-reburn" areas did lie within historical fire perimeters prior to 1984, although the majority had no recorded fire history (88% of sample pixels used in the non-reburn model, see *Fire history*).

We quantified fire severity using fire severity classes and canopy cover loss (CC loss) calculated from the Relativized delta Normalized Burn Ratio (RdNBR), a vegetation change index derived from Landsat imagery (Miller and Thode 2007). Relativized delta Normalized Burn Ratio was classified into low, moderate, or high-severity fire using thresholds developed from fires in the Sierra Nevada (Miller and Thode 2007). Canopy cover loss from RdNBR was calculated using an equation developed from field calibration of fires in the Sierra Nevada and Klamath mountains (Miller et al. 2009).

Fire progression

We created daily fire progression maps to determine the role of daily weather on fire severity. First, daily or near-daily fire progression maps were obtained from the Geospatial Multi-Agency Coordinating Group (GeoMAC, https://data-nifc.opendata.arcgis.com/). Fires that were missing near-daily fire progression data were excluded from our analysis of fire severity, excluding 18 fires and leaving 106 fires for the analysis. To fill in temporal gaps, we interpolated daily fire detection points from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery following Parks (2014). We used fire detection data from the USDA Forest Service Active Fire Mapping Program (https://fsapps.nwcg.gov/afm/), assigned fire detection points before noon to the previous day of burning and used inverse distance weighted interpolation of the five closest fire detection points to each pixel to produce daily fire progression maps for each fire. These maps were then used to assign portions of the GeoMAC-based fire progression maps representing >1 d to a single day.

Fire history

Fire history was assessed using MTBS data for reburns, and the FRAP historical fire perimeters data set for non-reburns. From the MTBS program, we calculated the time since the last fire covered by MTBS for every fire severity pixel as well as the severity (RdNBR) of the most recent fire. A separate time since last fire measure was generated from the FRAP data set, which is incomplete (Syphard and Keeley 2016) but which extends in time in our study area to 1878 on USFS lands. We used the FRAP data set to create a classified "years since last burn" layer for each fire with years divided into 15-yr increments plus a class for areas with no fires in the database.

Topography and water balance

The complex terrain of the Klamath Mountains has influenced patterns of both historical fire severity and recent fire severity (Taylor and Skinner 1998, Estes et al. 2017). We considered five topographic variables as potential influences on fire severity: elevation, slope, aspect, topographic position, and topographic wetness. A cosine transformation (Beers et al. 1966) was applied to aspect such that higher values represented north-eastern aspects. The Topographic Position Index, an index of how high or low a focal elevation pixel is relative to the surrounding terrain, was calculated using a 600 m neighborhood size. We also calculated the Topographic Wetness Index (TWI), a measure of expected moisture based on terrain and water flow (Beven and Kirkby 1979), using the "dynatopmodel" R package (Metcalfe et al. 2018).

Water balance metrics can represent gradients of fuel quantity and aridity which in turn influence fire severity (Parks et al. 2014*b*). We considered actual evapotranspiration (AET), which is a measure of water availability for plants and correlates with plant productivity and therefore fuel accumulation (Stephenson 1990, Parks et al. 2014*b*). We also considered climatic water deficit (CWD), the difference between potential evapotranspiration and AET. Climatic water deficit is a measure of water stress and is related to fuel moisture (Stephenson 1990, Parks et al. 2014*b*). Mean annual AET and CWD from 1981 to 2010, with a native resolution of 270 m, were obtained from the 2014 California Basin Characterization Model (Flint et al. 2013).

Weather

To evaluate the influence of daily weather on fire severity, five weather variables were matched to the fire progression maps. We first used the PRISM data set (Daly et al. 2008) to obtain daily maximum temperature at 4 km spatial resolution. We also calculated daily minimum relative humidity from PRISM's maximum temperature and maximum vapor pressure-deficit data sets following Daly et al. (2015). To obtain additional fire weather metrics, we used the GridMET data set (Abatzoglou 2013), which offers daily variables at 4-km resolution derived by combining PRISM data with the North American Land Data Assimilation System Phase 2 (NLDAS-2) data set (Mitchell et al. 2004). The first variable we used from this data set was the energy release component (ERC), which combines temperature, humidity, and precipitation over time to calculate the energy at the flaming front for a particular fuel type (Bradshaw et al. 1983) (calculated for fuel model G). We also considered average wind speed and wind direction. Wind direction was cosine-transformed to create two variables ranging from 0 to 2: one in which 0 is west wind and 2 is east wind ("eastness"), and one in which 0 is south wind and 2 is north wind ("northness"). The fire progression maps were used to assign daily conditions for each fire. Note that many daily fire perimeters were covered by just one or two pixels of the weather data sets, but we felt that these data sets were the best available.

Vegetation

Vegetation structure and composition, especially in terms of conifer forest vs. shrublands and hardwood forest, may strongly influence fire severity in the Klamath Mountains (Odion et al. 2010, Grabinski et al. 2017, Miller et al. 2018). To represent pre-fire–vegetation structure and composition, we used Landfire (Rollins 2009), which has versions representing vegetation in 2001, 2008, 2010, 2012, 2014, and 2016. For each fire, we selected the most recent Landfire data set which predated the fire, and obtained vegetation height, percentage canopy cover, and vegetation type data. We consolidated vegetation type data into nine broader classes (Table 1). We also used the Landfire data to exclude areas classified as roads, water, snow or ice, developed, or agricultural land.

The pre-fire normalized differenced vegetation index (NDVI) has also been shown to correspond with fire severity because it is an indicator of vegetation type and captures gradients of productivity and fuel accumulation (Parks et al. 2018). Therefore, we calculated NDVI using the pre-fire imagery from each fire as an additional metric of vegetation and fuels.

Management activities such as logging or replanting after a fire have been shown to affect fire severity in the Klamath Mountains (Thompson et al. 2007). We evaluated the potential influence of logging on fire severity using the U.S. Forest Service's Activity Tracking System (FACTS) database (https://data.fs.usda.gov/geodata/edw/datasets.php). From this database, we created two variables. For areas which had not burned since 1984, we generated a categorical "time since logging" variable: 0–15 yr, 15–30 yr, >30 yr, and no prior logging. For reburned areas which had experienced fire since 1984, we assessed whether or not the area had been logged between the initial fire and the reburn. We added these variables into our statistical models of fire severity (see *Statistical modeling*) but found that they did not improve model accuracy. Therefore, the logging variables were excluded from the final statistical models.

Area burned and land ownership

To provide context for our analysis of fire severity, we calculated annual area burned, annual area reburned, and the breakdown of fire

Table 1. Variables used in statistical models of fire severity.

Category	Variable	Reference/Source	Details
Response	Fire severity	Monitoring Trends in Burn Severity (MTBS, Eidenshink et al. 2007)	Relativized delta Normalized Burn Ratio (RdNBR) classified into low, moderate, and high-severity fire following Miller and Thode (2007)
Fire history	Prior fire severity (canopy cover loss)	MTBS	RdNBR converted into tree canopy cover loss following Miller et al. (2009)
Fire history	Years since last burn	FRAP fire perimeters (non-reburns) or MTBS (reburns)	Numeric for reburns, for non-reburns classified into: <15 yr, 15–29, 30–44, 45–59, ≥60, no prior fire
Topography	Elevation	National Elevation Data set (NED, https://apps.nationalmap.gov/)	30 m digital elevation model
Topography	Slope	From NED	
Topography	Aspect	From NED	Cosine-transformed (Beers et al. 1966) such that 0 is southwest, 2 is northeast
Topography	Topographic Position Index	Weiss (2001), from NED	600-m neighborhood size
Topography	Topographic Wetness Index	Beven and Kirkby (1979), from NED	Using "dynatopmodel" R package (Metcalfe et al. 2018)
Water balance	Actual evapotranspiration	Flint et al. (2013)	1981–2010 means
Water balance	Climatic water deficit	Flint et al. (2013)	1981–2010 means
Weather	Maximum temperature	PRISM (Daly et al. 2008)	
Weather	Minimum relative humidity	PRISM	Calculated following Daly et al. (2015)
Weather	Energy release component	Bradshaw et al. (1983), from GridMET (Abatzoglou 2013)	
Weather	Average wind speed	GridMET	
Weather	Wind direction	GridMET	Cosine-transformed into "eastness" (0 = west, 2 = east) and "northness" (0 = south, 2 = north)
Vegetation	Vegetation height	Landfire (Zhu et al. 2006)	Most recent pre-fire version of Landfire selected for each fire
Vegetation	Tree canopy cover	Landfire (Zhu et al. 2006)	
Vegetation	Vegetation type	Landfire (Zhu et al. 2006)	Classified into: sparsely vegetated, shrub, oak, pinyon-juniper, pine/mixed conifer, Douglas fir/hemlock, fir/subalpine, aspen, riparian
Vegetation	Normalized Differenced Vegetation Index	MTBS pre-fire Landsat image	
Land ownership	Land type	National Boundary Data set (https://apps.nationalmap.gov/), Late-Successional Reserves (LSRs) from the Northwest Forest Plan (https://www.fs.fed.us/r6/reo/)	Divided into wilderness, LSR, U.S. Forest Service, Bureau of Land Management, National Park Service, and other

severity classes within the study area from 1984 to 2018. We also evaluated whether variation in annual area burned and percentage of low or high-severity fire was associated with climatic warming by calculating Spearman rank correlations (r_S) with May–October maximum temperature and water-year (October–September) total precipitation for the North Coast region from the California Climate Tracker (https://wrcc.dri.edu/Climate/Tracker/CA/). Only significant ($P < 0.05$ with a Holm-Bonferroni correction applied) correlations were reported.

To assess the potential impact of land designation and ownership on fire severity, we divided the study area into the following land types: wilderness, other LSRs in the Northwest Forest Plan, USFS, Bureau of Land Management, National Park Service, and all other land ownerships. To determine whether rates of burning varied on USFS land according to wilderness or LSR designations, we used fire rotations. The fire rotation is the length of time needed to burn an area of interest (our study area) which is calculated by dividing the time period of interest by proportion of study area burned in that time period (Heinselman 1973). United States Forest Service lands in the study area included 5181 km^2 of wilderness, 8394 km^2 of other LSRs, and 13,562 km^2 of other USFS land.

Statistical modeling

To analyze influences on non-reburn and reburn fire severity, we used two statistical models. Individual fires ($n = 106$) were partitioned into their non-reburn and reburn portions for analysis, and therefore, 92 non-reburn fires and 61 reburn fires were represented in the analysis (Fig. 1; Appendix S1: Tables S1, S2). For each model, fire severity categorized as unchanged—low, moderate or high following Miller and Thode (2007) was the response variable. We derived a set of fire history, terrain, vegetation, and weather variables as predictors (Table 1). For the purpose of generating model predictions, rasters of all input variables were resampled to match the 30 m pixel size of the fire severity raster using bilinear interpolation for continuous variables and nearest neighbor resampling for categorical variables.

Prior to modeling, pixels from all fires were sampled using a grid with 800 m spacing between points to reduce the influence of spatial autocorrelation of predictor variables on the model results. Although individual fire severity and vegetation characteristics may be spatially autocorrelated at distances of up to 2000 m (Odion et al. 2010), sampling distances of <300 m are often sufficient to address problems related to spatial autocorrelation in statistical models of fire severity similar to ours (Kane et al. 2015, Povak et al. 2020, Taylor et al. 2020). Our use of 800 m follows Harris and Taylor (2017), who found that using closer spacings down to 200 m did not substantially alter their results but concluded that 800 m was a safer and more conservative choice if the study area is large enough to maintain a sufficient sample size at 800 m.

As our modeling framework, we used random forest (RF), which builds ensembles of classification trees (Breiman 2001). Random forest is adept at dealing with non-linear relationships between predictor and response variables and with interactions between variables, both of which are frequent characteristics of ecological data (Cutler et al. 2007). Because imbalanced class sizes in the response variable may affect RF results, we randomly sampled from the more abundant classes such that each class was of equal size (Chen et al. 2004) by specifying "sampsize" in the randomForest R package (Liaw and Wiener 2002). We used default values of 500 trees and the square root of the number of predictors considered at each node (Liaw and Wiener 2002).

The non-reburn and reburn models shared most of the same predictor variables, chosen a priori based on knowledge of the Klamath Mountains and of the drivers of fire severity. We confirmed that no pair of variables was strongly correlated (Spearman rank correlation ≥ 0.8 or ≤ -0.8) prior to analysis. The only differences between the variables considered for the two models were that the FRAP fire history was used in the non-reburn model while years since last burn from MTBS and prior fire severity (CC loss) were used in the reburn model. These variables and their distributions are shown in Figs. 2, 3.

To assess model accuracy, we randomly withheld 30% of individual fires from each model as a test data set. Models of fire severity are well-suited to such a validation process because each fire comprises an independent event (Parks et al. 2018). The training data set contained 9517 non-reburn sample pixels and 3713 reburn sample pixels, and the test data set contained 2895 non-reburn and 1738 reburn samples. Using the test sets, we generated confusion matrices, within-class classification error rates and overall error rates. We compared these metrics with corresponding ones from the out-of-bag (OOB) estimates, or the estimates from the portion of the data that is withheld when building each classification tree (Breiman 2001). We also quantified variable importance, both overall and within each severity class, based on the increase in overall and within-class classification error when an individual variable is permuted (Breiman 2001, Liaw and Wiener 2002). These importance values were converted to the "model improvement ratio" (MIR) which has the advantage of being comparable among models (Murphy et al. 2010). In the MIR, 1 indicates the most important variable, 0 indicates no contribution to model accuracy, and negative values indicate a negative contribution. To show the marginal effect of each predictor variable on fire severity, we also created partial dependence plots using the "pdp"

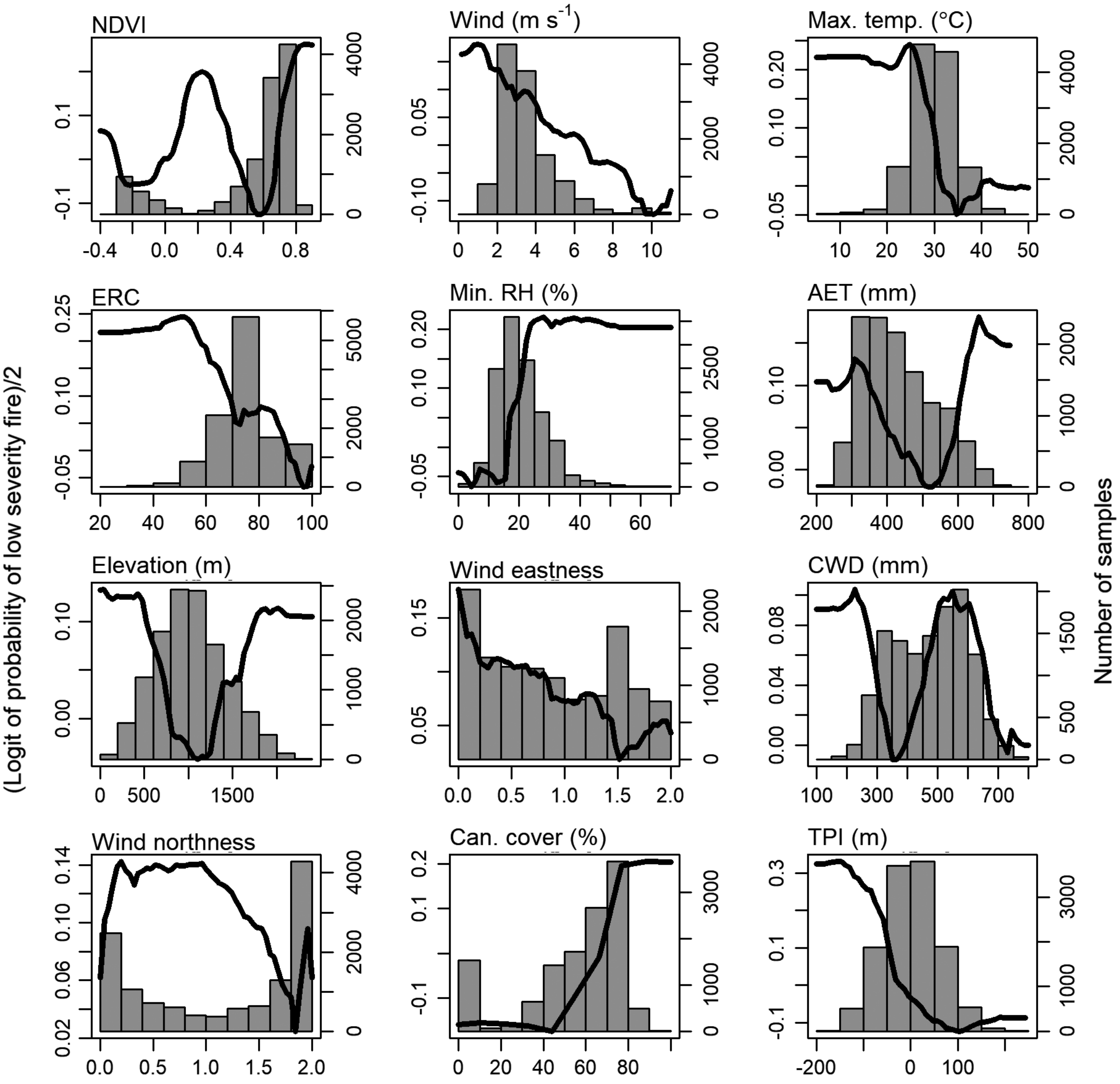

Fig. 2. Partial dependence plots showing the effects of individual variables on the probability of low-severity fire for non-reburn fires. Black lines indicate partial dependence, with higher *y*-axis values (left) indicating greater probability of low-severity fire. Histograms (gray bars, axes on right) show the distribution of each variable. Variables are ordered from most important to least important from top left to bottom right, and only the top 12 variables are shown (see Appendix S1: Fig. S1 for other variables). See Table 1 for full variable names.

R package (Greenwell 2017). Because both models predicted low-severity fire better than moderate or high severity, we chose to display the probability of low-severity fire using the partial dependence plots (Figs. 2, 3). For the reburn model, we performed additional model runs with just previous fire severity and with every variable except previous fire severity to further gauge the relative influence of prior fire severity on reburn severity.

RESULTS

Area burned, fire severity, and fire rotations

Annual area burned in the study area was positively correlated with May–October temperature

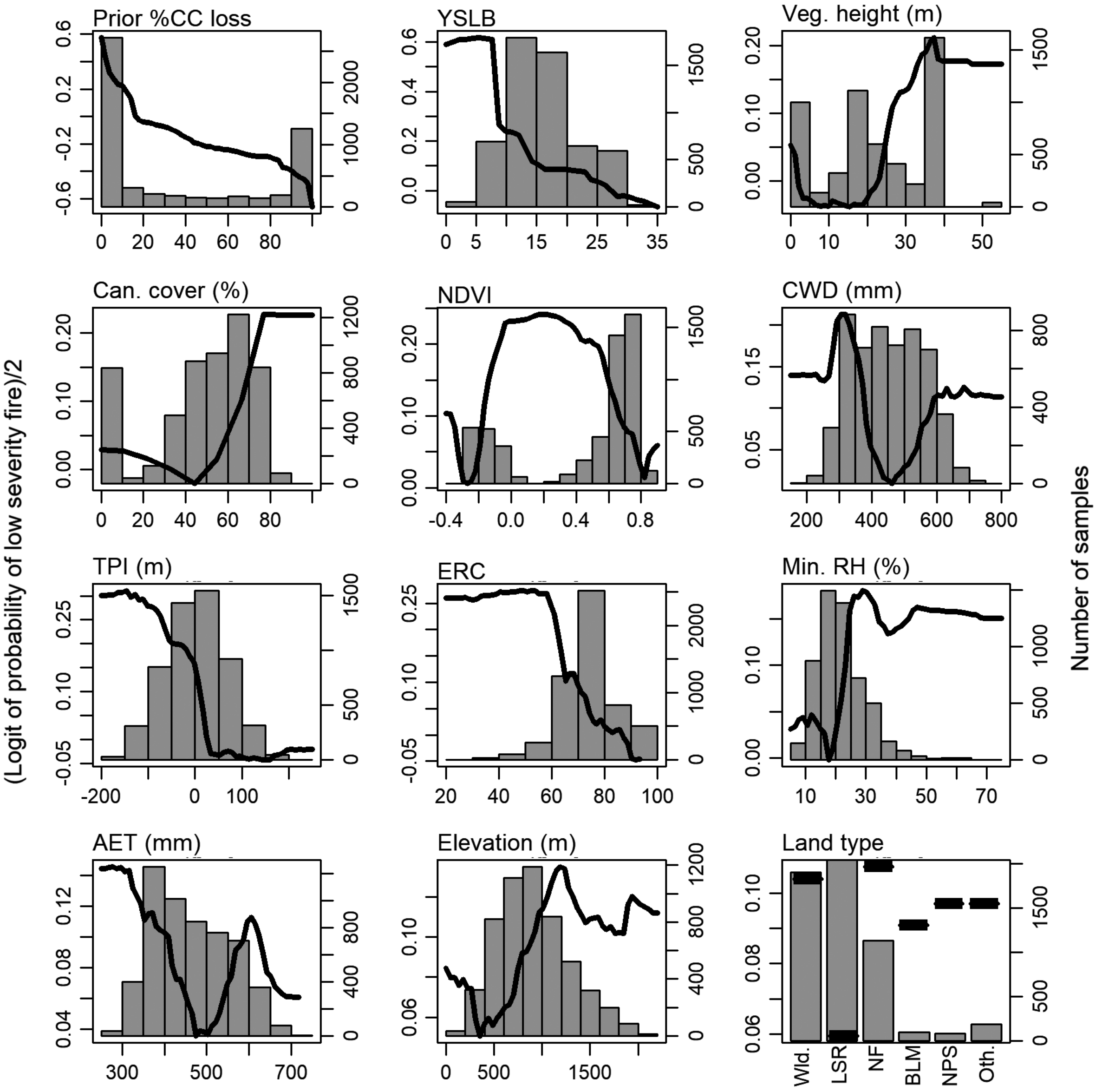

Fig. 3. Partial dependence plots showing the effects of individual variables on the probability of low-severity fire in reburns. Black lines indicate partial dependence, with higher *y*-axis values (left) indicating greater probability of low-severity fire. Histograms (gray bars, axes on right) show the distribution of each variable. Variables are ordered from most important to least important from top left to bottom right, and only the top 12 variables are shown (see Appendix S1: Fig. S2 for other variables). See Table 1 for full names of variables. Land types are as follows: wilderness, late-successional reserves, National Forest, Bureau of Land Management, National Park Service, other.

($r_S = 0.73$, $P < 0.001$; Fig. 4) and negatively correlated with water-year precipitation ($r_S = -0.42$, $P < 0.05$) between 1984 and 2018. Overall, fire severity in non-reburns from 1984 to 2018 was 47% low, 25% moderate, and 27% high. Fire severity was slightly higher in reburns: 41% low, 30% moderate, and 29% high. The annual percentages of low or high-severity fire were not significantly correlated with temperature or precipitation.

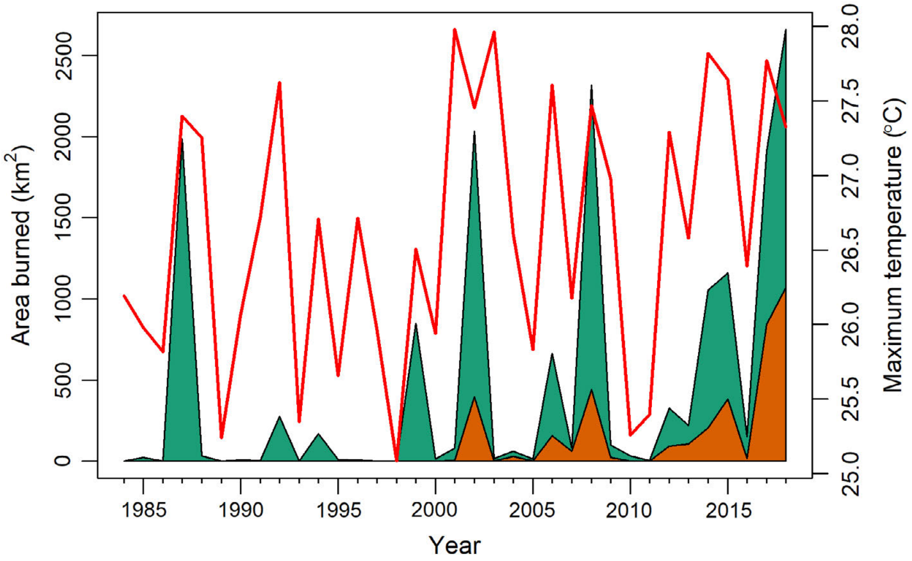

Fig. 4. Area burned annually from 1984 to 2018 (green) and reburned area (orange) in the study area, with May–October maximum temperature shown (red line).

Fire rotations from 1984 to 2018 were 67 yr on all USFS land: 49 yr in LSRs, 39 yr in wilderness areas, and 103 yr in other USFS lands. Considering just the 2002–2018 period of analysis, fire rotations shortened to 36, 24, and 66 yr, respectively, for these land types (42 yr for all USFS lands).

Model accuracy

The two statistical models had similar OOB classification error, but the reburn model had a lower test set error rate than the non-reburn model indicating better transferability (Table 2). The reburn model predicted high-severity fire with higher accuracy than the non-reburn model, though both performed relatively poorly at predicting the high-severity class (52% vs. 67% test set error). Both models performed best at predicting low severity and worst at predicting moderate-severity fire. Maps of predicted fire severity tended to be visually similar to observed severity, as illustrated in Fig. 5.

Non-reburn fire severity

The strongest influences on fire severity in non-reburns were NDVI and weather, with some moderately important terrain and water balance variables (Fig. 6). Although NDVI was important across all three fire severity classes, the MIR differed sharply by class for other variables indicating greater importance of weather for high-severity fire. Notably, wind speed was the most important variable predicting high-severity fire but in the bottom third of importance rankings for low severity and moderate severity, whereas tree canopy cover was the most important variable for low-severity fire but in the bottom third for high-severity fire.

Normalized differenced vegetation index was the most important variable, and its partial dependence plot showed that low-severity fire was least likely at 0.6 and most likely at high values of >0.8, followed by lower values of ˜0.2 (Fig. 2). Areas that burned with low wind speeds, low maximum temperatures, and high relative humidity were more likely to burn at low severity, and low ERC was also linked to low-severity fire (2nd–5th in overall importance). The two moderately important wind direction variables indicated that fire severity was lower when winds were from the west and the south. The Landfire-derived vegetation variables were in the bottom half of overall variable importance and indicated that low-severity fire was more likely in areas with high tree canopy cover and tall vegetation and least likely in pine/mixed conifer forest, oak woodlands, and shrublands.

Water balance and terrain were of moderate importance in the non-reburn model. Low-

Table 2. Confusion matrices from the non-reburn (top) and reburn (bottom) models of fire severity, showing predicted fire severity classes from the 30% of fires withheld as a test set and predictions from the "out-of-bag" sample from the model.

Model data set	Predicted severity	Low	Moderate	High	Error rate (%)
Test set, non-reburn (52.2%)	Low	946	276	256	36.0
	Moderate	365	233	196	70.7
	High	263	157	203	67.4
Out-of-bag, non-reburn (41.8%)	Low	2771	593	517	28.6
	Moderate	989	760	751	68.6
	High	632	500	2004	36.8
Test set, reburn (45.7%)	Low	419	120	46	28.4
	Moderate	187	227	115	57.1
	High	168	158	298	52.2
Out-of-bag, reburn (43.0%)	Low	1165	318	142	28.3
	Moderate	413	406	305	63.9
	High	177	242	545	43.5

Note: Overall classification error rates are shown in parentheses at left. Columns show observed fire severity, and the within-class error rate for each fire severity class is shown at right.

severity fire was least likely at intermediate elevations of 800–1200 m (7th most important; Fig. 2). Actual evapotranspiration and CWD (6th and 9th) both had bimodal relationships with the likelihood of low-severity fire indicating higher severity at intermediate values. The other terrain variables were relatively unimportant and indicated that fire severity was lower in valleys, gentle slopes, northeastern aspects, and areas with a high TWI.

Land type and time since last fire were of low importance in the non-reburn model. Wilderness areas and LSR were associated with low-severity fire, and areas with no recorded fire history were least likely to experience low-severity fire.

Reburn fire severity

In the reburn severity model, prior fire severity (CC loss) was more than twice as important as any other variable and indicated that areas burned at low (high) severity previously tended to burn again at low (high) severity (Fig. 3). In fact, the reburn severity model performed as well when run with prior CC loss as the only variable as it did when run with all other variables combined (both 51% test set error rate). Low-severity fire was more likely in areas burned <10 yr ago according to the years since last burn variable (2nd most important) (Fig. 3).

Variable importance ranks were notably different between the two models: vegetation including vegetation height and tree canopy cover were more important in the reburn model than the non-reburn model whereas weather variables such as temperature and wind speed were near the top of the non-reburn model but near the bottom of the reburn model (Figs. 6, 7). Variable importance was also similar for the low- and high-severity classes within the reburn model, in contrast to the non-reburn model.

The shape of variable response relationships with fire severity was broadly similar between both models with three exceptions. First, reburn severity was higher at the highest NDVI values (>0.6) whereas non-reburn severity was lower with high NDVI (Figs. 2, 3). Second, low-severity fire was more likely at intermediate elevations of 800–1200 m in reburns than non-reburns. Third, the relationship of fire severity in LSRs and USFS land flipped between the two models with relatively higher reburn severity in LSR and relatively lower reburn severity on USFS land.

DISCUSSION

Our goal was to identify how controls on fire severity change as reburns become more common in a region that experienced a long period of fire suppression followed by 34 yr of burning by wildfires. We found that the importance of fire severity drivers contrasted sharply between non-reburns, where weather was highly influential, and reburns, where prior fire severity and fuels were dominant. Our results suggest that in

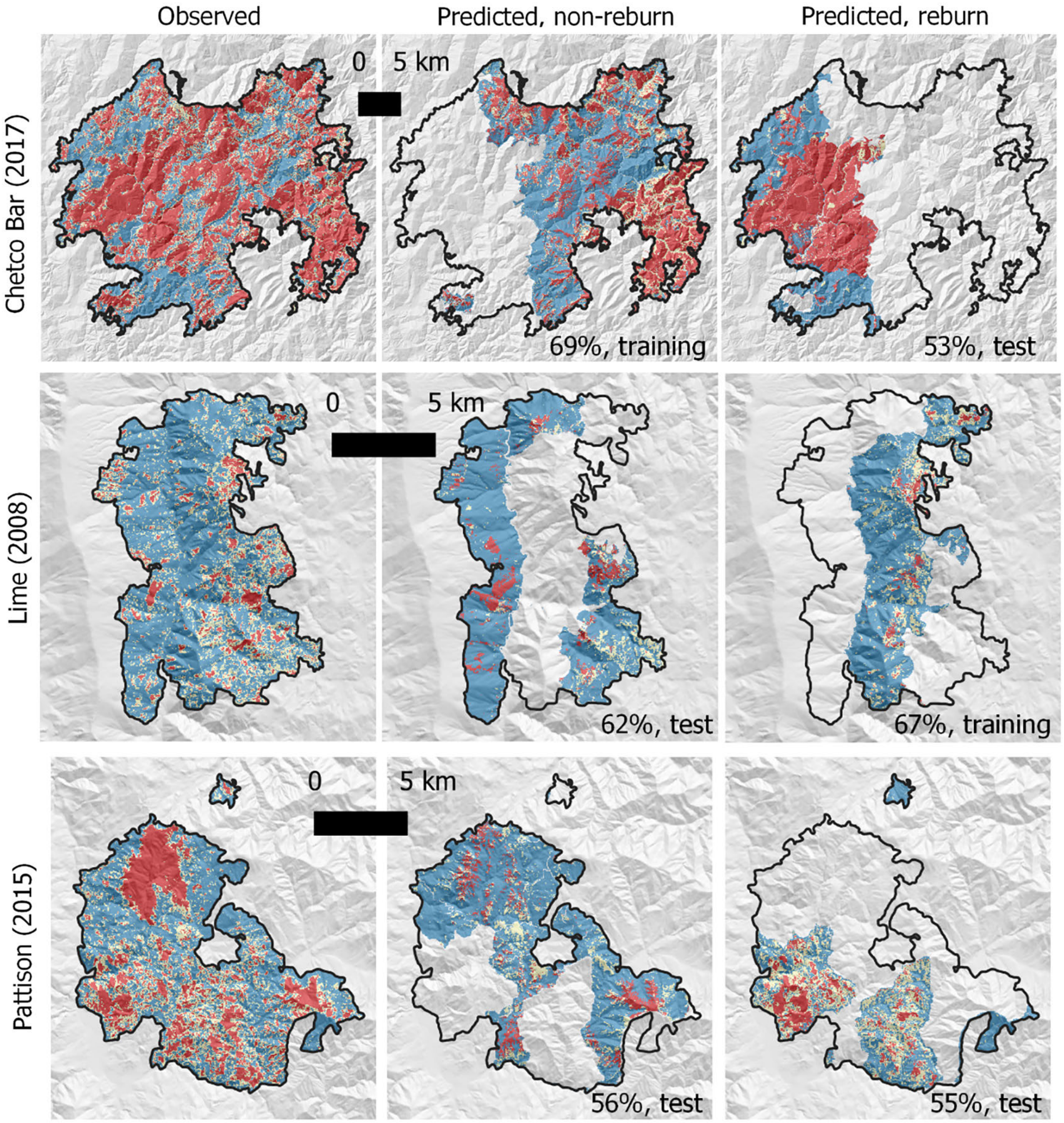

Fig. 5. Observed and modeled fire severity classes (blue = low, yellow = moderate, red = high) for three wildfires in the analysis, shown to illustrate the performance of the non-reburn and reburn models. The percentage match between observed and predicted fire severity is shown in the "predicted" columns along with whether the fire was in the training or test data set for each model.

a reburn scenario, fire severity is more predictable in the sense that it depends on fire history and fuels that are readily characterized and mapped in advance, rather than the stochastic influences of fire weather which are difficult to predict. This contrast in fire severity drivers has implications for forest and fire management as we enter an era of active fire regimes.

Although some work has found that fire severity is dampened in reburns (Parks et al. 2014*b*,

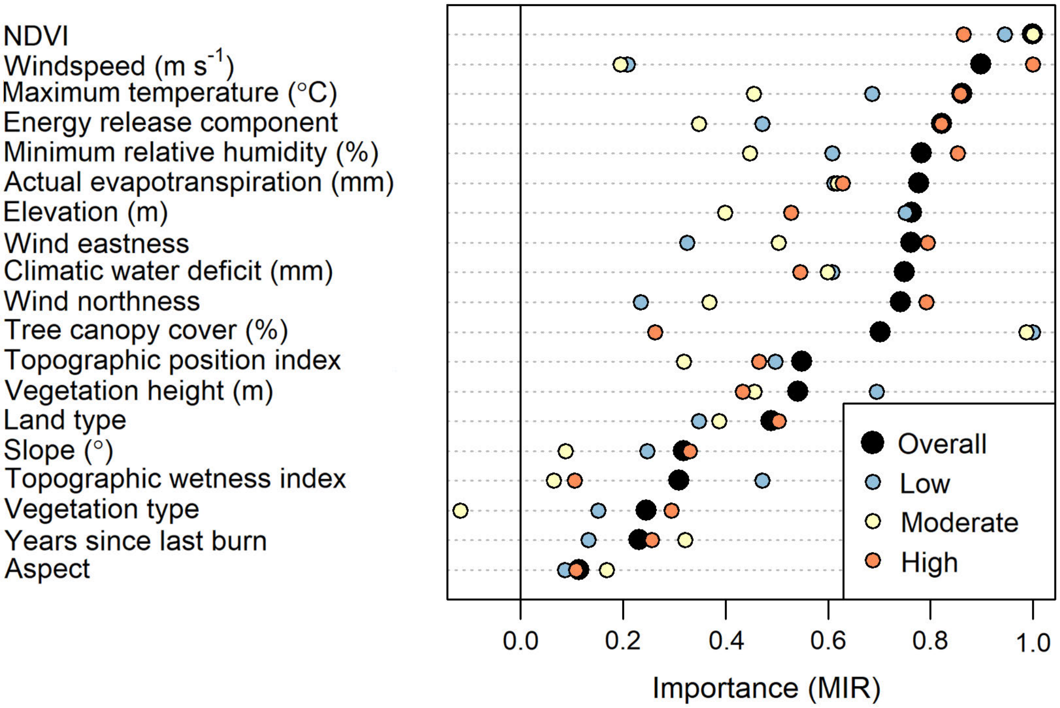

Fig. 6. Variable importance (model improvement ratio) from the random forest model of non-reburn fire severity as calculated across all fire severity classes and within each fire severity class (see legend). NDVI, normalized differenced vegetation index.

Harvey et al. 2016, Prichard et al. 2017), we found instead that reburn severity in the Klamath Mountains was higher on aggregate than non-reburn severity, in agreement with the findings of Grabinski et al. (2017) who studied a subset of the same reburns. Although fully explaining why fire severity was higher in reburns is beyond the scope of this study, several possibilities merit further investigation, including the following: (1) Abundant coarse woody debris left after non-reburn fires might increase fire hazard (Coppoletta et al. 2016), in which case fire severity might decrease after the first reburn once these fuels are consumed, (2) moderate and high-severity patches might grow in size with successive fires as higher-severity fire creeps into surrounding forest, in which case fire severity might continue to increase over successive fires barring active management, and (3) fire initiates an increases in pyrophytic shrubs and grasses (Coop et al. 2016, Lauvaux et al. 2016) that increase severity of subsequent fires due to positive feedbacks causing an upward drift in fire severity that is exacerbated by a warming climate (Serra-Diaz et al. 2018, Williams et al. 2019). This upward drift in fire severity suggests that a transition from fire exclusion to an active fire regime may be insufficient to stabilize fire severity and limit fire-initiated forest loss, particularly if fires tend to occur under extreme weather.

As area burned continues to increase across western U.S. forests (Abatzoglou and Williams 2016, Westerling 2016), focus will shift from what drives fire severity in areas with substantial fire deficits (Marlon et al. 2012) to how disturbance legacies shape reburn severity. According to Miller et al. (2012), 20th-century fire rotations in northwestern California (a similar study area to ours) reached a high of almost 1000 yr in 1960–1984 but declined to 95 yr for 1984–2008, similar to our calculated fire rotations of 87 yr for USFS land over that period. With the spate of recent large fires, our 2002–2018 fire rotations are approaching fire rotation estimates before fire suppression (Taylor and Skinner 1998, 2003, Stephens et al. 2007). Thus, the Klamath Mountains

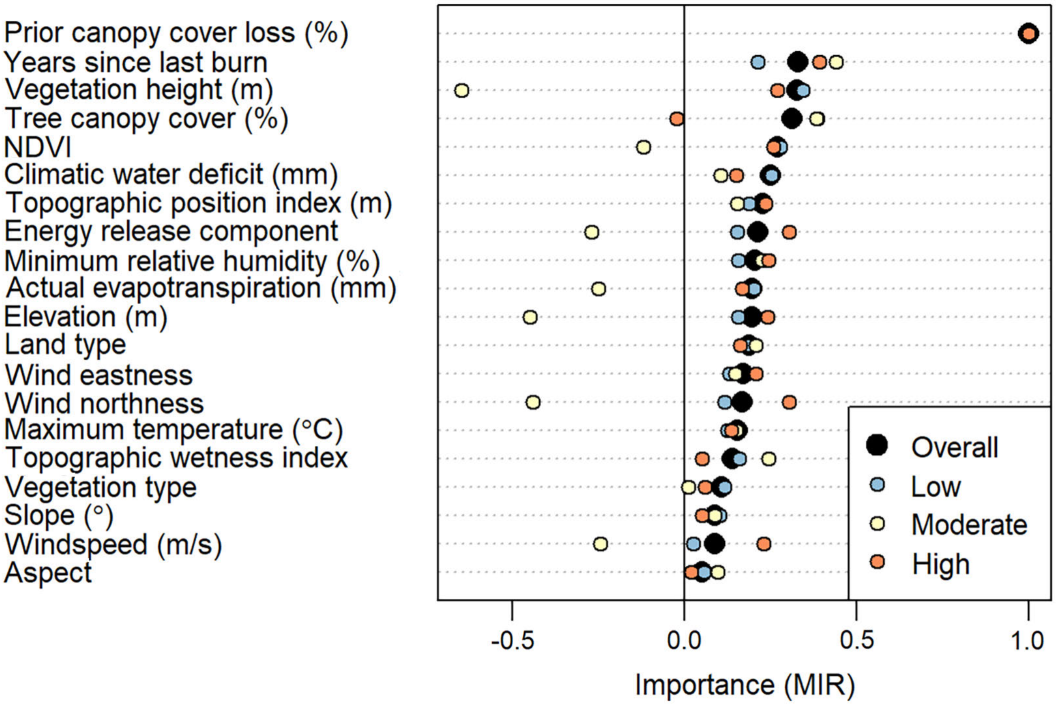

Fig. 7. Variable importance (model improvement ratio) from the random forest model of reburn fire severity as calculated across all fire severity classes and within each fire severity class (see legend). NDVI, normalized differenced vegetation index.

are rapidly transitioning from a region with a high fire deficit to one with an active fire regime, and area burned is likely to continue increasing in the future with climate change given the positive correlation we found between area burned and fire-season temperature.

Non-reburn fire severity

Fire weather, which was the key driver of especially high-severity fire in our non-reburn model, has been identified as a key driver of area burned and area burned at high severity in recent wildfires in other regions of the western USA (Lydersen et al. 2014, Abatzoglou and Williams 2016, Parks et al. 2018, Williams et al. 2019). Wind speed, which we found to be particularly influential, increases flame length and rate of spread amplifying fire effects and potential for passive or active crown fire, particularly in steep terrain (Agee and Skinner 2005, Andrews 2018). We also found that severity was lower (higher) with westerly (easterly) winds off the Pacific (Great Basin). High velocity winds from the northeast in this region are characteristically warm and dry (Schroeder and Buck 1970, Brewer et al. 2012) and often associated with large and severe wildfires in California (Skinner and Taylor 2018, Mass and Ovens 2019) and the Pacific Northwest (Schroeder and Buck 1970, Agee 1993).

The strong influence of weather on high-severity fire in non-reburns may account for the poor accuracy with which high-severity fire was predicted, because our weather data were daily and 4-km resolution whereas fire weather may vary dramatically hour-to-hour and over short distances in steep terrain. For these reasons, lack of sub-daily fire progression and fine-scale weather data are key limitations on the accuracy of statistical models of wildfire severity (Viedma et al. 2020). Moreover, incised topography and steep elevation gradients of the Klamath Mountains contribute to strong thermal inversions that trap smoke in the steep, narrow canyons reducing temperature (Robock 1988, Kochanski et al. 2019) and potentially fire effects, which we did not consider in our model. In summary, our relatively limited characterization of weather compared with terrain and fuels may explain why low-severity predictions were more generalizable than high-severity predictions (i.e., translated better to the independent test data set).

In contrast to high-severity fire, we found that low-severity fire in non-reburns was strongly influenced by fuels, specifically areas with higher canopy cover and tall vegetation indicating more mature forests with larger diameter, more fire-resistant trees which would reduce fire damage (Odion et al. 2004, Miller et al. 2012). Low-severity fire also occurred when NDVI was low (˜0.2), possibly due to sparse fuels sometimes associated with nutrient-poor soils on ultramafic rock (Whittaker 1960, Damschen et al. 2010), and where NDVI was high, possibly because high NDVI indicates typically moist meadows or subalpine forest. The relatively higher fire severity we observed at negative NDVI values was unexpected, yet the fact that we observed this response in the reburn model as well suggests that it was not simply the result of model overfitting. Normalized differenced vegetation index tends to be low in areas of drought-stressed or dead vegetation (Pettorelli et al. 2005, Brodrick and Asner 2017), but negative NDVI could also indicate wet areas or developed areas not represented by Landfire. Further analysis would be needed to determine the mechanisms behind this correspondence between negative NDVI and moderate–high-severity fire.

A hallmark of the Klamath Mountains is steep and complex terrain, and high-severity fire both before fire suppression (Taylor and Skinner 1998) and since 1984 (Weatherspoon and Skinner 1995, Jimerson and Jones 2003, Estes et al. 2017, Grabinski et al. 2017) was associated with ridgetops and southwestern aspects. Although we found that terrain had these same directional relationships with fire severity, the low importance of terrain in both our fire severity models is notable and suggests that the strong terrain controls on wildfire severity seen in the past may not necessarily carry into the future.

Reburn fire severity

Controls on reburn severity were markedly different than for non-reburns. A strong self-reinforcing effect of prior burn severity dominated our reburn severity model, being as important as all other variables combined. Moreover, the top five variables in the reburn model were fire history and vegetation variables. The importance of prior fire severity and vegetation/fuel variables is also evident in analyses of both small numbers of overlapping fires in the Klamath Mountains (Thompson et al. 2007, Estes et al. 2017), the Sierra Nevada (Collins et al. 2007, Harris and Taylor 2017), and American Southwest (Coop et al. 2016, Walker et al. 2018) and in multi-region and west wide studies (Parks et al. 2014*b*, Harvey et al. 2016, Stevens-Rumann et al. 2016) that include large numbers of overlapping fires. These studies, and our own, highlight a self-reinforcing pattern of reburn fire severity modulated by time since last fire and rates of fuel accumulation. Shorter periods (<10 yr) between reburns increase the probability of low-severity fire with a diminishing effect at longer fire intervals. A similar time since fire effect on reburn severity has been identified in other montane forests in California (Collins et al. 2009, Harris and Taylor 2017) and the western United States (Parks et al. 2014*b*, Harvey et al. 2016) with the effect lasting 10–20 yr.

Self-reinforcing fire severity in the Klamath Mountains is likely because severe fire initiates rapid establishment of evergreen shrubs and trees from sprouts or a soil seedbank which impedes conifer regeneration for at least several decades (Lauvaux et al. 2016, Tepley et al. 2017) with greater reduction as patch size increases. Self-reinforcing behavior in reburns in a landscape with an active fire regime would likely maintain these shrublands and non-conifer forest (Thompson and Spies 2009, Odion et al. 2010, Grabinski et al. 2017), particularly as fire activity increases with projected climate warming (Serra-Diaz et al. 2018). In addition, high-severity forest fire may encourage invasion of pyrogenic non-native plant species in the Klamath Mountains and throughout the western USA, which may promote further high-severity fire (Kerns et al. 2020, Reilly et al. 2020).

Limitations and model accuracy

Our study has a number of limitations. First, our analysis of drivers of fire severity was mainly limited to the period after 2002 when near-daily fire progression maps were available. We did not consider small fires <404 ha, although fire severity studies that have investigated inclusion of smaller fires concluded there would be little effect due to small area burned (Harris and Taylor 2017, Huang et al. 2020). Management practices such as salvage logging and tree planting post-fire can influence subsequent fire severity (Thompson et al. 2007), but considering these and other management practices as reported in the USFS Activity Tracking System (FACTS) database (https://data.fs.usda.gov/geodata/edw/datasets.php) did not improve the severity models. The record of these management actives is likely incomplete since they were not required to be reported to the FACTS database over our period of analysis. Although past logging should strongly influence fuels and therefore fire severity, the other vegetation variables in our model likely account, in part, for these effects on fuels. For example, recent logging should be reflected in decreased vegetation height.

Comparison of our model accuracy with other studies is challenging due to differences in the response variable (e.g., number of categories of severity) and the array of variables and data sets considered as predictors. Our random withholding of a set of fires to use as a test data set distinguishes our study from the prior work of Estes et al. (2017) and Grabinski et al. (2017) in the Klamath Mountains. Indeed, the gap between model accuracy as calculated using the OOB data vs. the test data sets in our study, particularly for non-reburns, underscores the importance of using a test data set of separate fire events when assessing accuracy. In this respect, the most relevant comparison is to Parks et al. (2018), who used some of the same predictor variables, included daily weather, and withheld individual fire events to assess model accuracy. They achieved modestly higher accuracy (area under curve = 0.68) for fires in the Klamath Mountains using only two fire severity classes (which should confer greater accuracy than three classes) and found fuel and weather to be more important than terrain as we did. We felt that including a moderate-severity class was important to represent the broad gradient between low-severity fire with minimal impact on canopy vegetation and high-severity fire that is stand-replacing or nearly stand-replacing, but moderate severity was predicted poorly. The breadth of fire effects included within "moderate severity" makes analysis of this category difficult (Lydersen et al. 2016) and makes reburn severity difficult to predict due to the diversity of post-fire–vegetation responses in moderate-severity areas (Collins et al. 2018). Future possibilities to improve statistical models of pixel-level fire severity such as ours include mapping sub-daily fire progression to more accurately characterize weather (Viedma et al. 2020), incorporating more complete information on forest and fire management activities, and quantifying other aspects of weather such as atmospheric inversions that trap smoke (Estes et al. 2017) and atmospheric instability leading to plume-driven fire behavior (Lydersen et al. 2014).

Conclusions and Management Implications

In the Klamath Mountains, non-reburns were strongly shaped by the interplay of fuel abundance and fire weather, with some modulation by topography. Low importance of terrain and vegetation characteristics likely reflects fuel buildup from a century of fire exclusion which overrode other controls on fire severity such as vegetation structure and terrain. Reburn severity, in contrast, was driven mainly by the initial burn severity and characteristics of post-fire–vegetation that developed after the initial fire. Initial burn severity was maintained by subsequent fires through strong self-reinforcing behavior; the importance of initial burn severity exceeded that of all other variables combined in the reburn model. Drivers of both non-reburn and reburn fire severity suggest that the historical patterns of wildfire severity that were controlled by topography (Taylor and Skinner 1998, 2003, Skinner et al. 2018, Hessburg et al. 2019) are shifting due to the effect of fire weather in a fuel-rich landscape on the one hand, and strong self-reinforcing behavior on the other. Consequently, the emerging patterns of fire severity in the Klamath Mountains will strongly determine future vegetation structure as the landscape continues to transition to an active fire regime.

Our findings that drivers of fire severity shift as landscapes transition to an active fire regime are relevant to resource agencies that seek to maintain and restore fire resilience to fire-excluded forest landscapes under a changing climate (Long et al. 2014, USDA Forest Service 2015, Board of Forestry 2018). Climate warming is expected to increase the length of the fire season (Westerling 2016), increase fuel aridity (Williams et al. 2019), and will likely increase the number of days that experience high and extreme fire weather (Goss et al. 2020, Abatzoglou et al. 2021). These climate factors and the high fuel loads characteristic of fire-excluded forests are strong contributors to the increase in forest area burned and forest area burned at high severity during the last three decades across the western United States (Abatzoglou and Williams 2016, Westerling 2016, Parks and Abatzoglou 2020) and in the Klamath Mountains. In the fuel-rich portions of the landscape, non-reburns had low- and moderate-severity fire effects when they burned under moderate fire weather conditions. Importantly, these low- and moderate-severity effects were sustained when these areas burned again within 10 yr, even if reburn weather conditions were more extreme. A reduced probability of high-severity fire after fuel reduction by wildfire or prescribed fire is typical in a wide range of forest ecosystems (Parks et al. 2014*a*, Harris and Taylor 2017, Prichard et al. 2017, Walker et al. 2018) and indicates landscape-scale burning can mitigate fuel conditions that contribute to high-severity fire and related undesirable shifts to non-forest vegetation (Lauvaux et al. 2016, Tepley et al. 2017).

Recent simulations of fire and forest dynamics in the Klamath Mountains also show that when landscape scale prescribed fire, and low-intensity wildfires, burn under moderate conditions fuels are reduced and the potential for vegetation change under future climate change is lowered when compared to a more extreme wildfire scenario (Maxwell et al. 2020). National direction allows for the use of unplanned ignitions, or wildfires, to meet multiple objectives, especially when the wildfire is likely to produce an ecological benefit and promote firefighter safety (2014 National Cohesive Wildland Fire Management Strategy). However, wildfire use for resource management or ecological benefit is not permitted on National Forest lands in the Klamath Mountains because their Land Management Plans do not yet provide for it. The active fire regime of mainly low- and moderate-severity fires that have developed over the past 34 yr has occurred under fire suppression management responses—control, confine, or contain which minimize costs while protecting lives and property and minimizing negative resource impacts (FLAME act 2009, Skinner et al. 2018). Our results suggest that improved resource outcomes and increased resilience to wildfire and climate change would likely be achieved through deliberate use of wildfire and prescribed fire for resource benefit and would increase area burned under more moderate and desirable conditions. As the active fire regime in the Klamath Mountains continues to develop, our data support changing National Forest Land Management Plans and accompanying Fire Management Plans to enable a more ecological approach to fire management where wildfires can be managed to create more fire resilient landscapes.

ACKNOWLEDGMENTS

Support for this research was provided by the USDA Forest Service Pacific Southwest Research Station (14-JV-11272167-037, 17-JV-11272167-048) and The Pennsylvania State University. We thank Carl N. Skinner for review of an earlier draft of this paper and Clint Isbell, Eric Knapp, and Frank Lake for discussion on recent fire patterns in the Klamath Mountains.

LITERATURE CITED

Abatzoglou, J. T. 2013. Development of gridded surface meteorological data for ecological applications and modelling. International Journal of Climatology 33:121–131.

Abatzoglou, J. T., C. S. Juang, A. P. Williams, C. A. Kolden, and A. L. R. Westerling. 2021. Increasing synchronous fire danger in forests of the western United States. Geophysical Research Letters 48:1–9.

Abatzoglou, J. T., and A. P. Williams. 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proceedings of the National Academy of Sciences of the United States of America 113:11770–11775.

Agee, J. K. 1993. Fire ecology of Pacific Northwest Forests. Island Press, Washington, D.C., U.S.A.

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

Alexander, J. D., N. E. Seavy, C. J. Ralph, and B. Hogoboom. 2006. Vegetation and topographical correlates of fire severity from two fires in the Klamath-Siskiyou region of Oregon and California. International Journal of Wildland Fire 15:237–245.

Andrews, P. L. 2018. The Rothermel surface fire spread model and associated developments: a comprehensive explanation. General Technical Report RMRS-GTR-371. USDA Forest Service Rocky Mountain Research Station, Fort Collins, Colorado, USA.

Beaty, R., and A. H. Taylor. 2001. Spatial and temporal variation of fire regimes in a mixed conifer forest landscape, Southern Cascades, California, USA. Journal of Biogeography 28:955–966.

Beers, T. W., P. E. Dress, and L. C. Wensel. 1966. Aspect transformation in site productivity research. Journal of Forestry 64:691–692.

Beven, K. J., and M. J. Kirkby. 1979. A physically based, variable contributing area model of basin hydrology. Hydrological Sciences Bulletin 24:43–69.

Board of Forestry. 2018. Strategic fire plan for California. California State Board of Forestry and Fire Protection, Sacramento, California, USA.

Bradshaw, L. S., J. E. Deeming, R. E. Burgan, and J. D. Cohen. 1983. The 1978 National Fire-Danger Rating System: technical documentation. General Technical Report INT-169. USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, Utah, USA.

Breiman, L. 2001. Random forests. Machine Learning 45:5–32.

Brewer, M. C., C. F. Mass, and B. E. Potter. 2012. The west coast thermal trough: climatology and synoptic evolution. Monthly Weather Review 140:3820–3843.

Brodrick, P. G., and G. P. Asner. 2017. Remotely sensed predictors of conifer tree mortality during severe drought. Environmental Research Letters 12:115013.

Buma, B., S. Weiss, K. Hayes, and M. Lucash. 2020. Wildland fire reburning trends across the US West suggest only short-term negative feedback and differing climatic effects. Environmental Research Letters 15:034026.

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

Chen, C., A. Liaw, and L. Breiman. 2004. Using random forest to learn imbalanced data. Technical Report 666. Statistics Department, University of California, Berkeley, California, USA.

Collins, B. M., M. Kelly, J. W. Wagtendonk, and S. L. Stephens. 2007. Spatial patterns of large natural fires in Sierra Nevada wilderness areas. Landscape Ecology 22:545–557.

Collins, B. M., J. M. Lydersen, R. G. Everett, and S. L. Stephens. 2018. How does forest recovery following moderate-severity fire influence effects of subsequent wildfire in mixed-conifer forests? Fire Ecology 14:3.

Collins, B. M., J. D. Miller, A. E. Thode, M. Kelly, J. W. Van Wagtendonk, and S. L. Stephens. 2009. Interactions among wildland fires in a long-established Sierra Nevada natural fire area. Ecosystems 12:114–128.

Coop, J. D., et al. 2020. Wildfire-driven forest conversion in western North American landscapes. BioScience 70:659–673.

Coop, J. D., S. A. Parks, S. R. Mcclernan, and L. M. Holsinger. 2016. Influences of prior wildfires on vegetation response to subsequent fire in a reburned southwestern landscape. Ecological Applications 26:346–354.

Coppoletta, M., K. E. Merriam, and B. M. Collins. 2016. Post-fire vegetation and fuel development influences fire severity patterns in reburns. Ecological Applications 26:686–699.

Cutler, D. R., T. C. Edwards, K. H. Beard, A. Cutler, K. T. Hess, J. Gibson, and J. J. Lawler. 2007. Random forests for classification in ecology. Ecology 88:2783–2792.

Daly, C., M. Halbleib, J. I. Smith, W. P. Gibson, M. K. Doggett, G. H. Taylor, J. Curtis, and P. P. Pasteris. 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. International Journal of Climatology 28:2031–2064.

Daly, C., J. I. Smith, and K. V. Olson. 2015. Mapping atmospheric moisture climatologies across the conterminous United States. PLOS ONE 10: e0141140.

Damschen, E. I., S. Harrison, and J. B. Grace. 2010. Climate change effects on an endemic-rich edaphic flora: resurveying Robert H. Whittaker's Siskiyou sites (Oregon, USA). Ecology 91:3609–3619.

Davis, R. J., B. Hollen, J. Hobson, J. E. Gower, and D. Keenum. 2016. Status and trends of northern spotted owl habitats. PNW-GTR-929. USDA Forest Service Pacific Northwest Research Station, Portland, Oregon, USA.

Eidenshink, J., B. Schwind, K. Brewer, Z. Zhu, B. Quayle, and S. Howard. 2007. A project for monitoring trends in burn severity. Fire Ecology 3:3–21.

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

FLAME act. 2009. Pages 1–14. S. 561, 111th United States Congress.

Flint, L. E., A. L. Flint, J. H. Thorne, and R. Boynton. 2013. Fine-scale hydrologic modeling for regional landscape applications: the California Basin Characterization Model development and performance. Ecological Processes 2:25.

Fry, D. L., and S. L. Stephens. 2006. Influence of humans and climate on the fire history of a ponderosa pine-mixed conifer forest in the southeastern Klamath Mountains, California. Forest Ecology and Management 223:428–438.

Goss, M., D. L. Swain, J. T. Abatzoglou, A. Sarhadi, C. A. Kolden, A. P. Williams, and N. S. Diffenbaugh. 2020. Climate change is increasing the likelihood of extreme autumn wildfire conditions across California. Environmental Research Letters 15:094016.

Grabinski, Z. S., R. L. Sherriff, and J. M. Kane. 2017. Controls of reburn severity vary with fire interval in the Klamath Mountains, California, USA. Ecosphere 8:e02012.

Greenwell, B. M. 2017. pdp: an R package for constructing partial dependence plots. R Journal 9:421–436.

Harris, L., and A. H. Taylor. 2015. Topography, fuels, and fire exclusion drive fire severity of the Rim Fire in an old-growth mixed-conifer forest, Yosemite National Park, USA. Ecosystems 18:1192–1208.

Harris, L., and A. H. Taylor. 2017. Previous burns and topography limit and reinforce fire severity in a large wildfire. Ecosphere 8:e02019.

Harvey, B. J., D. C. Donato, and M. G. Turner. 2016. Burn me twice, shame on who? Interactions between successive forest fires across a temperate mountain region. Ecology 97:2272–2282.

Hayasaka, H., and C. N. Skinner. 2009. 2008 Forest fires in the Northern California, USA. Pages 1–9 *in* The Eighth Symposium on Fire and Forest Meteorology. American Meteorological Society, Boston, Massachusetts, USA.

Heinselman, M. L. 1973. Fire in the virgin forests of the Boundary Waters Canoe Area, Minnesota. Quaternary Research 3:329–382.

Hessburg, P. F., et al. 2019. Climate, environment, and disturbance history govern resilience of western North American forests. Frontiers in Ecology and Evolution 7:1–27.

Huang, Y., Y. Jin, M. W. Schwartz, and J. H. Thorne. 2020. Intensified burn severity in California's northern coastal mountains by drier climatic condition. Environmental Research Letters 15:104033.

Jimerson, T. M., and D. W. Jones. 2003. Megram: blowdown, wildfire, and the effects of fuel treatment. Pages 55–59 *in* Fire Conference 2000: The First National Congress on Fire Ecology, Prevention, and Management. Tall Timbers Research Station, Tallahassee, Florida, USA.

Johnstone, J. F., et al. 2016. Changing disturbance regimes, ecological memory, and forest resilience. Frontiers in Ecology and the Environment 14:369–378.

Kane, V. R., C. A. Cansler, N. A. Povak, J. T. Kane, R. J. Mcgaughey, J. A. Lutz, D. J. Churchill, and M. P. North. 2015. Mixed severity fire effects within the Rim fire: relative importance of local climate, fire weather, topography, and forest structure. Forest Ecology and Management 358:62–79.

Kerns, B. K., C. Tortorelli, M. A. Day, T. Nietupski, A. M. G. Barros, J. B. Kim, and M. A. Krawchuk. 2020. Invasive grasses: A new perfect storm for forested ecosystems? Forest Ecology and Management 463:117985.

Knapp, E. E., C. N. Skinner, M. P. North, and B. L. Estes. 2013. Long-term overstory and understory change following logging and fire exclusion in a Sierra Nevada mixed-conifer forest. Forest Ecology and Management 310:903–914.

Kochanski, A. K., D. V. Mallia, M. G. Fearon, J. Mandel, A. H. Souri, and T. Brown. 2019. Modeling wildfire smoke feedback mechanisms using a coupled fire-atmosphere model with a radiatively active aerosol scheme. Journal of Geophysical Research Atmospheres 124:9099–9116.

Kruckeberg, A. R. 1985. California serpentines: flora, vegetation, geology, soils and management problems. University of California Press, Berkeley, California, USA.

Lake, F. K., and A. C. Christianson. 2019. Indigenous fire stewardship. *In* S. L. Manzello, editor. Encyclopedia of wildfires and wildland-urban interface (WUI) fires. Springer, Cham, Switzerland.

Lauvaux, C. A., C. N. Skinner, and A. H. Taylor. 2016. High severity fire and mixed conifer forest-chaparral dynamics in the southern Cascade Range, USA. Forest Ecology and Management 363:74–85.

Lewis, H. T. 1990. Reconstructing patterns of Indian burning in southwestern Oregon. Pages 80–84 *in* N. Hannon and R. K. Olmo, editors. Living with the land: the Indians of Southwest Oregon. Southern Oregon Historical Society, Ashland, Oregon, USA.

Lewis, H. T. 1993. Patterns of Indian burning in California: ecology and ethnohistory. Pages 55–116 *in* T. C. Blackburn and K. Anderson, editors. Before the wilderness: Environmental management by native Californians. Ballena Press, Menlo Park, California, USA.

Liaw, A., and M. Wiener. 2002. Classification and regression by randomForest. R News 2:18–22.

Long, J. W., L. Quinn-Davidson, and C. N. Skinner. 2014. Science synthesis to support socioecological resilience in the Sierra Nevada and southern Cascade Range. General Technical Report PSW-GTR-247. USDA Forest Service Pacific Southwest Research Station, Albany, California, USA.

Lydersen, J. M., B. M. Collins, J. D. Miller, D. L. Fry, and S. L. Stephens. 2016. Relating fire-caused change in forest structure to remotely sensed estimates of fire severity. Fire Ecology 12:99–116.

Lydersen, J., and M. North. 2012. Topographic variation in structure of mixed-conifer forests under an active-fire regime. Ecosystems 15:1134–1146.

Lydersen, J. M., M. P. North, and B. M. Collins. 2014. Severity of an uncharacteristically large wildfire, the Rim Fire, in forests with relatively restored frequent fire regimes. Forest Ecology and Management 328:326–334.

Marlon, J. R., et al. 2012. Long-term perspective on wildfires in the western USA. Proceedings of the National Academy of Sciences of the United States of America 109:E535–E543.

Mass, C. F., and D. Ovens. 2019. The northern California wildfires of 8–9 October 2017. Bulletin of the American Meteorological Society 100:235–256.

Maxwell, C. J., J. M. Serra-Diaz, R. M. Scheller, and J. R. Thompson. 2020. Co-designed management scenarios shape the responses of seasonally dry forests to changing climate and fire regimes. Journal of Applied Ecology 57:1328–1340.

Metcalfe, P., K. Beven, and J. Freer. 2018. dynatopmodel. R package v1.2.1. https://cran.r-project.org/package=dynatopmodel

Miller, J. D., E. E. Knapp, C. H. Key, C. N. Skinner, C. J. Isbell, R. M. Creasy, and J. W. Sherlock. 2009. Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA. Remote Sensing of Environment 113:645–656.

Miller, J. D., C. N. Skinner, H. D. Safford, E. E. Knapp, and C. M. Ramirez. 2012. Trends and causes of severity, size, and number of fires in northwestern California, USA. Ecological Applications 22:184–203.

Miller, J. D., and A. E. Thode. 2007. Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). Remote Sensing of Environment 109:66–80.

Miller, A. D., J. R. Thompson, A. J. Tepley, and K. J. Anderson-Teixeira. 2018. Alternative stable equilibria and critical thresholds created by fire regimes and plant responses in a fire-prone community. Ecography 41:1–12.

Mitchell, K. E., et al. 2004. The multi-institution North American Land Data Assimilation System (NLDAS): utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system. Journal of Geophysical Research 109:D07S90.

Murphy, M. A., J. S. Evans, and A. Storfer. 2010. Quantifying *Bufo boreas* connectivity in Yellowstone National Park with landscape genetics. Ecology 91:252–261.

Odion, D. C., E. J. Frost, J. R. Strittholt, H. Jiang, D. A. Dellasala, and M. A. Moritz. 2004. Patterns of fire severity and forest conditions in the western Klamath Mountains, California. Conservation Biology 18:927–936.

Odion, D. C., M. A. Moritz, and D. A. DellaSala. 2010. Alternative community states maintained by fire in the Klamath Mountains, USA. Journal of Ecology 98:96–105.

Parks, S. A. 2014. Mapping day-of-burning with coarse-resolution satellite fire-detection data. International Journal of Wildland Fire 23:215–223.

Parks, S. A., and J. T. Abatzoglou. 2020. Warmer and drier fire seasons contribute to increases in area burned at high severity in western US forests from 1985 to 2017. Geophysical Research Letters 47:1–10.

Parks, S., L. Holsinger, M. Panunto, W. M. Jolly, S. Dobrowski, and G. Dillon. 2018. High severity fire: evaluating its key drivers and mapping its probability across western US forests. Environmental Research Letters 13:1–13.

Parks, S. A., C. Miller, C. R. Nelson, and Z. A. Holden. 2014*a*. Previous fires moderate burn severity of subsequent wildland fires in two large western US wilderness areas. Ecosystems 17:29–42.

Parks, S. A., M. A. Parisien, C. Miller, and S. Z. Dobrowski. 2014*b*. Fire activity and severity in the western US vary along proxy gradients representing fuel amount and fuel moisture. PLOS ONE 9:1–8.

Perry, D. A., P. F. Hessburg, C. N. Skinner, T. A. Spies, S. L. Stephens, A. H. Taylor, J. F. Franklin, B. McComb, and G. Riegel. 2011. The ecology of mixed severity fire regimes in Washington, Oregon, and Northern California. Forest Ecology and Management 262:703–717.

Peterson, G. D. 2002. Contagious disturbance, ecological memory, and the emergence of landscape pattern. Ecosystems 5:329–338.

Pettorelli, N., J. O. Vik, A. Mysterud, J. M. Gaillard, C. J. Tucker, and N. C. Stenseth. 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends in Ecology and Evolution 20:503–510.

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 Ecology 35:293–318.

Prichard, S. J., C. S. Stevens-Rumann, and P. F. Hessburg. 2017. Tamm Review: shifting global fire regimes: Lessons from reburns and research needs. Forest Ecology and Management 396:217–233.

Reilly, M. J., M. G. McCord, S. M. Brandt, K. P. Linowksi, R. J. Butz, and E. S. Jules. 2020. Repeated, high-severity wildfire catalyzes invasion of non-native plant species in forests of the Klamath Mountains, northern California, USA. Biological Invasions 22:1821–1828.

Robock, A. 1988. Enhancement of surface cooling due to forest fire smoke. Science 242:911–913.

Rollins, M. G. 2009. LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. International Journal of Wildland Fire 18:235–249.

Sawyer, J. O. 2006. Northwest California: a natural history. University of California Press, Berkeley, California, USA.

Scholl, A. E., and A. H. Taylor. 2010. Fire regimes, forest change, and self-organization in an old-growth mixed-conifer forest, Yosemite National Park, USA. Ecological Applications 20:362–380.

Schroeder, M. J., and C. C. Buck. 1970. Fire Weather: a guide for application of meteorological information to forest fire control operations. Agricultural Handbook 360. USDA Forest Service, Washington, D.C., USA.

Seaber, P. R., F. P. Kapinos, and G. L. Knapp. 1987. Hydrologic unit maps. Water-Supply Paper 2294. USDI Geological Survey, Denver, Colorado, USA.

Serra-Diaz, J. M., C. Maxwell, M. S. Lucash, R. M. Scheller, D. M. Laflower, A. D. Miller, A. J. Tepley, H. E. Epstein, K. J. Anderson-Teixeira, and J. R. Thompson. 2018. Disequilibrium of fire-prone forests sets the stage for a rapid decline in conifer dominance during the 21st century. Scientific Reports 8:1–12.

Shrader, G. 1965. Trinity Forest. Pages 37–40 *in* Yearbook of the Trinity County Historical Society. Trinity County Historical Society, Weaverville, California, USA.

Skinner, C. N., and A. H. Taylor. 2018. Southern Cascades bioregion. Pages 195–218 *in* J. W. van Wagtendonk, N. G. Sugihara, S. L. Stephens, A. E. Thode, K. E. Shaffer, and J. A. Fites-Kaufman, editors. Fire in California's ecosystems. University of California Press, Oakland, California, USA.

Skinner, C. N., A. H. Taylor, J. K. Agee, C. E. Briles, and C. L. Whitlock. 2018. Klamath Mountains bioregion. Pages 171–193 *in* J. W. van Wagtendonk, N. G. Sugihara, S. L. Stephens, A. E. Thode, K. E. Shaffer, and J. A. Fites-Kaufman, editors. Fire in California's ecosystems. University of California Press, Oakland, California, USA.

Spies, T. A., P. F. Hessburg, C. N. Skinner, K. J. Puettmann, M. J. Reilly, R. J. Davis, J. A. Kertis, J. W. Long, and D. C. Shaw. 2018. Old growth, disturbance, forest succession, and management in the area of the Northwest Forest Plan. Pages 95–243 *in* Synthesis of science to inform land management within the Northwest Forest Plan area. PNW-GTR-966. USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA.

Stephens, S. L., R. E. Martin, and N. E. Clinton. 2007. Prehistoric fire area and emissions from California's forests, woodlands, shrublands, and grasslands. Forest Ecology and Management 251:205–216.

Stephenson, N. 1990. Climatic control of vegetation distribution: the role of the water balance. American Naturalist 135:649–670.

Stevens-Rumann, C. S., S. J. Prichard, E. K. Strand, and P. Morgan. 2016. Prior wildfires influence burn severity of subsequent large fires. Canadian Journal of Forest Research 46:1375–1385.

Syphard, A. D., and J. E. Keeley. 2016. Historical reconstructions of California wildfires vary by data source. International Journal of Wildland Fire 25:1221–1227.

Taylor, A. H. 2000. Fire regimes and forest changes in mid and upper montane forests of the southern Cascades, Lassen Volcanic National Park, California, USA. Journal of Biogeography 27:87–104.

Taylor, A. H., C. Airey-Lauvaux, B. L. Estes, L. Harris, and C. N. Skinner. 2020. Spatial patterns of nineteenth century fire severity persist after fire exclusion and a twenty-first century wildfire in a mixed conifer forest landscape, Southern Cascades, USA. Landscape Ecology 35:2777–2790.

Taylor, A. H., and C. N. Skinner. 1998. Fire history and landscape dynamics in a late-successional reserve, Klamath Mountains, California, USA. Forest Ecology and Management 111:285–301.

Taylor, A. H., and C. N. Skinner. 2003. Spatial patterns and controls on historical fire regimes and forest structure in the Klamath Mountains. Ecological Applications 13:704–719.

Taylor, A. H., A. M. Vandervlugt, R. S. Maxwell, R. M. Beaty, C. Airey, and C. N. Skinner. 2014. Changes in forest structure, fuels and potential fire behaviour since 1873 in the Lake Tahoe Basin, USA. Applied Vegetation Science 17:17–31.

Tepley, A. J., J. R. Thompson, H. E. Epstein, and K. J. Anderson-Teixeira. 2017. Vulnerability to forest loss through altered postfire recovery dynamics in a warming climate in the Klamath Mountains. Global Change Biology 23:4117–4132.

Thompson, J. R., and T. A. Spies. 2009. Vegetation and weather explain variation in crown damage within a large mixed-severity wildfire. Forest Ecology and Management 258:1684–1694.

Thompson, J., T. A. Spies, and L. M. Ganio. 2007. Reburn severity in managed and unmanaged vegetation in a large wildfire. Proceedings of the National Academy of Sciences of the United States of America 104:10743–10748.

Trouet, V., A. H. Taylor, A. M. Carleton, and C. N. Skinner. 2009. Interannual variations in fire weather, fire extent, and synoptic-scale circulation patterns in northern California and Oregon. Theoretical and Applied Climatology 95:349–360.

USDA Forest Service. 2015. USDA forest service strategic plan: FY 2015–2020. FS-1045. USDA Forest Service, Washington, D.C., USA.

Viedma, O., F. Chico, J. J. Fernández, C. Madrigal, H. D. Safford, and J. M. Moreno. 2020. Disentangling the role of prefire vegetation vs. burning conditions on fire severity in a large forest fire in SE Spain. Remote Sensing of Environment 247:111891.

Walker, R. B., J. D. Coop, S. A. Parks, and L. Trader. 2018. Fire regimes approaching historic norms reduce wildfire-facilitated conversion from forest to non-forest. Ecosphere 9:e02182.

Weatherspoon, C., and C. N. Skinner. 1995. An assessment of factors associated with damage to tree crowns from the 1987 wildfires in northern California. Forest Science 41:430–451.

Weiss, A. D. 2001. Topographic position and landforms analysis. Poster presentation. ESRI User Conference, San Diego, California, USA.

Westerling, A. L. 2016. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. Philosophical Transactions of the Royal Society of London B: Biological Sciences 371:1–10.

Whittaker, R. H. 1960. Vegetation of the Siskiyou Mountains, Oregon and California. Ecological Monographs 30:279–338.

Williams, A. P., J. T. Abatzoglou, A. Gershunov, J. Guzman-Morales, D. A. Bishop, J. K. Balch, and D. P. Lettenmaier. 2019. Observed impacts of anthropogenic climate change on wildfire in California. Earth's Future 7:892–910.

Zhu, Z., J. Vogelmann, D. Ohlen, J. Kost, X. Chen, and B. Tolk. 2006. Mapping existing vegetation composition and structure for the LANDFIRE prototype project. Pages 197–215 *in* The LANDFIRE Prototype Project: nationally consistent and locally relevant geospatial data for wildland fire management. RMRS-GTR-175. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado, USA.

Supporting Information

Additional Supporting Information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/ecs2.3734/full