

Automated workflow demonstrates mixed treatment impacts on burn severity across ecoregion scales

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ABSTRACT

Background. Intensifying wildfire activity in western North America has motivated focus on fuel treatments as a tool for moderating fire severity. Treatment effectiveness is influenced by complex interactions among biophysical settings, treatments and weather. **Aims.** This study introduces a standardized, scalable workflow to quantify wildfire-treatment outcomes across diverse landscapes. **Methods.** We evaluated federal fuel treatments across 50 wildfires in southern Oregon and Northern California (2012–2021). We analyzed outcomes across two distinct landscapes: the productive, western Klamath mountains (west) and the more arid southeastern Cascades (east) to predict the probability of high severity fire. **Results.** In the east, treatments reduced the probability of high-severity fire, especially treatments less than 9 years old. Thinning followed by prescribed fire mitigated high-severity effects even during extreme fire conditions. Conversely, in the west, large fire spread days primarily predicted high severity, masking the effect of treatments and other bottom-up drivers. **Conclusions.** In pine systems with low topographic complexity, fuel treatments that remove both canopy and surface fuels from stands lower the likelihood of high severity fire within 9 years of implementation, including under extreme fire conditions. **Implications.** This study proposes an open-source workflow to evaluate the conditions which treatments are effective across large landscapes.

Keywords: FACTS, fire ecology, forest management, fuel treatments, high severity fire, landscape effectiveness, mechanical thinning, prescribed fire, resilience, wildfire.

Introduction

Wildfires have increased in size and severity across western North America in recent decades (Westerling *et al.* 2006; Abatzoglou and Kolden 2013; Abatzoglou and Williams 2016; Iglesias *et al.* 2022). Land management practices, including fire suppression and the exclusion of Indigenous burning have led to increased fuel loads and tree densities in formerly frequent-fire forests (Kimmerer and Lake 2001; Marlon *et al.* 2012a, 2012b; Knapp *et al.* 2013; Parks *et al.* 2015). Rising temperatures and prolonged droughts amplify these fuel changes, further exacerbating burning conditions, fuel amounts available for combustion and increasing tree mortality (Abatzoglou and Williams 2016; Coop *et al.* 2022; Alizadeh *et al.* 2023). Given these novel conditions, wildfires in formerly frequent-fire forests are increasingly characterized by large spread events and high-severity patches (Miller *et al.* 2009b; Mallek *et al.* 2013; Potter and McEvoy 2021; Parks *et al.* 2023), which can have profound impacts on ecological recovery trajectories

Collection: Large-Scale Evaluation of Wildfire-Treatment Outcomes: Analyzing for Multiple Objectives

and multiple forest ecosystem services (Mallek *et al.* 2013; Moody *et al.* 2013; Stevens-Rumann *et al.* 2018; Tepley *et al.* 2018; Davis *et al.* 2019; Williams *et al.* 2022).

To mitigate negative impacts of contemporary wildfires, forest managers use a variety of treatments to manipulate, redistribute, or remove vegetation, which alter forest structure and fuel profiles to influence subsequent wildfire behavior and effects (Fulé *et al.* 2012; Martinson and Omi 2013; Kalies and Yocom Kent 2016; Ott *et al.* 2023; Davis *et al.* 2024). Depending on the ecological and operational context, the objectives of these practices can vary (e.g. objectives associated with hazardous fuels load reduction or ecological restoration) (Stephens *et al.* 2021). These treatments often result in similar outcomes in terms of vegetation modification and changes to forest structure: removing canopy fuel loads, reducing or rearranging surface fuels and/or promoting specific, often more fire-resistant, tree species (Agee and Skinner 2005; Stephens *et al.* 2012; Stevens *et al.* 2014; Kalies and Yocom Kent 2016). Some fuel treatments (e.g. mechanical thinning) are designed to reduce crown fire potential by removing small trees and ladder fuels and increasing the proportion of larger, more fire-resistant individuals. Other types of fuel treatments (e.g. broadcast burning or pile burning) are intended to reduce surface fuels and lower the intensity of future fires (Agee and Skinner 2005; Schwilk *et al.* 2009).

Because one of the main objectives of fuel treatments is to modify wildfire behavior, assessments of treatment effectiveness often focus on whether the treatment changed fire behavior when encountered by a wildfire (Fallon *et al.* 2025). However, changes in fire behavior alone do not constitute an outcome of a wildfire-treatment interaction if they are not linked to the response of a highly valued resource, asset, or human behavior (Scott *et al.* 2013). Wildfire-treatment outcomes may be defined in terms of mitigated impacts on human infrastructure (Knapp *et al.* 2021) or fire suppression activities (Gannon *et al.* 2023), but they are most commonly assessed at large scales in terms of the response of vegetation mortality, based on metrics of burn severity typically derived from remote sensing imagery (Kalies and Yocom Kent 2016; Hood 2023; Davis *et al.* 2024). To date, research in dry frequent-fire forests has consistently shown that fuel treatments, especially ones that combine mechanical thinning and prescribed burning, can substantially reduce subsequent wildfire burn severity compared to untreated areas (Martinson and Omi 2013; Brodie *et al.* 2024; Davis *et al.* 2024).

However, the degree to which treatments are effective at reducing high-severity fire varies among vegetation type, treatment type, and with environmental and fire weather conditions (Raymond and Peterson 2005; Grabinski *et al.* 2017; Taylor *et al.* 2022; Weston *et al.* 2022; Johnson *et al.* 2025). For example, thinning-only treatments in Pacific Northwest dry forests failed to reduce burn severity under

extreme fire weather conditions (Lydersen *et al.* 2017; Prichard *et al.* 2020; Chamberlain *et al.* 2024), while these same treatment types (and others) reduced severity even under extreme conditions in Colorado (Stevens-Rumann *et al.* 2025). The challenge in evaluating treatment effectiveness across key environmental gradients stems from the complex and interacting biophysical, fire weather and past management conditions that influence fire behavior and burn severity across local to landscape scales (Parks *et al.* 2018; Prichard *et al.* 2020; Johnson *et al.* 2025; Povak *et al.* 2025). The interactions and hierarchical relationships, along with smaller sample sizes from more localized studies, complicate our understanding of these environmental thresholds under which treatments have maximal impact at reducing high-severity fire (Martinson and Omi 2013; Chamberlain *et al.* 2024; Davis *et al.* 2024). Further, while a few studies have evaluated treatment effects on burn severity at ecoregion landscape scales, including hundreds of wildfire-treatment interactions (Bradstock *et al.* 2010; Prichard *et al.* 2020; Cansler *et al.* 2022; Povak *et al.* 2025), we currently lack standardized workflows for systematically conducting these types of analyses across very large landscapes with thousands of wildfire-treatment interactions.

Systematic and reproducible studies of large landscapes are needed to help build empirical understanding of how diverse forest management practices fare under a range of biophysical conditions (Chamberlain *et al.* 2024; Fallon *et al.* 2025). The climatic diversity and topographic complexity of the Klamath River Watershed in northern California and southern Oregon makes it an ideal study system to compare treatment impacts on burn severity across a variety of pre-fire landscape conditions (see the section 'Methods: Study area'). This landscape encompasses varied fire history, including previously studied fires that have burned under a diverse range of biotic and abiotic conditions (Skinner *et al.* 2006; Perry *et al.* 2011; Estes *et al.* 2017; Brodie *et al.* 2024; Chamberlain *et al.* 2024; Beckmann *et al.* 2025) and has experienced large recent wildfires burning at increasingly high severity (Taylor *et al.* 2021).

Here, we developed a novel, scalable and reproducible workflow to understand how environmental thresholds influence wildfire-treatment outcomes across large landscapes. Through a case study approach, our goal was to quantify where and when biophysical variation, wildfire characteristics and treatment characteristics can mediate the effects of treatments on one specific outcome related to fostering resilient landscapes: reducing high-severity fire. However, this flexible workflow could be applied to study other desirable outcomes of wildfire-treatment interactions like impacts on carbon-stocks, infrastructure or wildlife habitat, and containment success. Here, we quantified the effectiveness of treatments at reducing high-severity fire in over 3427 treatment interactions within 50 wildfires

between 2012 and 2021, making this, to our knowledge, among the largest systematic studies of treatment outcomes conducted to date. We conducted our case-study across two of the US Department of Agriculture (USDA) Forest Service Wildfire Crisis Strategy landscapes (WCSLs): the Klamath River Basin and Trinity Forest Health and Fire-Resilient Rural Communities landscapes in northwest California and southwest Oregon. We defined fuel treatment effectiveness as the reduction of area burned at high severity as compared to similar untreated areas. Our study asked (1) how did fuel treatments influence subsequent high severity wildfire as compared with untreated areas, (2) under what environmental and treatment conditions were fuel treatments most likely to improve fire severity outcomes, and (3) how did these relationships differ between more mesic and topographically complex landscapes in the western portion of our study area, to more xeric and topographically less complex landscapes in the eastern portion of our study area? To investigate these questions, we developed a semi-automated approach comprised of open-source code and empirical, geospatial data. With this workflow, future researchers and management analysts can explore the environmental thresholds that govern fuel treatment efficacy across other ecoregions or landscapes.

Methods

Study area

Our study area encompasses federally managed public lands in the Klamath River Basin and the Trinity Forest Health and Fire-Resilient Rural Communities WCSLs, US (Fig. 1), deemed high priority landscapes due to the heightened threat from wildfire to communities, critical infrastructure and natural resources (USFS 2022). To focus our analysis, we bisected the landscape into two portions, using a north running transect delineating the Klamath mountains and southern Cascades bioregions from west to east, respectively (Skinner *et al.* 2006).

The western study area is topographically complex and influenced by its proximity to the Pacific Ocean. Steep valleys and prominent ridges influence fire behavior and strong elevational gradients lead to temperature inversions that can have a major influence on fire activity (Estes *et al.* 2017; Taylor *et al.* 2022). This area has historically experienced a fire regime skewed towards frequent mostly low-severity fire but mixed with some moderate to high-severity effects often tied to topographic drivers of fire behavior. A large elevational gradient ranging from 200 to 2100m in forested areas promotes variation in structure and ecological communities. Lower-elevation areas include shrubland, hardwoods such as blue oak (*Quercus douglasii*), Brewer oak (*Quercus garryana* var. *breweri*), black oak (*Quercus kelloggii*), tanoak (*Notholithocarpus densiflorus*) and Pacific madrone (*Arbutus menziesii*), along with

mixed-conifer forest species. Proportion of conifers increases at mid elevations, with forests containing Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*), with sugar pine (*Pinus lambertiana*), incense cedar (*Calocedrus decurrens*) and white fir (*Abies concolor*) also common. Upper elevation forests are primarily coniferous sharing similar species to the mid-elevations. Species diversity is very high, with as many as 17 conifer species per square mile (Keeler-Wolf 1990).

The southeastern Cascades Foothills lie in the rain shadow of the Klamath Mountains, featuring a relatively milder bioclimatic and topographic profile with more gentle slopes at elevations ranging from 1300 to 2600 m. The dominant species in this area is ponderosa pine at mid-elevations, whereas sagebrush and grassland dominate the lower elevations and white fir and red fir become more prominent at higher elevations. The eastern study area historically experienced frequent, predominantly low severity fire. Across the landscape, the majority of fires occur during the summer months (May–September) and are ignited by lightning with a relatively larger proportion of anthropogenic ignitions in the eastern Cascades Foothills (Keeley and Syphard 2018).

Analytical workflow

We developed a reproducible analytical workflow to systematically understand how fuel treatments impacted vegetation burn severity as explained in the following sections (Fig. 2). In general, the workflow (1) prepares geospatial data, including selecting historical wildfires and treatments, generating environmental predictor variables and systematically samples points across the landscape, (2) creates fire-level models to select paired treated and untreated points based on important fire-level drivers, and (3) fits landscape-level models to determine which variables influence whether or not a treated sample is meaningfully different from an untreated sample. We leveraged open-source programming languages (R and Python) and geospatial data to provide users with a step-by-step, scripted workflow to isolate wildfire-treatment effects for a range of biophysical conditions across a multi-fire landscape. Throughout our analysis, we utilized random forest models because they can easily identify the non-linear, non-parametric relationships that exist between the biophysical predictors and the burn severity response variable.

Fire selection and fuel treatment history

We selected large wildfires (>405 ha) that intersected the study area and burned between 2012 and 2021 from the Monitoring Trends in Burn Severity (MTBS) fire perimeter data (Eidenshink *et al.* 2007). We then gathered vegetation management data on lands administered by the US Forest Service and Department of

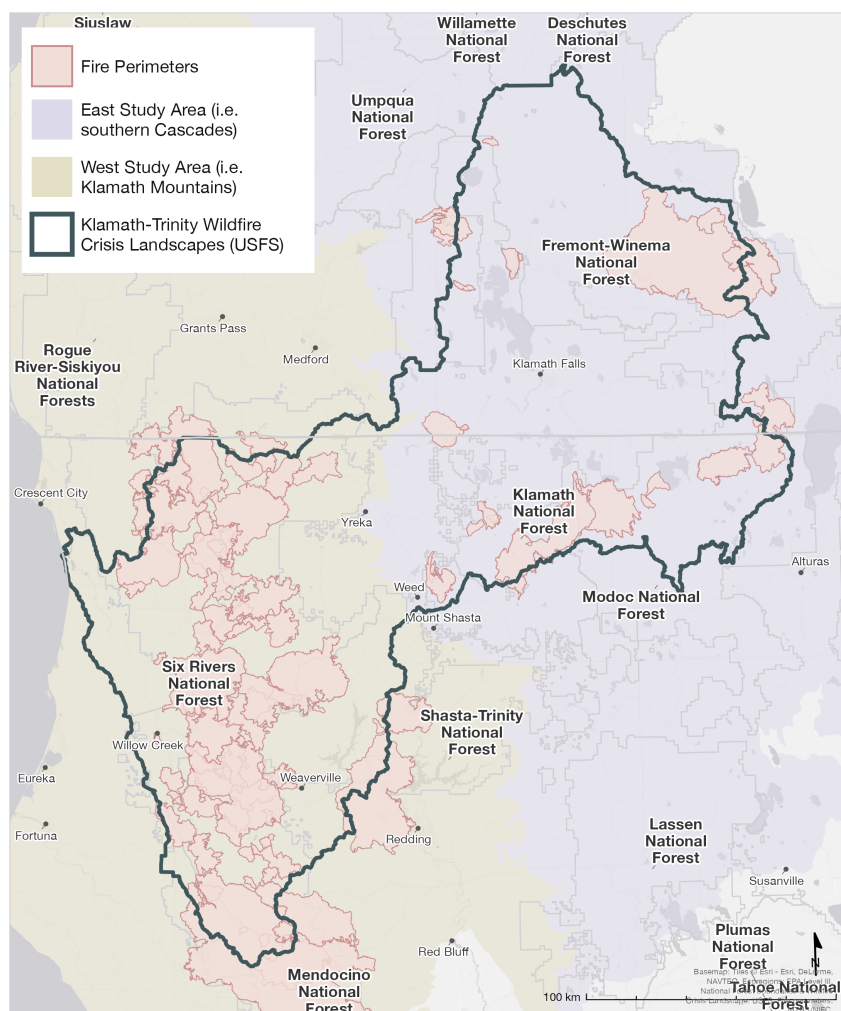


Fig. 1. Map of study area and the selected fire perimeters from 2012 to 2021. The shaded purple and green areas represent the ‘east’ and ‘west’ region across the Klamath-Trinity Wildfire Crisis Landscape, respectively, where the gray line represents the US Forest Service (USFS) and US National Parks Service administration delineations.

Interior agencies from the Forest Activity Tracking System (FACTS) and National Fire Plan Operations and Reporting System (NFPORS). All forest treatments that were completed 20 years or less before intersecting with a wildfire were retained for further analysis. Unplanned wildfire ignitions identified in the FACTS/NFPORS datasets were subsequently excluded as well. Based on this criteria, our final dataset contained 50 total wildfire perimeters with 15 and 35 in the east and west landscapes, respectively.

Adapting the categorization scheme of [Fallon *et al.* \(2025\)](#), we classified treatments into 10 initial categories where one or more treatments occurred: prescribed fire, removal, surface fuels reduction, rearrangement, total canopy removal, removal + prescribed fire, rearrangement + prescribed fire, removal + surface fuels reduction, total canopy removal + prescribed fire, total canopy removal + removal (Supplementary Material: Fuel Treatment Data, Supplementary Table S1). Note that the named order of categories with multiple treatments (e.g. ‘removal + prescribed fire’) does not necessarily imply the chronological order of the treatments.

All three treatment categories that included the class ‘total canopy removal’ were removed from the analysis due to limited sample size, resulting in seven treatment categories ([Fig. 3a](#)). Following [Fallon *et al.* \(2025\)](#), we defined the four unique treatment categories as the following: ‘prescribed fire’ treatments decreased fuel loads with fire (primarily through broadcast burning), ‘removal’ removed large woody biomass from the treated sites (most often, thinning), ‘surface fuels reduction’ decreased surface fuels (not including broadcast burning – most often pile burning) and ‘rearrangement’ altered fuel structure without removing biomass from treated sites (most often either mastication or pre-commercial thinning). These categories will herein be referred to as ‘treatment classes’. Post classification, we removed small treatments (≤ 5 ha) or treatments close to or intersecting final fire perimeters (≤ 15 m from fire perimeter) to reduce uncertainty of treatment-wildfire interaction ([Johnson and Kennedy 2019](#); [Povak *et al.* 2025](#)). We further combined overlapping treatments to create a spatially continuous treatment layer (Supplementary Table S2). A full description of treatment data

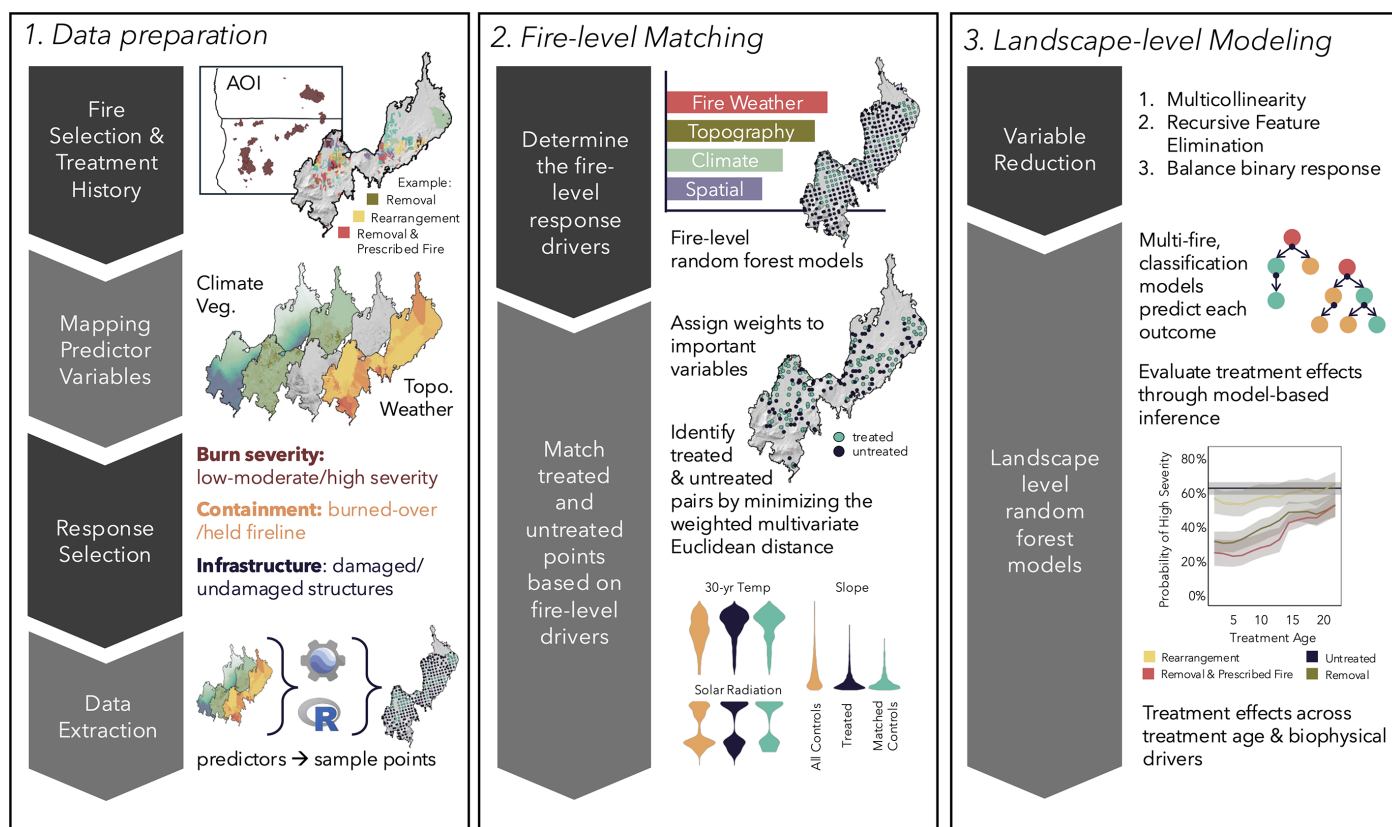


Fig. 2. A semi-automated, empirical workflow to evaluate the effects of fuel treatments across biophysical conditions. Our workflow is built with flexibility to support the evaluation of treatment effects across multiple measures of effectiveness. In this study, we focus on one response variable: vegetation burn severity (low-moderate vs high severity). The workflow includes three broad phases: Data preparation, Fire-level Matching, Landscape-level Modeling. (1) Geospatial data preparation includes the selection of previous fires and historical treatments, gathering geospatial datasets, selecting a response variable (burn severity) and data extraction, (2) fire-level matching aims to pair treated and untreated points based on fire-specific drivers of the response variable, and (3) landscape-level models use model-based inference to evaluate treatment effectiveness across multiple biophysical conditions.

processing is described in the Supplementary Material: Fuel Treatment Data.

To calculate the time since treatment implementation and wildfire-interaction – herein referred to as ‘treatment age’ – we used the completion date records included with FACTS and NFPORS data. We only considered treatments that had a minimum treatment age of ≥ 2 years so that treatments themselves did not influence the remotely-sensed measure of burn severity used in this study, which are derived from imagery collected 1 year pre- and 1 year post-fire.

Burn severity as a response variable

We used Landsat-based, multi-spectral imagery to derive Relative Differenced Normalized Burn Ratio (RdNBR) as a measure of burn severity, or vegetation loss (Miller and Thode 2007). We calculated $RdNBR_{offset}$ in Google Earth Engine (GEE) to account for potential differences in

pre- and post-fire imagery due to phenology or varying conditions which allowed for comparison across multiple fires (Parks *et al.* 2018). To create a binary response variable, $RdNBR_{offset}$ values were classified as either high severity ($RdNBR_{offset} \geq 652.4$) or low-moderate severity ($RdNBR_{offset} < 652.4$). We derived the threshold for high severity using the extended national basal area regression models from the Rapid Assessment of Vegetation Condition After Wildfire (RAVG) program which uses $RdNBR_{offset}$ to estimate basal area loss 1 year following a fire (Miller *et al.* 2009a; Miller and Quayle 2015). We defined the high-severity fire threshold as the $RdNBR_{offset}$ value corresponding to 90% basal area loss ($RdNBR_{offset} = 652.4$).

Mapping spatial predictors

To evaluate the influence of environmental conditions on treatment effectiveness, we produced a variety of geospatial predictor variables (Estes *et al.* 2017, p. 202;

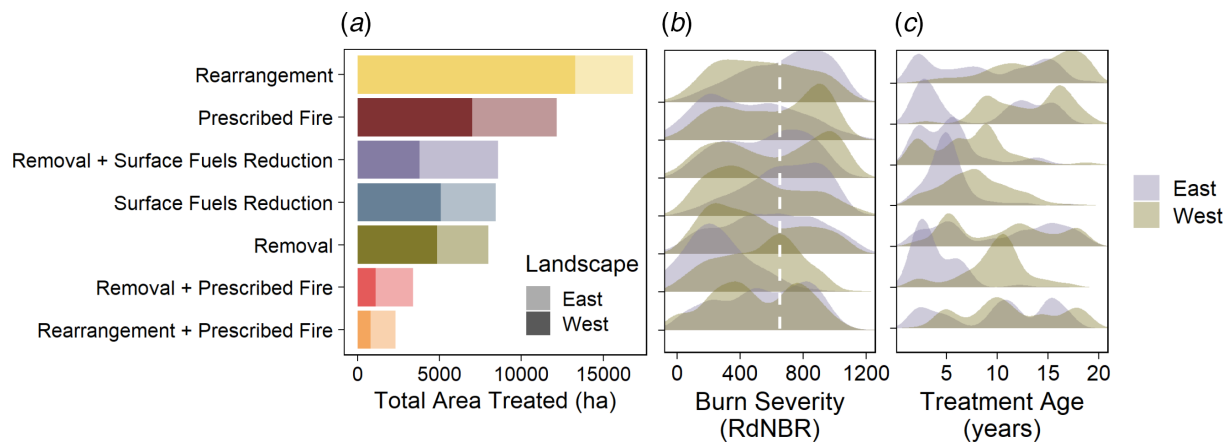


Fig. 3. (a) The total area (ha) of each final treatment class: Rearrangement, Prescribed Fire, Removal + Surface Fuels Reduction, Removal, Surface Fuels Reduction, Rearrangement + Prescribed Fire, Removal + Prescribed Fire for the east and west landscapes, separated by transparency (Fallon *et al.* 2025). (b) The distribution of burn severity (Relative Differenced Normalized Burn Ratio (RdNBR)) across each treatment class where the light gray dashed line represents high severity as defined as >90% basal area loss separated into east and west by purple and green respectively (Miller *et al.* 2009a). (c) The distribution of time since treatment implementation – ‘treatment age’ – separated by the east and west landscape (purple and green).

Cansler *et al.* 2022; Chamberlain *et al.* 2024), which were grouped into seven categories: Fire stats, Long-term climate, Short-term climate, Topography, Weather, Infrastructure, and Treatments (Fig. 2: ‘1. Data preparation’). All data related to the group ‘Treatments’ is described in the section ‘Methods: Fire selection and fuel treatment history’ as well as Supplementary Material: Fuel Treatment Data. A full description of geospatial data, acquisition and processing is in Supplementary Material.

Sample point data extraction

We sampled points at a 270 m grid spacing using the centroids of a coarsened version of our burn severity raster. We used a 270 m sampling to reduce the influence of spatial autocorrelation in our models following the previous work (Kane *et al.* 2015; Cansler *et al.* 2022; Chamberlain *et al.* 2024). We further excluded points that fell outside of federally managed public land boundaries, since private and state fuels management activities were not reported in our fuels treatment database. We limited our sample points to only forested pixels to minimize measurement uncertainty with remotely sensed burn severity in non-forested areas (see Supplementary Material: Masks) (Miller *et al.* 2009a). We classified all points that fell within treatments into their respective treatment class and all points that fell outside of treatments as ‘untreated’.

Fire-level models for paired matching

The ultimate goal of our matching process was to ensure that treated and untreated sample points represented similar distributions of key environmental conditions. Matching treatment and untreated distributions help to ensure that the observed effect of treatments relative to untreated

areas is more likely the result of the treatment itself, rather than underlying differences in environmental conditions. Our sample refinement and matching process expands upon methods developed in past studies on treatment effectiveness (Povak *et al.* 2020; Cansler *et al.* 2022; Chamberlain *et al.* 2024). Primarily, the matching process (1) constructs fire-level models to identify the most important biophysical predictors of burn severity, (2) pairs each treated point with an untreated counterpart based on similarity across those predictors, and (3) ensures comparable distributions of key fire-level biophysical conditions across treated and untreated groups (Fig. 2: ‘2. Fire-level Models’). The matching process was completed at a fire-level scale in part due to computational limitations at landscape scales but also because factors controlling burn severity can vary by each fire event.

Fire clustering

A handful of fires ($n = 11$) did not have adequate sample sizes for fitting fire-level random forest models (>150 sample points). In these cases, we employed a clustering process to cluster like-fires prior to fitting models. We iteratively grouped fires with <150 treated sample points until the cumulative sample size in a group exceeded 150. We grouped fires using two fire-level bioclimatic variables: mean 30 year climatic moisture deficit and mean actual evapotranspiration. Past work suggests that these climate variables provide reliable proxies for broad trends in vegetation structure and composition (Stephenson *et al.* 1998; Parks *et al.* 2018); thus, we assumed they would provide a reasonable measure for grouping fires.

Fire-level models to identify response drivers

Because the factors associated with fire effects vary across individual fire events (or clusters of fires; Supplementary Fig. S1), we identified matching variables at the fire- or cluster-level. Specifically, we fit spatial random forest classification models predicting high severity as a function of a variety of environmental factors for each fire or cluster of fires (Table 1, Supplementary Table S4). Ultimately, we used each model to identify the most important biophysical variables to match environmentally similar untreated points for each treatment point (see methods below on paired matching). We fit spatial random forest models - that is, including principal components of neighborhood matrices (PCNMs) as predictors - to account for spatial autocorrelation in model residuals without the need to spatially subsample our sample points (Borcard and Legendre 2002; Murakami and Griffith 2015). We used the `meigen` and `meigen_f` function from the `sp Moran` package in R to produce first 30 PCNMs as predictors for our fire-level, matching models (Murakami 2024). Herein, all random forest models were fit using the `tidymodels` R package with the `ranger` engine (Wright *et al.* 2024; Kuhn and Wickham 2025). All model fits used 80% of the original data (training) and model accuracy was calculated from the remaining 20 percent of the data (testing).

Prior to fitting spatial random forest models for each fire or cluster of fires, we addressed multicollinearity among non-spatial predictors. First, we calculated the pairwise Pearson's correlation coefficient between each continuous predictor variable. We then ranked each pairwise correlation from most to least correlated. If the correlation coefficient was ≥ 0.6 between two variables (Chamberlain *et al.* 2024), we selected the variable that was more predictive of our response variable: high severity. Specifically, we fit two univariate random forest classification models (using default hyperparameters) to predict the given response and retained the variable (of the two correlated variables) that had a higher, test data model accuracy. We used this method to recursively remove variables until the Pearson's correlation coefficient was < 0.6 between all predictor variables, resulting in a non-collinear set of predictors for each fire or cluster-level model.

Next, for each fire or cluster of fires, we fit a random forest classification model predicting high severity as a function of the reduced set of non-collinear predictors and the PCNMs. We used 5-fold cross-validation (CV) to tune two model hyperparameters: number of splits at each node (`mtry`) and minimum node size (`min_n`). We set the number of trees in each model to 1000. We again separated our data using an 80–20 training-testing split, and derived model accuracy from the testing dataset and the average across the five CV folds. Lastly, we calculated global variable importance for each model using the permutation

variable importance method. We only matched untreated points using non-spatial variables, since our goal was to ensure that untreated points were similar to treated points in terms of environmental conditions.

Paired matching

We used the selected predictor variables for each fire or cluster of fires and their corresponding global variable importance values to match each treated sample point with a single untreated point. Predictor variables with importance values < 0 were removed from the weighted variable matrix. First, we discarded all untreated points that intersected any treatment record (including records excluded from our treatment class). Next, for each treated point, we identified all untreated points that represented the same coarse vegetation type. Then, from these candidate untreated points, we identified a single untreated point that was most similar by minimizing the multivariate Euclidean distance of the scaled environmental predictors (Cansler *et al.* 2022; Chamberlain *et al.* 2024). Predictors were scaled using the global variable importance to ensure that more important variables had a stronger influence in the matching process. Untreated points could be resampled to ensure matching occurred between points with similar biophysical characteristics. From this process, we produced a final dataset spanning all fires, in which each treated point had a paired untreated point, and the distributions of the key drivers of burn severity were relatively balanced between treated and untreated points.

Landscape-level random forest models

We used random forest classification models to evaluate the effect of treatments, relative to untreated points, on the probability of high severity fire, while also exploring how treatment effectiveness varied non-linearly across key environmental gradients (Fig. 2: '3. Landscape-level Models'). We divided our paired sampled points to produce two separate, landscape-level models to predict high severity. The data was separated by the east and west portions of the study area due to their distinctly different fire regimes (15 and 35 wildfires, respectively). (Skinner *et al.* 2006; Miller *et al.* 2009b; Omernik and Griffith 2014; Hessburg *et al.* 2016; Estes *et al.* 2017). We included the key drivers of burn severity that fell within each predictor group based on previous research: Long-term climate, Short-term Climate, Weather, Topography, and Treatments (Supplementary Table S4). We performed variable reduction separately for both the east and west random forest models. First, we reduced multicollinearity by iteratively removing less important variables when pairwise Pearson's correlation coefficient was ≥ 0.6 (described in 'Methods: Fire-level models to identify response

Table 1. Predictors included in the west and east landscape-level random forest classification models after matching untreated points and variable reduction (see 'Methods: Landscape-level random forest models'). Supplementary Table S4 displays the full list of predictors considered in the fire- and landscape-level models before the variable reduction process.

Group	Variable	Description	Resolution	Units	Regional model	References
Treatments	Treatment Class	Categorized treatment activities into seven final classes. Untreated areas classed as untreated.	NA	Unitless, (categorical)	East, West	Fallon <i>et al.</i> (2025)
	Treatment Age	The fire year subtracted by the most recent year of treatment implementation.	NA	Years	East, West	Fallon <i>et al.</i> (2025)
Fire Stats	Area of Day of Burn	Area of fire progression on a given day of burning.	30 m	ha	East, West	Parks (2014)
Long-term Climate	30 year Mean Reference Evapotranspiration	The 30 year average of mean reference evapotranspiration calculated using the Hargreaves equation.	90 m	mm	East	Wang <i>et al.</i> (2016)
	30 year Mean Summer Precipitation	Mean precipitation for the summer months.	90 m	mm	East	Wang <i>et al.</i> (2016)
Short-term Climate	1000 hr Dead Fuel Moisture	The Gridmet 1000 hr dead fuel moisture extracted at the day of burning using the MODIS and VIIRS fire progression maps.	4 km	Percent	West	Abatzoglou (2013); Parks (2014)
	Snow Cover Frequency	The frequency of snow cover for a given pixel where the number of days of snow presence is divided by 365.	1 km	Fraction	East	Nolin <i>et al.</i> (2021); Crumley <i>et al.</i>
Topography	Mean Topographic Position Index	The mean topographic position index across three scales: 270 m, 810 m, 2430 m.	10 m	Unitless	West	USGS (2022)
Weather	Vapor Pressure Deficit	The Gridmet vapor pressure deficit extracted at the day of burning using the MODIS and VIIRS fire progression maps.	4 km	kPa	East, West	Abatzoglou (2013); Parks (2014)
	Shortwave Radiation	The Gridmet short wave radiation extracted at the day of burning using the MODIS and VIIRS fire progression maps.	4 km	W/m ²	East	Abatzoglou (2013); Parks (2014)

MODIS, MODerate Resolution Imaging Spectroradiometer; NA, not available; VIIRS, Visible Infrared Imaging Radiometer Suite.

drivers'). Second, we performed recursive feature elimination where we created an initial classification random forest with all the remaining variables and calculated the model's accuracy. Then, we recursively re-ran the random forest model while we sequentially removed the variable with the lowest importance until the model performance was < 95% of the initial model accuracy (Povak *et al.* 2020; Cansler *et al.* 2022; Chamberlain

et al. 2024). The model and selected variables in the penultimate iteration were retained as final random forest model for each landscape. However, certain variables were forced into the final model if they were dropped during recursive feature elimination. These variables include treatment class, treatment age and the most recently dropped variable from any completely removed predictor group (Povak *et al.* 2020).

With the final variables selected, we trained random forest models for the west and the east parts of the landscape and tuned the model's hyperparameters (described in 'Methods: Fire-level models to identify response drivers'). For each final landscape model, we evaluated the model fit with the testing dataset accuracy and the mean accuracy across the 5 CV folds. While we did not include spatial eigenvectors in our final models to aid interpretability, Moran's I of model residuals was calculated at varying lag distances to assess bias from spatial autocorrelation (reported in Supplementary Fig. S2).

To evaluate conditions under which treatment effectiveness was maximized within the landscape, we evaluated partial dependence plots (PDPs) to visualize when and where the magnitude of the reduction in burn severity within certain treatment types compared to untreated controls changed across environmental gradients. PDPs show the mean effect of a given predictor on a model's prediction by varying that predictor's value across a grid of values while holding all other variables at their observed values and by taking the mean of those predictions across the dataset. We produced 2-way partial PDPs for each of our continuous variables using the *DALEXtra* package ($n = 500$), grouped by treatment class (Maksymiuk *et al.* 2023). For the categorical predictor, treatment class, we calculated an adjusted PDP to account for its interaction with treatment age. In our dataset, treatments were selected that were implemented 2–20 years before the wildfire, whereas untreated observations were assigned an arbitrary fixed value of 21 years. To ensure realistic combinations when estimating mean PDPs for each treatment class, treatment age was constrained to plausible values reflected in our dataset. Specifically, when observed treatment age exceeded 20 years, a random age between 2 and 20 years was assigned for treated classes. For untreated observations, treatment age remained fixed at 21 years. We calculated 95% confidence intervals for mean predictions, variable importance and PDPs by refitting models on 1000 bootstrapped datasets.

Results

Our random forest models had moderately high accuracy (Table 2). The east model had an accuracy of 86.3% when applied to the testing dataset, with a 12.9% commission and 14.6% omission error rate for high severity, and a mean CV accuracy of 86.5% for the final model. The west model had a testing dataset accuracy of 85.1%, with a 14.1% commission and 15.0% omission error rate, and a mean CV accuracy of 85.4% for the final model for high severity.

In the west landscape, the mean probability of high severity ranged from 42.2–48.5% for all treatment types, whereas untreated area had 52.1% probability of high severity (Fig. 4a). Removal + prescribed fire treatments had the lowest likelihood of high severity whereas prescribed fire, alone, had the highest. In the east landscape, treatments that include prescribed burns (removal + prescribed burn, rearrangement + prescribed burn, and prescribed burn) were the least likely to burn at high severity (31.9–37.8%, Fig. 4b). Other treatment types ranged from 39.8–43.4% mean probability of high severity, while untreated areas were 61.7% likely to burn at high severity. Across all bootstraps in the west landscape the mean likelihood of high severity for all treatment types showed no significant difference from each other and other untreated areas, whereas in the east landscape all treatments had significantly lower mean probabilities of high-severity fire than untreated areas.

In both landscapes, daily area burned was the most important predictor of high-severity fire (Fig. 4), and we observed a positive relationship between daily area burned and predicted probability of high severity for both untreated and treated sample points (Figs 5 and 6), except for removal + prescribed burns in the east landscape, where the probability of high severity only increased by 4% from the smallest to largest daily area burned (Fig. 6). The number of displayed variables differs across the two landscapes because the Recursive Feature Elimination (RFE) variable reduction process (Fig. 4). Daily vapor pressure deficit (VPD) was an important predictor for both landscapes (Fig. 5). In the west landscape, treated and untreated showed a strong positive relationship between VPD and probability of high severity (Fig. 6), whereas the east landscape, prescribed fire and removal + prescribed fire treatments dampened the positive relationship with VPD and high severity (Fig. 7).

Among treatment variables included in the landscape models, treatment age was the strongest but only in the east landscape (Figs 5 and 8). Across all treatments, when treatments are implemented <9 years prior to the wildfire occurrence, the mean probability of high severity for all treatments, except for rearrangement, was 14% lower than for treatments that were ≥ 9 years old (Fig. 8b). Removal + prescribed fire treatments displayed the lowest probability of high severity, especially when treatment ages was <5 years at which point the relationship between treatment age and probability of high severity became less extreme. Both removal + prescribed fire and prescribed fire treatments that were implemented <17 years before a subsequent wildfire had significantly lower probabilities of high severity as compared to untreated areas. In contrast, there was no significant relationship between the years since treatment implementation and probability of high severity for the western landscape's model (Fig. 7a).

Table 2. The confusion matrix for the west and east models, using the testing dataset for the respective landscapes.

Prediction	Truth			
	West model		East model	
	Low-moderate severity	High severity	Low-moderate severity	High severity
Low-moderate severity	1004	177	695	119
High severity	164	991	101	680

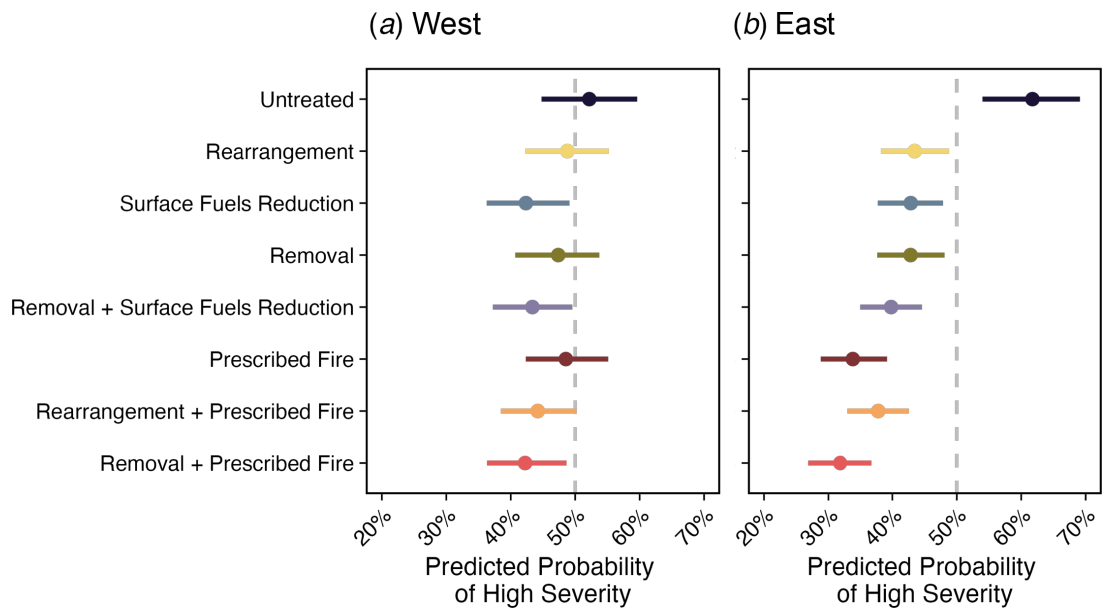


Fig. 4. The mean predicted probability of high severity among treatment classes across the Klamath-Trinity Landscape for the east and west random forest classification models. The partial dependence mean probability of high severity for each class was calculated by predicting each treatment class across all other predictors values then taking the mean response. The error bars for each treatment class represents the 95th confidence interval of the mean probability using 1000 bootstrapped datasets to fit our model.

Discussion

We developed and applied a semi-automated workflow to evaluate the effects of fuel treatments on burn severity across 50 wildfires in the Klamath-Trinity study area, revealing important differences in the key drivers of high severity fire between the east and west landscapes. Ultimately, we did not detect a meaningful treatment impact on wildfire severity in the topographically complex west landscape (Fig. 8). On this landscape, the likelihood of high severity fire was greater on large burn days, on drier parts of the landscape and under more extreme wind conditions, regardless of treatment status (Fig. 8). In the east landscape, treatments had a more meaningful impact on high severity where these effects were mediated primarily by treatment age and subsequently by daily area burned. In this landscape, the likelihood of high-severity fire was

greater on large burn days, but generally not within treatments that were less than 9 years old, and especially not when those treatments included prescribed fire.

The outsized association of daily area burned in both east and west landscapes is consistent with research on how extreme single-day fire growth events disproportionately contribute to larger high-severity patches, overall fire size and reduced refugia (Collins *et al.* 2021; Coop *et al.* 2022; Parks *et al.* 2023, 2025; Balik *et al.* 2024; McFarland *et al.* 2025). Daily fuels, fire weather, topography and fire feedbacks can align to produce these large single-day growth events (Andela *et al.* 2019; Potter and McEvoy 2021; Brown *et al.* 2023). In our models, this variable can act as a proxy for the many interactions of fire weather conditions that are associated with high severity (Parks *et al.* 2018), such as wind speed and atmospheric instability, but are not resolved and captured fully by our predictor data.

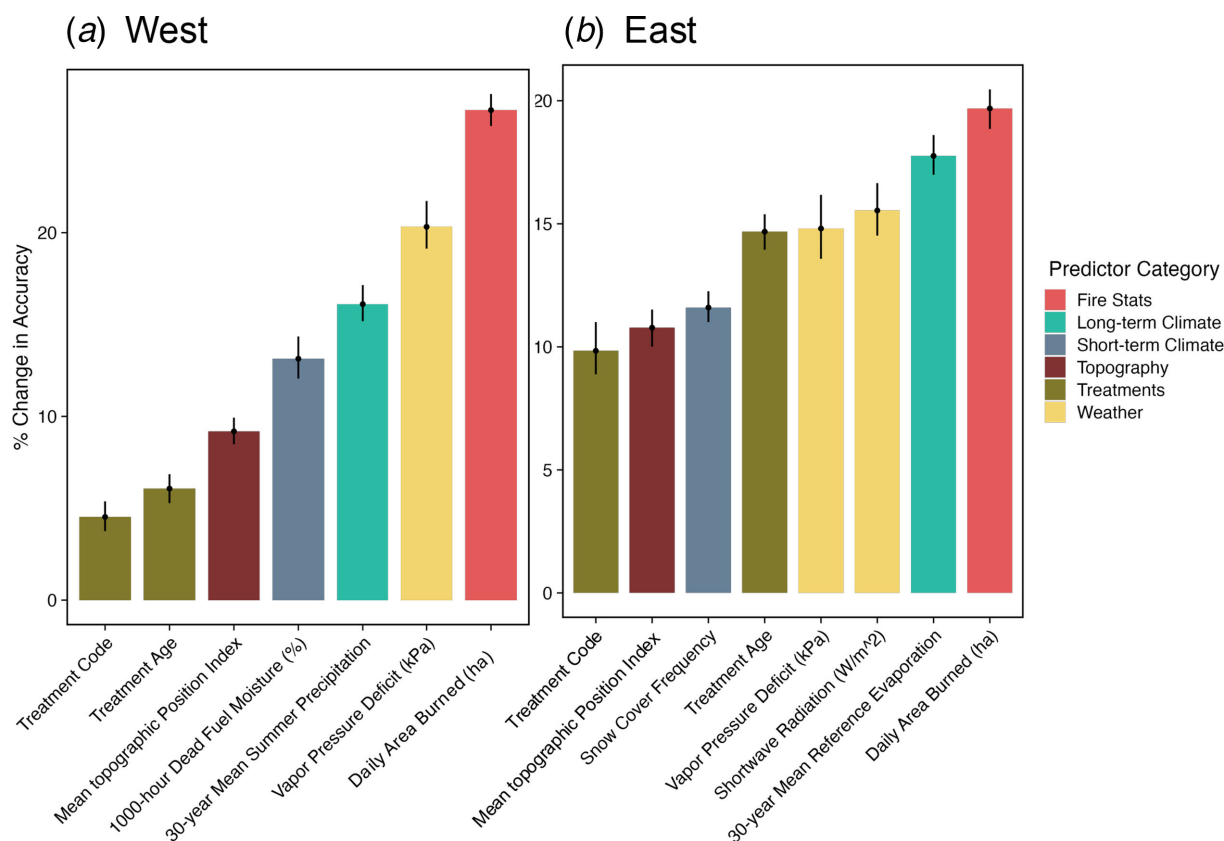


Fig. 5. Variable importance of the west (a) and east (b) random forest classification model. Predictor variables are grouped and colored into six categories: Fire Stats, Long-term Climate, Short-term Climate, Topography, Treatments and Weather. The error bars for each variable represent the 95th confidence interval for each predictor variable through 1000 bootstrapped models.

Fuel treatments in the eastern landscape

The eastern portion of the Klamath River Watershed landscape, which is part of the southern Cascades ecoregion, contains primarily coniferous, historically frequent-fire forests. This study corroborates previous reviews' and studies' findings that, in such forest types, thinning followed by a prescribed burn (removal + prescribed fire) is the most effective treatment for mitigating subsequent risk of high severity (Schwilk *et al.* 2009; Stephens *et al.* 2012; Kalies and Yocom Kent 2016; Prichard *et al.* 2017; Davis *et al.* 2024). Several of the papers investigated individual fires among those in our analyses (Brodie *et al.* 2024; Chamberlain *et al.* 2024; Sanna *et al.* 2025), and our study extends this finding to the eastern Klamath Watershed scale. On our landscape, removal + prescribed burn treatments were most commonly a commercial thin followed by a broadcast burn. This crucial combination of management practices that includes the reduction of canopy, surface and ladder fuels (Agee and Skinner 2005), are most effective at preventing high-severity effects relative to other treatment types.

Further, our results suggest that removal + prescribed fire treatments can significantly mitigate likelihood of high-severity fire under extreme fire growth events. Generally, treatments that contained prescribed fire (prescribed fire and rearrangement + prescribed fire) were more resilient to high-severity effects on large growth days compared to untreated areas (Fig. 7). While this finding is broadly consistent with the literature (Davis *et al.* 2024), our study is the first to systematically demonstrates this finding using consistent methodology across many fires and, as the west landscape importantly demonstrates, shows that this finding is not necessarily true in all landscapes or ecoregions. Where removal + prescribed fire treatments are not feasible due to cost, logistical, or operational restraints, our results suggest that primarily treatments that include prescribed fire to decrease dead surface fuel loads can alone can lower fire severity (Fig. 4) (Kalies and Yocom Kent 2016; Espinosa *et al.* 2019; Davis *et al.* 2024). However, importantly, of all treatment types, rearrangement treatments (commonly mastication) showed the most similarity to untreated areas in their effects (Figs 4 and 7), demonstrating on a large scale that treatments that move canopy fuels to the surface without removing them through some

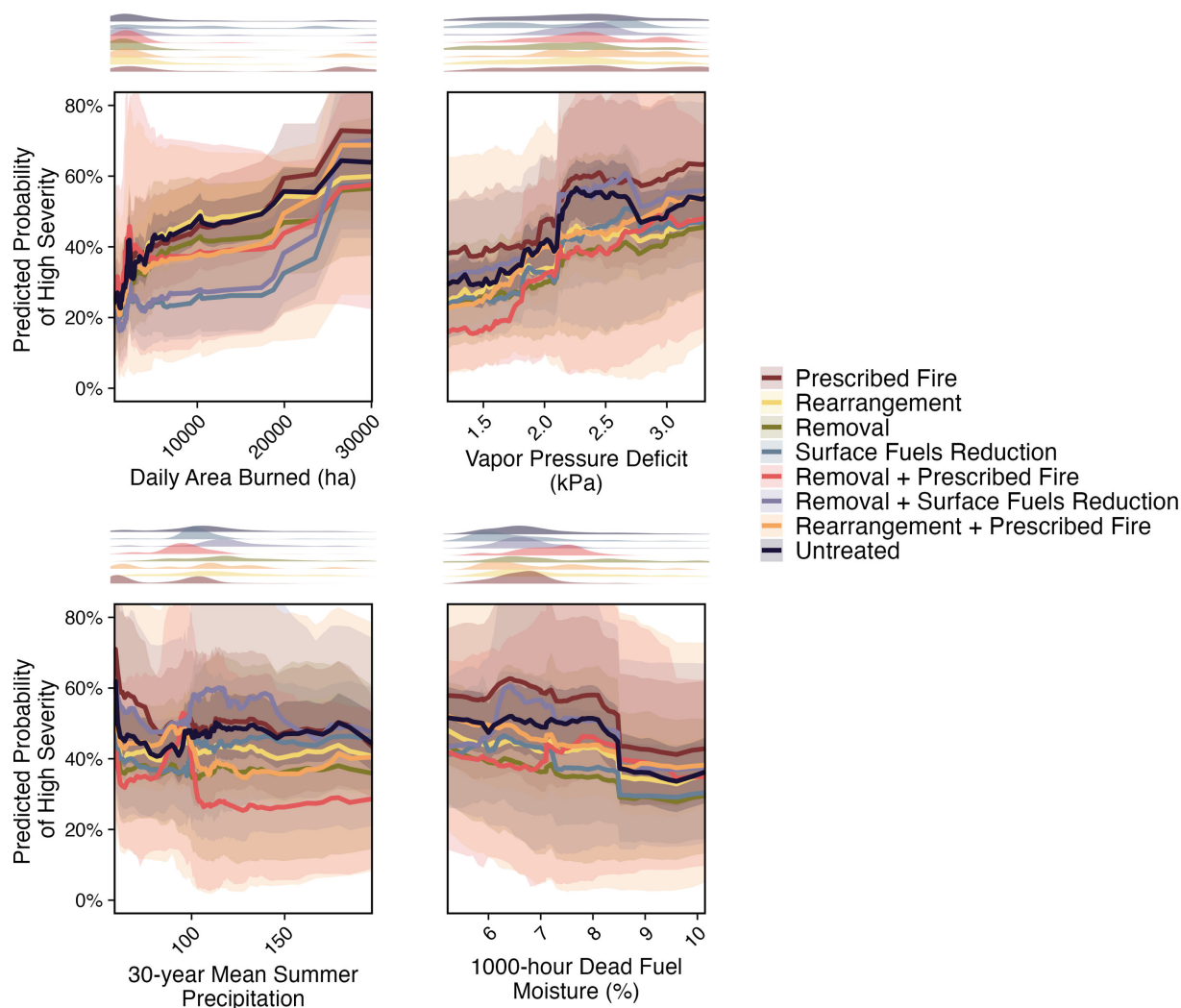


Fig. 6. Partial dependence plots for the west study area of the Klamath-Trinity Landscape separated by each treatment type for the four most important continuous predictor variables. Importance was determined by permutation variable importance from the landscape random forest classification model. Each solid line displays the mean relationship between each treatment type and environmental variable across all other environmental variable combinations. The shaded region represents the 95th confidence interval across variables by treatment type through 1000 bootstrapped models.

type of prescribed fire are the least likely to be effective for reducing the incidence of high-severity fire. Previous studies have similarly demonstrated the influence of unburned piles on increased fire severity if wildfires encounter these incomplete treatments (Safford *et al.* 2009; Safford and Saberi 2025). The lack of difference between rearrangement-only treatments and untreated areas shows the clear importance of removing excess fuel in these frequent-fire forest systems (Martinson and Omi 2013; Prichard *et al.* 2021).

The east landscape showed clear reductions in the probability of high severity for all treatment types that were implemented <9 years before the wildfire, except for rearrangement treatments, as compared to untreated areas (Fig. 8b). Removal + prescribed fire treatments

had the maximum effectiveness when implemented <5 years prior to wildfire. Effectiveness declined with time since treatment, with probability of high severity increasing to levels similar to prescribed fire alone. This pattern in removal + prescribed fire treatments may reflect rapid post-treatment regrowth of understory vegetation and accumulation of fine surface fuels, coupled with the reduction of canopy and overstory biomass which could allow for more detectable change in vegetation severity by remote sensing. (Prichard and Kennedy 2014; Dodge *et al.* 2019; Cansler *et al.* 2022; Brodie *et al.* 2024). Longer term effects of removal + prescribed fire treatments may have not been detectable because of a limited number of older treatments in this class (>9 years, Supplementary Table S3). These

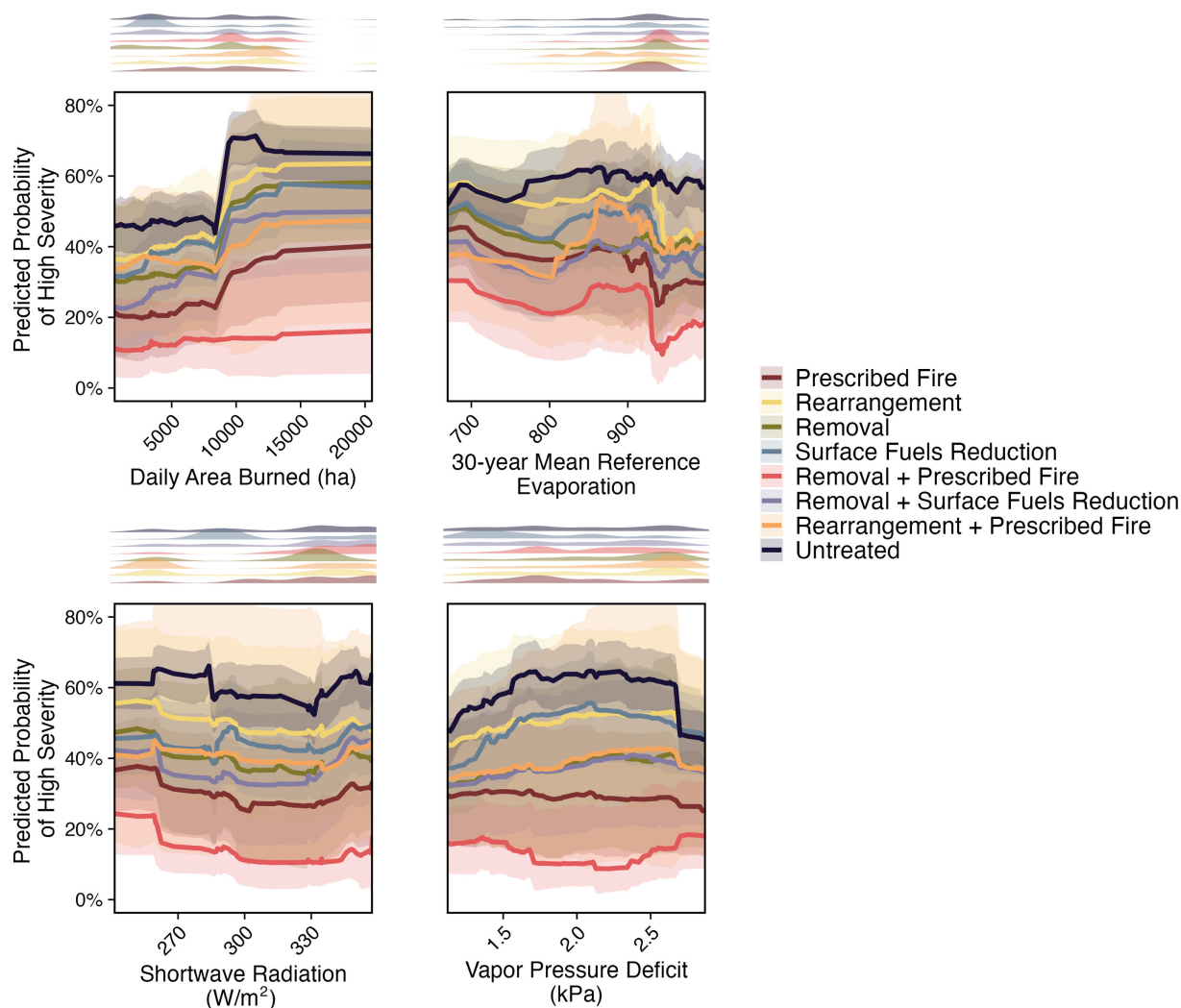


Fig. 7. Partial dependence plots for the east study area of the Klamath-Trinity Landscape separated by each treatment type for the four most important continuous predictor variables. Importance was determined by permutation variable importance from the landscape random forest classification model. Each solid line displays the mean relationship between each treatment type and environmental variable across all other environmental variable combinations. The shaded region represents the 95th percentile across variables by treatment type through 1000 bootstrapped models.

differences may be due to variability in productivity across regions (including in comparison to our western region in this study), which can dictate the longevity of a treatment, especially for a surface fuels reduction treatment like prescribed fire (Radcliffe *et al.* 2025).

Fuel treatments in the western landscape

Why were associations between treatment and proportion of high severity fire less pronounced in the western landscape? The west landscape contained treatments with a greater mean time since treatment implementation (12.6 years, Supplementary Table S3) than the eastern landscape (8.1 years, Supplementary Table S3), which could be ample time for surface fuels to accumulate in the western landscape with a consequent reduced effect of treatments on

subsequent burn severity. In addition, greater annual precipitation in the western landscape leads to high productivity and plant growth, which may require more frequent and repeated prescribed burning and mechanical treatments to maintain low levels of shrub cover and surface fuels. The rapid regrowth of vegetation including understory shrubs in the western Klamath can be a challenge for forest management since this layer can burn at high severity (Skinner *et al.* 2006; Hessburg *et al.* 2016). Studies have found treatments that are implemented less than 5–10 years before a fire to be most effective at reducing burn severity, while older treatment may not be successful at reducing high-severity fire effects in the western landscape (Thompson and Spies 2009; Grabinski *et al.* 2017; Taylor *et al.* 2021; Beckmann *et al.* 2025). Different regeneration patterns, like abundance of an often resprouting hardwood

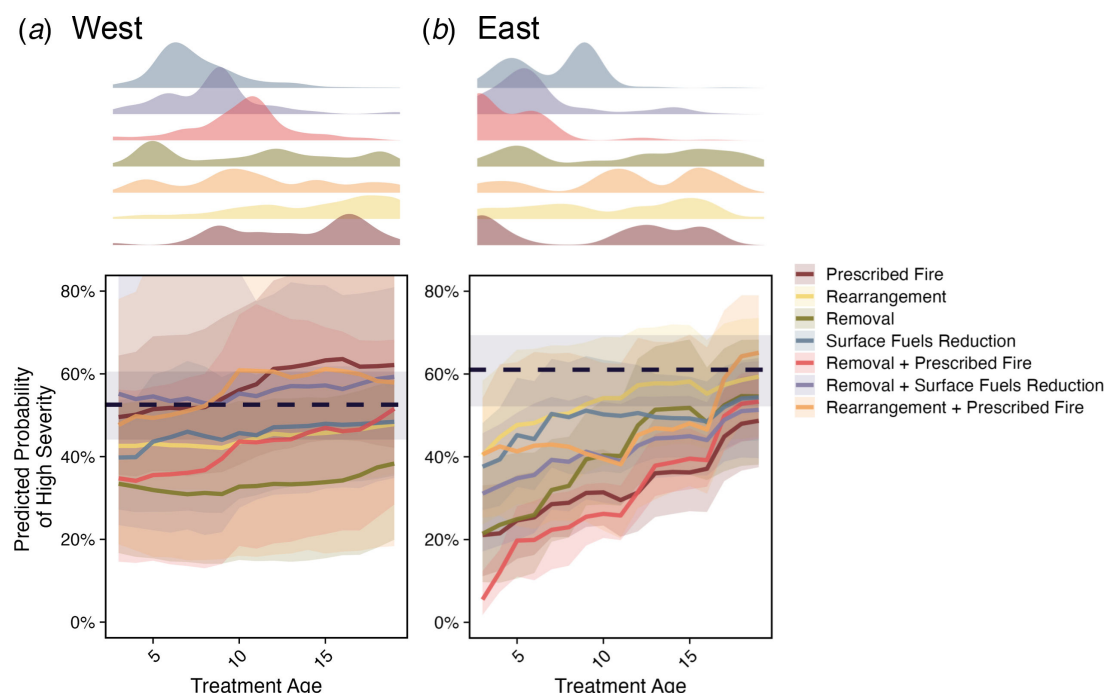


Fig. 8. Partial dependence plots for treatment age the west (a) and east (b) study area of the Klamath-Trinity Landscape separated by each treatment type. The dashed, navy untreated line represents the mean probability of high severity for untreated points. Importance was determined by permutation variable importance from the landscape random forest classification model. Each solid line displays the mean relationship between each treatment type and environmental variable across all other environmental variable combinations. The shaded region represents the 95th percentile across variables by treatment type through 1000 bootstrapped models.

subcanopy or a more patchy conifer establishment, could contribute to more ladder fuels in regenerating post-fire forests (Donato *et al.* 2009; Thompson and Spies 2009; Perry *et al.* 2011; Croteau *et al.* 2013). For reducing burn severity, it is not only important to reduce tree density, ladder and surface fuels but frequent retreatment is also imperative.

Treated and untreated areas in the western landscape fires experienced some of the largest growth days in either landscape data set (Supplementary Fig. S3), showing the positive, non-linear association between large spread events and high-severity effects (Fig. 5) (McFarland *et al.* 2025; Parks *et al.* 2025). In the western landscape, daily area burn had an outsize contribution to model performance (Fig. 4a). Historically, the western landscape, most notably in the Klamath Mountains, wildfire outcomes would have been strongly influenced by interactions of topography and vegetation (Skinner *et al.* 2006; Perry *et al.* 2011). In recent years, extreme weather interacting with uncharacteristically high fuel loads has become a more important driver of severe fires (Grabinski *et al.* 2017; Taylor *et al.* 2021).

Our results highlight the challenges of quantifying the effects of forest management practices on vegetation burn severity across multiple fires burning

under different fire, but also in landscapes with complex topography, high productivity and resulting rapid regeneration. For example, in the western landscape, the extreme topographic variability and proximity to the Pacific Ocean can produce atmospheric inversions, the dynamics of which greatly influence fire spread and subsequent effects (Estes *et al.* 2017). Inversion days and portions of the landscape subject to inversions were not well captured by our data sources. Fine-scale topographic and vegetation variation (i.e. local changes in topographic position and treatment regeneration) could also contribute to the likelihood of high severity, leading to large fire spread days which could potentially override treatment efficacy (Price and Bradstock 2012). For landscape-level studies, daily area burned may be a better predictor of high severity fire, yet fire-level studies are still necessary to understand local biophysical interactions that contribute to these large spread events (Estes *et al.* 2017; Beckmann *et al.* 2025).

Minimal treatment effects observed in our study poses a challenge for managers in the Klamath mountains. As more extreme fire weather and longer fire seasons are likely to occur in this landscape (Westerling 2016; Goss *et al.* 2020), more intensive and frequent forest management might be needed to counteract this trend. This could include

repeated management within a single management unit. Although not all forest management on the west side may meet the objective of reducing high-severity fire effects across long time scales, other desirable outcomes may be realized including enhanced cultural values, habitat creation, or meeting silvicultural goals. This area contains a rich and documented history of Indigenous burning by the Karuk and Yurok people (Long *et al.* 2021; Greenler *et al.* 2024). Current collaborations between federal land management agencies and cultural practitioners show promise for increasing the scale of fuels work and wildfire used for resource benefit in this portion of our study area (Aldworth *et al.* 2024).

Conclusions

To our knowledge our study is one of the largest systematic evaluations of wildfire-fuel treatment outcomes with respect to burn severity conducted to date, with 50 fires and 3427 wildfire-treatment interactions evaluated. The workflow presented here is designed to be reproducible in landscapes across the western US, thereby enabling further evaluation of context- and place-specific wildfire treatment outcomes on fire severity and other values of interest, which our study shows are highly dependent on the environmental conditions present at the time of the wildfire-treatment interaction. The semi-automated workflow is available in the github repository: github.com/hannah-vandusen-csu/WildfireTreatmentOutcomes_v1.com. We encourage future use of this methodology to derive region-specific recommendations to inform future design of fuel treatment regimes. Using results from our study, coupled with future analyses that utilize our workflow to assess other landscapes and other treatment outcomes, managers and policymakers may gain a more comprehensive understanding of how to prioritize and leverage fuel reduction and restoration treatments to increase landscape resilience, facilitate safer and more effective firefighting, and protect critical infrastructure in contemporary fire-prone landscapes.

Supplementary material

Supplementary material can be accessed from the article page online.

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Data availability. The scripting workflow for this study is hosted at http://github.com/hannah-vandusen-csu/WildfireTreatmentOutcomes_v1.com. The data and a static script repository are available to generate these results at <https://doi.org/10.5061/dryad.1zcrjdg6q>.

Declaration of use of AI. The use of AI was not used by the authors of this work for the creation, investigation and writing of this manuscript.

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