Forest Ecology and Management 606 (2026) 123529

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Burn severity across forest types and burning conditions for forest treatments on the southern rockies Front Range

Sarah L. Hettema [a,*], Camille Stevens-Rumann [a,b], Hannah Van Dusen [a,c], Mike A. Battaglia [c], Anthony G. Vorster [d,e], Jens Stevens [f]

[a] Department of Forest and Rangeland Stewardship, Colorado State University, Fort Collins, CO 80523, USA
[b] Colorado Forest Restoration Institute, Colorado State University, Fort Collins, CO 80523, USA
[c] USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO 80526, USA
[d] Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO 80523, USA
[e] Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO 80523, USA
[f] USDA Forest Service, Pacific Northwest Research Station, Seattle, WA 98103, USA

ARTICLE INFO

Keywords:
Burn severity
Forest treatment
Forest type
Burning condition
Fuel treatment effectiveness
Treatment wildfire interaction

ABSTRACT

As extreme wildfire events become more frequent, understanding how forest treatments interact with wildfire is increasingly critical. However, assessing wildfire-treatment outcomes is challenging due to interactions among treatments, weather, topography, and fuels. We investigated wildfires from southern Wyoming to northern New Mexico to evaluate under what conditions treatments reduce the ecological impacts of fire, as measured by remotely sensed burn severity. We determined (1) factors influencing the relationship between treatments and burn severity, (2) how burn severity differed across forest and treatment types, and (3) how extreme burning conditions influenced outcomes. Treatment effects varied by forest types, with generally lower burn severity outcomes in lower elevation, frequent fire forest types compared to spruce - fir and lodgepole pine (higher elevation, infrequent fire) forests. Areas that previously burned at low to moderate severity or with prescribed fire had the lowest burn severity outcomes across forest types and even during extreme burning conditions. In contrast, treatments without fire (tree removal and/or surface fuels reduction) had mixed effects across forest types and had equivalent burn severity to untreated areas in infrequent fire forests during extreme burning conditions.

1. Introduction

Compared to historical conditions, contemporary western North American forested ecosystems have warmer and drier climatic conditions that increase fuel aridity (Abatzoglou and Williams, 2016) and the probability of extreme fire weather conditions (Collins, 2014). Many forests are shifting away from historical fire regimes due to fire suppression policies, land use changes, and/or changing climate (Collins et al., 2019; Fernández-Guisuraga and Fernandes, 2024; Moreira et al., 2020; Tolhurst and McCarthy, 2016; Whitman et al., 2019). The implementation of proactive forest management is increasing to mitigate the negative effects of wildfires (Hessburg et al., 2021); however, efforts to expand the pace and scale of forest management treatments (USDA Forest Service, 2022) are constrained by factors such as lack of infrastructure, funding limitations, and management restrictions (Collins et al., 2010; Woolsey et al., 2024).

Forest treatments, including those aimed at restoration or fuels reduction, modify the composition, structure, and distribution of vegetation on the landscape to achieve various management goals. Fuels reduction treatments focus on decreasing the amount and continuity of fuels in order to change fire behavior, whereas, restoration treatments, often including fuel reduction, focus on shifting species composition and tree spatial patterns to better reflect historical forest structure and/or increase resilience to disturbance (Stephens et al., 2020). While objectives between reduction and restoration treatments vary, they include reducing wildfire severity, mitigating infrastructure loss, improving safety in suppression operations, and/or promoting resilient forests on fire-adapted landscapes (Davis et al., 2024).

Previous studies have used a variety of metrics to measure how effective a treatment was in meeting management objectives, with many

* Corresponding author.
E-mail address: sarah.hettema@colostate.edu (S.L. Hettema).

https://doi.org/10.1016/j.foreco.2026.123529
Received 8 October 2025; Received in revised form 9 January 2026; Accepted 12 January 2026
Available online 17 January 2026

focusing on burn severity outcomes to quantify ecological impacts. In these studies, there is gathering consensus that treatments in historically frequent fire forests that focus on reducing canopy fuel through thinning and surface fuel through burning can minimize burn severity under all but the most extreme fire weather conditions (Davis et al., 2024; Kalies and Yocom Kent, 2016; Stephens et al., 2012a). In general, studies have found fuel treatments that reduce surface fuels through burning (e.g., past wildfires, prescribed burns and thinning, or clear-cutting with prescribed understory or broadcast burns) are more effective at reducing burn severity compared to treatments that only thin or thin and pile burn (Cansler et al., 2022; Chamberlain et al., 2024; Fulé et al., 2012; Prichard et al., 2020; Stephens et al., 2012a; Vorster et al., 2024). The efficacy of the combination of thinning and prescribed burning can be attributed to reducing surface and ladder fuels and intermediate sized trees, thus reducing the risk of active crown fire (Agee and Skinner, 2005; Stephens et al., 2012a). However, there are also many locations where high surface and canopy fuel loads prevent the use of burning without thinning or prevent burning at all (Addington et al., 2020).

Management actions and previous research have been concentrated in lower elevation, dry forests with historically frequent low and mixed severity fire regimes (Davis et al., 2024; Kalies and Yocom Kent, 2016) but there is an increasing need to understand how forest treatments impact forests at higher elevations with historically less frequent mixed to high severity fire regimes. Common treatments in frequent fire forests such as ponderosa pine (*Pinus ponderosa*) and mixed-conifer forests include mechanical or hand thinning, prescribed burning, pile burning, previous wildfire, and the combination of these prescriptions (Addington et al., 2018). These are often implemented to reduce fuel loads, shift species composition toward fire-tolerant species, and reduce stand density to pre-European settlement densities. Treatments in lodgepole pine (*Pinus contorta*) and spruce - fir (i.e. *Picea engelmannii* and *Abies lasiocarpa*) forests are often implemented for other management goals (e.g. timber management, wildlife habitat, etc.) and include clear cuts, patch cuts, group selection, and previous wildfire (Alexander, 1987; Hood et al., 2012). It is unclear if treatments in lodgepole pine and subalpine forests that remove or rearrange fuel are effective at reducing burn severity, especially since these forests have fewer fire resistant species (Stevens et al., 2020) and different fuel profiles (Davis et al., 2024).

In high elevation forests, burn area has increased significantly relative to the last two millennia (Higuera et al., 2021) and recent decades (Kampf et al., 2022), with some recent fire seasons burning larger areas than the previous several decades (Kampf et al., 2022). These changes underscore the growing need to understand how management actions interact with wildfire in forests characterized by infrequent, high severity fire regimes. A key management challenge in these forests is balancing the objective of protecting people and property while recognizing that these ecosystems are adapted to high severity fires. The variability in forest types and historical fire regimes creates unique challenges for understanding burn severity in an ecological context and may influence the effect of treatments in high elevation forests (Davis et al., 2024).

Burn severity is influenced by many factors beyond treatments. Numerous studies have shown fire weather and antecedent climate strongly influence fire behavior and subsequent burn severity (e.g. Cansler et al., 2022; Prichard et al., 2020; Wasserman, Mueller,2023). Topography, especially its complexity, contributes to a mosaic of landscape features that have been shown to alter burn severity (Harris and Taylor, 2017; Povak et al., 2025). Forest fuels or variation in forest types also impact burn severity regardless of burning conditions (Stevens-Rumann et al., 2016). In addition to these factors known to influence fire behavior and subsequent burn severity, extreme fire weather conditions further complicate our understanding of how forest management actions affect fire severity.

Extreme fire weather—characterized by high wind speeds, elevated temperatures, and low relative humidity—often leads to rapid fire spread which can overwhelm suppression efforts, endanger lives and property, and cause long-term ecological damage (Calkin et al., 2015; Duane et al., 2021; Tedim et al., 2020). The threshold for extreme fire weather is often based on the 95th percentile Energy Release Component (ERC), a measure of potential fire intensity (Collins, 2014). Treatments have many objectives (e.g. restoration, fuels reduction, etc.) and are often designed to mitigate fire effects under certain conditions, such as 95 % fire weather, yet many recent wildfires are burning under conditions exceeding what the treatments were designed for (Vorster et al., 2024). If a wildfire exceeds the capacity of a treatment there can be negative ecological outcomes, such as large high severity patches which can lead to regeneration failures and impacts on water resources, as well as social outcomes, such as the loss of infrastructure.

Thinning-only treatments in frequent fire forests are less effective under extreme conditions compared to treatments that included burning, likely because thinning does not always include surface fuel removal and often covers a smaller area (Chamberlain et al., 2024; Lydersen et al., 2017; Prichard et al., 2020; Taylor et al., 2022). Studies have also found that treatments which include fire and are sufficiently intense (i.e. reduce basal area and consume surface fuels) can be still effective in extreme conditions (Chamberlain et al., 2024; Taylor et al., 2022; Walker et al., 2018, Brodie et al., 2024). With increasingly extreme burning conditions occurring (Coop et al., 2022), additional research is needed on the impacts of fire weather conditions on burn severity and a treatment's ability to reduce burn severity.

Recent wildfires in western North America are increasing in size and severity (Abatzoglou and Williams, 2016; McFarland et al., 2025), yielding negative socioecological outcomes (Rodman et al., 2022). Along the Front Range of Colorado, northern New Mexico, and southern Wyoming, some of these large-scale fires with days of extreme fire spread burned through multiple forest and treatment types, providing an opportunity to examine where treatments are being implemented, what kind of treatments are occurring, and how those treatments interact with wildfire. We investigated wildfires from southern Wyoming to northern New Mexico that burned through forest treatments from 2002 to 2022 to evaluate under what fire weather, climatic, topographic, and fuel conditions forest treatments reduce burn severity. Our research aimed to answer: (1) what factors influence how and when treatments modify burn severity, (2) how do burn severity outcomes differ across forest and treatment types, and (3) how do extreme fire conditions influence burn severity within treatment types? We hypothesize that (1) fire weather variables will have the largest impact on predicting burn severity; (2) frequent fire forest types will have lower burn severities across treatment types compared to infrequent fire forest types and treatments with fire will be most effective at reducing burn severity across forest types; and (3) treatments will have the lowest burn severities under non-extreme conditions.

2. Methods

2.1. Study area

In this study, we focused on wildfires with treatment interactions along the Front Range of the southern Rocky Mountains from southern Wyoming to northern New Mexico (Fig. 1; Fig. A1). In 2022, the USDA Forest Service (USFS) identified ten priority landscapes throughout the United States that are experiencing an increased risk of severe fire, negative ecological outcomes, and threats to community infrastructure and property (USDA Forest Service, 2022). The Colorado Front Range and New Mexico Enchanted Circle were identified as two of these landscapes. Our study area combines these two priority landscapes as well as forested area east of the continental divide.

The forested ecosystems of the Front Range span an elevational gradient of about 1700–3500 m with variable bioclimatic and topographic conditions resulting in a range of forest types (Peet,1981). The region spans a large latitudinal gradient, which influences forest type

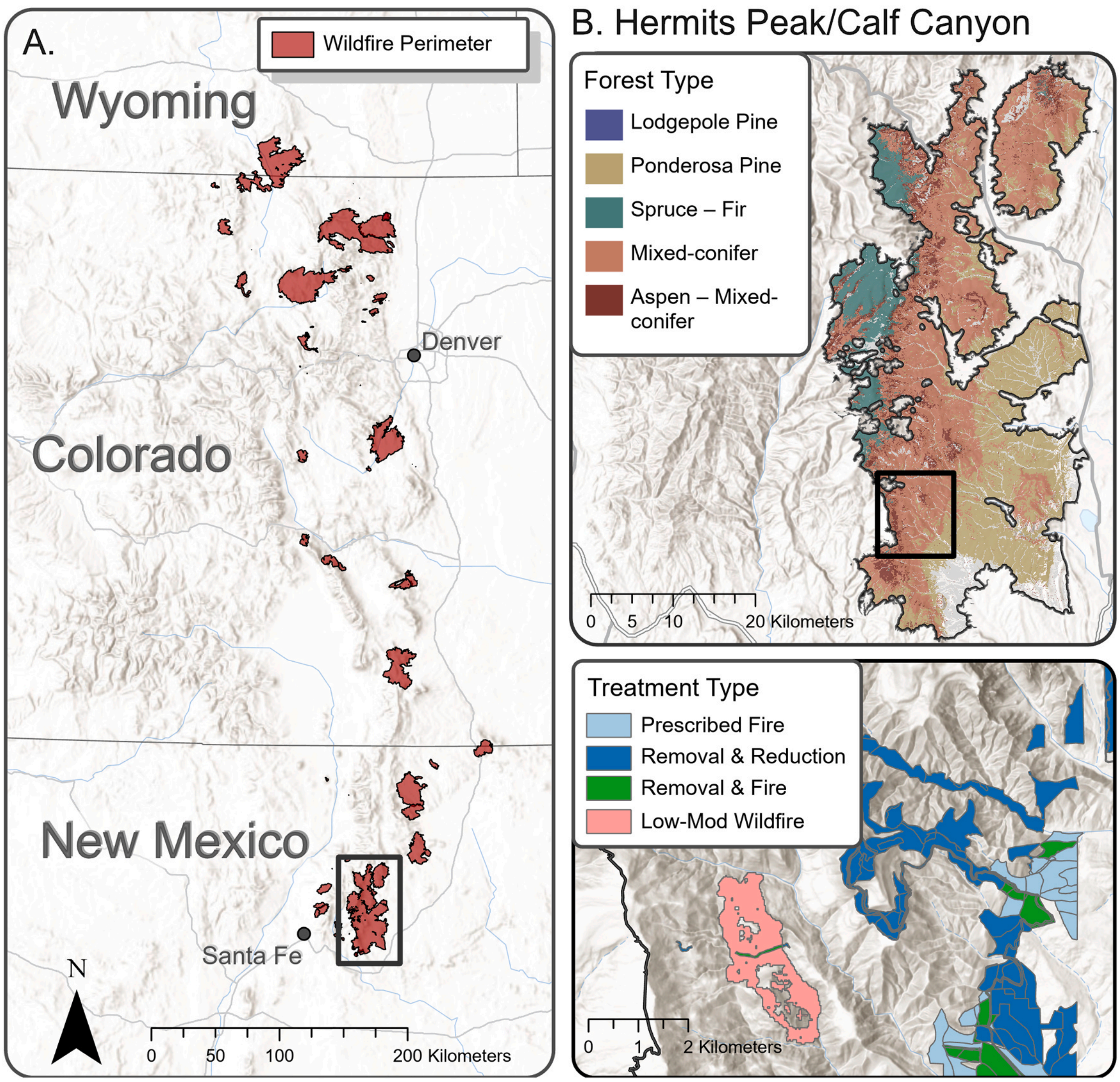

Fig. 1. (A) Map of Front Range study area showing wildfires sampled with forest treatments and (B) Hermits Peak/Calf Canyon fire as an example of the range of forest types and treatments across fires.

establishment and composition, with elevation distributions of forest types varying across latitudes (Peet, 1978). In general, the elevation of vegetation zones and tree lines decreases with increasing latitude (Peet, 1978). For example, in southern latitudes lodgepole pine is absent but becomes the primary species dominating mid-elevations in the northern half of the range (Peet, 1978). At lower elevations, ponderosa pine and mixed-conifer forests historically experienced low and mixed severity, frequent fire regimes with a fire return interval of 1–35 years (Hood et al., 2021; McKinney, 2019; Sherriff and Veblen, 2007). With increasing elevation, mixed-conifer forests experienced longer fire return intervals (20 to > 100 years) and mixed severity (i.e. Hessburg et al., 2007; Hood et al., 2021; Tepley and Veblen, 2015). Aspen mixed-conifer forests occur across elevation gradients with fire return intervals of 10–45 years and moderate to high severity (Hood et al., 2021; Tepley and Veblen, 2015).

Spruce - fir and lodgepole pine forests are typically found above 2400 m and experienced longer fire return intervals and high severity stand replacing fire (Sherriff and Veblen, 2007; Veblen et al., 2000). Spruce - fir experienced fire return intervals of a hundred to several hundred years (e.g. Kipfmueller and Baker, 2000; Veblen et al., 1994; Howe and Baker, 2003; Sibold et al., 2006; Veblen et al., 2000) and slow post-fire regeneration (~100 years) (Pelz, 2016). Lodgepole pine experienced fire return intervals typically greater than a century (i.e. Veblen et al., 1991; Whitlock et al., 2003) and quickly regenerated post fire when serotinous cones were present (Tower, 1909; Clements, 1910). Post-fire resilience in forests with high severity fire regimes was historically maintained by landscape heterogeneity (e.g., non-forest and varying stand age) (Prichard et al., 2021) whereas forests with frequent fire maintained lower surface fuel loading and lower stand density resulting in lower fire severities (Addington et al., 2018). Based on historical fire return intervals, we considered ponderosa pine, mixed-conifer, and aspen – mixed-conifer to be frequent fire forests and lodgepole pine and spruce – fir to be infrequent fire forests.

2.2. Data layers

2.2.1. Burn severity

For our burn severity response variable, we evaluated indices from the Monitoring Trends in Burn Severity (MTBS) program (Eidenshink et al., 2007) and the composite Google Earth Engine (GEE) method developed by Parks et al. (2018a). The Parks et al. (2018a) method was better correlated to field-based Composite Burn Index (CBI) measurements (Vorster et al., 2024) and offered a flexible approach to deriving burn severity indices for fires less than 400 ha, allowing us to include small fires in our analysis. We used the Landsat-derived Relativized Burn Ratio (RBR) because it has been shown to correlate more strongly with

CBI than other satellite-derived burn severity metrics (Parks et al., 2014a). In addition, RBR provides improved spatial accuracy for distinguishing areas of low to moderate burn severity relative to other commonly used spectral indices (Furniss et al., 2020; Parks et al., 2014a). For each fire of interest, we derived RBR in GEE using a mean composite of one year pre- and post-fire images using a modified script from Parks et al. (2018a). To derive the composite image window, we set fire season dates to the recommended period for forests in the southern Rocky Mountains (day of year: 152–258; Parks et al., 2019).

2.2.2. Treatment history

We utilized the common attributes layer from the Forest Service Activity Tracking System (FACTS) database (USDA Forest Service, 2024a) and previous wildfire extents from the Colorado Forest Restoration Institute's (CFRI) interagency fire perimeter database, which includes fire records for the entire study area (CFRI, 2023). Using FACTS and previous wildfire extents, we identified wildfires from 2002 to 2022 that burned through a previous forest treatment area. This resulted in wildfires ranging in size from less than one hectare to 138,279 ha (Fig. A1). We also identified areas of previous wildfire to analyze its effects on subsequent wildfires. We classified previous wildfire as either low to moderate (RBR $<$ 298) or high severity (RBR $\geq$ 298) (Parks et al., 2014a) using the RBR maps derived in GEE (Parks et al., 2018a). Previous high severity wildfire was excluded from the analysis because vegetation type conversion following reburn events can reduce the accuracy of remotely sensed burn severity measurements (Morgan et al., 2014). Additionally, in frequent fire forests, areas that burn at high severity may be more likely to reburn at high severity due to their biophysical settings and/or resulting vegetation changes (Grabinski et al., 2017; Harris and Taylor, 2017; Lydersen et al., 2017; Parks et al., 2014b).

We categorized the combined treatment data into four treatment types: previous low to moderate severity wildfire (low-mod wildfire), removal and/or surface fuel reduction, prescribed fire, and removal and fire (Table 1; Fallon et al., 2024). The removal and/or surface fuels reduction category included treatments involving removal only, surface fuels reduction only, or a combination of both (Table 1; Table A1). There is a wide range of treatments in this “removal and/or surface fuel reduction” category (Table A1; Fig. A2), including some treatment types that reduce surface fuels and others that are known to increase surface fuels (e.g., commercial thin). Overlapping treatments were considered unique treatment units. Within these units, attributes were combined by retaining the most recent treatment year and defining treatment size as the overlapping area. Our final treatment variables included treatment type, time since treatment, and treatment size (Table 2).

Table 1
Treatment type classifications for this study based on original Forest Service Activity Tracking System (FACTS) treatment category and total area (hectares) of final treatment types. See Table A1 for original FACTS treatments and proportion of final treatment type.

Intermediate Category	Final Treatment Type	Area (ha)
Previous Wildfire	Low-Mod Wildfire	151,281
Removal	Removal and/or Surface Fuel Reduction	12,158
Surface Reduction		
Rearrangement, Removal, & Surface Reduction		
Removal & Surface Reduction		
Prescribed Fire	Prescribed Fire	2963
Removal & Low-Mod Wildfire	Removal and Fire	476
Rearrangement, Removal, Surface Reduction, & Low-Mod Wildfire		
Removal & Prescribed Fire		
Removal, Prescribed Fire, & Low-Mod Wildfire		
Rearrangement, Removal, & Prescribed Fire		
Rearrangement, Removal, Surface Reduction, & Prescribed Fire		

2.2.3. Fuel

To determine potential forest type within fires and treatments, we used the LANDFIRE Biophysical Settings potential vegetation cover dataset (Rollins, 2009). The biophysical setting vegetation layer represents the pre Euro-American reference conditions and acted as a baseline forest type for the range of fire dates (Rollins, 2009). We reclassified these forest types into six categories including non-forest, ponderosa pine, mixed-conifer, aspen – mixed-conifer, lodgepole pine, and spruce - fir (Table A2). Fires that contained more than 30 % non-forest land were removed from analysis, resulting in 63 wildfires. In addition, we used the National Land Cover Database (NLCD) Tree Canopy Cover layer to account for the year prior to wildfire canopy cover (Table 2; Housman et al., 2023).

2.2.4. Topography

Topographic variables were derived from a 1/3 arc-second DEM from the USGS 3DEP program (Table 2; U.S. Geological Survey, 2023). Slope, northness, topographic position index, and terrain roughness were calculated using the terrain function in the terra R package (Hijmans, 2024). The topographic wetness index was calculated using the wbt_wetness_index function in the whitebox R package (Lindsay, 2016; Wu and Brown, 2022) and heat load index (HLI) was calculated using the hli function in the spatialEco R package (Evans and Murphy, 2023).

2.2.5. Climate

We created climate variables to quantify anomalies between the 30-year prior to fire climate average and year prior to fire average. For each climate variable, we calculated the 30-year mean and the fire-year mean using PRISM data prior to the fire year (4 km resolution; Daly et al., 2008, 2015) in GEE. We then derived z-scores for each variable and computed the difference between the 30-year average and the fire-year average. The climate anomaly variables included monthly total precipitation, mean temperature, minimum vapor pressure deficit (min VPD), and maximum vapor pressure deficit (max VPD) (Table 2).

2.2.6. Fire weather

For fires greater than 400 ha, we derived day-of-burning (DOB) maps following the methods developed by Parks (2014). This method maps the most likely DOB by interpolating VIIRS and MODIS hotspot detections. The 400 hectare threshold is based on the resolution imitations of MODIS and VIIRS data (1 km resolution), which limits the ability to accurately map smaller fires. Therefore, we used the recorded ignition date as the DOB for smaller fires ($<$ 400 ha). To account for weather conditions on the DOB, we created mean composites of weather variables based on the day the fire burned through a given area, using data from GridMET (4 km resolution; Abatzoglou, 2013). The GridMET fire weather variables included wind speed, maximum temperature, minimum relative humidity, mean vapor pressure deficit (VPD), and energy release component (Table 2). We defined extreme fire weather conditions based on the area burned during daily spread events, using the extreme threshold for the northwestern forested mountains ecoregion: extreme (DOB area $>$ 4127 ha d^{-1}) and non-extreme (DOB area $<$ 4127 ha d^{-1}; Balik et al., 2024).

2.3. Statistical analysis

Before sampling points, we created a mask to ensure only forested and federal lands were represented in our dataset. To create a forest area mask, we used the LANDFIRE existing vegetation type layer (tree = 1, non-tree = 0) (Rollins, 2009) combined with NLCD Tree Canopy Cover layer ($\geq$10 % canopy cover = 1, $<$10 % canopy cover = 0) (Housman et al., 2023), classifying forested areas as 1 and non-forested areas as 0.

Table 2
List of predictor variables for the generalized linear mixed model (GLMM) model with variable name, short description, use in analysis, and data source.

Variable	Description	Analysis	Source
Treatment			
Time Since Treatment	Fire year minus year treatment was complete (year)	Final Model	CFRI, (2023); USDA Forest Service, (2024a)
Treatment Type	Recategorized treatment data (see Table 1 for categories)	Final Model	CFRI, (2023); USDA Forest Service, (2024a)
Treatment Size	Size of treatment polygon (m^2)[a]	Final Model	Hijmans, (2024)
Topography			
Elevation	Elevation (meters) from USGS digital elevation model (DEM)	Removed –multicollinearity	U.S. Geological Survey, (2023)
Slope	Slope angle of a pixel (degrees)	Removed –multicollinearity	Hijmans, (2024)
Topographic Position Index	Difference between raster cell and neighborhood elevation	Final Model	Hijmans, (2024)
Topographic Wetness Index	Moisture content of pixel based on topography	Final Model	Lindsay, (2016); Wu and Brown, (2022)
Northness	North/south direction of slope face	Final Model	Hijmans, (2024)
Terrain Roughness	Elevation difference among cells	Final Model	Hijmans, (2024)
Heat Load Index (HLI)	Measure of solar radiation, accounts for how slope steepness and aspect influence temperature	Final Model	Evans and Murphy, (2023)
Fuel			
Canopy Cover	NLCD vertically projected percent cover of the live canopy layer for a specific area	Final Model	Housman et al., (2023)
Forest Type	Recategorized LANDFIRE Biophysical Setting to treated forest types (see Table A2 for categories)	Final Model	Rollins, (2009)
Fire Weather			
Hectares Burned	Total hectares burned on the pixel's day-of-burning (ha)	Final Model	Parks, (2014)
Extreme Condition	Binary extreme (DOB area > 4127 ha d^{-1} = 1) or not-extreme (DOB area < 4127 ha d^{-1} = 0) condition	Final Model	Balik et al., (2024)
Wind Speed	Daily wind velocity (meters/second) at 10 m[b]	Final Model	Abatzoglou, (2013)
Max Temperature	Daily maximum temperature (Kelvin)[b]	Removed –multicollinearity	Abatzoglou, (2013)
Min Relative Humidity	Daily minimum relative humidity (%)[b]	Removed –multicollinearity	Abatzoglou, (2013)
Fire Weather VPD	Daily mean vapor pressure deficit[b]	Final Model	Abatzoglou, (2013)
Energy Release Component	Daily modeled mean daily energy release component (NFDRS fire danger index)[b]	Removed –multicollinearity	Abatzoglou, (2013)
Climate			
Precipitation Anomaly	Anomalous annual precipitation (including rain and melted snow)[c]	Final Model	Daly et al., (2008), (2015)
Temperature Anomaly (Mean)	Anomalous annual mean temperature[c]	Final Model	Daly et al., (2008), (2015)
VPD Minimum Anomaly	Anomalous annual minimum vapor pressure deficit (VPD)[c]	Removed –multicollinearity	Daly et al., (2008), (2015)
VPD Maximum Anomaly	Anomalous annual maximum vapor pressure deficit[c]	Final Model	Daly et al., (2008), (2015)

[a] Calculated using the expanse() function in the *terra* package
[b] Derived from University of Idaho Gridded Surface Meteorological Dataset (GRIDMET)
[c] 30 year average z-score minus fire-year z-score

We also limited sampling to only federal lands using the Forest Service surface ownership parcels layer (USDA Forest Service, 2024b) since the FACTS treatment data tracks federal lands management. Forested federal lands were reclassified into treated (1) and untreated (0). A 100-meter buffer was applied around the treated areas to account for potential treatment shadow and this area was not used in subsequent analysis.

We generated points in treated and untreated areas proportional to the forest type make-up of treated areas to reduce differences due to biophysical setting and ecology, ensuring meaningful comparisons between treatments and untreated areas. First, we calculated the percentage of each forest type across a given fire. Sampling intensity for treated areas was determined based on the total area treated (m^2); treatments < 40 acres of total area were assigned 10 sample points, while treatments > 40 acres were sampled at a rate of 3.5 % of treatment total area. Each sampling point represented an area of 900 m^2 (30 by 30 m pixel), matching the resolution of the response variable. Sampling points within the treated area were stratified by forest type, proportional to the forest type composition of the treated area. The untreated areas were sampled within forest types at the same proportions to the treated points to have approximately equal number of points across forest types. We extracted each predictor variable at each point resulting in 10,171 total points (4699 treated, 5472 untreated) for the final model (Table 3).

To answer question (1) and achieve a model that was sufficiently complex yet interpretable while minimizing overfitting, we first assessed multicollinearity among numeric predictor variables using Spearman's rank correlation. For each highly correlated pair ($r > |0.7|$) (Cansler et al., 2022; Povak et al., 2020), we retained the variable with the strongest correlation to RBR values. Elevation, slope, max temperature, minimum relative humidity, energy release component, and VPD minimum anomaly were removed from the final model due to multicollinearity (Table 2).

We fit a generalized linear mixed model (GLMM) with a Gaussian distribution and an identity link using RBR as our response variable (lme4 R package, Bates et al., 2015). GLMMs are useful for analyzing data with non-normal distributions and hierarchical or nested structures, because they account for random effects and correlations within grouped data (Bolker et al., 2009). They assume data follows a specified distribution (i.e. Gaussian, Poisson), random effects are normally distributed, and allow observations within groups to be correlated (Bolker et al., 2009). Our fixed effects represented aspects of treatment history, fuel, topography, fire weather, and climate. We set individual fire event as a random effect to account for potential spatial autocorrelation between points in individual fires, and variability due to specific pre-fire and burning conditions. To test for spatial autocorrelation in our model, we used the moran.test function from the spdep R package (Bivand, 2022). A nearest neighbor distance of 270 m was selected based on previous research, which identified this sampling resolution decreased fine-scale spatial autocorrelation (Cansler et al., 2022; Povak

Table 3
Summary of sampled points by forest type and extreme condition, showing the number of treated points, total number of points (treated + untreated), percentage of total points, mean relativized burn ratio (RBR), and standard deviation (SD) RBR of all points.

	Ponderosa Pine	Mixed-conifer	Aspen - Mixed-conifer	Lodgepole Pine	Spruce - Fir	Non-extreme	Extreme
Untreated	1118	1700	678	1362	614	3925	1547
Low-Mod Wildfire	944	915	143	44	47	1670	423
Prescribed Fire	92	102	57	47	1	253	46
Removal - Surface Reduction	344	325	270	819	443	1069	1132
Removal & Fire	60	28	16	2	0	79	27
Treated Points	1440	1370	486	912	491	3071	1628
Total Points	2558	3070	1164	2274	1105	6996	3175
Percentage (%)	25.1	30.2	11.4	22.4	10.9	68.8	31.2
Mean RBR	166	209	224	334	351	208	321
SD RBR	124	149	166	184	214	158	191

et al., 2020; Prichard et al., 2020). The Moran's I statistic for our model was 0.04, and the result was not statistically significant ($p = 0.07$), indicating no evidence of spatial autocorrelation in the residuals. We assessed significance at $\alpha = 0.05$ throughout the study. We considered an effect size small if it had an estimate less than the absolute value of 10 RBR.

For question (2), we assessed differences in RBR across treatment and forest types using a non-parametric Kruskal-Wallis test, a method for comparing medians among multiple groups (Kruskal and Wallis, 1952). To account for multiple comparisons, we conducted a post-hoc pairwise comparison using Dunn's test with a Bonferroni adjustment (dunn.test R package, Dinno, 2014; Dunn, 1964). This allowed us to identify specific group differences while controlling for Type I error. We replicated this analysis for question (3) to assess RBR differences across treatment types and extreme fire weather conditions for frequent (ponderosa pine, mixed-conifer, and aspen – mixed-conifer) and infrequent (lodgepole pine and spruce – fir) fire forest groups. We considered looking at the pairwise comparison for extreme conditions by forest type but due to sample size limitations, we were unable to compare extreme conditions across forest types. For all pairwise comparisons, we only considered groups with a sample size greater than 40 points. All analyses were performed using R Statistical Software (v4.3.3; R Core Team, 2024).

3. Results

3.1. Factors influencing treatment effects on burn severity

We compared the distributions and conducted a post-hoc Dunn's test of predictor variables describing biophysical setting to determine if untreated points reflected the conditions found in treated areas. The distributions of canopy cover for untreated and treated points showed canopy cover was significantly higher in untreated areas compared to treated areas (Fig. 2A; Fig. A3A). Removal - surface reduction, removal & fire, and previous low-mod wildfire treatments had greater sampled point density compared to untreated areas around 10 % canopy cover (Fig. 2A). Northness followed a bimodal distribution with removal - surface reduction and untreated points occurring more frequently on north facing slopes (northness = 1 for north; Fig. 2B; Fig. A3B). Whereas prescribed fire and previous low-mod wildfire points were more common on south facing slopes (northness = −1 for south; Fig. A3B). HLI had a left-skewed distribution, with prescribed fire and removal & fire treatments exhibiting slightly higher densities at greater HLI values (i.e.

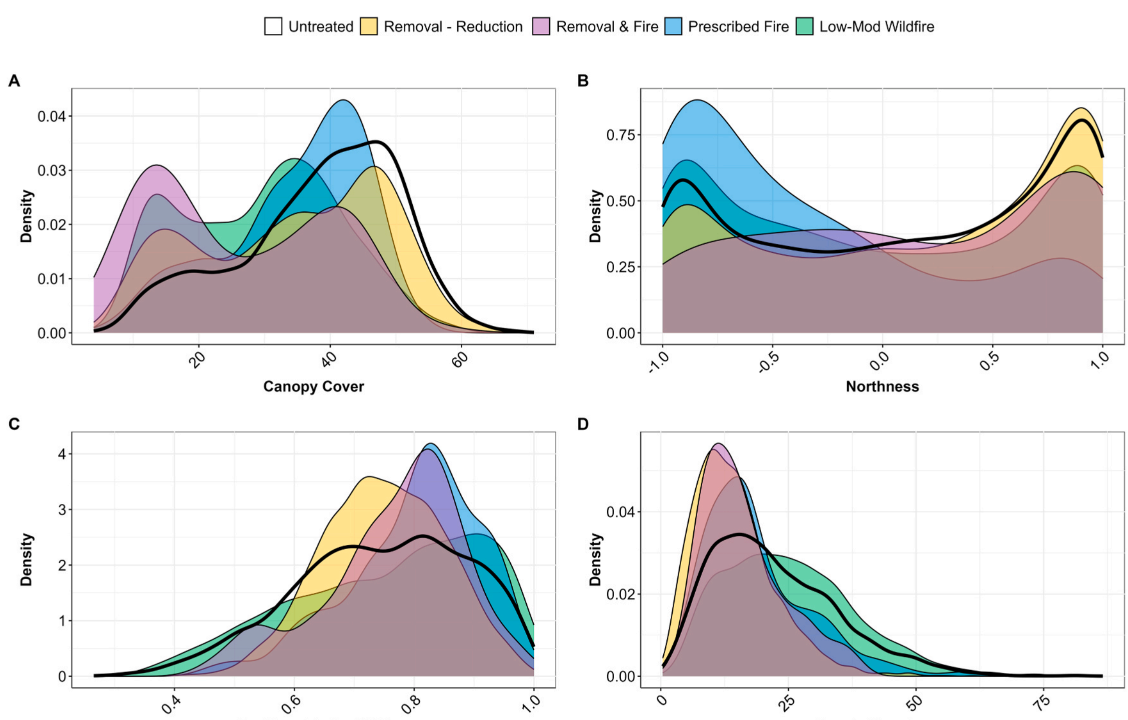

Fig. 2. Sampled point density plots representing the distribution of fuel (A. canopy cover) and topographic predictor variables (B. northness, C. heat load index, and D. terrain roughness) for treated and untreated points. Northness values near −1 represent south facing slopes and values near 1 represent north facing slopes. The bolded black lines highlight the untreated distributions.

warmer) (Fig. 2C). The distribution of terrain roughness was right-skewed, with removal - surface reduction, removal & fire, and prescribed fire treatments showing slightly higher densities at lower terrain roughness values (i.e. less rugged terrain) (Fig. 2D; Fig. A3D).

The GLMM showed that forest type, treatment type, size, and age, extreme condition, fire weather VPD, northness, HLI, precipitation anomaly, temperature anomaly, and VPD max anomaly were significant predictors of burn severity and had large effect sizes (Table 4). Spruce - fir, mixed-conifer, lodgepole pine, and aspen – mixed-conifer forests were all associated with higher burn severities compared to ponderosa pine, the baseline forest type (Table 4). Specifically, for treated and non-treated points, lodgepole pine (mean RBR = 334 ± 184) and spruce - fir (mean RBR = 351 ± 214) had the highest average burn severity (Table 3). Mixed-conifer (mean RBR = 209 ± 149) and aspen – mixed-conifer (mean RBR = 224 ± 166) had moderate average burn severity while ponderosa pine (mean RBR = 166 ± 124) had the lowest average burn severity. Compared to the untreated baseline, previous low-mod wildfire (Estimate = −82.2, SE = 6.0), prescribed fire (Estimate = −59.2, SE = 9.9), removal - surface reduction (Estimate = −29.2, SE = 5.1), and removal & fire (Estimate = −35.4, SE = 14.8) treatment types had significantly lower burn severity estimates (Table 4).

Canopy cover, time since treatment, treatment size, hectares burned, terrain roughness, and topographic wetness index were statistically significant but had relatively small effect sizes. Northness (Estimate = 15.9, SE = 2.8; Fig. 3A), fire weather VPD (Estimate = 18.6, SE = 3.9; Fig. 3C), precipitation anomaly (Estimate = 26.6, SE = 5.2; Fig. 3E), and VPD max anomaly (Estimate = 68.9, SE = 10.2; Fig. 3F) had significant positive effects in the model. HLI (Estimate = −71.8, SE = 13.7; Fig. 3B) and mean temperature anomaly (Estimate = −39.6, SE = 7.1; Fig. 3D) had significant negative effects.

Table 4
Generalized linear mixed model (GLMM) results for predicting burn severity with fixed and random effects. The table shows estimates, standard errors, statistics, and p-values. Positive estimates indicate higher burn severity, while negative estimates suggest lower severity. The random effect included 63 individual fire events. Fixed effect degrees of freedom equal 10,147 (calculated as n – p). Variables in regular text are significant at α = 0.05. Variables in italicized text are not statistically significant.

	Estimate	Std. Error	Statistic	*P*
(Intercept)	103.631	19.434	5.332	< 0.001
Canopy Cover	2.192	0.134	16.421	< 0.001
Forest Type (relative to ponderosa pine)				
Spruce - Fir	77.131	6.733	11.456	< 0.001
Mixed-conifer	22.679	4.221	5.373	< 0.001
Lodgepole pine	75.85	5.676	13.363	< 0.001
Aspen – Mixed-conifer	23.965	5.756	4.163	< 0.001
Treatment Type (relative to untreated)				
Low - Moderate Wildfire	-82.172	6.004	-13.687	< 0.001
Prescribed Fire	-59.167	9.896	-5.979	< 0.001
Removal - Surface Reduction	-29.222	5.088	-5.744	< 0.001
Removal & Fire	-35.439	14.812	-2.393	0.017
Time Since Treatment	1.441	0.44	3.275	0.001
Treatment Size	0	0	-5.472	< 0.001
Fire Weather				
Extreme Condition	24.441	6.93	3.527	< 0.001
Hectares Burned	0.002	0.001	3.177	0.001
Fire Weather VPD	18.627	3.893	4.785	< 0.001
Wind Speed	*1.432*	*1.134*	*1.263*	*0.207*
Topography				
Northness	15.864	2.839	5.588	< 0.001
Heat Load Index (HLI)	-71.819	13.666	-5.255	< 0.001
Terrain Roughness	-0.524	0.156	-3.357	0.001
Topographic Position Index	*0.271*	*0.734*	*0.369*	*0.712*
Topographic Wetness Index	-3.275	1.221	-2.683	0.007
Climate				
Precipitation Anomaly	26.552	5.198	5.108	< 0.001
Temperature Anomaly	-39.623	7.084	-5.593	< 0.001
VPD Maximum Anomaly	68.863	10.206	6.747	< 0.001
Observations	10171			
AIC	129699.4			
Marginal R^2 / Conditional R^2	0.181 / 0.414			

3.2. *Burn severity outcomes across forest and treatment types*

The previous low-mod wildfire treatments had significantly lower burn severities compared to untreated areas across all forest types. A post-hoc Dunn's test indicated that in ponderosa pine forests compared to untreated points, removal - surface reduction ($p = 0.03$), prescribed fire ($p < 0.001$), and previous low-mod wildfire ($p < 0.001$) had significantly lower mean burn severities (Fig. 4A), however, removal and fire was not significantly different than untreated ($p = 0.81$).

In mixed-conifer forests, prescribed fire ($p < 0.001$) and previous low-mod wildfire ($p < 0.001$) showed significantly lower burn severities compared to untreated (Fig. 4B), but removal - surface reduction did not ($p = 0.09$). In aspen – mixed-conifer, removal - surface reduction ($p = 0.001$), prescribed fire ($p < 0.001$), and previous low-mod wildfire ($p < 0.001$) had significantly lower burn severities compared to untreated (Fig. 4C). For lodgepole pine forests, removal - surface reduction ($p < 0.001$), prescribed fire ($p < 0.001$), and previous low-mod wildfire ($p < 0.001$) had significantly lower burn severities compared to untreated (Fig. 4D). In spruce - fir forests, previous low-mod wildfire ($p = 0.001$) had a significantly lower subsequent burn severity compared to untreated; however, removal - surface reduction had a significantly higher burn severity ($p < 0.001$; Fig. 4E).

3.3. *Impact of extreme fire conditions by frequent and infrequent fire forest group*

Areas that burned under extreme conditions (> 4127 ha d^{-1}; Balik et al., 2024) were associated with higher burn severities (estimate: 24.441 ± 6.93, $p < 0.001$; Table 4, Fig. 5). Our Kruskal-Wallis test revealed a significant interaction between treatment type and extreme condition ($\chi^2 = 1743.5$, df = 9, p-value < 0.001) suggesting that burn severity (RBR) varies across combinations of treatment type and extreme conditions. In frequent fire forests, in non-extreme conditions, removal - surface reduction ($p < 0.001$), prescribed fire ($p < 0.001$), and previous low-mod wildfire ($p < 0.001$) had significantly lower burn severity compared to untreated points (Fig. 5A), but removal & fire did not ($p = 0.09$). For infrequent fire forests, removal - surface reduction ($p < 0.001$), prescribed fire ($p = 0.02$), and previous low-mod wildfire ($p < 0.001$) had significantly lower burn severity compared to untreated points (Fig. 5A). During extreme conditions in frequent fire forests, removal – surface reduction ($p = 0.05$), prescribed fire ($p = 0.05$), and previous low-mod wildfire ($p < 0.001$) had significantly lower burn severities compared to untreated points (Fig. 5B). For infrequent fire forests during extreme conditions, there was not a significant difference in burn severity between untreated and removal – surface reduction treatments ($p = 0.36$; Fig. 5B). Other treatment - forest group combinations had insufficient sample sizes ($n < 40$) and were not analyzed (Table A3).

4. Discussion

We found treatments, including prescribed fire and previous low-mod wildfire, resulted in lower burn severity than untreated areas across most forest types under both extreme and non-extreme conditions. Treatments without fire (removal and/or surface fuels reduction treatments) had more complex effects that depended on both forest type (historically frequent or infrequent fire) and on whether the fire burned under extreme conditions. In historically frequent fire forests, treatments without fire reduced burn severity relative to untreated areas under both extreme and non-extreme conditions, but in historically infrequent fire forests, they only reduced severity under non-extreme conditions.

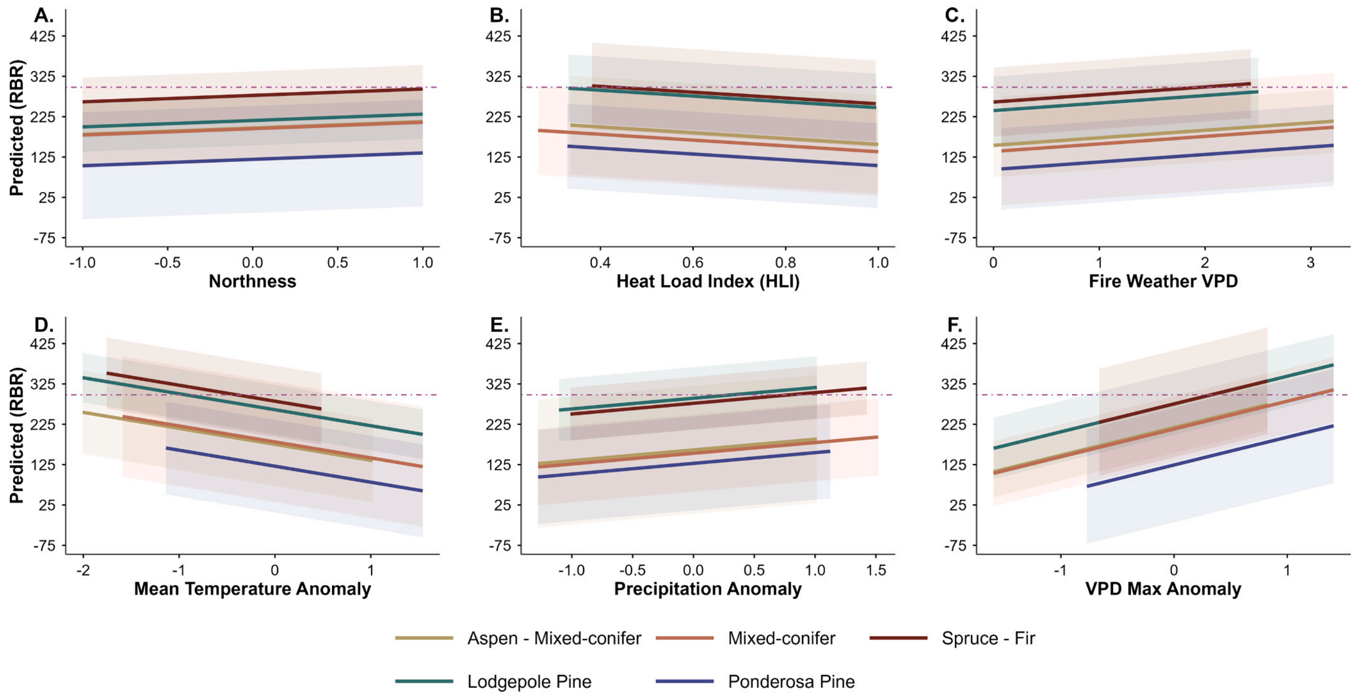

Fig. 3. Relationships of predicted burn severity (relativized burn ratio; RBR) and important variables by forest type: (A) northness; (B) heat load index (HLI), (C) fire weather vapor pressure deficit (VPD), (D) mean temperature anomaly, (E) precipitation anomaly, and (F) VPD max anomaly. Lines represent forest types. Shaded areas represent the 95 % confidence intervals. The dashed line represents the RBR threshold for high severity (> 298, Parks et al., 2014a). Northness values near −1 represent south facing slopes and values near 1 represent north facing slopes. Positive HLI values represent areas with higher solar radiation. Negative temperature anomaly is associated with higher than average fire year temperatures, positive precipitation anomaly is associated with lower than average fire year precipitation values, and positive vpd max anomaly is associated with lower than average vpd max values. Climate anomalies were calculated by taking the difference between the 30-year average and the year of fire average.

4.1. Climatic and weather effects on burn severity

Of the weather and climate variables, we found extreme condition, fire weather VPD, temperature anomaly, and precipitation anomaly were significant predictors of burn severity. The negative relationship between temperature anomaly and burn severity suggests that larger temperature anomalies, indicating fire years that are cooler relative to the 30-year average, are associated with a decrease in burn severity across all forest types (Fig. 3D). Our study also demonstrated a positive relationship between precipitation anomaly and burn severity. Positive anomaly values indicate that in fire years where precipitation was below average, burn severity was higher. Our results add evidence to the linkage of increased temperature (Parks and Abatzoglou, 2020) and reduced precipitation relative to long term climate averages resulting in increased fuel aridity (Abatzoglou and Williams, 2016) and area burned at high severity (Holden et al., 2007). As expected, fire weather VPD and burn severity had a positive relationship suggesting that on days where the atmosphere had a high evaporative demand burn severity tended to increase (Fig. 3C). Past studies across forest types in the southwestern U. S. have linked high seasonal VPD values to increased fire activity and area burned at high severity (Mueller et al., 2020; Seager et al., 2015; Williams et al., 2015).

4.2. Treatment effects across forest types and in extreme conditions

Our findings indicate that, on average, all sampled forest types burned at higher severities compared to ponderosa pine (Table 4). This demonstrates that even though ponderosa pine forests have experienced infilling and increases in forest density from a century of fire suppression along the Front Range (Battaglia et al., 2018), these forests retain fire resistant qualities (Stevens et al., 2020). Frequent fire forests, such as ponderosa pine, mixed-conifer, and aspen – mixed-conifer, exhibited lower burn severities on average compared to higher elevation forests (Table 3; Fig. 5). These patterns reflect differences in fuel loading, moisture availability, species adaptations, and fire behavior across elevation gradients, highlighting the need for elevation and forest type specific management strategies (Davis et al., 2024).

While our model found time since treatment to be an important predictor of burn severity, it had a small effect size (Table 4). However, only a limited range of treatment ages were considered, with the oldest treatments representing 20 years pre-fire and recent treatments (< 10 years) more heavily represented in our models (Fig. A4). Older treatments can be missing from treatment databases. For example, treatment data was found to be sparse in the Cameron Peak burn area before 2007 (Vorster et al., 2024). We were likely missing more treatments for older fires that had a more incomplete treatment record just before the fire. Further, the Front Range is a low productivity system; thus, it is likely that treatments may reduce burn severity for longer than treatments that occur in higher productivity systems (i.e. Sierra Nevada, Pacific Northwest, Black Hills; Hunter et al., 2007; Radcliffe et al., 2024; Stephens et al., 2012b). Combined, this likely limits our full understanding of the importance of treatment age, though we saw a positive correlation indicating that newer treatments were associated with lower burn severity.

As hypothesized, treatments with prescribed fire and previous low-mod wildfire reduced burn severity (Fig. 4 & 5). However, in ponderosa pine, we observed similar burn severity between removal and fire treatments and untreated areas (Fig. 4A). Results for other forest types were not tested due to the small sample size of this type of treatment (Table 3). Previous studies in primarily frequent fire forests have also concluded that treatments with fire result in reduced burn severity compared to controls; this is thought to be because treatments that include fire reduce surface fuels (i.e. litter, duff, and small woody debris), increase canopy base height, and change vertical fuel continuity

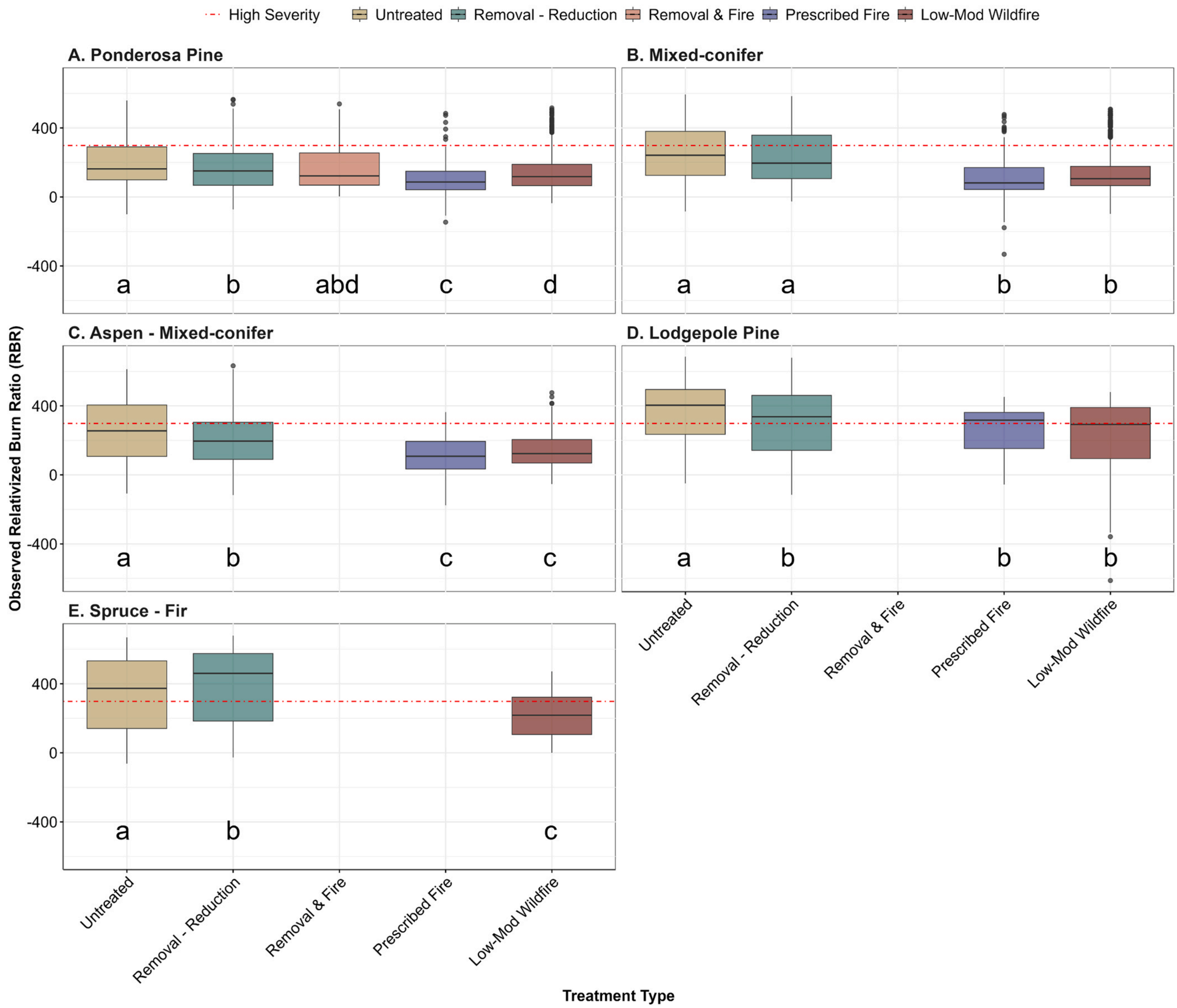

Fig. 4. Burn severity differences across treatment types for (A) ponderosa pine, (B) mixed-conifer, (C) aspen – mixed-conifer, (D) lodgepole pine, and (E) spruce - fir. Letters indicate significant differences among treatment groups ($p < 0.05$, Dunn's Test). Groups that share a letter are not significantly different. The red dashed line represents the relativized burn ratio (RBR) threshold for high severity (> 298, Parks et al., 2014a). Treatment groups missing a box had less than 40 sample points.

– reducing the likelihood of high severity fire (Cansler et al., 2022; Davis et al., 2024; Kalies and Yocom Kent, 2016; Martinson and Omi, 2013; Prichard and Kennedy, 2012; Prichard et al., 2020; Vorster et al., 2024). The removal and fire treatment in ponderosa pine may not have removed as much fuel as the previous low-mod wildfire treatment, possibly because the prescribed fire was less intense and failed to fully consume a high proportion of the surface and ladder fuels like tree regeneration and shrubs. Additionally, it is likely we did not capture the full range of conditions within this category in our dataset due to the small sample size ($n = 60$), which represented 16 unique treatment combinations (Fig. A5). The limited sample size is partly due to very few prescribed fires on the Front Range in the past two decades.

The effects of removal and/or surface reduction treatments depended on extreme conditions (as represented by daily fire spread) and forest type. Under extreme conditions, these treatments reduced burn severity in historically frequent fire forests, whereas in infrequent fire forests, removal and/or surface fuels reduction treatments had equivalent subsequent burn severity to untreated areas (Fig. 5B). Across all burning conditions, burn severity in removal and/or surface fuels reduction treatments was lower in ponderosa pine, aspen – mixed-conifer, and lodgepole pine compared to untreated areas; however, this treatment type in spruce - fir resulted in higher subsequent burn severity (Fig. 4E). Our findings build on previous studies (Chamberlain et al., 2024; Lydersen et al., 2017; Prichard et al., 2020) by distinguishing treatment response across both fire regime and fire weather conditions.

In our study area, most removal and/or surface reduction treatments were implemented in high-elevation, infrequent fire forest types (Table 3; Fig. A6D & A6E), which historically burned at high severity. Additionally, treatments in frequent fire forests that involve just thinning alone can be ineffective under extreme conditions (Chamberlain et al., 2024; Lydersen et al., 2017; Prichard et al., 2020) and, when surface biomass is not removed, may contribute to higher severity outcomes (Omi et al., 2006). This may be attributed to increased surface fuel loads following removal treatments (Fulé et al., 2012; Prichard et al., 2010; Stephens et al., 2012a), which elevate the likelihood of fire behavior that can result in higher tree mortality. The most common treatment in this category was yarding (Fig. A2) which burned at high

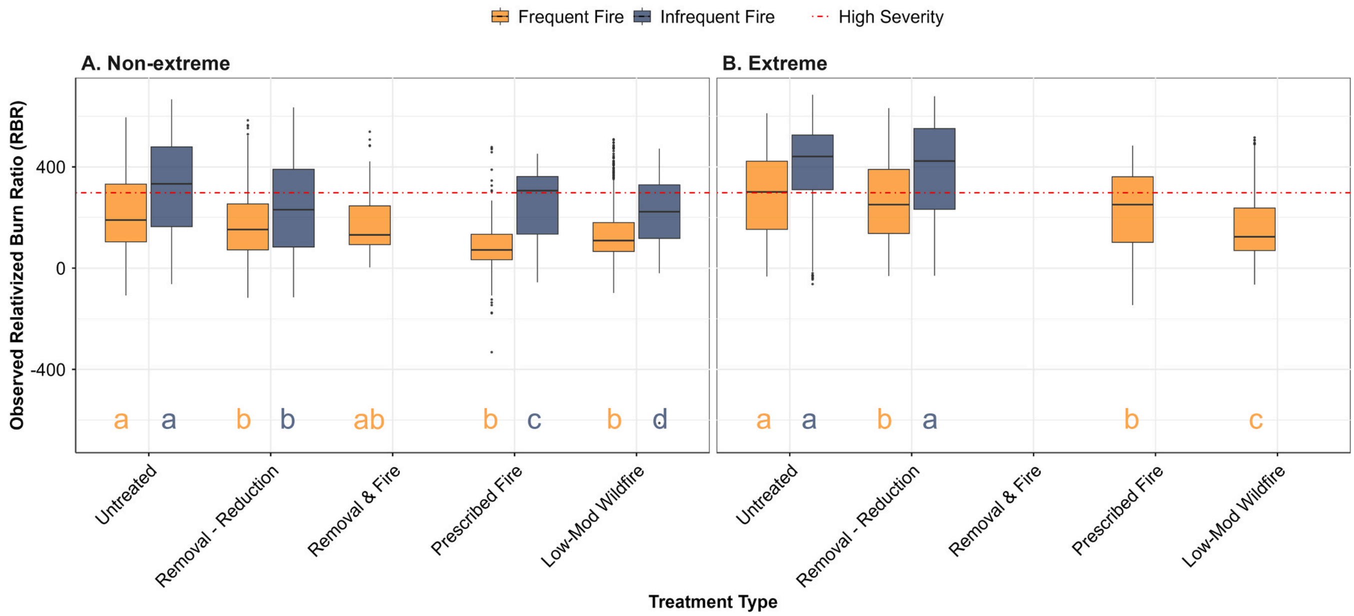

Fig. 5. Observed burn severity differences across treatment types for (A) non-extreme and (B) extreme conditions by historically frequent and infrequent fire forests. Frequent fire forests include ponderosa pine, mixed-conifer, and aspen – mixed-conifer. Infrequent fire forests include lodgepole pine and spruce - fir. Orange (frequent fire group) and blue letters (infrequent fire group) indicate significant differences among treatment groups ($p < 0.05$, Dunn's Test). Groups that share a letter are not significantly different. Groups with missing bars had insufficient sample sizes ($n < 40$). The red dashed line represents the relativized burn ratio (RBR) threshold for high severity (> 298, Parks et al., 2014a).

severities in lodgepole pine (Fig. A6D) and spruce fir (Fig. A6E). In some cases, surface fuel reduction treatments may be the only management option, particularly in areas with high fuel loads, near infrastructure, or in areas with non-fire resistant trees. Despite limitations, removal and/or surface fuels reduction treatments remain an important tool for enhancing forest resistance and resilience to disturbances, including wildfire (Hood et al., 2016; Knapp et al., 2021), especially in historically frequent fire forests burning under moderate conditions.

In lodgepole pine and spruce - fir forests, we observed that management actions had minimal impact on reducing subsequent burn severity, which remained predominantly high. While this finding was expected based on the historical fire regimes, there is increasing concern over the size of recent wildfires in these forest types. Fire frequencies in these high elevation forests have increased in the last several decades compared to the previous 2000 years (Higuera et al., 2021), and the 2020 fire season alone burned more late snow zone areas than the previous 36 years combined (Kampf et al., 2022). High elevation, infrequent fire forests are warming at higher rates (Pepin et al., 2015), specifically experiencing more critical fire danger days than forests at lower elevations (Alizadeh et al., 2023). Treatments often aim to meet timber or wildlife objectives rather than reduce burn severity, so evaluating them by severity changes is assessing only a portion of the treatment goals. Furthermore, these forest types historically experienced high severity fire, so measuring treatment effectiveness by reductions in burn severity is less ecologically-based in these forest types and is more relevant to protection of infrastructure and human values. Metrics like rate of spread or barriers to spread may be more appropriate, though we did not assess them here.

4.3. Limitations

Our analysis relied on the FACTS common attributes database, which does not include all federal, state, or private fuels treatments and lacks silvicultural prescriptions details on treatment intensity, tree size/species targeted, and biomass removal. These limitations, along with remote sensing methods that capture only canopy-level changes, make it difficult to assess the full range of treatment effects, especially on surface fuels and small trees. Future work could explore ways to quantify treatment intensity and structural change more accurately. Additionally, future research should evaluate more specific treatment type categories to understand differences between treatments combined in this study. There have been recent efforts to compile treatment data from various sources (e.g. Call et al., 2025), which includes treatments from FACTS and the National Fire Plan Operations and Reporting System (NFPORS). These efforts may allow researchers to investigate more specific treatment categories and reduce variability within aggregated categories.

Fire weather beyond our classification of extreme and non-extreme conditions and fire weather VPD was not a strong predictor of burn severity, possibly due to the course spatial resolution (4 km) of GRIDMET data. Many treatments and fires occurred at finer scales than this data can capture, potentially obscuring fire weather relationships. Wind was also not a significant driver of burn severity, though there is abundant evidence that wind drove many of the large wildfires in our dataset (Duane et al., 2021). This is likely due to the coarse resolution of the wind data and while wind may drive fire behavior it may not be as highly correlated to burn severity (Wagenbrenner et al., 2016). Additionally, our definition of extreme conditions based on daily fire spread (> 4127 ha d^{-1}; Balik et al., 2024) may have overlooked severe fire behavior in smaller spread events. Future work could benefit from region specific thresholds or indices that better capture drivers of extreme fire behavior.

To make meaningful comparisons across treatments, we distributed points in untreated areas of similar forest types as treated forests. While this approach minimized major biophysical differences (e.g., ponderosa pine at lower, drier sites versus spruce - fir at higher, mesic sites), other factors such as weather conditions on the day-of-burning or topographic influences not captured by forest type were not explicitly controlled. As a result, the effects of certain treatments on burn severity may be stronger or weaker than we are currently identifying. Similar studies identified treated and untreated controls by either subsampling points and matching bioclimatic settings and fire weather (Cansler et al., 2022) or selecting control units that represent similar site and burning conditions as the treatments (Chamberlain et al., 2024). Nonetheless, in our study, topographic predictor variables were generally similar between treated and untreated areas (Fig. 2). Lastly, forest treatment locations are limited by steep slopes, inaccessible terrain, and road access (Woolsey et al., 2024). Treated areas may have lower burn severity partially because they occurred in drier sites with less fuels and less prone to severe wildfire compared to the untreated areas.

4.4. Management Recommendations

Our results highlight that previous low-mod wildfire was the only treatment to have a lower mean burn severity compared to untreated areas across forest types and fire weather conditions. Wildfires are altering more landscapes than intentional treatments combined, in much of the western US (e.g. Coppoletta et al., 2022 in California) and there is growing evidence to the ecological value of these wildfires, especially those areas that burned at low-mod severity (Parks et al., 2015, Kreider et al., 2023). We did not differentiate between previous low-mod severity wildfires that were managed for resource benefit and those that underwent full suppression, though few on the Front Range have been managed as resource benefit; however, our findings suggest that wildfires burned at low-mod severity can result in reduced subsequent severity. Managers may consider these areas treated landscapes when the objective is to mitigate future burn severity and inform the implementation of future treatments. This suggests that managing wildfire, under mild to moderate conditions away from communities, as a tool to reduce fuels would be effective at expanding pace and scale of treatments, assisting with treatment maintenance, and potentially reducing subsequent burn severity, which may improve tree survival for fire-adapted species and forest types (North et al., 2012, 2024).

Previous wildfire of low to moderate-severity may reduce more fuel on the landscape than prescribed fire alone (Parks et al., 2018b; Prichard et al., 2021; Shive et al., 2025), can lower subsequent burn severity, is less limited by landscape and accessibility constraints that limits other management (Fig. 2D), and serves as barriers to spread for 10–20 years (Parks et al., 2014b; Rodman et al., 2023), likely longer along the Front Range. However, managed wildfire is not without risk, if an extreme weather event occurs during an incident there is a possibility of a large spread event and high severity outcomes (Li et al., 2025; Prichard et al., 2021). Despite these risks, our findings suggest that low-mod severity in current wildfire footprints, whether managed or not, is moderating subsequent burn severity and fire effects more than other management actions. Managers should carefully weigh the potential benefits of moderating future burn severity against the risk of high severity outcomes when subsequent fires occur.

Prescribed fire treatments resulted in lower burn severity outcomes in frequent fire forests and under extreme wildfire conditions. In contrast, treatments without fire were comparable to untreated areas during extreme conditions and had varied results across forest types, underscoring the importance of reducing surface fuels following mechanical operations. When feasible, we recommend managers leverage multiple forest treatment strategies to achieve outcomes known to reduce burn severity (i.e. reduction of surface and ladder fuels through a combination of thinning and burning) in frequent fire forests.

Previous low-mod wildfire reduced subsequent burn severity under non-extreme conditions in infrequent fire forests, suggesting that forest treatments designed to better emulate wildfire may be an effective management strategy where the goal is to reduce burn severity. In high elevation forests with high severity, infrequent fire regimes, implementing treatments would primarily address fire management goals (e.g. reduction of hazardous fuels, construction of containment features to protect human structures) rather than ecological restoration goals, which aim to maintain natural fire regimes. In landscapes dominated by high elevation forests, strategies such as allowing wildfires to burn under moderate conditions, implementing treatments that restore historical heterogeneity (i.e. varying successional stages and incorporating non-forest patches) (Hessburg et al., 2019; Prichard et al., 2021), and focusing management efforts on mid-elevations to help prevent fire spread into high elevation forests (Remy et al., 2024; Sibold et al., 2006) may be more effective but more research is needed.

5. Conclusions

Our results suggest previous low-mod wildfire reduces burn severity most consistently on the Front Range; it is also the most common fuels modification in this study. Prescribed fire also resulted in lower burn severity across all forest types that had enough data to analyze (prescribed fire in spruce - fir was not analyzed). These findings reinforce previous findings that treatments that incorporate fire and mimic the intensity of previous low-mod wildfire lead to improved burn severity outcomes. However, this excluded removal and fire treatments which were not different from untreated areas and were only accounted for in ponderosa pine forests. Additionally, our results align with prior research on treatments ability to moderate burn severity and underscore the need for further studies in high elevation forests. Understanding where management actions and wildfires are occurring across forest types will help refine future treatment strategies. As wildfires continue to increase in size and severity, investing in treatments, especially prescribed fires, that promote forest resistance and resilience and protect people, property, and resources remains critical.

CRediT authorship contribution statement

Sarah L. Hettema: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Camille Stevens-Rumann:** Writing – review & editing, Project administration, Methodology, Funding acquisition. **Hannah Van Dusen:** Writing – review & editing, Software, Methodology, Data curation. **Mike A. Battaglia:** Writing – review & editing, Project administration, Funding acquisition. **Anthony G. Vorster:** Writing – review & editing, Methodology. **Jens Stevens:** Writing – review & editing, Project administration, Funding acquisition.

Funding

This work was supported in part by the U.S. Department of Agriculture, Forest Service with funding from the Infrastructure Investment and Jobs Act of 2021 (grant number 23-JV-11221636–158) and the Southwest Climate Adaptation Science Center.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank Sean Parks for his help with conceptualization and technical support, and Anson Call, Caden Chamberlain, and Jody Vogeler for their thoughtful edits and comments that improved this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2026.123529.

Data availability

Data will be made available on request.

References

Abatzoglou, J.T., 2013. Development of gridded surface meteorological data for ecological applications and modelling. Int. J. Climatol. 33 (1), 121–131. https://doi.org/10.1002/joc.3413.

Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proc. Natl. Acad. Sci. 113 (42), 11770–11775. https://doi.org/10.1073/pnas.1607171113.

Addington, R.N., Aplet, G.H., Battaglia, M.A., Briggs, J.S., Brown, P.M., Cheng, A.S., Dickinson, Y., Feinstein, J.A., Pelz, K.A., Regan, C.M., Thinnes, J., Truex, R., Fornwalt, P.J., Gannon, B., Julian, C.W., Underhill, J.L., & Wolk, B. (2018). *Principles and practices for the restoration of ponderosa pine and dry mixed-conifer forests of the Colorado Front Range*. RMRS-GTR-373. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 121 p.

Addington, R.N., Tavernia, B.G., Caggiano, M.D., Thompson, M.P., Lawhon, J.D., Sanderson, J.S., 2020. Identifying opportunities for the use of broadcast prescribed fire on Colorado's Front Range. For. Ecol. Manag. *458*. https://doi.org/10.1016/j.foreco.2019.117655.

Agee, J.K., Skinner, C.N., 2005. Basic principles of forest fuel reduction treatments. For. Ecol. Manag. 211 (1–2), 83–96. https://doi.org/10.1016/j.foreco.2005.01.034.

Alexander, R.R., 1987. *Ecology, silviculture, and management of the Engelmann spruce—subalpine fir type in the central and southern Rocky Mountains* (No. 659). US Department of Agriculture, Forest Service.

Alizadeh, M.R., Abatzoglou, J.T., Adamowski, J., Modaresi Rad, A., AghaKouchak, A., Pausata, F.S.R., Sadegh, M., 2023. Elevation-dependent intensification of fire danger in the western United States. Nat. Commun. 14 (1), 1773. https://doi.org/10.1038/s41467-023-37311-4.

Balik, J.A., Coop, J.D., Krawchuk, M.A., Naficy, C.E., Parisien, M.-A., Parks, S.A., Stevens-Rumann, C.S., Whitman, E., 2024. Biogeographic patterns of daily wildfire spread and extremes across North America. Front. For. Glob. Change *7*. https://doi.org/10.3389/ffgc.2024.1355361.

Bates, D., Mächler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67 (1). https://doi.org/10.18637/jss.v067.i01.

Battaglia, M.A., Gannon, B., Brown, P.M., Fornwalt, P.J., Cheng, A.S., Huckaby, L.S., 2018. Changes in forest structure since 1860 in ponderosa pine dominated forests in the Colorado and Wyoming Front Range, USA. For. Ecol. Manag. 422, 147–160. https://doi.org/10.1016/j.foreco.2018.04.010.

Bivand, R., 2022. R Packages for analyzing spatial data: a comparative case study with areal data. Geogr. Anal. 54 (3), 488–518. https://doi.org/10.1111/gean.12319.

Bolker, B.M., Brooks, M.E., Clark, C.J., Geange, S.W., Poulsen, J.R., Stevens, M.H.H., White, J.-S.S., 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends Ecol. Evol. 24 (3), 127–135. https://doi.org/10.1016/j.tree.2008.10.008.

Brodie, E.G., Knapp, E.E., Brooks, W.R., Drury, S.A., Ritchie, M.W., 2024. Forest thinning and prescribed burning treatments reduce wildfire severity and buffer the impacts of severe fire weather. Fire Ecol. 20 (1), 17. https://doi.org/10.1186/s42408-023-00241-z.

Calkin, D.E., Thompson, M.P., Finney, M.A., 2015. Negative consequences of positive feedbacks in US wildfire management. For. Ecosyst. 2 (1), 9. https://doi.org/10.1186/s40663-015-0033-8.

Call, A., Tomczyk, N., Withnall, K.A., Dappen, P.R., Heusinkveld, D., Mueller, S., Holloway, B., Shennan, K., Herring, J., Franko, A., Colavito, M.M., Kimple, A.D., Meador, A.S., Stevens-Rumann, C.S., 2025. A new geodatabase of fuel treatments across federal lands in the USA. Sci. Data 12 (1), 1485. https://doi.org/10.1038/s41597-025-05859-z.

Cansler, C.A., Kane, V.R., Hessburg, P.F., Kane, J.T., Jeronimo, S.M.A., Lutz, J.A., Povak, N.A., Churchill, D.J., Larson, A.J., 2022. Previous wildfires and management treatments moderate subsequent fire severity. For. Ecol. Manag. 504, 119764. https://doi.org/10.1016/j.foreco.2021.119764.

CFRI, 2023. Interagency Fire Perimeter Database [Data set]. Colorado Forest Restoration Institute.

Chamberlain, C.P., Meigs, G.W., Churchill, D.J., Kane, J.T., Sanna, A., Begley, J.S., Prichard, S.J., Kennedy, M.C., Bienz, C., Haugo, R.D., Smith, A.C., Kane, V.R., Cansler, C.A., 2024. Learning from wildfires: A scalable framework to evaluate treatment effects on burn severity. Ecosphere 15 (12). https://doi.org/10.1002/ecs2.70073.

Clements, F.E., 1910. The life history of lodgepole burn forests (No. 79). US Department of Agriculture, Forest Service.

Collins, B.M., 2014. Fire weather and large fire potential in the northern Sierra Nevada. Agric. For. Meteorol. 189–190, 30–35. https://doi.org/10.1016/j.agrformet.2014.01.005.

Collins, B.M., Stephens, S.L., Moghaddas, J.J., Battles, J., 2010. Challenges and Approaches in Planning Fuel Treatments across Fire-Excluded Forested Landscapes. J. For. 108 (1), 24–31. https://doi.org/10.1093/jof/108.1.24.

Collins, L., Bennett, A.F., Leonard, S.W.J., Penman, T.D., 2019. Wildfire refugia in forests: Severe fire weather and drought mute the influence of topography and fuel age. Glob. Change Biol. 25 (11), 3829–3843. https://doi.org/10.1111/gcb.14735.

Coop, J.D., Parks, S.A., Stevens-Rumann, C.S., Ritter, S.M., Hoffman, C.M., 2022. Extreme fire spread events and area burned under recent and future climate in the western USA. Glob. Ecol. Biogeogr. 31 (10), 1949–1959. https://doi.org/10.1111/geb.13496.

Coppoletta, M., Brendecke, W., Bauer, R., Tompkins, R., Heide, F., 2022. Post-fire restoration opportunities for conifer forest in the 2021 Dixie and Sugar Fires. Pacific Southwest Region Ecology Program. USDA For. Serv. 48.

R. Core Team (2024). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. ⟨https://www.R-project.org/⟩.

Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtis, J., Pasteris, P.P., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int. J. Climatol. 28 (15), 2031–2064. https://doi.org/10.1002/joc.1688.

Daly, C., Smith, J.I., Olson, K.V., 2015. Mapping Atmospheric Moisture Climatologies across the Conterminous United States. PLOS ONE 10 (10), e0141140. https://doi.org/10.1371/journal.pone.0141140.

Davis, K.T., Peeler, J., Fargione, J., Haugo, R.D., Metlen, K.L., Robles, M.D., Woolley, T., 2024. Tamm review: A meta-analysis of thinning, prescribed fire, and wildfire effects on subsequent wildfire severity in conifer dominated forests of the Western US. For. Ecol. Manag. 561, 121885. https://doi.org/10.1016/j.foreco.2024.121885.

Dinno, A., 2014. Dunn.test: Dunn's Test of multiple comparisons using rank sums. R. Package Version 1. 3. 6. https://doi.org/10.32614/CRAN.package.dunn.test.

Duane, A., Castellnou, M., Brotons, L., 2021. Towards a comprehensive look at global drivers of novel extreme wildfire events. Clim. Change 165 (3–4), 43. https://doi.org/10.1007/s10584-021-03066-4.

Dunn, O.J., 1964. Multiple Comparisons Using Rank Sums. Technometrics 6 (3), 241–252. https://doi.org/10.1080/00401706.1964.10490181.

Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z.-L., Quayle, B., Howard, S., 2007. A Project for Monitoring Trends in Burn Severity. Fire Ecol. 3 (1), 3–21. https://doi.org/10.4996/fireecology.0301003.

Evans, J.S., & Murphy, M.A. (2023). spatialEco. R package version 2.0-2. ⟨https://github.com/jeffreyevans/spatialEco⟩.

Fallon, K., Abatzoglou, J.T., Hurteau, M.D., Butz, R.J., Buchanan, B., Pierce, J., McNamara, J., Cattau, M., Sadegh, M., 2024. Fuel Treatment Efficacy Across California's Forests: How do Wildfire Covariates Impact the Treatment Outcome? ESS Open Arch. https://doi.org/10.22541/essoar.172590227.72370322/v1.

Fernández-Guisuraga, J.M., Fernandes, P.M., 2024. Enhanced post-wildfire vegetation recovery in prescribed-burnt Mediterranean shrubland: A regional assessment. For. Ecol. Manag. 561, 121921. https://doi.org/10.1016/j.foreco.2024.121921.

Fulé, P.Z., Crouse, J.E., Roccaforte, J.P., Kalies, E.L., 2012. Do thinning and/or burning treatments in western USA ponderosa or Jeffrey pine-dominated forests help restore natural fire behavior. For. Ecol. Manag. 269, 68–81. https://doi.org/10.1016/j.foreco.2011.12.025.

Furniss, T.J., Kane, V.R., Larson, A.J., Lutz, J.A., 2020. Detecting tree mortality with Landsat-derived spectral indices: Improving ecological accuracy by examining uncertainty. Remote Sens. Environ. 237, 111497. https://doi.org/10.1016/j.rse.2019.111497.

Grabinski, Z.S., Sherriff, R.L., Kane, J.M., 2017. Controls of reburn severity vary with fire interval in the Klamath Mountains, California, USA. Ecosphere 8, 11.

Harris, L., Taylor, A.H., 2017. Previous burns and topography limit and reinforce fire severity in a large wildfire. Ecosphere 8 (11). https://doi.org/10.1002/ecs2.2019.

Hessburg, P.F., Salter, R.B., James, K.M., 2007. Re-examining fire severity relations in pre-management era mixed conifer forests: inferences from landscape patterns of forest structure. Landsc. Ecol. 22 (S1), 5–24. https://doi.org/10.1007/s10980-007-9098-2.

Hessburg, P.F., Miller, C.L., Parks, S.A., Povak, N.A., Taylor, A.H., Higuera, P.E., Prichard, S.J., North, M.P., Collins, B.M., Hurteau, M.D., Larson, A.J., Allen, C.D., Stephens, S.L., Rivera-Huerta, H., Stevens-Rumann, C.S., Daniels, L.D., Gedalof, Z., Gray, R.W., Kane, V.R., Salter, R.B., 2019. Climate, Environment, and Disturbance History Govern Resilience of Western North American Forests. Front. Ecol. Evol. *7*. https://doi.org/10.3389/fevo.2019.00239.

Hessburg, P.F., Prichard, S.J., Hagmann, R.K., Povak, N.A., Lake, F.K., 2021. Wildfire and climate change adaptation of western North American forests: a case for intentional management. Ecol. Appl. 31 (8). https://doi.org/10.1002/eap.2432.

Higuera, P.E., Shuman, B.N., Wolf, K.D., 2021. Rocky Mountain subalpine forests now burning more than any time in recent millennia. Proc. Natl. Acad. Sci. 118 (25). https://doi.org/10.1073/pnas.2103135118.

Hijmans, R. (2024). terra: Spatial Data Analysis. R package version 1.7-78. ⟨https://CRAN.R-project.org/package=terra⟩.

Holden, Z.A., Morgan, P., Crimmins, M.A., Steinhorst, R.K., Smith, A.M.S., 2007. Fire season precipitation variability influences fire extent and severity in a large southwestern wilderness area, United States. Geophys. Res. Lett. 34 (16). https://doi.org/10.1029/2007GL030804.

Hood, S.M., Smith, H.Y., Wright, D.K., & Glasgow, L.S. (2012). *Management guide to ecosystem restoration treatments: two-aged lodgepole pine forests of central Montana, USA*. RMRS-GTR-294. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 126 p.

Hood, S.M., Baker, S., Sala, A., 2016. Fortifying the forest: thinning and burning increase resistance to a bark beetle outbreak and promote forest resilience. Ecol. Appl. 26 (7), 1984–2000. https://doi.org/10.1002/eap.1363.

Hood, S.M., Harvey, B.J., Fornwalt, P.J., Naficy, C.E., Hansen, W.D., Davis, K.T., Battaglia, M.A., Stevens-Rumann, C.S., Saab, V.A., 2021. Fire Ecology of Rocky Mountain Forests. In: In Fire Ecology and Management: Past, Present, and Future of US Forested Ecosystems. Managing Forest Ecosystems, 39. SpringerNature, pp. 287–336. https://doi.org/10.1007/978-3-030-73267-7_8.

Housman, I.W., Schleeweis, K., Heyer, J.P., Ruefenacht, B., Bender, S., Megown, K., Goetz, W., & Bogle, S. (2023). *National Land Cover Database Tree Canopy Cover Methods v2021.4. GTAC-10268-RPT1*.

Howe, E., Baker, W.L., 2003. Landscape Heterogeneity and Disturbance Interactions in a Subalpine Watershed in Northern Colorado, USA. Ann. Assoc. Am. Geogr. 93 (4), 797–813. https://doi.org/10.1111/j.1467-8306.2003.09304002.x.

Hunter, M.E., Shepperd, W.D., Lentile, L.B., Lundquist, J.E., Andreu, M.G., Butler, J.L., & Smith, F.W. (2007). *A Comprehensive Guide to Fuels Treatment Practices for Ponderosa Pine in the Black Hills, Colorado Front Range, and Southwest*. RMRS-GTR-198. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 93 p.

Kalies, E.L., Yocom Kent, L.L., 2016. Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. For. Ecol. Manag. 375, 84–95. https://doi.org/10.1016/J.FORECO.2016.05.021.

Kampf, S.K., McGrath, D., Sears, M.G., Fassnacht, S.R., Kiewiet, L., Hammond, J.C., 2022. Increasing wildfire impacts on snowpack in the western U.S. Proc. Natl. Acad. Sci. 119 (39). https://doi.org/10.1073/pnas.2200333119.

Kipfmueller, K.F., Baker, W.L., 2000. A fire history of a subalpine forest in south-eastern Wyoming, USA. J. Biogeogr. 27 (1), 71–85. https://doi.org/10.1046/j.1365-2699.2000.00364.x.

Knapp, E.E., Bernal, A.A., Kane, J.M., Fettig, C.J., North, M.P., 2021. Variable thinning and prescribed fire influence tree mortality and growth during and after a severe drought. For. Ecol. Manag. 479, 118595. https://doi.org/10.1016/j.foreco.2020.118595.

Kreider, M.R., Jaffe, M.R., Berkey, J.K., Parks, S.A., Larson, A.J., 2023. The scientific value of fire in wilderness. Fire Ecol. 19 (1), 36. https://doi.org/10.1186/s42408-023-00195-2.

Kruskal, W.H., Wallis, W.A., 1952. Use of ranks in one-criterion variance analysis. J. Am. Stat. Assoc. 47 (260), 583–621. https://doi.org/10.1080/01621459.1952.10483441.

Li, S., Baijnath-Rodino, J.A., York, R.A., Quinn-Davidson, L.N., Banerjee, T., 2025. Temporal and spatial pattern analysis of escaped prescribed fires in California from 1991 to 2020. Fire Ecol. 21 (1), 3. https://doi.org/10.1186/s42408-024-00342-3.

Lindsay, J.B., 2016. Whitebox GAT: a case study in geomorphometric analysis. Comput. Geosci. 95, 75–84. https://doi.org/10.1016/j.cageo.2016.07.003.

Lydersen, J.M., Collins, B.M., Brooks, M.L., Matchett, J.R., Shive, K.L., Povak, N.A., Kane, V.R., Smith, D.F., 2017. Evidence of fuels management and fire weather influencing fire severity in an extreme fire event. Ecol. Appl. 27 (7), 2013–2030. https://doi.org/10.1002/EAP.1586.

Martinson, E.J., & Omi, P.N. (2013). *Fuel treatments and fire severity: A meta-analysis*. RMRS-RP-103WWW. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 38 p.

McFarland, J.R., Coop, J.D., Balik, J.A., Rodman, K.C., Parks, S.A., Stevens-Rumann, C.S., 2025. Extreme Fire Spread Events Burn More Severely and Homogenize Postfire Landscapes in the Southwestern United States. Glob. Change Biol. 31 (2). https://doi.org/10.1111/GCB.70106.

McKinney, S.T. (2019). *Fire regimes of ponderosa pine (Pinus ponderosa) ecosystems in Colorado: a systematic review and meta-analysis*. US Department of Agriculture, Forest Service, Rocky Mountain Research Station, Missoula Fire Sciences Laboratory. ⟨www.fs.usda.gov/database/feis/fire_regimes/CO_ponderosa_pine/all.pdf⟩.

Moreira, F., Ascoli, D., Safford, H., Adams, M.A., Moreno, J.M., Pereira, J.M.C., Catry, F.X., Armesto, J., Bond, W., González, M.E., Curt, T., Koutsias, N., McCaw, L., Price, O., Pausas, J.G., Rigolot, E., Stephens, S., Tavsanoglu, C., Vallejo, V.R., Fernandes, P.M., 2020. Wildfire management in Mediterranean-type regions: paradigm change needed. Environ. Res. Lett. 15 (1), 011001. https://doi.org/10.1088/1748-9326/ab541e.

Morgan, P., Keane, R.E., Dillon, G.K., Jain, T.B., Hudak, A.T., Karau, E.C., Sikkink, P.G., Holden, Z.A., Strand, E.K., 2014. Challenges of assessing fire and burn severity using field measures, remote sensing and modelling. Int. J. Wildland Fire 23 (8), 1045. https://doi.org/10.1071/WF13058.

Mueller, S.E., Thode, A.E., Margolis, E.Q., Yocom, L.L., Young, J.D., Iniguez, J.M., 2020. Climate relationships with increasing wildfire in the southwestern US from 1984 to 2015. For. Ecol. Manag. 460, 117861. https://doi.org/10.1016/j.foreco.2019.117861.

North, M., Collins, B.M., Stephens, S., 2012. Using Fire to Increase the Scale, Benefits, and Future Maintenance of Fuels Treatments. J. For. 110 (7), 392–401. https://doi.org/10.5849/jof.12-021.

North, M.P., Bisbing, S.M., Hankins, D.L., Hessburg, P.F., Hurteau, M.D., Kobziar, L.N., Meyer, M.D., Rhea, A.E., Stephens, S.L., Stevens-Rumann, C.S., 2024. Strategic fire zones are essential to wildfire risk reduction in the Western United States. Fire Ecol. 20 (1), 50. https://doi.org/10.1186/s42408-024-00282-y.

Omi, P.N., Martinson, E.J., & Chong, G.W. (2006). *Effectiveness of pre-fire fuel treatments*. JFSP Project 03-2-1-07. Joint Fire Science Program Governing Board.

Parks, S., Dillon, G., Miller, C., 2014a. A New Metric for Quantifying Burn Severity: The Relativized Burn Ratio. Remote Sens. 6 (3), 1827–1844. https://doi.org/10.3390/rs6031827.

Parks, S., Holsinger, L., Voss, M., Loehman, R., Robinson, N., 2018a. Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential. Remote Sens. 10 (6), 879. https://doi.org/10.3390/rs10060879.

Parks, S.A., 2014. Mapping day-of-burning with coarse-resolution satellite fire-detection data. Int. J. Wildland Fire 23 (2), 215–223. https://doi.org/10.1071/WF13138.

Parks, S.A., Abatzoglou, J.T., 2020. Warmer and DRier Fire Seasons Contribute to Increases in Area Burned at High Severity in Western US Forests From 1985 to 2017. Geophys. Res. Lett. 47 (22). https://doi.org/10.1029/2020GL089858.

Parks, S.A., Miller, C., Nelson, C.R., Holden, Z.A., 2014b. Previous fires moderate burn severity of subsequent wildland fires in two large Western US wilderness areas. Ecosystems 17 (1), 29–42. https://doi.org/10.1007/s10021-013-9704-x.

Parks, S.A., Holsinger, L.M., Miller, C., Nelson, C.R., 2015. Wildland fire as a self-regulating mechanism: the role of previous burns and weather in limiting fire progression. Ecol. Appl. 25 (6), 1478–1492. https://doi.org/10.1890/14-1430.1.

Parks, S.A., Holsinger, L.M., Panunto, M.H., Jolly, W.M., Dobrowski, S.Z., Dillon, G.K., 2018b. High-severity fire: evaluating its key drivers and mapping its probability across western US forests. Environ. Res. Lett. 13 (4), 044037. https://doi.org/10.1088/1748-9326/aab791.

Parks, S.A., Holsinger, L.M., Koontz, M.J., Collins, L., Whitman, E., Parisien, M.A., Loehman, R.A., Barnes, J.L., Bourdon, J.F., Boucher, J., Boucher, Y., Caprio, A.C., Collingwood, A., Hall, R.J., Park, J., Saperstein, L.B., Smetanka, C., Smith, R.J., Soverel, N., 2019. Giving ecological meaning to satellite-derived fire severity metrics across North American forests. Remote Sens. 11 (14). https://doi.org/10.3390/rs11141735.

Peet, R.K., 1978. Latitudinal variation in Southern Rocky Mountain Forests. J. Biogeogr. 5 (3), 275. https://doi.org/10.2307/3038041.

Peet, R.K., 1981. Forest. Veg. Colo. Front Range. Veg. 45 (1), 3–75. https://doi.org/10.1007/BF00240202.

Pelz, K., 2016. Engelmann spruce regeneration following natural disturbances and forest management: A literature and expert-knowledge review focused on southwestern Colorado. Colorado Forest Restoration Institute. ⟨https://cfri.colostate.edu/wp-content/uploads/sites/22/2017/10/2016-CFRI-Spruce-Regeneration-in-SW-Colorado-compressed.pdf⟩.

Pepin, N., Bradley, R.S., Diaz, H.F., Baraer, M., Caceres, E.B., Forsythe, N., Fowler, H., Greenwood, G., Hashmi, M.Z., Liu, X.D., Miller, J.R., Ning, L., Ohmura, A., Palazzi, E., Rangwala, I., Schöner, W., Severskiy, I., Shahgedanova, M., Wang, M.B., Yang, D.Q., 2015. Elevation-dependent warming in mountain regions of the world. Nat. Clim. Change 5 (5), 424–430. https://doi.org/10.1038/nclimate2563.

Povak, N.A., Kane, V.R., Collins, B.M., Lydersen, J.M., Kane, J.T., 2020. Multi-scaled drivers of severity patterns vary across land ownerships for the 2013 Rim Fire, California. Landsc. Ecol. 35 (2), 293–318. https://doi.org/10.1007/s10980-019-00947-z.

Povak, N.A., Prichard, S.J., Hessburg, P.F., Griffey, V., Salter, R.B., Furniss, T.J., Cova, G., Gray, R.W., 2025. Evidence for strong bottom-up controls on fire severity during extreme events. Fire Ecol. 21 (1). https://doi.org/10.1186/s42408-025-00368-1.

Prichard, S.J., Kennedy, M.C., 2012. Fuel treatment effects on tree mortality following wildfire in dry mixed conifer forests, Washington State, USA. Int. J. Wildland Fire 21 (8), 1004. https://doi.org/10.1071/WF11121.

Prichard, S.J., Peterson, D.L., Jacobson, K., 2010. Fuel treatments reduce the severity of wildfire effects in dry mixed conifer forest, Washington, USA. Can. J. For. Res. 40 (8), 1615–1626. https://doi.org/10.1139/X10-109.

Prichard, S.J., Povak, N.A., Kennedy, M.C., Peterson, D.W., 2020. Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires. Ecol. Appl. https://doi.org/10.1002/eap.2104.

Prichard, S.J., Hessburg, P.F., Hagmann, R.K., Povak, N.A., Dobrowski, S.Z., Hurteau, M.D., Kane, V.R., Keane, R.E., Kobziar, L.N., Kolden, C.A., North, M., Parks, S.A., Safford, H.D., Stevens, J.T., Yocom, L.L., Churchill, D.J., Gray, R.W., Huffman, D.W., Lake, F.K., Khatri-Chhetri, P., 2021. Adapting western North American forests to climate change and wildfires: 10 common questions. Ecol. Appl. 31 (8). https://doi.org/10.1002/eap.2433.

Radcliffe, D.C., Bakker, J.D., Churchill, D.J., Alvarado, E.C., Peterson, D.W., Laughlin, M.M., Harvey, B.J., 2024. How are long-term stand structure, fuel profiles, and potential fire behavior affected by fuel treatment type and intensity in Interior Pacific Northwest forests. For. Ecol. Manag. 553, 121594. https://doi.org/10.1016/j.foreco.2023.121594.

Remy, C.C., Krofcheck, D.J., Keyser, A.R., Hurteau, M.D., 2024. Restoring frequent fire to dry conifer forests delays the decline of subalpine forests in the southwest United States under projected climate. J. Appl. Ecol. 61 (7), 1508–1519. https://doi.org/10.1111/1365-2664.14689.

Rodman, K.C., Davis, K.T., Chambers, M.E., Chapman, T.B., Fornwalt, P.J., Hart, S.J., Marshall, L.A.E., Rhoades, C.C., Schloegel, C.A., Stevens-Rumann, C.S., & Veblen, T.T. (2022). *The historic 2020 fire year in northern Colorado and southern Wyoming: A landscape assessment to inform post-fire forest management*.

Rodman, K.C., Davis, K.T., Parks, S.A., Chapman, T.B., Coop, J.D., Iniguez, J.M., Roccaforte, J.P., Sánchez Meador, A.J., Springer, J.D., Stevens-Rumann, C.S., Stoddard, M.T., Waltz, A.E.M., Wasserman, T.N., 2023. Refuge-yeah or refuge-nah? Predicting locations of forest resistance and recruitment in a fiery world. Glob. Change Biol. 29 (24), 7029–7050. https://doi.org/10.1111/gcb.16939.

Rollins, M.G., 2009. LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. Int. J. Wildland Fire 18 (3), 235. https://doi.org/10.1071/WF08088.

Seager, R., Hooks, A., Williams, A.P., Cook, B., Nakamura, J., Henderson, N., 2015. Climatology, Variability, and Trends in the U.S. Vapor Pressure Deficit, an Important Fire-Related Meteorological Quantity. J. Appl. Meteorol. Climatol. 54 (6), 1121–1141. https://doi.org/10.1175/JAMC-D-14-0321.1.

Sherriff, R.L., Veblen, T.T., 2007. A Spatially-Explicit Reconstruction of Historical Fire Occurrence in the Ponderosa Pine Zone of the Colorado Front Range. Ecosystems 10 (2), 311–323. https://doi.org/10.1007/s10021-007-9022-2.

Shive, K.L., Knight, C.A., Steel, Z.L., Stanley, C.K., Wilson, K.N., 2025. Leveraging wildfire to augment forest management and amplify forest resilience. Ecosphere 16 (6). https://doi.org/10.1002/ecs2.70306.

Sibold, J.S., Veblen, T.T., González, M.E., 2006. Spatial and temporal variation in historic fire regimes in subalpine forests across the Colorado Front Range in Rocky Mountain National Park, Colorado, USA. J. Biogeogr. 33 (4), 631–647. https://doi.org/10.1111/j.1365-2699.2005.01404.x.

Stephens, S.L., Mciver, J.D., Boerner, R.E.J., Fettig, C.J., Fontaine, J.B., Hartsough, B.R., Kennedy, P.L., Schwilk, D.W., 2012a. The Effects of Forest Fuel-Reduction Treatments in the United States. BioScience 62 (6), 549–560. https://doi.org/10.1525/bio.2012.62.6.6.

Stephens, S.L., Collins, B.M., Roller, G., 2012b. Fuel treatment longevity in a Sierra Nevada mixed conifer forest. For. Ecol. Manag. 285, 204–212. https://doi.org/10.1016/j.foreco.2012.08.030.

Stephens, S.L., Battaglia, M.A., Churchill, D.J., Collins, B.M., Coppoletta, M., Hoffman, C.M., Lydersen, J.M., North, M.P., Parsons, R.A., Ritter, S.M., Stevens, J.T., 2020. Forest Restoration and Fuels Reduction: Convergent or Divergent. BioScience 71 (1), 85–101. https://doi.org/10.1093/biosci/biaa134.

Stevens, J.T., Kling, M.M., Schwilk, D.W., Varner, J.M., Kane, J.M., 2020. Biogeography of fire regimes in western U.S. conifer forests: A trait-based approach. Glob. Ecol. Biogeogr. 29 (5), 944–955. https://doi.org/10.1111/geb.13079.

Stevens-Rumann, C.S., Prichard, S.J., Strand, E.K., Morgan, P., 2016. Prior wildfires influence burn severity of subsequent large fires. Can. J. For. Res. 46 (11), 1375–1385. https://doi.org/10.1139/cjfr-2016-0185.

Taylor, A.H., Harris, L.B., Skinner, C.N., 2022. Severity patterns of the 2021 Dixie Fire exemplify the need to increase low-severity fire treatments in California's forests. Environ. Res. Lett. 17 (7). https://doi.org/10.1088/1748-9326/ac7735.

Tedim, F., Leone, V., Coughlan, M., Bouillon, C., Xanthopoulos, G., Royé, D., Correia, F.J.M., Ferreira, C., 2020. Extreme wildfire events. Extreme Wildfire Events and Disasters. Elsevier, pp. 3–29. https://doi.org/10.1016/B978-0-12-815721-3.00001-1.

Tepley, A.J., Veblen, T.T., 2015. Spatiotemporal fire dynamics in mixed-conifer and aspen forests in the San Juan Mountains of southwestern Colorado, USA. Ecol. Monogr. 85 (4), 583–603. https://doi.org/10.1890/14-1496.1.

Tolhurst, K.G., McCarthy, G., 2016. Effect of prescribed burning on wildfire severity: a landscape-scale case study from the 2003 fires in Victoria. Aust. For. 79 (1), 1–14. https://doi.org/10.1080/00049158.2015.1127197.

Tower, G.E., 1909. A study of the reproductive characteristics of lodgepole pine. Proc. Soc. Am. For. 4, 84–106.

U.S. Geological Survey. (2023). *1/3rd arc-second Digital Elevation Models (DEMs) - USGS National Map 3DEP Downloadable Data Collection: U.S. Geological Survey*.

USDA Forest Service. (2022). *Confronting the Wildfire Crisis: A 10-Year Implementation Plan.*

USDA Forest Service, 2024a. *FACTS Common Attributes* [Data set]. USDA Forest Service, Washington, DC.

USDA Forest Service, 2024b. Surface Ownership Parcels [Data set]. USDA Forest Service, Washington, DC.

Veblen, T.T., Hadley, K.S., Reid, M.S., 1991. Disturbance and Stand Development of a Colorado Subalpine Forest. J. Biogeogr. 18 (6), 707. https://doi.org/10.2307/2845552.

Veblen, T.T., Hadley, K.S., Nel, E.M., Kitzberger, T., Reid, M., Villalba, R., 1994. Disturbance regime and disturbance interactions in a Rocky Mountain Subalpine Forest. J. Ecol. 82 (1), 125. https://doi.org/10.2307/2261392.

Veblen, T.T., Kitzberger, T., Donnegan, J., 2000. Climatic and Human Influences on Fire Regimes in Ponderosa Pine Forests in the Colorado Front Range. Ecol. Appl. 10 (4), 1178. https://doi.org/10.2307/2641025.

Vorster, A.G., Stevens-Rumann, C., Young, N., Woodward, B., Choi, C.T.H., Chambers, M.E., Cheng, A.S., Caggiano, M., Schultz, C., Thompson, M., Greiner, M., Aplet, G., Addington, R.N., Battaglia, M.A., Bowker, D., Bucholz, E., Buma, B., Evangelista, P., Huffman, D., West Fordham, A., 2024. Metrics and Considerations for Evaluating How Forest Treatments Alter Wildfire Behavior and Effects. J. For. 122 (1), 13–30. https://doi.org/10.1093/jofore/fvad036.

Wagenbrenner, N.S., Forthofer, J.M., Lamb, B.K., Shannon, K.S., Butler, B.W., 2016. Downscaling surface wind predictions from numerical weather prediction models in complex terrain with WindNinja. Atmos. Chem. Phys. 16 (8), 5229–5241. https://doi.org/10.5194/acp-16-5229-2016.

Walker, R.B., Coop, J.D., Parks, S.A., Trader, L., 2018. Fire regimes approaching historic norms reduce wildfire-facilitated conversion from forest to non-forest. Ecosphere 9 (4). https://doi.org/10.1002/ecs2.2182.

Wasserman, T.N., Mueller, S.E., 2023. Climate influences on future fire severity: a synthesis of climate-fire interactions and impacts on fire regimes, high-severity fire, and forests in the western United States. Fire Ecol. 19 (1), 43. https://doi.org/10.1186/s42408-023-00200-8.

Whitlock, C., Shafer, S.L., Marlon, J., 2003. The role of climate and vegetation change in shaping past and future fire regimes in the northwestern US and the implications for ecosystem management. For. Ecol. Manag. 178 (1–2), 5–21. https://doi.org/10.1016/S0378-1127(03)00051-3.

Whitman, E., Parisien, M.-A., Thompson, D.K., Flannigan, M.D., 2019. Short-interval wildfire and drought overwhelm boreal forest resilience. Sci. Rep. 9 (1), 18796. https://doi.org/10.1038/s41598-019-55036-7.

Williams, A.P., Seager, R., Macalady, A.K., Berkelhammer, M., Crimmins, M.A., Swetnam, T.W., Trugman, A.T., Buenning, N., Noone, D., McDowell, N.G., Hryniw, N., Mora, C.I., Rahn, T., 2015. Correlations between components of the water balance and burned area reveal new insights for predicting forest fire area in the southwest United States. Int. J. Wildland Fire 24 (1), 14. https://doi.org/10.1071/WF14023.

Woolsey, G.A., Tinkham, W.T., Battaglia, M.A., Hoffman, C.M., 2024. Constraints oN Mechanical Fuel Reduction Treatments in United States Forest Service Wildfire crisis strategy priority landscapes. J. For. 122 (4), 335–351. https://doi.org/10.1093/jofore/fvae012.

Wu, Q. & Brown, A. (2022). whitebox: 'WhiteboxTools' R Frontend. R package version 2.2.0. ⟨https://CRAN.R-project.org/package=whitebox⟩.