Sanna *et al. Fire Ecology* (2025) 21:44
https://doi.org/10.1186/s42408-025-00387-y

Fire Ecology

Association for Fire Ecology

ORIGINAL RESEARCH

Open Access

Assessing fuel treatments and burn severity using global and local analyses

Astrid Sanna[1*], Caden Chamberlain[1], Susan J. Prichard[1], C. Alina Cansler[2], Andrew T. Hudak[3], Craig Bienz[4], L. Monika Moskal[1] and Van R. Kane[1]

Abstract

Background Wildfires in western U.S. dry forest ecosystems have increased in size and severity during recent decades due primarily to more than a century of fire suppression, exclusion of Indigenous fire, and a rapidly warming climate. Fuel treatments have been employed to restore historical forest conditions and mitigate burn severity. However, their influence on burn severity in the context of other environmental variables and firefighting operations has not been extensively explored. The 2021 Bootleg Fire in south-central Oregon provided an opportunity to evaluate the effectiveness of mechanical thinning (Tx), broadcast burning (Rx), and both treatments combined (TxRx) near the Sycan Marsh Preserve, where pre-fire LiDAR data were also available.

Results We assessed burn severity 1 year after the Bootleg Fire accounting for the local variability of top environmental drivers, fuel treatments, and firefighting operations. We modeled the influence of burn severity drivers using Random Forest and examined mean predictor effects (global scale) and their spatially explicit variability across observations (local scale) using SHapley Additive exPlanations (SHAP) analysis. Within units treated with broadcast burning, the percentage of area burned at low severity was over 80%. In contrast, units treated with thinning-only and untreated forests were dominated by area burned at moderate (45%) and high (42%) severity, respectively. All treatment types facilitated firefighting operations. Broadcast burning units, in which suppression activities occurred during the Bootleg Fire, showed a marginal decrease in predicted burn severity. Under consistent severe weather conditions, our results underscored the central role of fuel characteristics, including fuel treatments, and their local variability in influencing burn severity. The most important determinant of burn severity was Rx, followed by top drivers representing fuel structure and accumulation.

Conclusions Our study highlights that fuel characteristics and broadcast burning disproportionally impacted burn severity, with Rx being the most effective and economical treatment. By creating a reproducible framework to explain burn severity, at both global and local scales, we gained nuanced insights about the drivers of burn severity that could inform and enhance fire and fuel management practices across multi-ownership landscapes.

Keywords Bootleg fire, South-central Oregon, Dry conifer forests, Fuel treatments, Prescribed fire, Firefighting, Burn severity, LiDAR, Random forest, SHAP analysis

Resumen

Antecedentes Los incendios de vegetación en ecosistemas de bosques secos del oeste de los Estados Unidos se han incrementado en tamaño y severidad en décadas recientes, primariamente debido a una centuria de supresión

*Correspondence:
Astrid Sanna
astrid87@uw.edu
Full list of author information is available at the end of the article

SpringerOpen

© The Author(s) 2025. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

de incendios, la exclusión de las quemas realizadas otrora por los indígenas, y un rápido calentamiento del clima. Los tratamientos de combustibles han sido empleados para restaurar las condiciones históricas de los bosques y mitigar la severidad de esos incendios. Sin embargo, su influencia en la severidad de las quemas en el contexto de de otras variables ambientales y operaciones de combate de incendios no ha sido extensivamente explorada. El incendio de Bootleg de 2021 en el centro de Oregón, proveyó de una oportunidad para evaluar la efectividad de raleo mecánico (Tx), la quema prescripta bajo dosel (Rx) y la combinación de ambos tratamientos (TxRx) en las cercanías de la Preserva de Sycan Marshe, donde datos de LIDAR previos al fuego estaban disponibles.

Resultados Determinamos la severidad un año después del incendio de Bootleg, teniendo en cuenta los factores ambientales conducentes más importantes, los tratamientos de los combustibles, y las operaciones de combate. Modelamos la influencia de los factores conductores de la severidad del fuego usando el modelo de Bosques al Azar, y examinamos los efectos medios predichos (escala global) y su variabilidad espacial explícita a través de las observaciones (escala local), usando el análisis de las "explicaciones aditivas de Shapley" (SHapley Additive exPlanations, o SHAP). Dentro de las unidades tratadas con quemas prescriptas bajo dosel (Px), el porcentaje de área quemada a baja severidad fue del 80%. En contraste, las unidades tratadas con solo raleo (Tx) y bosques no tratados fueron dominados por áreas quemadas a severidad moderada (45%) y alta (42%), respectivamente. Todos los tipos de tratamientos en las cuales las actividades de supresión ocurrieron durante el incendio de Bootleg, mostraron una disminución marginal en la severidad pronosticada. Bajo condiciones climáticas consistentemente severas, nuestros resultados subestimaron el rol central de las características de los combustibles, incluyendo los tratamientos del combustible, y como la variación local influencia la severidad. El determinante más importante de la severidad del fuego fueron las quemas prescriptas bajo dosel, seguido por otros factores conducentes que representaron la estructura y acumulación del combustible.

Conclusions Nuestro estudio subraya que las características de los combustibles y las quemas prescriptas bajo dosel impactan desproporcionadamente en la severidad del fuego, siendo las quemas prescriptas bajo dosel (Rx) el tratamiento más efectivo y económico. Mediante la creación de un marco conceptual que explique la severidad del fuego, tanto a escala local como global, ganamos información con percepciones y matices sobre los factores conducentes de la severidad del fuego que pueden informar y mejorar las prácticas de manejo del fuego y de los combustibles a través de diversos paisajes con diferentes propietarios.

Introduction

In historically fuel-limited dry forest ecosystems of western North America, continuous accumulation of biomass resulting from fire suppression and the exclusion of Indigenous fire combined with a rapidly warming climate has led to uncharacteristically large and severe wildfires (Allen et al. 2002; Van Mantgem et al. 2013; Halofsky et al. 2020; Hanan et al. 2021; Parks et al. 2023) and departures from historical fire regimes (Wallace Covington 2000; Fry and Stephens 2006; Haugo et al. 2019; Hagmann et al. 2021). In ecosystems dominated by ponderosa pine (*Pinus ponderosa*) and dry mixed-conifer forests, resilient stand conditions were historically characterized by low levels of surface and ladder fuels, low density and competition, and included old (> 150 years), large, drought-tolerant trees (Arno et al. 1995; Hagmann et al. 2019; North et al. 2022). These pre-settlement forest structures were common across dry western forests and maintained by low-intensity fires, which burned frequently in highly flammable understories characterized by fine fuels including herbaceous species and pine needles (Agee 1993).

In these dry fire-prone forests, managed wildfire—the strategic use of naturally-ignited fires to achieve restoration objectives (Collins and Stephens 2007)—has the potential to reestablish and maintain resilient stand conditions through a negative feedback mechanism. For example, several studies evaluating the influence of 40 years of managed wildfires in the Illilouette Creek Basin (California) have found an increase in forest structure and landscape heterogeneity and potential improvement of resilience to disturbances (Collins et al. 2016; Boisramé et al. 2017a, b), providing reference conditions to inform restoration programs and ecological research (Chamberlain et al. 2023). Additionally, a study conducted in the Bob Marshall Wilderness (Montana, USA) found that two lightning-ignited fires occurring 7 years apart shifted the stand structure back to open, mixed-conifer forests dominated by large ponderosa pines (Larson et al. 2013), which can reduce burn severity by limiting the accumulation of ladder fuels and decreasing canopy continuity (Hakkenberg et al. 2024). While earlier studies suggest that the effect of past fires on subsequent burn severity weakens over time (Parks et al. 2014b) and under extreme fire weather (Parks et al. 2015), recent findings indicate that even decades-old wildfires can continue to moderate burn severity under such conditions (Tortorelli et al. 2024). These differing perspectives underscore the complexity of fire-vegetation interactions and suggest that the effectiveness of past fires in mitigating burn severity depends on multiple factors, including fire history, ecosystem characteristics, and climatic conditions (Prichard et al. 2017).

In addition to managed wildfire, where current forest structure and fuel accumulations are substantially departed from historical conditions, fuel reduction treatments are employed to restore historical fire regimes, support forest resilience by mitigating fire behavior (Agee and Skinner 2005), and potentially reduce fire suppression efforts and costs (Agee et al. 2000; Moghaddas and Craggs 2007; Urza et al. 2023). The effectiveness of site-level treatments has been extensively studied (Fulé et al. 2012; Kalies and Yocom Kent 2016; Davis et al. 2024) and assessed in the context of varying topographic, climatic, weather, and fuel conditions (Prichard et al. 2020; Cansler et al. 2022). While broadcast burning, a type of prescribed fire, alone may be effective at mitigating burn severity by reducing ladder and surface fuels (Vaillant et al. 2009), prior thinning may be necessary in high-density stands to restore resilient horizontal forest structure, and prevent or at least reduce crown fire risk (Agee and Skinner 2005; Urza et al. 2023). Past studies have generally found that fuel treatments that combined thinning followed by broadcast burning were more effective than either thinning alone or broadcast burning alone (Hudak et al. 2011; Prichard and Kennedy 2014; Prichard et al. 2020, 2021; Cansler et al. 2022).

Despite extensive literature documenting the mitigating effects of fuel treatments on burn severity, understanding their role amid other burn severity drivers remains a complex challenge. This difficulty largely stems from limited pre-fire fuel data, variability in weather conditions during wildfires, and a lack of studies similar to Brodie et al. (2023), which used an experimental design to separate treatment effects from confounding factors such as fire weather, topography, and pre-existing fuel conditions. Additionally, there is a knowledge gap regarding the interaction between firefighting operations and fuel treatments in influencing burn severity—though Harris et al. (2021) provided an initial investigation—and a need for improved methodologies to better account for spatially explicit variability in burn severity drivers. In a recent study, Chamberlain et al. (2024) developed and applied a remote sensing-based analytical framework to assess the effectiveness of fuel treatments in moderating burn severity across the Bootleg Fire footprint. This and other studies (Kane et al. 2015a; Parks et al. 2018; Povak et al. 2020; Prichard et al. 2020; Cansler et al. 2022) have widely investigated drivers of burn severity at the fire scale using ensemble machine learning (ML) models. However, a few studies to date have examined how the localized relative importance of burn severity drivers, including fire suppression, varies spatially across a landscape. For example, Povak et al. (2020) highlighted the value of spatially explicit approaches by assessing localized variations in burn severity predictors, yet their methods did not directly account for interactions among variables.

Although our study area covered only a section of the Bootleg Fire as constrained by the availability of pre-fire LiDAR data, it provided a valuable opportunity to examine how fuel treatments and other environmental predictors influenced burn severity under consistent severe fire weather conditions. This area encompassed a diverse fuel treatment history—including broadcast burning (Rx), mechanical thinning (Tx), and their combination (TxRx)—within a complex landscape characterized by undulating landforms and a mosaic of dry forest (treated and untreated), riparian, and wetland ecosystems. The size of the study area and the unusually detailed information on fuel and fire management provided by The Nature Conservancy (TNC) allowed us to provide a detailed investigation of patterns of burn severity and their drivers.

Through this study, we aimed to quantify the effectiveness of fuel treatments on burn severity while addressing research gaps related to their influence among other burn severity drivers. To achieve this, we applied SHapley Additive exPlanations (SHAP; Lundberg & Lee 2017; Molnar 2023) analysis, an interpretable machine learning (ML) technique used to explain black-box models such as Random Forest (RF; Breiman, Leo 2001). Unlike more commonly used approaches to interpret ML models (Kane et al. 2015a; Parks et al. 2018; Povak et al. 2020; Prichard et al. 2020; Cansler et al. 2022), SHAP provides both a global interpretation of mean predictor effects and a spatially explicit assessment of local variability, capturing and quantifying complex interactions among variables. By integrating SHAP analysis with an RF model, our study builds upon previous research by providing a nuanced understanding of how fuel treatments and environmental variables influence burn severity patterns across the landscape.

Our objectives were to:

(1) Assess the distribution and variability of burn severity across different fuel treatments and untreated forests.
(2) Evaluate the influence of fuel treatments, firefighting operations, and the most important environ-

mental drivers on burn severity at both global and local scales, while accounting for their interactions.

Methods

This study employed a multi-step approach to evaluate the influence of fuel treatments, environmental variables, and firefighting operations on burn severity. We begin by describing the study area, including its fire history, climate, vegetation, and fuel treatment history. We then outline the burn severity assessment, detailing the selection and computation of the relativized burn ratio (RBR) and the rationale for using Sentinel-2 data. Next, we describe the management data, including fuel treatment classifications and firefighting operations. We follow this with descriptions of LiDAR-derived forest structure and topographic metrics, weather and climate data, and vegetation-related variables, which were incorporated into the analysis. Finally, we detail the data extraction and compilation process, including predictor selection, preprocessing steps, and the dataset used for RF modeling and SHAP analysis.

Study area

Our 1800-ha study area is located in the Fremont-Winema National Forest, South-Central Oregon, USA. It matches the extent of the LiDAR data collected 3 years prior to the Bootleg Fire, covering only a portion of the much larger wildfire (Fig. 1). The Bootleg Fire was ignited by lightning on July 6, 2021. It burned a total of 167,445 ha over 41 days in the Fremont-Winema National Forest, in south-central Oregon. The wildfire impacted the ancestral homeland of the Klamath Tribes, causing ecological and cultural damage, as well as loss of natural resources. The Bootleg Fire was the third-largest fire in Oregon's history since 1900, and it exhibited extreme fire behavior, resulting in extensive high severity effects (Chamberlain et al. 2024).

Across our study area, elevation ranges between ~ 1500 and ~ 1680 m. Climate is characterized by cold, snowy winters, and hot, dry summers (Agee 1993). Based on 1991–2020 climate normals (Wang et al. 2023), mean annual precipitation and precipitation as snow were 531 and 115 mm, respectively, and mean annual temperature was 7 °C, ranging from 26 °C in summer and − 6 °C in winter. The forest is dominated by ponderosa and lodgepole pine (*P. ponderosa* and *P. contorta*). Understory vegetation includes bitterbrush (*Purshia tridentata*), *Ceanothus* spp., manzanita (*Arctostaphylos* spp.), kinnikinick (*Arctostaphylos uva-ursi*), quaking aspen (*Populus tremuloides*), and willow (*Salix* spp.). Historically, the Fremont-Winema NF was predominantly composed of large and old ponderosa pines, and the fire regime was characterized by frequent, low-intensity fires (Agee 2003; Hagmann et al. 2013).

Over the 16 years prior to the Bootleg Fire, the study area was co-managed through a collaborative partnership between The Nature Conservancy (TNC), The Klamath Tribes (TKT), and the USDA Forest Service (USFS). The goals driving fuel treatments included the restoration of historical forest composition by recreating spatial complexity, a frequent and low-intensity fire regime, forest functions to support wildlife, and understory vegetation critical for tribes. Additionally, one of the goals was to create a safe environment for fire training programs (Bienz et al. 2020). Restoration goals were facilitated through climate adapted prescriptions with reference to historic reconstructions plots (Churchill et al. 2013) stratified by climate water deficit.

In our study area, fire and fuels managers implemented 41 treatment units. Treatment types included mechanical thinning followed by pile burning (Tx, 7% of total area), broadcast burning (Rx, 32% of total area), and thinning followed by broadcast burning (TxRx, 51% of total area). The untreated forests were considered as a single untreated unit (10% of the total area). Thinning treatments were conducted between 2012 and 2017, except for one unit treated in 2005. Treatments involving broadcast burning were conducted between 2017 and 2021, except for one unit treated in 2008. In most Tx units, thinning was employed to restore wildlife habitat, and resilient forest structure and composition using individuals, clumps, and openings (ICO, Churchill et al. 2016) prescriptions. Trees were harvested using a disc saw, followed by whole-tree yarding to transport the entirety of each tree to the landings. There, delimbing occurred, resulting in the accumulation of slash piles. These piles were subsequently burned as a preparatory step before broadcast burning. The entire harvesting process took place from December to March to protect soils by working on frozen ground with snow. In some areas, Rx was applied on its own to reduce overstory tree density through thermal thinning (i.e., stem and crown scorching). In Rx and TxRx units, based on information provided by TNC and as shown in the 2020 National Agricultural Imagery Program (NAIP, 0.6 m) mosaic (Fig. 3), burn severity resulting from broadcast burning was heterogeneous, reflecting variable fuel conditions, and ignition patterns. Local managers estimated that average tree mortality after broadcast burning was less than 5% across the treated area. Some areas less than 2 ha had more than 5% tree mortality (Fig. 2; C. Bienz, The Nature Conservancy, Oregon, USA, pers. comm.).

Data derived from MODIS active fire maps (Giglio et al. 2009) indicated that the Bootleg Fire burned through our study area from July 13th to July 21st,

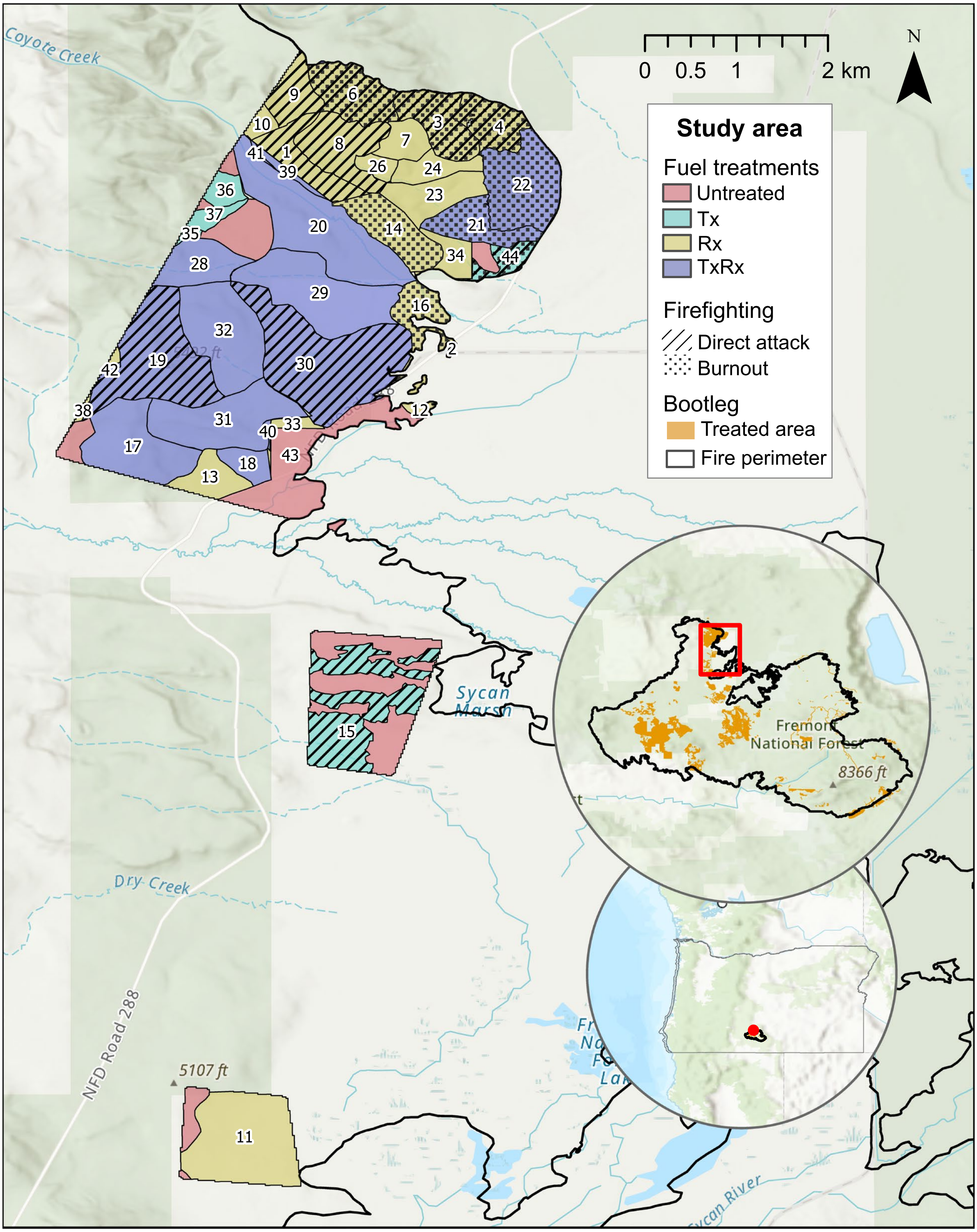

Fig. 1 Map showing the study area footprint, fuel treatments, and firefighting operations. Each individual polygon represents a unit, except for the untreated area, which is characterized by multiple polygons all labeled as unit 43. Embedded overview maps include extent indicators (red rectangle and dot) to show the location of the study area (near Sycan Marsh, south-central Oregon, US) at different scales

Fig. 2 Photos of fuel treatments before the 2021 Bootleg Fire and fire tornado effects after the wildfire. **A** Post thinning (Tx) fuel conditions and soil disturbance. **B** Post broadcast burning (Rx) with < 5% mortality. **C** Tree uprooted by a wildfire tornado. **D** Post broadcast burning with > 5% mortality. **E** High severity burns in forested riparian area (northeast corner of TxRx unit 20; Coyote Creek; April 25th, 2024). Photos were taken at three different locations within our study area (near Sycan Marsh, south-central Oregon, US). Photo credit: Craig Bienz (TNC; **A**, **B**, **D**); Alina Cansler (**C**); Astrid Sanna (**E**)

progressing with the prevailing wind direction from southwest to northeast. During days of burning, fire weather was characterized by low fuel moisture and relative humidity, and high temperature and energy release component (ERC) (Table 1). Based on these metrics, our entire study area burned mostly under similarly severe fire weather conditions, except for wind speed. Maximum wind speed exceeded 32 km/h on several days but reached 64 km/h on July 18th for a short period of time. On that day, local managers observed extreme fire behavior, including a fire-tornado which uprooted several trees (Fig. 2D).

Table 1 Incident Action Plans fire weather data provided by TNC during the 2021 Bootleg Fire, representing our study area near Sycan Marsh, Oregon. 100-h FM = 100-h fuel moisture. 1000-h FM = 1000-h fuel moisture. Min. RH = minimum relative humidity. Max. temp = maximum temperature. ERC = energy release component. Maximum wind speed exceeded 32 km/h on several days

July 2021 (day)	100-h FM (%)	1000-h FM (%)	Min. RH (%)	Max. temp (°C)	ERC (BTU/ft^2)
13	< 8	< 9	14.5	33.2	66.0
14	< 8	< 9	14.0	34.3	65.0
15	< 8	< 9	12.0	32.2	68.0
17	< 7	< 9	12.0	32.2	67.0
19	< 7	< 9	13.0	30.6	64.0
20	< 7	< 9	13.0	31.1	64.0
21	< 7	< 9	13.0	31.1	74.0

Burn severity data

Burn severity is defined as a "scaled index gauging the magnitude of ecological change caused by fire" (Key and Benson 2006). The composite burn index (CBI) is a common ground measurement of burn severity that aggregates post-fire effects (Key and Benson 2006) and is used to validate satellite-derived burn severity observations (e.g., Prichard et al. 2020).

Following methods described in Howe et al. (2022) and Parks et al. (2021), we calculated the relativized burn ratio (RBR; Parks et al. 2014a) across the entire fire perimeter using Google Earth Engine (Gorelick et al. 2017), and then clipped it to the study area extent. We selected RBR over other indices for two reasons: (1) Parks et al. (2014a) demonstrated that RBR better represents CBI measurements; (2) based on a comparison against burn severity distributions of the delta normalized burn ratio (dNBR), relativized dNBR (RdNBR), and delta normalized difference vegetation index (dNDVI) by fuel treatment type, RBR had fewer outliers and best discriminated fuel treatment classes.

The index was computed using 1-year pre- and post-fire mean composite imagery collected during the growing season (June 1–September 30) to capture survivorship potential and delayed mortality (Key and Benson 2006) in response to the Bootleg Fire. CBI observations from 2022 were not available in our study area, hence we used Parks et al. (2021, Table 7) RBR thresholds corresponding to CBI classes to interpret burn severity. Our 2020 mean composite imagery used to calculate RBR did not account for the possible effect of the pre-Bootleg Rx treatment conducted over unit 8, in 2021. However, given its small size (~ 2% of the total study area), the very low burn severity observed in 2022 (Fig. S5)—indicating a small reflectance change between 2020 and 2022—and the similar forest structure observed through a visual assessment of NAIP 2020 and 2022 (Figure S1), we decided to retain unit 8 in our analysis.

We calculated RBR employing Sentinel-2 Level 2 A surface reflectance data. The Near Infrared (NIR) and the Shortwave Infrared (SWIR 2) bands necessary to calculate RBR have a native resolution of 10 and 20 m respectively; to exploit the finest scale available, we created our burn severity raster at a pseudo 10-m resolution (Howe et al. 2022). Additionally, we further assessed burn severity by visually inspecting pre- and post-fire imagery extracted from the NAIP collection. We downloaded 2020 and 2022 multispectral (red, green, blue, NIR bands) NAIP imagery at 0.6 m resolution using GEE (Fig. 3B).

Management data

To assess the influence of different fuel treatment types on burn severity, we created a single fuel-treatment vector layer by combining data provided by TNC with data extracted from the Interagency Fuel Treatment Decision Support System (IFTDSS 2021) database. We considered the combined untreated areas as a single control unit after verifying that the forest types matched those found in treated units based on the 2020 LANDFIRE (Ryan and Opperman 2013) Existing Vegetation Type dataset (EVT; https://landfire.gov/evt.php). The final fuel treatment vector layer included Tx, Rx, TxRx, and untreated classes.

Additionally, to evaluate the effect of fire suppression on burn severity, we collected firefighting operations data by requesting the local fire program manager (K. Sauerbrey, The Nature Conservancy, Oregon, USA), who was on the scene during the wildfire, to fill out a survey developed by Washington DNR (Anna Barros and Gretchen Engbring, Washington, USA, pers. comm.). The survey documented whether treatment units were utilized by firefighters for wildfire suppression and, if so, the specific methods employed—direct attack, burnout operations, or both. For the purpose of our analysis, we simplified those data into a single binary variable, representing the presence or absence of fire suppression by treatment unit.

LiDAR-derived forest structure and topographic metrics

To investigate the influence of pre-Bootleg forest structure on burn severity, we obtained 2018 pre-fire LiDAR data from USFS and 2021 post-fire LiDAR from the open source USGS server (USGS LiDAR 2021). Mean first returns per square meter were 11 and 15 respectively. We used FUSION/LDV LIDAR Analysis and Visualization software version 4.51 (McGaughey 2020) to calculate forest and topographic metrics at 30-m and 15-m resolution, respectively (Table 2; Table S1). Pre-fire LiDAR were collected before some of the broadcast burning treatments were conducted. For this reason, forest metrics were computed using exclusively first returns with a 2-m cutoff, limiting the inclusion of understory vegetation while accounting for the presence of taller saplings.

Weather data

To evaluate the effect of wind and other weather variables on burn severity, we calculated wind metrics using wind data computed with WindNinja software version 3.8 (Forthofer 2007) and extracted other daily fire weather variables from the University of Idaho Gridded Surface Meteorological (GRIDMET; Abatzoglou 2013) dataset available in GEE (Table S1). Hourly-interpolated, topography-driven wind vectors were calculated for each

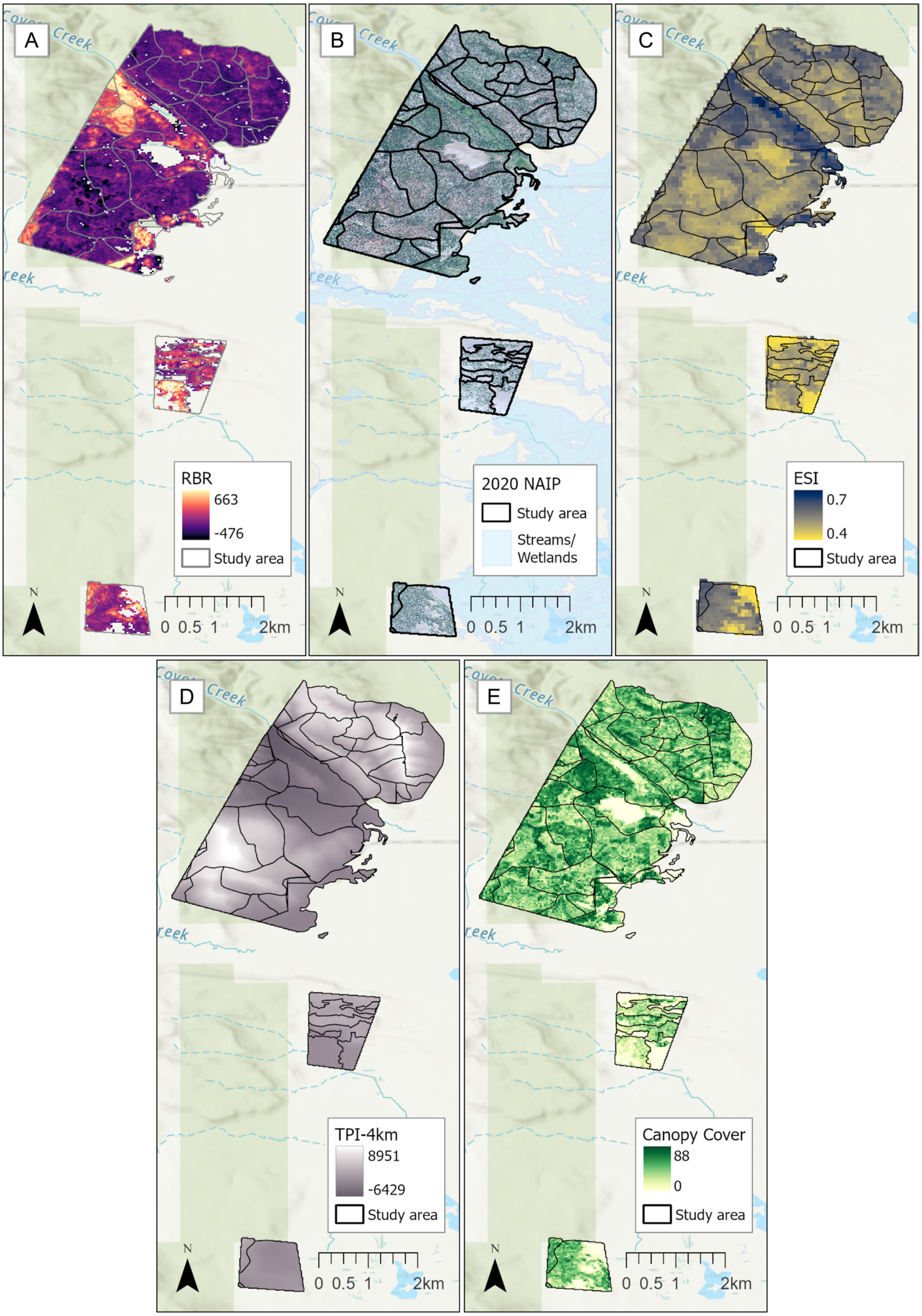

Fig. 3 **A** Raster of continuous relativized burn ratio (RBR) at 10-m resolution, including only pixels representing canopy cover > 10%, and representing 1-year post-fire burn severity following the 2021 Bootleg Fire near Sycan Marsh (south-central Oregon, US). **B** Map including 2020 NAIP imagery at 0.6-m resolution. The background map shows streams and wetlands cover. **C** Evaporative stress index (ESI). **D** Topographic position index (TPI-4km). **E** Canopy cover (above 2 m)

Table 2 Subset of predictors included in the final Random Forest model representing data covering the study area near Sycan Marsh, Oregon. All topographic variables were calculated applying 15-, 45-, 135-, and 270-m windows, except for topographic position index which was calculated applying 200-, 500-, 1000-, 2000-, and 4000-m windows

Predictors	Resolution (m)	Unit	Source/software
Management			
Broadcast burning	10	Unitless	TNC; IFTDSS
Mechanical thinning	10	Unitless	TNC; IFTDSS
Firefighting	10	Unitless	Survey
Forest structure			
Canopy cover	30	%	FUSION
Canopy rumple	30	Unitless	FUSION
Topography			
Topographic position index	15	Unitless	FUSION
Aspect	15	Degrees AZ	FUSION
Slope	15	Degrees	FUSION
Solar radiation index	15	Unitless	FUSION
Weather			
Maximum temperature	4000	Kelvin	Abatzoglou 2013; NIROPS
Northsouthness maximum wind speed	90	Cosine transformed radians	WindNinja
Vegetation			
Evaporative stress index	70	Unitless	Fisher 2018
Climate			
Actual Evapotranspiration 1981–2010	90	mm	Cansler et al. 2022 (Appendix B)
Snow cover frequency	500	%	Crumley et al. 2020
Distance to streams and wetlands	10	m	ODSL; ODFW

fire day, following directions detailed in WindNinja's tutorial 3 (https://weather.firelab.org/windninja/tutorials/). Using the Point Initialization option, we selected weather stations within a 10,000-m buffer around the study area. We used wind speed, and wind direction vectors produced at 90-m point spacing, to derive daily maximum wind speed, and related ordinal eastwestness (sine transformed radians) and northsouthness (cosine transformed radians) direction layers (Table 2; Table S1). Infrared imagery-derived heat perimeters were obtained from the 2021 National Infrared Operations (NIROPS; USDA 2021) dataset for most days throughout the entire wildfire progression.

Daily wind and GRIDMET layers were intersected with NIROPS perimeters to create 10-m raster layers capturing weather variability based on daily wildfire progression. Additionally, we obtained Incident Action Plans fire weather data from TNC. This dataset, which was provided as a summary table (Table 1), was used to interpret our results, since it offered critical information to understand fire weather conditions observed on the ground.

Climate data

To account for the effect of climate on burn severity, we used 30-year climate normals whenever possible, as they provide a stable and representative baseline for long-term climate patterns, reducing the influence of short-term climate variability. Climate layers, including 1981–2010 actual evapotranspiration (AET) and 1981–2010 climatic water deficit (CWD) grids were produced following methods described in Appendix B of Cansler et al. (2022). We used the ClimateNA software (Wang et al. 2016) to compute more recent climatic normals (1991–2020), including Hargreaves climatic moisture deficit (CMD; representing the difference between reference evapotranspiration and monthly precipitations), mean annual precipitation, May–September precipitation, and precipitation as snow (Table 2; Table S1).

Additionally, we included snow cover metrics such as snow cover frequency (SCF) and snow disappearance day (SDD), to account for the influence of soil moisture and vegetation growth on burn severity. SCF measures snow cover persistence as the proportion of days with snow cover over a given water year (October 2020–September 2021). On the other hand, SDD represents the last day of snow cover during a water year. We produced snow cover metrics using MODIS/Terra Snow Cover Daily L3 Global 500-m SIN Grid (Version 6) dataset, and by running the GEE script provided by Crumley et al. (2020).

Vegetation data

To evaluate the possible effect of different vegetation types on burn severity, we downloaded the Fire Resistance Score (FRS; Stevens et al. 2020) and the 2020 LANDFIRE EVT using LF Map Viewer (www.landfire.gov/viewer/). FRS is a summary of functional traits of fire-adapted conifer tree communities used to quantify the resistance of forest communities to tree-killing fire. Existing vegetation type (EVT) represents associations of plant community types that are commonly found within landscapes featuring similar substrates, ecological processes, and/or environmental gradients. Given the dominance of the ponderosa pine forest, woodland, and savanna forest type (57%), and the relative low cover of all other vegetation classes (< 5% each), the EVT layer was re-coded as a binary variable representing dominant (value = 1) and non-dominant (value = 0) vegetation, respectively (Table S1).

To evaluate vegetation stress right before the Bootleg Fire, we used the Level-4 evaporative stress index (ESI; Fisher 2018), which is calculated using the Priestley-Taylor Jet Propulsion Laboratory (PT_JPL) algorithm and was obtained by following tutorials published on the ECOSTRESS homepage (https://ecostress.jpl.nasa.gov). ESI, among other ECOSTRESS-derived metrics, is calculated using the thermal infrared brightness temperature of plants collected from the space station. ESI is a drought index ranging from 0 to 1 (0 = water stress, 1 = no water stress) calculated as the ratio of evapotranspiration (i.e., water used by plants; ET) over potential evapotranspiration (i.e., maximum rate of atmospheric demand; PET). Both ET and PET are ECOSTRESS-derived metrics. The ESI layer used in this analysis was derived from data collected on July 10, 2021, just 3 days before the Bootleg Fire approached our study area, according to NIROPS (Table 2; Table S1).

Distance to streams and wetlands data

To capture the possible effect of riparian and wetland ecosystems on burn severity within our study area, we created a distance-to-streams-and-wetlands layer. We sourced wetlands data from the Oregon Department of State Lands Statewide Wetlands Inventory (ODSL 2021), and whole stream routes from the Oregon Department of Fish and Wildlife data clearinghouse (ODFW 2021). After merging and rasterizing the geospatial datasets, we calculated the distance for each pixel using the R function distance from the raster package (version 3.6–20) (Table 2; Table S1).

Extracting and compiling data

All layers used in this analysis were either vector shapefiles or rasters. To build a comprehensive and coherent dataset, vector shapefiles were rasterized matching the extent and projection of the RBR raster. The statistical methods employed in this study were limited to numeric variables—whether binary, discrete, or continuous. For this reason, we recoded variables representing multiple classes into binary variables. EVT classes were simplified to dominant (1) and non-dominant (0) vegetation types. The fuel treatment layer, originally representing four classes (i.e., Tx, Rx, TxRx, and untreated), was recoded into two binary variables: Tx and Rx. These variables indicate the presence (1) or absence (0) of these treatments. This reduction was necessary to limit the dimensionality of our data frame, decrease data sparsity (i.e., increase the proportion of non-zero observations), and enhance model interpretability.

We created our dataframe using gridded sampling (Povak et al. 2020; Chamberlain et al. 2024) and extracted rasterized values at 90-m intervals from our pool of predictors. We chose a 90-m spacing to ensure a sufficiently large sample size for Random Forest modeling while minimizing spatial autocorrelation. We retained only entries with canopy cover > 10% (derived from pre-fire LiDAR) based on the Forest Inventory and Analysis (FIA) program definition of forest (https://apps.fs.usda.gov/fiadb static-api/static/html/RPA_forest_filter.html). We then validated this threshold through visual assessment of the 2020 NAIP imagery covering our study area.

We reduced our pool of predictors by (1) retaining only variables that had a Spearman correlation coefficient < 0.6 and that were more highly correlated with RBR; (2) recursively eliminating features (i.e., backwards selection) with Random Forest, optimizing for a higher variance explained. Recursive feature elimination (RFE) was conducted using the function rfe from the caret package (version 6.0–94; Kuhn 2008). While this process removed mechanical thinning, we retained this variable given our interest in understanding the local effect of fuel treatments on burn severity. The final data frame included 17 predictors (Table 2) and 1846 observations.

Analysis

Objective 1: evaluating burn severity by treatment type

To evaluate the influence of fuel treatments on burn severity and capture its variability within each treatment class, we created violin plots showing the distribution of burn severity by fuel treatment type (untreated, Tx, Rx, TxRx), and by individual units, respectively. CBI thresholds derived specifically for RBR were used to quantify the percentage of area burned at low (≤ 135), moderate (136–300), and high (≥ 301) severity for each treatment class (Parks et al. 2021).

Objective 2: random forests and SHAP analysis

We fit a Random Forest regression (RF; Breiman, Leo 2001) model with an explanatory focus and applied SHapley Additive exPlanations (SHAP; Lundberg & Lee 2017; Molnar 2023) analysis to uncover both the mean predictor effects (global impact) and the spatially explicit local variability (local effect) of predictors influencing burn severity. Our model utilized the complete dataset of 1846 observations, prioritizing a comprehensive understanding of burn severity variations within our study area over predictive accuracy on new, unseen data.

We ran the entire analysis using R programming language (RStudio Team 2020). Functions from the tidymodels framework (version 1.1.0) were used to build our modeling workflow and the ranger package (version 0.15.1; Wright and Ziegler 2017) was used to train the RF model. Hyperparameter tuning was systematically evaluated through tenfold cross-validation to determine how different numbers of features considered for splitting at each node (mtry) and the minimum number of observations required to form a new node in a tree (min_n) performed, based on the pseudo-R^2 metric. The best parameters (mtry = 4, min_n = 5) were then used to train the final RF model. Subsequently, we employed the DALEXtra package (version 2.3.0; Maksymiuk et al. 2021) to evaluate the model performance, and extract predicted values and residuals. Given that the contagious effect of fire spread is inherently a spatial process, we assessed the possible presence of spatial autocorrelation (SA) in the residuals to verify that our model did not violate the assumption of independence. To assess SA, we produced and interpreted a Moran's I plot with a lag distance of 90 m (representing the sampling distance) by using the correlogram function in the elsa package (version 1–1.28; Naimi et al. 2019).

SHAP analysis is a statistical approach based on Shapley values, a method from the coalitional game theory employed to explain black-box models such as RF (Lundberg et al. 2019). While a coalition in a game represents a group of players, a coalition in a black-box model represents a group of features (i.e., predictors). After evaluating the contribution of each feature value to a predicted value across all possible coalitions, the average contribution of a feature value (i.e., Shapley value) is calculated. Additionally, it provides a means to explicitly quantify and visualize the local interaction effect between pairs of predictors. Thus, while accounting for all possible interactions, SHAP analysis allowed us to examine (1) the local importance of each predictor value at the scale of a 90-m pixel; and (2) the global importance of each predictor at the scale of the study area with respect to burn severity.

In our case, SHAP values represent the local importance of each feature value for the burn severity prediction of a specific data point. Specifically, they quantify the contribution of each feature value to the deviation from the mean prediction. Therefore, for a specific prediction, the sum of the contributions of all feature values equals the deviation. Finally, SHAP global importance is calculated by taking the mean of the absolute SHAP values for each feature (e.g., Rx) across all the data points (i.e., 1846 observations), which quantifies the overall impact of each feature on the model's predictions.

SHAP values can be positive or negative, indicating whether the effect of the feature value increases or decreases the predicted outcome, respectively. In the context of this study, a negative SHAP value would suggest that the feature value was associated with a decrease in the burn severity prediction, while a positive SHAP value would suggest an increase. The magnitude of SHAP values reflects the strength of the effect of each feature on the prediction, with larger absolute values indicating a greater influence. We conducted SHAP analysis using the treeshap package (0.2.5; Yang 2022), and created a SHAP maps for each predictor at 90-m resolution (sampling distance). Finally, we used SHAP maps and dependence plots to examine the spatial patterns of the local effect of each predictor.

Results

We found that the influence of fuel reduction on burn severity varied by treatment prescription. Within units treated with broadcast burning, the percentage of area burned at low severity was over 80%. In contrast, units treated with thinning-only and untreated forests were dominated by area burned at moderate (45%) and high (42%) severity, respectively (Fig. 4A and B).

Our RF model achieved an R^2 of 0.94 and a root mean square error (RMSE) of 31.8 for predicting RBR. The model fit revealed a mostly linear relationship between observed and predicted RBR values (Fig. S2). Residuals spatial autocorrelation exhibited a Moran's I value that ranged between 0.1 and 0.0, indicating spatial independence in the residuals (Figure S2). Global variable importance values revealed that top predictors of RBR included Rx, ESI, 4000-m window topographic position index (TPI-4 km), and canopy cover, in descending order of importance, while firefighting and Tx were ranked third-to-last and last, respectively (Fig. 4C).

The local influence of each predictor's value on predicted burn severity varied across our study area (Fig. 7). Rx SHAP values ranged between −29 and 150. Observations indicating the implementation of Rx (Rx = 1) corresponded to lower predicted burn severity (negative

SHAP values), while areas not treated with Rx (Rx = 0) corresponded to higher predicted burn severity (positive SHAP values) (Figs. 5A; 7A). Tx SHAP values ranged between − 6 and 6. The distributions of observations representing the presence of Tx (Tx = 1) and its absence (Tx = 0) revealed an unclear effect on predicted burn severity. Some areas treated exclusively with Tx were associated with marginally higher predicted burn severity, and some that were untreated (Tx = 0, Rx = 0) exhibited lower predicted burn severity. Firefighting SHAP values ranged between − 13 and 13 (Figs. 5F; 7F). Firefighting efforts that were conducted in units treated with Rx were associated with a marginal decrease in predicted burn severity. Where Rx was absent, firefighting operations were linked to both a marginal increase and decrease in predicted RBR. Areas where firefighters did not intervene (Firefighting = 0) exhibited mostly higher predicted burn severity (Figs. 5E; 7E). However, the magnitude of the influence of this variable remained consistently low compared to top predictors.

ESI SHAP values ranged between − 68 and 97, showing a positive increasing trend in RBR with increasing ESI values ranging between 0.4 and 0.7. Areas experiencing lower water stress were associated with higher predicted RBR (Figs. 5B; 7B). TPI-4km SHAP values ranged between − 54 and 152, showing a steep negative slope between − 4000 and 0 TPI-4km. The trend then plateaued over the 0–8000 TPI-4km range. Valleys, represented by more negative TPI-4km values, were positively correlated with increasing predicted RBR, while those representing hills and ridges (more positive TPI-4km) were associated with lower burn severity (Figs. 5C; 7C). Additionally, based on exploratory analysis, we observed a strong negative correlation (Spearman = − 0.80) between TPI-4km and CMD (Figure S3) averaged over 30 years (1991–2020). Because TPI-4km was more highly correlated with RBR than CMD, CMD was excluded from the pool of predictors but retained for interpretation.

Canopy-cover SHAP values ranged between − 39 and 102, showing a positive, mostly linear relationship with observed canopy cover. Pixels featuring > 40% canopy cover were associated with increasing burn severity (Figs. 5D; 7D). Finally, the SHAP interaction values between canopy cover and Rx—ranging approximately from − 30 to 40—indicate that the relationship between canopy cover and burn severity (RBR) was strongly influenced by the presence or absence of broadcast burning. In untreated areas (Rx = 0), higher canopy cover was associated with increasingly positive SHAP interaction values. Conversely, in areas where Rx was applied (Rx = 1), SHAP interaction values remained relatively stable and close to zero across all canopy cover levels (Fig. 6).

Discussion

Influence of fuel treatments on wildfire predicted burn severity

We observed a substantial difference in percentages of area burned at low, moderate, and high severity between units that were treated with broadcast burning and those that were not (Fig. 4B), suggesting that likely fire behavior and consequent burn severity varied in response to fuel structure and accumulation (Agee and Skinner 2005; Vaillant et al. 2006; Ritchie et al. 2007; Safford et al. 2009, 2012).

Based on SHAP analysis, the presence or absence of broadcast burning (Rx) and mechanical thinning (Tx) were the most and least important determinants of wildfire burn severity, respectively (Fig. 4C). The comparable high percentages of area burned at low severity within Rx and TxRx (Tx followed by Rx) units, suggest that broadcast burning alone can be as effective as combined thinning and burning treatments in mitigating burn severity. This approach has both economic and ecological implications for forest managers. Specifically, where conditions exist to allow Rx on its own and where commercial thinning cannot offset treatment costs, Rx can be a more cost-effective method for reducing burn severity than TxRx (Bienz et al. 2019; Holland et al. 2022). Tx treatments may also have higher environmental impacts than Rx, including risks of soil disturbance and compaction and injuries to live trees (Picchio et al. 2020). Over time, repeated application of Rx can act as a thinning agent by killing small trees, creating more canopy openings, and increasing canopy base height. However, reintroducing

(See figure on next page.)

Fig. 4 Graphs showing 1-year post-fire burn severity analysis following the 2021 Bootleg Fire near Sycan Marsh (south-central Oregon, US). **A** Relativized burn ratio (RBR) distributions by treatment type. Solid and dotted horizontal lines represent low (≤ 135) and moderate (136–300) burn severity thresholds, respectively. **B** Percentages of area burned across different severity classes by treatment type (thinning = Tx; broadcast burning = Rx, Tx followed by Rx = TxRx). **C** SHapley Additive exPlanations (SHAP) importance plots presenting the global impact (left) and the local effect (right) of each predictor on burn severity in decreasing order of importance. Left plot: *x*-axis shows the mean of the absolute SHAP values. Right plot: *x*-axis shows negative and positive SHAP values to indicate a decrease and an increase in predicted burn severity, respectively (relative to the predicted mean). The magnitude of SHAP values reflects the strength of the local effect of each feature value on the prediction, with larger absolute values indicating a greater influence

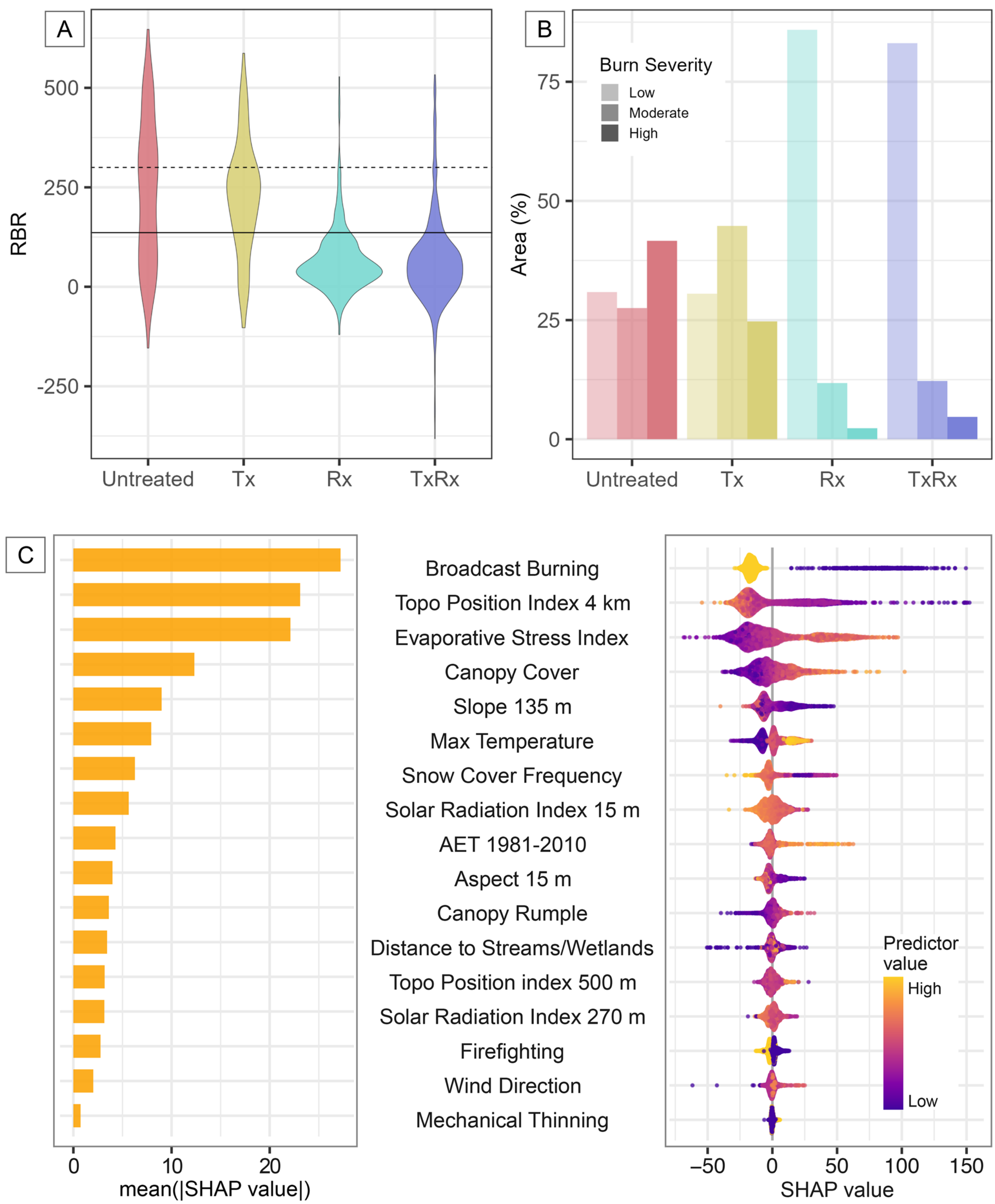

Fig. 4 (See legend on previous page.)

fire through controlled burning (without thinning) in fire-excluded forests may pose substantial risks, including higher, undesired tree mortality due to high severity burns caused by abundant pre-fire fuel accumulation (Miller and Urban 2000), and recruitment of surface fuels through post-fire tree mortality (Agee 2003).

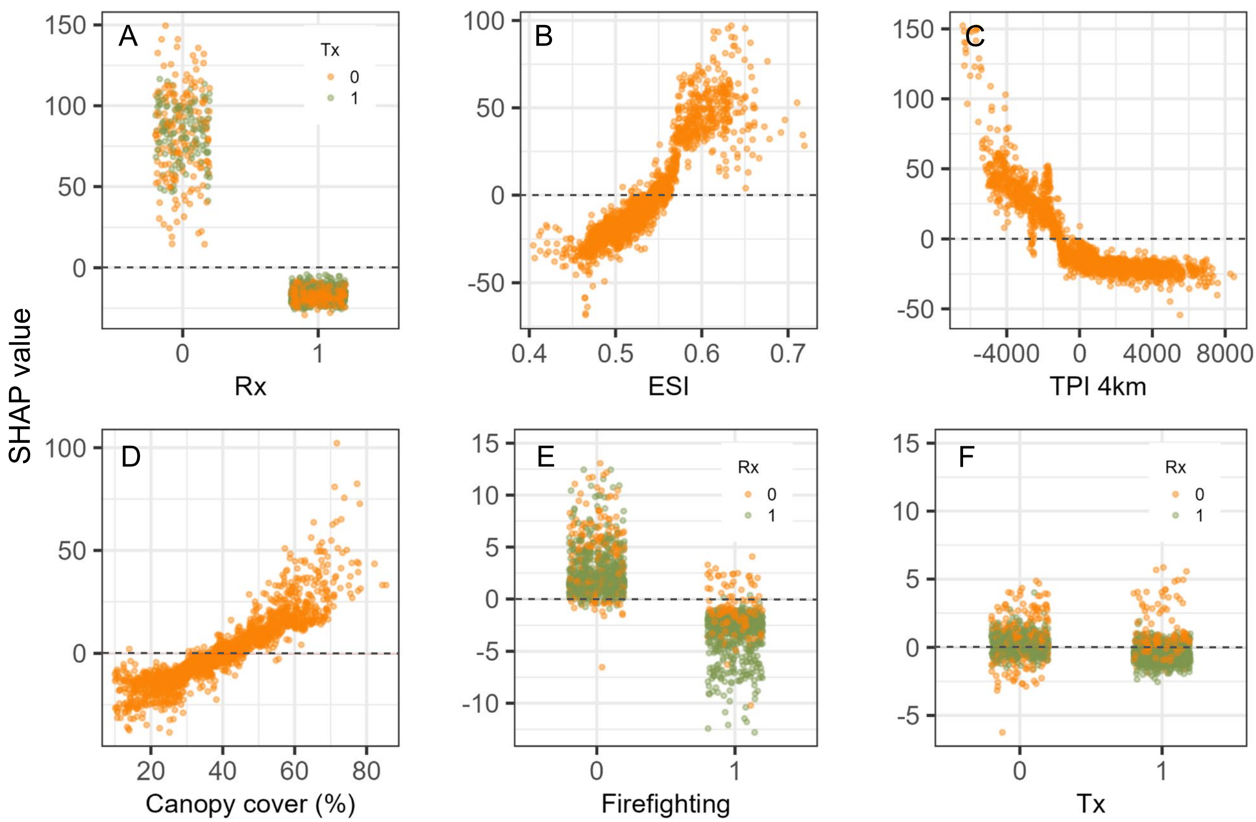

Fig. 5 Dependence plots showing 1-year post-fire burn severity analysis following the 2021 Bootleg Fire near Sycan Marsh (south-central Oregon, US). Each plot shows important predictor values (*x*-axes) against SHapley Additive exPlanations (SHAP) values (*y*-axes). On the *y*-axis, negative SHAP values indicate a decrease in the predicted burn severity, while positive SHAP values indicate an increase (relative to the predicted mean). The magnitude of SHAP values reflects the strength of the local effect of each feature value on the prediction, with larger absolute values indicating a greater influence. Predictors are presented in order of decreasing importance, from **A** to **F**. **A** Broadcast burning (Rx) is colored by thinning (Tx) values (0 = absent, 1 = present), and untreated observations are represented by Rx = 0 and Tx = 0. **E** Firefighting and **F** Tx are colored by Rx values (0 = absent, 1 = present). Firefighting operations were conducted only in treated units, thus firefighting = 1 and Rx = 0 indicate Tx observations subjected to fire suppression, while firefighting = 0 and Rx = 0 indicate either Tx or untreated observations where fire was not suppressed. In plot **F**, untreated observations are represented by Tx = 0 and Rx = 0

Nevertheless, within our study area, on sites where time since Rx was < 5 years, the extent of high severity burns caused by this prescription was substantially smaller compared to that observed in Tx units and untreated forests affected by the Bootleg Fire.

Our findings on the effectiveness of fuel treatments largely corroborate results from prior research. Studies have shown that fuel treatments including broadcast burning were more effective at mitigating burn severity than thin only treatments (Prichard and Kennedy 2014; Yocom Kent et al. 2015; Prichard et al. 2020; Cansler et al. 2022; Chamberlain et al. 2024), and that effectiveness declined as treatment age increased (Finney et al. 2005; Hudak et al. 2011). Moreover, in three reviews, it was found that thinning followed by broadcast burning was consistently the most effective treatment, and that, in comparison, Rx and Tx alone were either less effective (Fulé et al. 2012; Davis et al. 2024) or led to mixed results (Kalies and Yocom Kent 2016).

Differences in burn severity between units treated with broadcast burning and those that were not can likely be attributed to surface fuel reduction in Rx treatments compared to potential increases in surface fuels through Tx treatments (Vaillant et al. 2006; Knapp et al. 2017). Broadcast burning disrupts both vertical and horizontal fuel continuity by consuming surface fuels (Agee and Skinner 2005; Reinhardt et al. 2008), thus limiting crown scorch and tree mortality even under extreme weather conditions (Prichard and Kennedy 2014; Yocom Kent et al. 2015; Povak et al. 2020; Prichard et al. 2020; Brodie et al. 2023). In contrast, extensive crown scorch, and torching can be caused by increased surface fuels from logging slash, fuel aridity, and wind speed resulting from thinning (Agee and Skinner 2005; Whitehead 2008; Ma

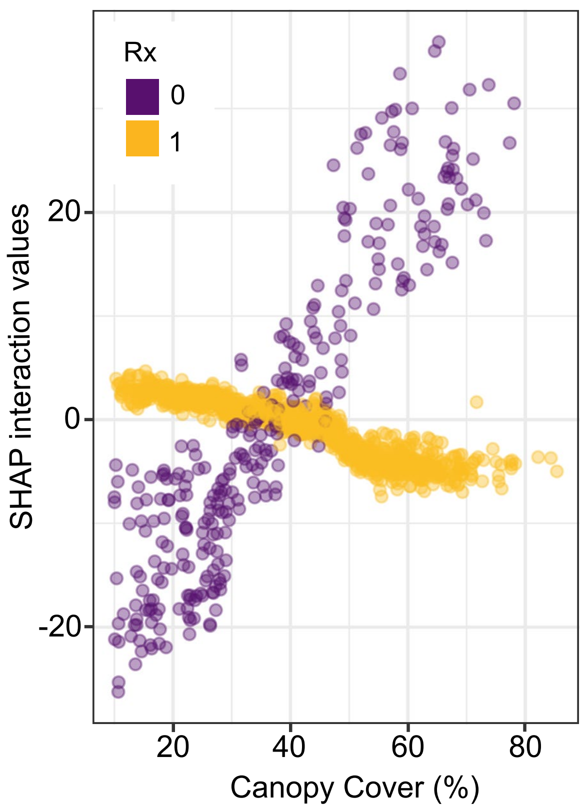

Fig. 6 Dependence plot showing the interaction between canopy cover and broadcast burning (Rx) in relation to 1-year post-fire burn severity following the 2021 Bootleg Fire near Sycan Marsh (south-central Oregon, US). The plot displays canopy cover values (*x*-axis) against SHapley Additive exPlanations (SHAP) interaction values (*y*-axis), colored by Rx values (0 = absent; 1 = present)

et al. 2010; Kane 2021) and exacerbated by hot summer temperatures.

Although we could not conduct pre-Bootleg fuel surveys in our retrospective study, consultations with the local manager (C. Bienz, The Nature Conservancy, Oregon, USA, pers. comm.) indicated that Rx and TxRx units had lower fuel loads compared to untreated forests and Tx units. Therefore, we interpreted the occurrence of broadcast burning as a proxy for pre-fire fuel accumulation in the lower strata, leveraging the recent timing of this prescription (< 5 years, except for one unit treated in 2008). Although less effective than treatments including Rx, thinning units had somewhat lower RBR than untreated units (i.e., mean Tx RBR = 208; mean untreated RBR = 244), possibly due to lower fuel loads and the influence of firefighting operations. Likely, untreated forests were more susceptible to crown fire than thinned units due to differences in forest structure. Specifically, based on exploratory analysis, LiDAR-derived metrics revealed lower mean canopy height, canopy base height, horizontal and vertical canopy complexity, and higher canopy cover where forests were untreated (Figure S4).

Despite the broad trends indicating the effectiveness of treatments, we observed local variability in burn severity across both treated and untreated forests. For instance, we observed patches of low burn severity in untreated, freshwater forested wetlands near units 13 and 1 (Fig. 1), where moist soil provided a refuge for encroaching trees against the spread of fire. Although fire severity was generally lower in Rx and TxRx units, we also observed patches of high severity burns within units treated with broadcast burning. This was particularly evident in areas featuring one or a combination of the following conditions:

(1) Controlled burns were not applied consistently, especially near the Coyote Creek riparian zones (Fig. 1, unit 20) where fuel was not treated to avoid potential negative impacts on the riparian system (Stone et al. 2010), and soil was drier due to hot summer temperatures (C. Bienz, The Nature Conservancy, Oregon, USA, pers. comm.);
(2) Canopy cover was continuous and exceeded 40%;
(3) Rx alone was conducted 13 years prior to the Bootleg Fire.

For instance, the TNC fire manager informed us that post-thinning fuel found in the northeast corner and other areas within TxRx unit 20 was not treated with broadcast burning; rather, it was piled and burned (K. Sauerbrey, The Nature Conservancy, Oregon, USA, pers. comm.). The presence of residual slash coupled with drier fuel conditions, high canopy cover (> 40%), and the advance of high intensity fire from the adjacent untreated unit, likely contributed to the high severity noted in that area (RBR > 450). Moreover, unit 20 was characterized by a riparian zone dominated by fire-sensitive species

(See figure on next page.)
Fig. 7 Maps showing the 1-year post-fire burn severity analysis for the 2021 Bootleg Fire near Sycan Marsh (south-central Oregon, US). Each map represents rasterized (90 m) SHapley Additive exPlanations (SHAP) values for **A** broadcast burning (Rx), **B** evaporative stress index (ESI), **C** topographic position index (TPI-4km), **D** canopy cover, **E** firefighting, and **F** thinning (Tx), which are displayed in order of descending importance. Each raster matches the extent of the study area and is overlaid by the fuel treatments layer (black lines). Negative SHAP values indicate a decrease in the predicted burn severity, while positive SHAP values indicate an increase (relative to the predicted mean). The magnitude of SHAP values reflects the strength of the local effect of each feature value on the prediction, with larger absolute values indicating a greater influence

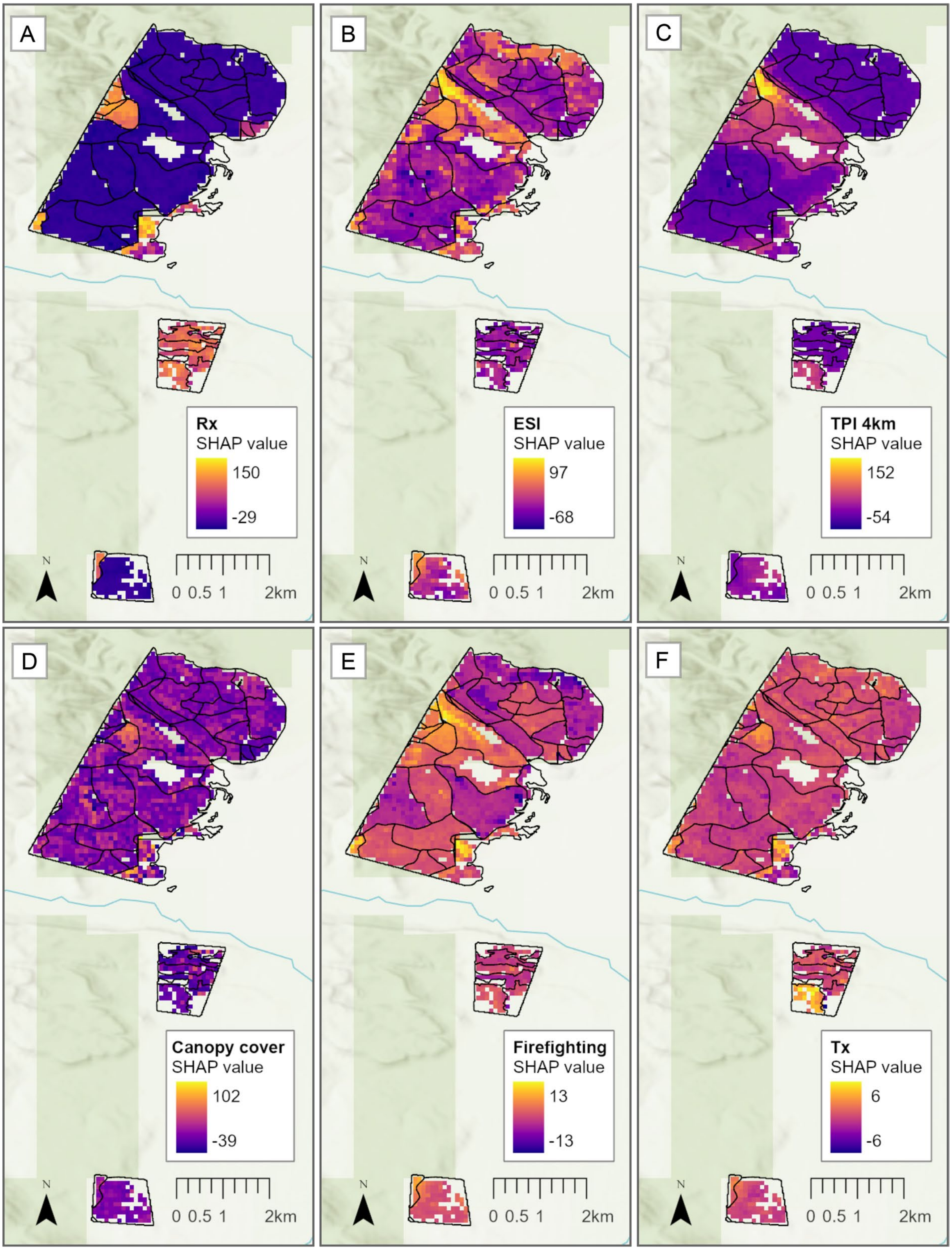

Fig. 7 (See legend on previous page.)

including willows and lodgepole pines, which burned at high severity (Fig. 2E). We also observed patches of high and moderate burn severity in Rx unit 11, where broadcast burning was conducted 13 years prior to the Bootleg Fire. This unit experienced a mountain pine beetle (*Dendroctonus ponderosae* Hopkin; Bentz 2008) outbreak in 2008, affecting both lodgepole and ponderosa pines. Due to the low timber prices, that year TNC opted to use broadcast burning as a method to reduce stand density, thereby decreasing the vulnerability of the remaining pines to drought stress and further insect attacks. When the wildfire burned into unit 11, it likely encountered young trees sensitive to fire, as well as snags and surface fuels from the death of trees following the insect outbreak and broadcast burning, resulting in moderate and high severity burns (Agee 2003; Schoennagel et al. 2012). These findings underscore limitations related to categorically labeling fuel treatments, suggesting that more detailed studies accounting for within-treatment fuel structure and accumulation, possibly leveraging available airborne or terrestrial LiDAR data (Andersen et al. 2005; Loudermilk et al. 2009; Lin et al. 2024), could enhance our understanding of fire behavior and effects.

Influence of fire suppression on wildfire predicted burn severity

Treated units facilitated burnout and direct attack operations, providing safer zones for firefighters during the Bootleg Fire (K. Sauerbrey, The Nature Conservancy, Oregon, USA, pers. comm.; Harbert et al. 2007). As shown in other case studies (e.g., Murphy et al. 2007; Rogers et al. 2008), the rate of fire spread decreased in most of the treated units. According to the TNC fire manager, reduced fire intensity and flame length were observed as the fire burned into units treated with broadcast burning (K. Sauerbrey, The Nature Conservancy, Oregon, USA, pers. comm.). Rx units were particularly suitable for firefighting operations, having been previously used for fire training programs in collaboration with The Klamath Tribes.

Where fire suppression occurred, our model predicted variable effects in Tx units (Fig. 5E) and a relatively small decrease in burn severity in units treated with Rx. Notably, units 15 and 44 were the only Tx units used in firefighting operations. In unit 15, despite direct attacks holding the Bootleg Fire for over 24 h, the fire eventually gained momentum to the west burning through untreated forests and then crossed the fire lines as a crown fire, leading to a mix of burn severities (Fig. 5E). Conversely, although the model did not capture a significant effect, in unit 44 direct attack and burnout operations successfully suppressed the wildfire, resulting in low burn severity. While results suggested that firefighting operations contributed to lowering burn severity in Rx units, the decrease was marginal. Overall, we observed predominantly low burn severity within these units, regardless of whether firefighting activities occurred. This finding contrasts with the work by Harris et al. (2021), who found a substantial influence of fire suppression in units previously treated with prescribed fires.

Influence of top environmental drivers on wildfire predicted burn severity

In our study area, the most important environmental drivers of burn severity included evaporative stress index (ESI), 4-km window topographic position index (TPI-4km), and LiDAR-derived canopy cover, all of which varied locally across our study area. Unlike more commonly used vegetation indices such as NDVI (Parks et al. 2018; Povak et al. 2020; Lee et al. 2024), which represents spectral greenness and saturates in dense vegetation (Huang et al. 2021), ESI is an indirect measure of plant water use (Fisher 2018). This makes it less sensitive to canopy closure and more effective at capturing relative variations in fuel structure. Specifically, areas with green, denser, and more continuous vegetation cover were characterized by ESI values > 0.5; whereas areas with green, sparser vegetation cover were characterized by ESI values < 0.5 (Fig. 3C). These fuel patterns—coupled with ESI's inability to differentiate vegetation from soil and the generally higher temperatures of soil compared to live vegetation—suggest that lower ESI values (indicating higher water stress) may have been disproportionately influenced by soil temperatures, limiting ESI's ability to capture water stress as intended. Nonetheless, the positive relationship between increasing ESI values and burn severity indicated that densely forested areas—characterized by higher evapotranspiration and therefore greater site productivity and biomass accumulation (Stephenson 1998; Aguilos et al. 2021)—experienced more severe burns. These results aligns with previous research indicating that greater and more continuous vegetation cover can lead to higher burn severity (Agee and Skinner 2005; Vaillant et al. 2006; Ritchie et al. 2007; Safford et al. 2009, 2012).

Considering the relatively small study area, the substantial impact of TPI-4km was initially unexpected. Coarse scale TPIs (2000-m window or greater) typically reflect broader landscape conditions (Dillon et al. 2011; Kane et al. 2015a; Harris and Taylor 2017), capturing variation in fuel distribution and bioclimatic factors (e.g., AET) at larger spatial scales (Dillon et al. 2011; Kane et al. 2015b). Some studies have also indicated that TPI importance was less substantial when the effect of explicit (e.g., canopy cover) or implicit (e.g. fuel treatments) fuel-related variables were included in their analyses (Birch et al. 2015; Parks et al. 2018; Povak et al. 2020; Prichard et al. 2020). In our study area, we posit that rather than representing an explicit effect of topography on burn severity, coarse-scale TPI served as a broad surrogate for other factors. Specifically, it reflected both the variation in fuel structure and accumulation driven by fuel treatments (Figure S3A) and the variation in climatic moisture deficit influenced by undulating landforms (Hargreaves and Allen 2003; Wang et al. 2016).

TPI values representing flatter terrains and valleys corresponded mostly to untreated forests and Tx units, all of which experienced moderate to high severity burns. Additionally, the strong negative correlation observed between TPI-4km and 1991–2020 CMD normal (Figure S3C) corroborates the potential influence of topographic position on microclimate (Ma et al. 2010). The occurrence of higher CMD coupled with negative TPI-4km values indicated the existence of persistent drier conditions in valleys and on flatter terrain, where accumulation of live and dead fuel was higher. These findings suggest that the 4-km window TPI likely captured human-driven modifications to fuel distribution and the influence of topography on fuel moisture availability (Fig. 7C).

Finally, similarly to Birch et al. (2015), we found that canopy cover was the most important direct measurement of forest structure influencing burn severity. Specifically, canopy cover over 40% (Fig. 5D) was associated with increasing predicted burn severity (Rodman et al. 2023) but only where broadcast burning was absent (Fig. 6). This suggests that burn severity was driven by surface fuels (Kalies and Yocom Kent 2016; Davis et al. 2024) and that Rx buffered against the effects of increasing canopy cover.

Conclusions

Understanding the complex relationships that drive burn severity is critical for informing future land management programs. Our findings indicate that fuel accumulation, structure, and continuity played a central role in influencing burn severity. Broadcast burning served as a proxy for surface fuel loads, and its presence weakened the influence of canopy cover on burn severity. ESI captured fuel continuity, with denser, more connected vegetation showing higher values, while TPI reflected differences in fuel structure, fuel accumulation, and moisture availability, distinguishing areas with different treatment histories.

Among these factors, broadcast burning had the strongest influence on burn severity, revealing that moderate- and high-severity burns disproportionately affected sites without Rx. Units treated with Rx and TxRx had comparable percentages of area burned at low severity, suggesting that where forest structure conditions allow, managers can use broadcast burning alone to mitigate burn severity while reducing costs and soil disturbance.

By addressing burn severity from both global (study area) and local (individual prediction) perspectives, we identified relationships that would have been overlooked or misinterpreted in an exclusively global analysis. Additionally, integrating the expertise of local managers with scientific analysis enhanced the accuracy of burn severity assessment and improved our interpretation of the results. This study provides a reproducible framework for explaining burn severity at both global and local scales. It also offers valuable insights to guide and improve fire and fuel management practices across multi-ownership landscapes.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-025-00387-y.

Supplementary Material 1. Appendix: LiDAR metrics description. Tables: Comprehensive list of rasterized predictors included in the initial data frame (Table S1). Figures: NAIP imagery showing unit 8 (Fig. S1); Random Forest model performance and residuals' spatial autocorrelation (Fig. S2); Violin plots for topographic position index (TPI-4km), climatic moisture deficit (CMD), and evaporative stress index (ESI), and scatterplot showing TPI-4km-CMD relationship (Fig. S3); Violin plots of LiDAR-derived forest structure metrics by treatment type (Fig. S4); Violin plots showing relativized burn ratio (RBR) distribution for individual units by treatment type (Fig. S5); Map of Bootleg-Fire burn severity and fuel treatments beyond our study area (Fig. S6).

Acknowledgements

The Nature Conservancy funded and supported this work. We thank K. Sauerbrey for providing critical information on fire and fuel management, N. Povak for his statistical insights, Alexander Howe for his assistance in computing burn severity data, L. van Wagtendonk for her ecological insights, and R. Haugo for his support in this work. This research was supported (in part) by the U.S. Department of Agriculture, Forest Service.

Authors' contributions

AS: conceptualization, methodology, investigation, formal analysis, data curation, visualization, and writing. CC: methodology, data preparation, review. SP: writing, review. CAC: data acquisition and preparation, review. ATH: data acquisition, review. CB: data acquisition, review. LMM: review. VK: review, supervision, funding acquisition. All authors provided editorial input during the preparation of the manuscript.

Funding

The Nature Conservancy (ID: WA-G-220211-013) and Joint Fire Science Program Project (ID: 23-2-02-15) funded and supported this work.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests
The authors declare that they have no competing interests. The opinions, findings, and conclusions expressed in this publication are the authors' and do not reflect the views of their institutions. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. government.

Author details
[1]School of Environmental and Forest Sciences, University of Washington, Seattle, WA 98195, USA. [2]W.A. Franke College of Forestry & Conservation, University of Montana, Missoula, MT 59812, USA. [3]USDA Forest Service, Rocky Mountain Research Station, 1221 South Main Street, Moscow, ID 83843, USA. [4]The Nature Conservancy, 821 SE 14 Avenue, Portland, OR 97214, USA.

Received: 15 August 2024 Accepted: 26 June 2025
Published online: 29 July 2025

References

Abatzoglou, J. T. 2013. Development of Gridded Surface Meteorological Data for Ecological Applications and Modelling. *International Journal of Climatology* 33 (1): 121–131. https://doi.org/10.1002/joc.3413.

Agee, James K. 1993. *Fire Ecology of Pacific Northwest Forests*. 513.

Agee, James K. 2003. Monitoring Postfire Tree Mortality in Mixed-Conifer Forests of Crater Lake, Oregon, USA. *Natural Areas Journal* 23 (2): 114–120.

Agee, James K, Berni Bahro, Mark A Finney, Philip N Omi, David B Sapsis, Carl N Skinner, Jan W van Wagtendonk, and C Phillip Weatherspoon. 2000. The Use of Shaded Fuelbreaks in Landscape ®re Management. *Forest ecology and management*.

Agee, James K., and Carl N. Skinner. 2005. Basic Principles of Forest Fuel Reduction Treatments. *Forest Ecology and Management* 211 (1–2): 83–96. https://doi.org/10.1016/j.foreco.2005.01.034.

Aguilos, Maricar, Ge. Sun, Asko Noormets, Jean-Christophe. Domec, Steven McNulty, Michael Gavazzi, Prajaya Prajapati, Kevan J. Minick, Bhaskar Mitra, and John King. 2021. Ecosystem Productivity and Evapotranspiration Are Tightly Coupled in Loblolly Pine (Pinus Taeda L.) Plantations along the Coastal Plain of the Southeastern U.S. *Forests* 12 (8): 1123. https://doi.org/10.3390/f12081123.

Allen, C. D., M. Savage, D. A. Falk, K. F. Suckling, T. W. Swetnam, T. Schulke, P. B. Stacey, P. Morgan, M. Hoffman, and J. T. Klingel. 2002. Ecological Restoration of Southwestern Ponderosa Pine Ecosystems: A Broad Perspective. *Ecological Applications* 12 (5): 1418–1433.

Andersen, Hans-Erik., Robert J. McGaughey, and Stephen E. Reutebuch. 2005. Estimating Forest Canopy Fuel Parameters Using LIDAR Data. *Remote Sensing of Environment* 94 (4): 441–449. https://doi.org/10.1016/j.rse.2004.10.013.

Arno, Stephen F., Michael G. Hartwell, Intermountain Research Station (Ogden, Utah), and Joe H. Scott. 1995. *Age-Class Structure of Old Growth Ponderosa Pine/Douglas-Fir Stands and Its Relationship to Fire History /*. Ogden, UT : U.S. Dept. of Agriculture, Forest Service, Intermountain Research Station,. https://doi.org/10.5962/bhl.title.68858.

Bentz, Barbara. 2008. *Mountain Pine Beetle, Dendroctonus Ponderosae (Coleoptera: Curculionidae, Scolytinae)*.

Bienz, Craig, Russell Parsons, Nancy Grulke, and Katie Sauerbrey. 2020. Sharing the Road: Managers and Scientists Transforming Fire Management. In: Hood, Sharon M.; Drury, Stacy; Steelman, Toddi; Steffens, Ron, [Eds.]. *Proceedings of the Fire Continuum-Preparing for the Future of Wildland Fire; 2018 May 21-24; Missoula, MT*. Proceedings RMRS-P-78. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 9–21. 78:9–21.

Bienz, Craig, Russell Parsons, Chris Moran, Katie Sauerbrey, Kalaena Medford, and Usa Oregon. 2019. *Proceedings for the 6th International Fire Behavior and Fuels Conference Multi-Scale Approach to Fuel Reduction in a Fragmented Landscape in Eastern Oregon*.

Birch, Donovan S., Penelope Morgan, Crystal A. Kolden, John T. Abatzoglou, Gregory K. Dillon, Andrew T. Hudak, and Alistair M. S. Smith. 2015. Vegetation, Topography and Daily Weather Influenced Burn Severity in Central Idaho and Western Montana Forests. *Ecosphere* 6 (1): 1–23. https://doi.org/10.1890/ES14-00213.1.

Boisramé, Gabrielle F. S., Sally E. Thompson, Maggi Kelly, Julia Cavalli, Kate M. Wilkin, and Scott L. Stephens. 2017a. Vegetation Change during 40 Years of Repeated Managed Wildfires in the Sierra Nevada, California. *Forest Ecology and Management* 402 (October): 241–252. https://doi.org/10.1016/j.foreco.2017.07.034.

Boisramé, Gabrielle, Sally Thompson, Brandon Collins, and Scott Stephens. 2017b. Managed Wildfire Effects on Forest Resilience and Water in the Sierra Nevada. *Ecosystems* 20 (4): 717–732. https://doi.org/10.1007/s10021-016-0048-1.

Breiman, Leo. 2001. *Random Forests*. 45. https://doi.org/10.1023/A:1010933404324.

Brodie, Emily, Eric E. Knapp, Wesley Brooks, Stacy A. Drury, and Martin W. Ritchie. 2023. *FForest Thinning and Prescribed Burning Treatments Reduce Wildfire Severity and Buffer the Impacts of Severe Fire Weather*. Preprint. In: Review. https://doi.org/10.21203/rs.3.rs-3287202/v1.

Cansler, C. Alina., Van R. Kane, Paul F. Hessburg, Jonathan T. Kane, Sean M.A.. Jeronimo, James A. Lutz, Nicholas A. Povak, Derek J. Churchill, and Andrew J. Larson. 2022. Previous Wildfires and Management Treatments Moderate Subsequent Fire Severity. *Forest Ecology and Management* 504 (January) : 119764. https://doi.org/10.1016/j.foreco.2021.119764.

Chamberlain, Caden P., Gina R. Cova, Van R. Kane, C. Alina Cansler, Jonathan T. Kane, Bryce N. Bartl-Geller, Liz van Wagtendonk, Sean M. A. Jeronimo, Peter Stine, and Malcolm P. North. 2023. Sierra Nevada Reference Conditions: A Dataset of Contemporary Reference Sites and Corresponding Remote Sensing-Derived Forest Structure Metrics for Yellow Pine and Mixed-Conifer Forests. *Data in Brief* 51 (December) : 109807. https://doi.org/10.1016/j.dib.2023.109807.

Chamberlain, Caden P., Garrett W. Meigs, Derek J. Churchill, Jonathan T. Kane, Astrid Sanna, James S. Begley, Susan J. Prichard, et al. 2024. Learning from Wildfires: A Scalable Framework to Evaluate Treatment Effects on Burn Severity. *Ecosphere* 15 (12) : e70073. https://doi.org/10.1002/ecs2.70073.

Churchill, Derek J, Sean MA Jeronimo, Andrew J Larson, Paul Fischer, Matt C Dahlgreen, and Jerry F Franklin. 2016. *The ICO Approach to Quantifying and Restoring Forest Spatial Pattern: Implementation Guide*.

Churchill, Derek J., Andrew J. Larson, Matthew C. Dahlgreen, Jerry F. Franklin, Paul F. Hessburg, and James A. Lutz. 2013. Restoring Forest Resilience: From Reference Spatial Patterns to Silvicultural Prescriptions and Monitoring. *Forest Ecology and Management* 291 (March): 442–457. https://doi.org/10.1016/j.foreco.2012.11.007.

Collins, Brandon M., Jamie M. Lydersen, Danny L. Fry, Katherine Wilkin, Tadashi Moody, and Scott L. Stephens. 2016. Variability in Vegetation and Surface Fuels across Mixed-Conifer-Dominated Landscapes with over 40 Years of Natural Fire. *Forest Ecology and Management* 381 (December): 74–83. https://doi.org/10.1016/j.foreco.2016.09.010.

Collins, Brandon M., and Scott L. Stephens. 2007. Managing Natural Wildfires in Sierra Nevada Wilderness Areas. *Frontiers in Ecology and the Environment* 5 (10): 523–527. https://doi.org/10.1890/070007.

Crumley, Ryan L., Ross T. Palomaki, Anne W. Nolin, Eric A. Sproles, and J. Eugene. 2020. SnowCloudMetrics: Snow Information for Everyone. *Remote Sensing* 12 (20): 3341. https://doi.org/10.3390/rs12203341.

Davis, Kimberley T., Jamie Peeler, Joseph Fargione, Ryan D. Haugo, Kerry L. Metlen, Marcos D. Robles, and Travis Woolley. 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. *Forest Ecology and Management* 561 (June) : 121885. https://doi.org/10.1016/j.foreco.2024.121885.

Dillon, Gregory K., Zachary A. Holden, Penelope Morgan, Michael A. Crimmins, Emily K. Heyerdahl, and Charles H. Luce. 2011. Both Topography and Climate Affected Forest and Woodland Burn Severity in Two Regions of the Western US, 1984 to 2006. *Ecosphere* 2 (12): art130. https://doi.org/10.1890/ES11-00271.1.

Finney, Mark A., Charles W. McHugh, and Isaac C. Grenfell. 2005. Stand- and Landscape-Level Effects of Prescribed Burning on Two Arizona Wildfires. *Canadian Journal of Forest Research* 35 (7): 1714–1722. https://doi.org/10.1139/x05-090.

Fisher, Joshua B. 2018. *Level-4 Evaporative Stress Index*.

Forthofer, Jason M. 2007. Modeling Wind in Complex Terrain for Use in Fire Spread Prediction. Colorado State University. https://www.firelab.org/sites/default/files/2021-04/Forthofer_2007_thesis.pdf.

Fry, Danny L., and Scott L. Stephens. 2006. Influence of Humans and Climate on the Fire History of a Ponderosa Pine-Mixed Conifer Forest in the Southeastern Klamath Mountains, California. *Forest Ecology and Management* 223 (1–3): 428–438. https://doi.org/10.1016/j.foreco.2005.12.021.
Fulé, Peter Z., Joseph E. Crouse, John Paul Roccaforte, and Elizabeth L. Kalies. 2012. Do Thinning and/or Burning Treatments in Western USA Ponderosa or Jeffrey Pine-Dominated Forests Help Restore Natural Fire Behavior? *Forest Ecology and Management* 269 (April): 68–81. https://doi.org/10.1016/j.foreco.2011.12.025.
Giglio, Louis, Tatiana Loboda, David P. Roy, Brad Quayle, and Christopher O. Justice. 2009. An Active-Fire Based Burned Area Mapping Algorithm for the MODIS Sensor. *Remote Sensing of Environment* 113 (2): 408–420. https://doi.org/10.1016/j.rse.2008.10.006.
Gorelick, Noel, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. 2017. Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone. *Remote Sensing of Environment* 202 (December): 18–27. https://doi.org/10.1016/j.rse.2017.06.031.
Hagmann, R. K., P. F. Hessburg, S. J. Prichard, N. A. Povak, P. M. Brown, P. Z. Fulé, R. E. Keane, et al. 2021. Evidence for Widespread Changes in the Structure, Composition, and Fire Regimes of Western North American Forests. *Ecological Applications* 31 (8) : e02431. https://doi.org/10.1002/eap.2431.
Hagmann, R. Keala., Jerry F. Franklin, and K. Norman Johnson. 2013. Historical Structure and Composition of Ponderosa Pine and Mixed-Conifer Forests in South-Central Oregon. *Forest Ecology and Management* 304 (September): 492–504. https://doi.org/10.1016/j.foreco.2013.04.005.
Hagmann, R. Keala., Andrew G. Merschel, and Matthew J. Reilly. 2019. Historical Patterns of Fire Severity and Forest Structure and Composition in a Landscape Structured by Frequent Large Fires: Pumice Plateau Ecoregion, Oregon, USA. *Landscape Ecology* 34 (3): 551–568. https://doi.org/10.1007/s10980-019-00791-1.
Hakkenberg, Christopher R., Matthew L. Clark, Tim Bailey, Patrick Burns, and Scott J. Goetz. 2024. Ladder Fuels Rather than Canopy Volumes Consistently Predict Wildfire Severity Even in Extreme Topographic-Weather Conditions. *Communications Earth & Environment* 5 (1): 721. https://doi.org/10.1038/s43247-024-01893-8.
Halofsky, JE, DL Peterson, and BJ Harvey. 2020. Changing Wildfire, Changing Forests: The Effects of Climate Change on Fire Regimes and Vegetation in the Pacific Northwest, USA. *Fire Ecology* 16 (1). https://doi.org/10.1186/s42408-019-0062-8.
Hanan, EJ, JN Ren, CL Tague, CA Kolden, JT Abatzoglou, RR Bart, MC Kennedy, ML Liu, and JC Adam. 2021. How Climate Change and Fire Exclusion Drive Wildfire Regimes at Actionable Scales. *Environmental Research Letters* 16 (2). https://doi.org/10.1088/1748-9326/abd78e.
Harbert, Steve, Andrew Hudak, Research Forester, Laura Mayer, Tim Rich, and Sarah Robertson. 2007. *Pacific Northwest Region, USDA Forest Service Oregon State Office, USDI Bureau of Land Management*.
Hargreaves, George H., and Richard G. Allen. 2003. History and Evaluation of Hargreaves Evapotranspiration Equation. *Journal of Irrigation and Drainage Engineering* 129 (1): 53–63. https://doi.org/10.1061/(ASCE)0733-9437(2003)129:1(53).
Harris, Lucas B., Stacy A. Drury, Calvin A. Farris, and Alan H. Taylor. 2021. Prescribed Fire and Fire Suppression Operations Influence Wildfire Severity under Severe Weather in Lassen Volcanic National Park, California, USA. *International Journal of Wildland Fire* 30 (7): 536–551. https://doi.org/10.1071/WF20163.
Harris, Lucas, and Alan H. Taylor. 2017. Previous Burns and Topography Limit and Reinforce Fire Severity in a Large Wildfire. *Ecosphere* 8 (11). https://doi.org/10.1002/ecs2.2019.
Haugo, Ryan D., Bryce S. Kellogg, C. Alina Cansler, Crystal A. Kolden, Kerry B. Kemp, James C. Robertson, Kerry L. Metlen, Nicole M. Vaillant, and Christina M. Restaino. 2019. The Missing Fire: Quantifying Human Exclusion of Wildfire in Pacific Northwest Forests, USA. *Ecosphere* 10 (4) : e02702. https://doi.org/10.1002/ecs2.2702.
Holland, Timothy G., Samuel G. Evans, Jonathan W. Long, Charles Maxwell, Robert M. Scheller, and Matthew D. Potts. 2022. The Management Costs of Alternative Forest Management Strategies in the Lake Tahoe Basin. *Ecology and Society* 27 (4). https://doi.org/10.5751/ES-13481-270443.
Howe, Alexander A., Sean A. Parks, Brian J. Harvey, Saba J. Saberi, James A. Lutz, and Larissa L. Yocom. 2022. Comparing Sentinel-2 and Landsat 8 for Burn Severity Mapping in Western North America. *Remote Sensing* 14 (20): 5249. https://doi.org/10.3390/rs14205249.
Huang, Sha, Lina Tang, Joseph P. Hupy, Yang Wang, and Guofan Shao. 2021. A Commentary Review on the Use of Normalized Difference Vegetation Index (NDVI) in the Era of Popular Remote Sensing. *Journal of Forestry Research* 32 (1): 1–6. https://doi.org/10.1007/s11676-020-01155-1.
Hudak, Andrew T., Ian Rickert, Penelope Morgan, Eva Strand, Sarah A. Lewis, Peter R. Robichaud, Chad Hoffman, and Zachary A. Holden. 2011. *Review of Fuel Treatment Effectiveness in Forests and Rangelands and a Case Study from the 2007 Megafires in Central, Idaho, USA*. RMRS-GTR-252. Ft. Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. https://doi.org/10.2737/RMRS-GTR-252.
IFTDSS. 2021. Interagency Fuel Treatment Decision Support System. *Interagency fuel treatment decision support system*. 2021. https://iftdss.firenet.gov.
Kalies, Elizabeth L., and Larissa L. Yocom Kent. 2016. Tamm Review: Are Fuel Treatments Effective at Achieving Ecological and Social Objectives? A Systematic Review. *Forest Ecology and Management* 375 (September):84–95. https://doi.org/10.1016/j.foreco.2016.05.021.
Kane, Jeffrey M. 2021. Stand Conditions Alter Seasonal Microclimate and Dead Fuel Moisture in a Northwestern California Oak Woodland. *Agricultural and Forest Meteorology* 308–309 (October) : 108602. https://doi.org/10.1016/j.agrformet.2021.108602.
Kent, Yocom, L. Larissa, Kristen L. Shive, Barbara A. Strom, Carolyn H. Sieg, Molly E. Hunter, Camille S. Stevens-Rumann, and Peter Z. Fulé. 2015. Interactions of Fuel Treatments, Wildfire Severity, and Carbon Dynamics in Dry Conifer Forests. *Forest Ecology and Management* 349 (August): 66–72. https://doi.org/10.1016/j.foreco.2015.04.004.
Key, Carl H, and Nathan C Benson. 2006. *Landscape Assessment (LA)*. 55.
Knapp, Eric E., Jamie M. Lydersen, Malcolm P. North, and Brandon M. Collins. 2017. Efficacy of Variable Density Thinning and Prescribed Fire for Restoring Forest Heterogeneity to Mixed-Conifer Forest in the Central Sierra Nevada, CA. *Forest Ecology and Management* 406 (December): 228–241. https://doi.org/10.1016/j.foreco.2017.08.028.
Kuhn, Max. 2008. Building Predictive Models in R Using the Caret Package. *Journal of Statistical Software* 28 (November):1–26. https://doi.org/10.18637/jss.v028.i05.
Larson, Andrew J., R. Travis Belote, C. Alina Cansler, Sean A. Parks, and Matthew S. Dietz. 2013. Latent Resilience in Ponderosa Pine Forest: Effects of Resumed Frequent Fire. *Ecological Applications* 23 (6): 1243–1249. https://doi.org/10.1890/13-0066.1.
Lee, Kangsan, Willem J. D. Van Leeuwen, Jeffrey K. Gillan, and Donald A. Falk. 2024. Examining the Impacts of Pre-Fire Forest Conditions on Burn Severity Using Multiple Remote Sensing Platforms. *Remote Sensing* 16 (10): 1803. https://doi.org/10.3390/rs16101803.
Lin, Di., Vincenzo Giannico, Raffaele Lafortezza, Giovanni Sanesi, and Mario Elia. 2024. Use of Airborne LiDAR to Predict Fine Dead Fuel Load in Mediterranean Forest Stands of Southern Europe. *Fire Ecology* 20 (1): 58. https://doi.org/10.1186/s42408-024-00287-7.
Loudermilk, E. L., J. K. Hiers, J. J. O'Brien, R. J. Mitchell, A. Singhania, J. C. Fernandez, W. P. Cropper, and K. C. Slatton. 2009. Ground-Based LIDAR: A Novel Approach to Quantify Fine-Scale Fuelbed Characteristics. *International Journal of Wildland Fire* 18 (6): 676–685. https://doi.org/10.1071/WF07138.
Lundberg, Scott M., Gabriel G. Erion, and Su-In Lee. 2019. *Consistent Individualized Feature Attribution for Tree Ensembles*. arXiv. http://arxiv.org/abs/1802.03888.
Lundberg, Scott M, and Su-In Lee. 2017. *A Unified Approach to Interpreting Model Predictions*.
Ma, Siyan, Amy Concilio, Brian Oakley, Malcolm North, and Jiquan Chen. 2010. Spatial Variability in Microclimate in a Mixed-Conifer Forest before and after Thinning and Burning Treatments. *Forest Ecology and Management* 259 (5): 904–915. https://doi.org/10.1016/j.foreco.2009.11.030.
Mantgem, Van, J. Phillip, Jonathan C. B. Nesmith, MaryBeth Keifer, Eric E. Knapp, Alan Flint, and Lorriane Flint. 2013. Climatic Stress Increases Forest Fire Severity across the Western U Nited S ates. *Edited by Josep Penuelas. Ecology Letters* 16 (9): 1151–1156. https://doi.org/10.1111/ele.12151.
Maksymiuk, Szymon, Alicja Gosiewska, and Przemyslaw Biecek. 2021. *Landscape of R Packages for eXplainable Artificial Intelligenc*. arXiv. http://arxiv.org/abs/2009.13248.

McGaughey, Robert J. 2020. *FUSION/LDV: Software for LIDAR Data Analysis and Visualization*. 2020. http://forsys.cfr.washington.edu/software/fusion/FUSION_manual.pdf.

Miller, Carol, and Dean L. Urban. 2000. Modeling the Effects of Fire Management Alternatives on Sierra Nevada Mixed-Conifer Forests. *Ecological Applications* 10 (1): 85–94. https://doi.org/10.2307/2640988.

Moghaddas, Jason J., and Larry Craggs. 2007. A Fuel Treatment Reduces Fire Severity and Increases Suppression Efficiency in a Mixed Conifer Forest. *International Journal of Wildland Fire* 16 (6): 673. https://doi.org/10.1071/WF06066.

Molnar, Christoph. 2023. Interpretable Machine Learning. *A Guide for Making Black Box Models Explainable*. Second. https://christophm.github.io/interpretable-ml-book/index.html.

Murphy, Kate, Tim Rich, and Tim Sexton. 2007. *An Assessment of Fuel Treatment Effects on Fire Behavior, Suppression Effectiveness, and Structure Ignition on the Angora Fire. R5-TP-025*. USDA Forest Service. https://www.tahoelivingwithfire.com/wp-content/uploads/2018/11/murphy_usfs_2007_a.pdf.

Naimi, Babak, Nicholas A. S. Hamm, Thomas A. Groen, Andrew K. Skidmore, Albertus G. Toxopeus, and Sara Alibakhshi. 2019. ELSA: Entropy-Based Local Indicator of Spatial Association. *Spatial Statistics* 29 (March): 66–88. https://doi.org/10.1016/j.spasta.2018.10.001.

North, Malcolm P., Ryan E. Tompkins, Alexis A. Bernal, Brandon M. Collins, Scott L. Stephens, and Robert A. York. 2022. Operational Resilience in Western US Frequent-Fire Forests. *Forest Ecology and Management* 507 (March) : 120004. https://doi.org/10.1016/j.foreco.2021.120004.

ODFW. 2021. *Oregon Hydrography Whole Stream Routes*. 2021. https://nrimp.dfw.state.or.us/DataClearinghouse/default.aspx?p=202&XMLname=1124.xml.

ODSL. 2021. *Statewide Wetlands Inventory*. 2021. https://maps.dsl.state.or.us/swi/.

Parks, Sean A., Lisa M. Holsinger, Kori Blankenship, Gregory K. Dillon, Sara A. Goeking, and Randy Swaty. 2023. Contemporary Wildfires Are More Severe Compared to the Historical Reference Period in Western US Dry Conifer Forests. *Forest Ecology and Management* 544 (September) : 121232. https://doi.org/10.1016/j.foreco.2023.121232.

Parks, Sean A., Lisa M. Holsinger, Carol Miller, and Cara R. Nelson. 2015. Wildland Fire as a Self-Regulating Mechanism: The Role of Previous Burns and Weather in Limiting Fire Progression. *Ecological Applications* 25 (6): 1478–1492. https://doi.org/10.1890/14-1430.1.

Parks, Sean A., Lisa M. Holsinger, Matthew H. Panunto, W. Matt Jolly, Solomon Z. Dobrowski, and Gregory K. Dillon. 2018. High-Severity Fire: Evaluating Its Key Drivers and Mapping Its Probability across Western US Forests. *Environmental Research Letters* 13 (4) : 044037. https://doi.org/10.1088/1748-9326/aab791.

Parks, Sean A., Lisa M. Holsinger, Morgan A. Voss, Rachel A. Loehman, and Nathaniel P. Robinson. 2021. Correction: Parks et al. Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential. Remote Sens. 2018, 10, 879. *Remote Sensing* 13 (22): 4580. https://doi.org/10.3390/rs13224580.

Parks, Sean A., Carol Miller, Cara R. Nelson, and Zachary A. Holden. 2014a. Previous Fires Moderate Burn Severity of Subsequent Wildland Fires in Two Large Western US Wilderness Areas. *Ecosystems* 17 (29–42): 29–42. https://doi.org/10.1007/s10021-013-9704-x.

Parks, Sean, Gregory Dillon, and Carol Miller. 2014b. A New Metric for Quantifying Burn Severity: The Relativized Burn Ratio. *Remote Sensing* 6 (3): 1827–1844. https://doi.org/10.3390/rs6031827.

Picchio, Rodolfo, Piotr S. Mederski, and Farzam Tavankar. 2020. How and How Much, Do Harvesting Activities Affect Forest Soil, Regeneration and Stands? *Current Forestry Reports* 6 (2): 115–128. https://doi.org/10.1007/s40725-020-00113-8.

Povak, Nicholas A., Van R. Kane, Brandon M. Collins, Jamie M. Lydersen, and Jonathan T. Kane. 2020. Multi-Scaled Drivers of Severity Patterns Vary across Land Ownerships for the 2013 Rim Fire, California. *Landscape Ecology* 35 (2): 293–318. https://doi.org/10.1007/s10980-019-00947-z.

Prichard, Susan J., Paul F. Hessburg, R. Keala Hagmann, Nicholas A. Povak, Solomon Z. Dobrowski, Matthew D. Hurteau, Van R. Kane, et al. 2021. Adapting Western North American Forests to Climate Change and Wildfires: 10 Common Questions. *Ecological Applications* 31 (8) : e02433. https://doi.org/10.1002/eap.2433.

Prichard, Susan J., and Maureen C. Kennedy. 2014. Fuel Treatments and Landform Modify Landscape Patterns of Burn Severity in an Extreme Fire Event. *Ecological Applications* 24 (3): 571–590. https://doi.org/10.1890/13-0343.1.

Prichard, Susan J., Nicholas A. Povak, Maureen C. Kennedy, and David W. Peterson. 2020. Fuel Treatment Effectiveness in the Context of Landform, Vegetation, and Large, Wind-driven Wildfires. *Ecological Applications* 30 (5) : e02104. https://doi.org/10.1002/eap.2104.

Prichard, Susan J., Camille S. Stevens-Rumann, and Paul F. Hessburg. 2017. Tamm Review: Shifting Global Fire Regimes: Lessons from Reburns and Research Needs. *Forest Ecology and Management* 396 (July): 217–233. https://doi.org/10.1016/j.foreco.2017.03.035.

Reinhardt, Elizabeth D., Robert E. Keane, David E. Calkin, and Jack D. Cohen. 2008. Objectives and Considerations for Wildland Fuel Treatment in Forested Ecosystems of the Interior Western United States. *Forest Ecology and Management* 256 (12): 1997–2006. https://doi.org/10.1016/j.foreco.2008.09.016.

Ritchie, Martin W., Carl N. Skinner, and Todd A. Hamilton. 2007. Probability of Tree Survival after Wildfire in an Interior Pine Forest of Northern California: Effects of Thinning and Prescribed Fire. *Forest Ecology and Management* 247 (1–3): 200–208. https://doi.org/10.1016/j.foreco.2007.04.044.

Rodman, Kyle C., Kimberley T. Davis, Sean A. Parks, Teresa B. Chapman, Jonathan D. Coop, Jose M. Iniguez, John P. Roccaforte, et al. 2023. Refuge-yeah or Refuge-nah? Predicting Locations of Forest Resistance and Recruitment in a Fiery World. *Global Change Biology* 29 (24): 7029–7050. https://doi.org/10.1111/gcb.16939.

Rogers, Gene, Wendel Hann, Charley Martin, Tessa Nicolette, and Morgan Pence. 2008. *Fuel Treatment Effects on Fire Behavior, Suppression Effectiveness, and Structure Ignition Grass Valley Fire*. R5-TP-026a. https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fsbdev3_045471.pdf.

RStudio Team. 2020. *RStudio*. 2020. http://www.rstudio.com.

Ryan, Kevin C., and Tonja S. Opperman. 2013. LANDFIRE – A National Vegetation/Fuels Data Base for Use in Fuels Treatment, Restoration, and Suppression Planning. *Forest Ecology and Management* 294 (April): 208–216. https://doi.org/10.1016/j.foreco.2012.11.003.

Safford, H. D., J. T. Stevens, K. Merriam, M. D. Meyer, and A. M. Latimer. 2012. Fuel Treatment Effectiveness in California Yellow Pine and Mixed Conifer Forests. *Forest Ecology and Management* 274 (June): 17–28. https://doi.org/10.1016/j.foreco.2012.02.013.

Safford, Hugh D., David A. Schmidt, and Chris H. Carlson. 2009. Effects of Fuel Treatments on Fire Severity in an Area of Wildland-Urban Interface, Angora Fire, Lake Tahoe Basin, California. *Forest Ecology and Management* 258 (5): 773–787. https://doi.org/10.1016/j.foreco.2009.05.024.

Schoennagel, Tania, Thomas T. Veblen, José F. Negron, and Jeremy M. Smith. 2012. Effects of Mountain Pine Beetle on Fuels and Expected Fire Behavior in Lodgepole Pine Forests, Colorado, USA. Edited by Han Y. H. Chen. *PLoS ONE* 7 (1): e30002. https://doi.org/10.1371/journal.pone.0030002.

Stephenson, Nathan. 1998. Actual Evapotranspiration and Deficit: Biologically Meaningful Correlates of Vegetation Distribution across Spatial Scales. *Journal of Biogeography* 25 (5): 855–870. https://doi.org/10.1046/j.1365-2699.1998.00233.x.

Stevens, Jens T., Matthew M. Kling, Dylan W. Schwilk, J. Morgan Varner, and Jeffrey M. Kane. 2020. Biogeography of Fire Regimes in Western U.S. Conifer Forests: A Trait-based Approach. Edited by Thomas Gillespie. *Global Ecology and Biogeography* 29 (5): 944–55. https://doi.org/10.1111/geb.13079.

Stone, Katharine R., David S. Pilliod, Kathleen A. Dwire, Charles C. Rhoades, Sherry P. Wollrab, and Michael K. Young. 2010. Fuel Reduction Management Practices in Riparian Areas of the Western USA. *Environmental Management* 46 (1): 91–100. https://doi.org/10.1007/s00267-010-9501-7.

Tortorelli, Claire M., Andrew M. Latimer, and Derek J. N. Young. 2024. Moderating Effects of Past Wildfire on Reburn Severity Depend on Climate and Initial Severity in Western U S Forests. *Ecological Applications* 34 (7) : e3023. https://doi.org/10.1002/eap.3023.

Urza, Alexandra K., Brice B. Hanberry, and Theresa B. Jain. 2023. Landscape-Scale Fuel Treatment Effectiveness: Lessons Learned from Wildland Fire Case Studies in Forests of the Western United States and Great Lakes Region. *Fire Ecology* 19 (1): 1. https://doi.org/10.1186/s42408-022-00159-y.

USDA. 2021. *NIROPS*. 2021. https://fsapps.nwcg.gov/nirops/pages/about.

USGS LiDAR. 2021. *OR_SouthwestCentralSycan_2021_B21*. 2021. https://rockyweb.usgs.gov/vdelivery/Datasets/Staged/Elevation/LPC/Projects/OR_SouthwestCentralSycan_2021_B21.
Vaillant, Nicole M., Jo Ann Fites-Kaufman, and Scott L. Stephens. 2006. Effectiveness of Prescribed Fire as a Fuel Treatment in Californian Coniferous Forests. *International Journal of Wildland Fire* 18 (2): 165. https://doi.org/10.1071/WF06065.
Van Kane, R., C. Alina Cansler, Nicholas A. Povak, Jonathan T. Kane, Robert J. McGaughey, James A. Lutz, Derek J. Churchill, and Malcolm P. North. 2015a. Mixed Severity Fire Effects within the Rim Fire: Relative Importance of Local Climate, Fire Weather, Topography, and Forest Structure. *Forest Ecology and Management* 358 (December): 62–79. https://doi.org/10.1016/j.foreco.2015.09.001.
Van Kane, R., James A. Lutz, C. Alina Cansler, Nicholas A. Povak, Derek J. Churchill, Douglas F. Smith, Jonathan T. Kane, and Malcolm P. North. 2015b. Water Balance and Topography Predict Fire and Forest Structure Patterns. *Forest Ecology and Management* 338 (February): 1–13. https://doi.org/10.1016/j.foreco.2014.10.038.
Wallace Covington, William. 2000. Helping Western Forests Heal. *Nature* 408 (6809): 135–36. https://doi.org/10.1038/35041641.
Wang, Tongli, Hamann Andreas, Spittlehouse Dave, and Carroll Carlos. 2023. *ClimateNA*. 2023. https://climatena.ca.
Wang, Tongli, Andreas Hamann, Dave Spittlehouse, and Carlos Carroll. 2016. Locally Downscaled and Spatially Customizable Climate Data for Historical and Future Periods for North America. *Edited by Inés Álvarez. PLOS ONE* 11 (6) : e0156720. https://doi.org/10.1371/journal.pone.0156720.
Whitehead, Roger J. 2008. *Effect of Commercial Thinning on Within-Stand Microclimate and Fine Fuel Moisture Conditions in a Mature Lodgepole Pine Stand in Southeastern British Columbia*. Victoria, B.C.: Canadian Wood Fibre Centre.
Wright, Marvin N., and Andreas Ziegler. 2017. Ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R." *Journal of Statistical Software* 77 (March):1–17. https://doi.org/10.18637/jss.v077.i01.
Yang, Jilei. 2022. *Fast TreeSHAP: Accelerating SHAP Value Computation for Trees*. arXiv. http://arxiv.org/abs/2109.09847.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.