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Prescribed fire, managed burning, and previous wildfires reduce the severity of a southwestern US gigafire

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ABSTRACT

In many parts of the western United States, wildfires are becoming larger and more severe, threatening the persistence of forest ecosystems. Understanding the ways in which management activities such as prescribed fire and managed wildfire can mitigate fire severity is essential for developing effective forest conservation strategies. We evaluated the effects of previous fuels reduction treatments, including prescribed fire and wildfire managed for resource benefit, and other wildfires on the burn severity of the 2022 Black Fire in southwestern New Mexico, USA. The Black Fire burned over 131,000 ha in mostly low- to middle-elevation ponderosa pine and mixed conifer forests, but burned only ~4 % at high-severity, leading us to question what factors led to this fire burning in such an ecologically beneficial way and aligning with the natural range of variation in terms of burn severity for this region. In a landscape scale analysis, we found that areas that experienced more prescribed fire, wildfire managed for resource benefit, and wildfire (hereafter 'treated area') best explained patterns of burn severity in the 2022 Black Fire, outweighing the importance of fire weather and vegetation factors. A fully treated area experienced 51 % less high severity fire than an untreated area, on average, across the Black fire landscape. In a fine-scale fire progression analysis, we found that high-severity fire that encountered a previously treated area experienced a 21–55 % decrease in burn severity within 250 m of the treated area boundary. In sum, we found that previous treatments and wildfires that occurred within the Black fire perimeter were highly effective in influencing patterns of burn severity and appear to be the reason why the Black fire was restorative, and not catastrophic. Our results suggest that the severity of other large fire events can be reduced by increasing the pace and scale of treatment activities within low- and middle-elevation pine and mixed conifer forest landscapes.

1. Introduction

Wildfire is an important natural disturbance globally (Bowman et al., 2010). For millions of years, fire has shaped the distribution and evolution of life on earth (Keeley and Pausas, 2022). In recent decades, components of the fire regime (e.g., the timing, size, or severity) have begun to change rapidly in some systems. For example, in western United States forests, the annual area burned at high severity has increased by eightfold since 1985 (Parks and Abatzoglou, 2020) and increasing high-severity patch size has been homogenizing forests (Singleton et al., 2021; Cova et al., 2023). The cause of changing fire regimes is context-specific and therefore depends on the system in question (Jones et al., 2022a). But the primary drivers typically include a combination of warming and drying climate conditions (Abatzoglou and Williams, 2016; Juang et al., 2022) as well as past and ongoing fire exclusion resulting in homogenous conditions with unnaturally large accumulations of fuel (Koontz et al., 2020; Francis et al., 2023; Kreider et al., 2024).

In historically fuel-limited systems, such as seasonally dry forests, land managers can produce more desirable fire behavior by reducing fuel loads in forests through restoration activities including prescribed burning, mechanical thinning, and unplanned wildfires managed for resource benefit (Agee and Skinner, 2005). Most fires in these systems burn under a range of moderate weather conditions and, under these conditions, fuels reduction activities appear to change fire behaviors within treatment boundaries; but uncertainty exists about their

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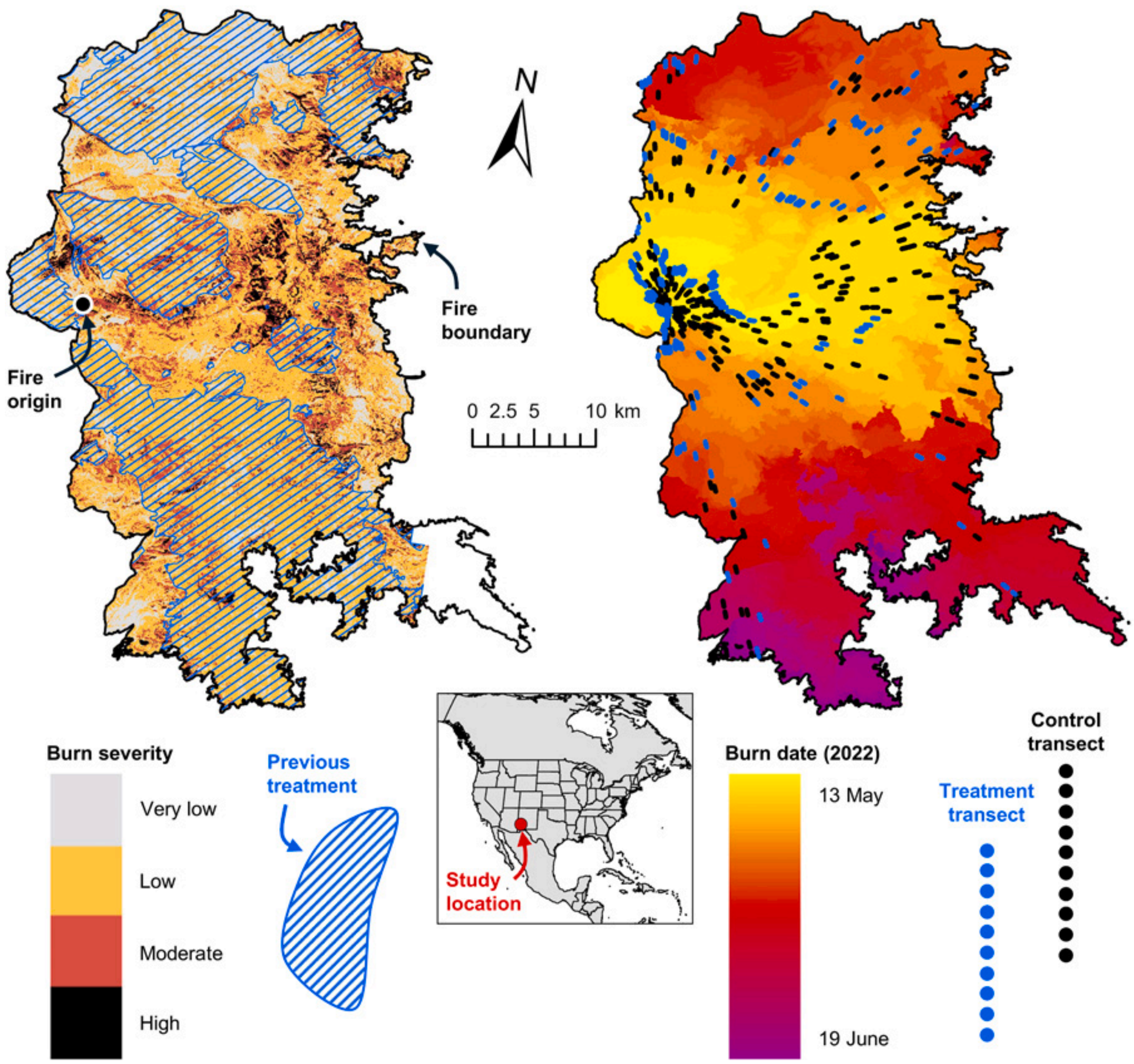

Fig. 1. Patterns of burn severity, previous treatment, and burn progression in the 2022 Black Fire, which burned in southwestern New Mexico, USA.

influence beyond the treatment boundary and under the most extreme weather conditions (McKinney et al., 2022). For example, strong ambient winds as well as fire-induced internal winds that are produced during many large fire events are thought to override potential effects of forest fuels reduction (Coen et al., 2018). If fuels reduction does not alter fire severity, then there would be little justification for land management agencies to invest billions of dollars annually in management actions that are ineffective.

A great deal of research has been conducted on fuels treatment effectiveness (Prichard et al., 2020). Fuels treatments are predicted to be effective from first principles (i.e., theoretical models based on physics) (Agee, 1993; Agee and Skinner, 2005), and numerous empirically-informed simulation studies have been conducted demonstrating expected reductions in fire severity resulting from fuels reduction (Ager et al., 2010; Collins et al., 2011; Hurteau, 2017; Jones et al., 2022b; Remy et al., 2024). Empirical evidence from small-scale and/or distributed controlled forest experiments and observational studies also exist with similar conclusions (Stephens and Moghaddas, 2005; Stephens et al., 2009; North and Hurteau, 2011). Considerably less evidence exists showing the effect of fuels reduction in reducing burn severity in real, large landscape fires (Johnson et al., 2019), in part because the implementation of landscape-scale fuels reduction treatments is limited by various constraints (Collins et al., 2010), which does little to combat the perception that fuels reduction treatments are ineffective to influence real fire behavior during the most severe weather conditions.

One of the challenges with adequately evaluating the effects of fuels reduction on fire severity is a scale-dependency issue. As the spatial extent of a fire increases, the proportion treated must increase to cause a reduction in fire severity (McKinney et al., 2022). Unfortunately, in many landscapes, treatment sizes are generally quite small relative to the area burned by wildfire (North et al., 2021). In untreated areas, climate-driven mortality causing live tree biomass to become dead fuels and increasing temperature and atmospheric dryness are making these fuels more available to burn (Abatzoglou and Williams, 2016; Goodwin et al., 2020, 2021; Juang et al., 2022). When substantial fuel is available for combustion, wildfires can generate their own weather because of significant energy release (Stephens et al., 2018, 2022). In these types of conditions, small, treated areas are unlikely to modify fire behavior significantly. This scale issue excepted, the evidence that does exist for fuels reduction efficacy is promising (Prichard et al., 2010; Lydersen et al., 2017), but more empirical evidence regarding how landscape-scale fuels treatments influence real fire behavior and post-fire effects is needed.

Here, we evaluated the association between previously implemented fuels reduction and forest restoration activities (including prescribed fire and managed wildfire), previous wildland fire entries, and fire severity in the 2022 Black Fire that occurred in southwestern New Mexico. Over

54 % of the > 131,000 ha burned area had been previously treated, providing an ideal opportunity to examine the influence of extensive past treatments on fire behavior in a 'gigafire' (Linley et al., 2022). Our central question was: "How did previous landscape-scale fuels treatments influence burn severity patterns in a large fire event?" To answer this question, we conducted two analyses examining the influence of previous treatments on fire effects at different scales. First, we conducted a landscape-scale random forest analysis that examined the relative importance of a suite of predictor variables on severe fire extent, including previous treatments, vegetation lifeform, and fire weather. Second, we conducted a fine-scale fire progression analysis, examining the way fire severity changed as it progressed along transects that eventually intersected previous treatments, and compared those observations to fire behavior along control transects (those that did not intersect previous treatments). Together, these analyses provide a multi-scale view of the effects of extensive fuels reduction treatments on fire severity in a large wildfire event.

2. Methods

2.1. Study area

Our study was located on the Gila National Forest in southwestern New Mexico, USA, which has a rich history of prescribed fire and managed fire used for resource benefit (Hunter et al., 2011). The vegetation within the fire perimeter was primarily ponderosa pine (*Pinus ponderosa*) forest, woodlands, and savannahs (~36 %) and pinyon-juniper woodland (~32 %) composed of pinyon pine (*Pinus edulis*) and various species in the genus *Juniperus* spp. including one-seed (*J. monosperma*) and alligator (*J. deppeana*). Mixed-conifer forest containing Douglas-fir (*Pseudotsuga menziesii*) and white fir (*Abies concolor*) with a suite of other species was also present (~14 %). Gambel oak (*Quercus gambelii*), shrub live oak (*Q. turbinella*), and gray oak (*Q. grisea*) was also commonly associated with some conifer assemblages, especially ponderosa pines.

The Black Fire ignited on 13 May 2022 along Forest Road 150 approximately 54 km northeast of Silver City, NM, and continued to expand through mid-June. Most of the fire progression occurred between 13 May and 14 June with the largest single-day progressions occurring on 16 May (15,123 ha) and 17 May (8659 ha). At the time of the Black Fire ignition, mean wind speeds were the highest and average relative humidity was the lowest that had been observed in at least the previous decade (Beaverhead Weather Station), resulting in red flag fire danger warnings. The Black Fire eventually burned 131,577 ha of forestland, making it the second largest fire in state history, only surpassed by the 2022 Hermit's Peak/Calf Canyon Fire that burned 138,188 ha. Although large, only ~4 % of the total area in the Black Fire perimeter burned at high severity (>75 % canopy mortality). Twenty-one percent of the area within the perimeter either was unchanged or burned at very low severity (0–5 % canopy mortality); 61 % burned at low severity (5–25 % canopy mortality), and 14 % burned at moderate severity (25–75 % canopy mortality) (Fig. 1).

2.2. Geospatial data

We produced two primary geospatial layers for the 2022 Black Fire that were used in our analyses: a 4-class burn severity raster product and a shapefile that merged all areas that had previously received treatments and/or experienced wildfires. We developed the 4-class burn severity raster via a process currently used by United States Forest Service wildland fire personnel based on techniques developed by Miller and Thode (2007) and the Monitoring Trends in Burn Severity program (MTBS) (Eidenshink et al., 2007). Briefly, we acquired pre- and post-fire images using Landsat Collection 2 in Google Earth Engine (Gorelick et al., 2017) (pre-fire image: LC08_034037_20210907; post-fire image: LC09_034037_20230905) with a spatial resolution of 30 m × 30 m. We processed the images using the relativized dNBR (RdNBR) methodology, which removes the biasing effect of the pre-fire condition (Miller et al., 2009). To create a four-class fire severity raster, we clipped the resulting RdNBR layer to three broad vegetation types (forest, pinyon/juniper, and riparian/grassland) and, within each vegetation type, independently calibrated the RdNBR to match observed fire severity (Miller and Thode, 2007; Miller et al., 2009). Calibration thresholds were identified in collaboration form Gila National Forest wildland fire staff (M. Cornwell and J. Kirker, *personal communication*). Rapid Assessment of Vegetation Condition after Wildfire (RAVG) and Burned Area Emergency Response (BAER) geospatial data was also used as auxiliary data to inform calibration and corroboration of observed fire severity from local wildland fire professionals.

We identified previous prescribed fire, wildland fire for resource benefit, and mechanical treatments within the 2022 Black Fire perimeter using the United States Forest Service's Forest Activity Tracking

Table 1
Geospatial predictor variables included in the landscape-scale random forest analysis.

Variable	Description	Units	Resolution	Source
Previous treatments	Areas that experienced prescribed fire or wildfire managed for resource benefit between 2000 and 2021.	ha	N/A	USDA Forest Service Southwestern Region
Actual evapo-transpiration	Average monthly combination of transpiration from vegetation and evaporation from soil surfaces.	mm	1 km	USGS Data Portal
Fuel temperature	Maximum daily fuel temperature reading embedded within a standard pine dowel, fully exposed to sunlight, above a representative fuel bed.	°F	Attributed to daily burn progression polygon	Beaverhead Remote Automatic Weather Station (RAWS)
Relative humidity	Maximum daily percent ratio of the actual amount of water vapor in the air to the amount of water vapor required for saturation at existing temperature.	%	Attributed to daily burn progression polygon	Beaverhead Remote Automatic Weather Station (RAWS)
Air temperature	Maximum daily temperature measured in the ambient air surrounding weather station instrumentation	°F	Attributed to daily burn progression polygon	Beaverhead Remote Automatic Weather Station (RAWS)
Wind gust	Maximum daily wind speed measured at a height of six feet above the ground	mph	Attributed to daily burn progression polygon	Beaverhead Remote Automatic Weather Station (RAWS)
Climatic water deficit	Average monthly climatic water deficit derived using a one-dimensional soil water balance model	mm	0.1 DD	TerraClimate
Drought index	The average monthly Palmer Drought Severity Index, which combines temperature and precipitation data to estimate relative dryness	unitless	0.01 DD	TerraClimate
Hardwood forest	Proportion of area dominated by hardwood forest defined by existing vegetation type physiognomy	Proportion	30 m	LANDFIRE
Conifer forest	Proportion of area dominated by conifer forest defined by existing vegetation type physiognomy	Proportion	30 m	LANDFIRE
Shrubland	Proportion of area dominated by shrubland defined by existing vegetation type physiognomy	Proportion	30 m	LANDFIRE
Grassland	Proportion of area dominated by grassland defined by existing vegetation type physiognomy	Proportion	30 m	LANDFIRE

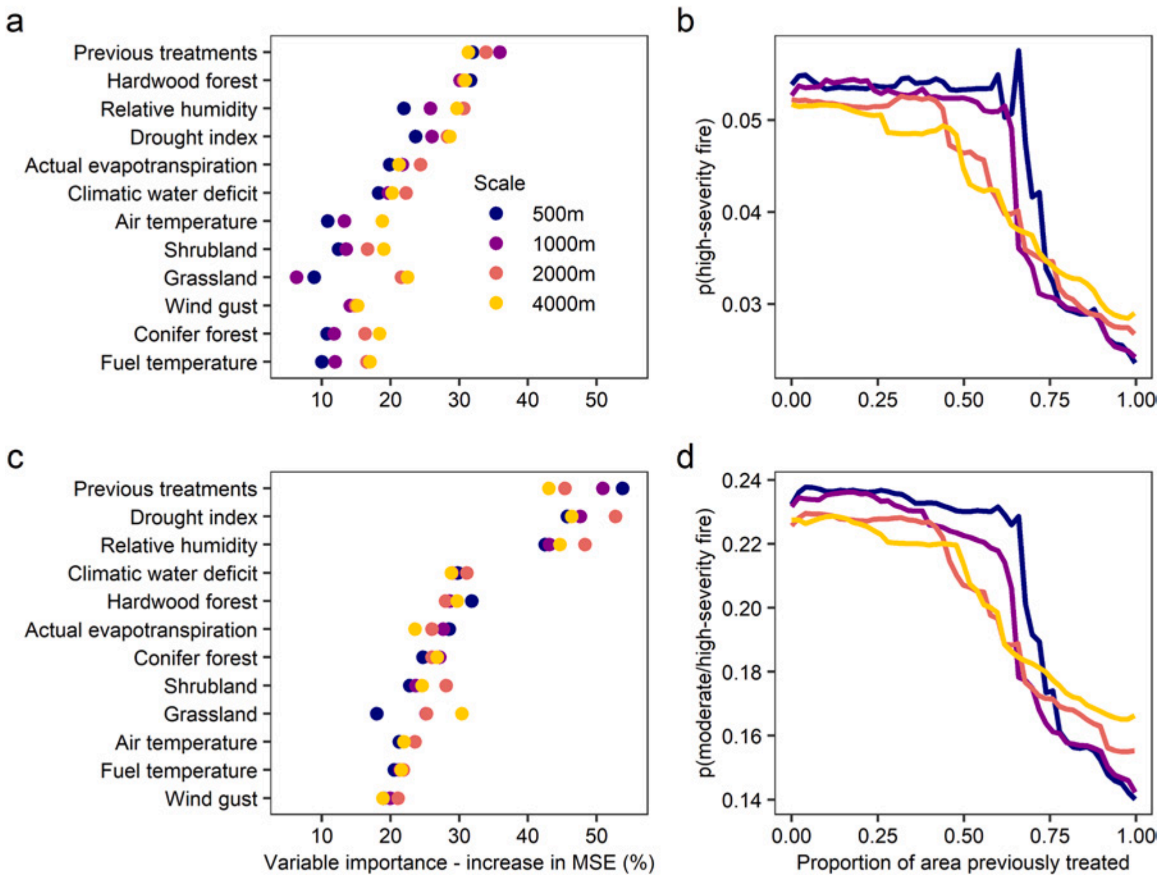

Fig. 2. Results from the landscape-scale random forest analysis evaluating drivers of burn severity patterns. (a) Variable importance plot for the analysis using high severity fire as the response variable. (b) Partial dependence plot showing the functional relationship between previously treated area and the probability of high severity fire. (c) Variable importance plot for the analysis using moderate-to-high severity fire as the response variable. (d) Partial dependence plot showing the functional relationship between previously treated area and the probability of moderate-to-high severity fire.

System (FACTS) geospatial treatment database of record. Previous wildland fire perimeters were identified using the United States Forest Service's institutional wildland fire perimeter geospatial layer. All data is exclusive to National Forest System lands and are publicly available (https://data.fs.usda.gov/geodata/edw/datasets.php). Both the FACTS and the wildland fire datasets were filtered to include years 2000 through 2021 due to longevity of wildland fire treatments and data consistency (reporting in FACTS was inconsistent before the year 2000). Note that FACTS data only applies to National Forest System lands, so we did not analyze burn severity or treatment impacts in a small section in the southeastern part of the Black Fire that occurred on private land (Fig. 1).

The FACTS database was further filtered by "Activity Code" to identify treatments that physically impacted fuels and/or forest structure (https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fseprd539041.pdf). Activity Code for mechanical treatments was filtered with a range between and including 4101 and 4242; these codes include all treatments that remove trees from the landscape. Fire treatments were filtered using Activity Codes 1111, 1113, 1117, and 1119 (1111 and 1113 are prescribed fire, 1117 and 1119 are wildfire for resource benefit). In total, prescribed fire treatments covered 19,407 ha, mechanical treatment covered 0 ha, and wildfire (both unmanaged fire and wildfire managed for resource benefit) covered 69,179 ha. Because of the spatial overlap of treatments, the sum of treatment acres exceeds the actual total treatment footprint. Accounting for overlap, the total treatment footprint was 71,690 ha of the 131,577 ha Black Fire footprint (54.5 %). We grouped prescribed, managed, and unmanaged fire into a single category for our analysis. Our view is it may not matter physically or ecologically which type of fire burned; it all represents fire on the same topography, through the same fuels, under similar conditions.

2.3. Landscape-scale analysis

We conducted an analysis using random forest (Breiman, 2001) to evaluate the landscape-scale drivers of burn severity in the 2022 Black Fire at multiple spatial scales. Constrained to the perimeter of the Black Fire, we generated 1000 points with random x-y coordinates. Then, we generated buffered circles surrounding those 1000 points with varying radii: 500 m, 1000 m, 2000 m, and 4000 m. Within each buffered circle at each scale, we summarized a suite of response and predictor variables. We computed two response variables: the proportion of each circle that burned at high severity, and the proportion of each circle that burned at moderate-or-high severity. Then, in addition to the previously treated area, we summarized 11 vegetation and fire-weather variables to include in the random forest model as predictors. These variables included actual evapotranspiration, fuel temperature, relative humidity, maximum air temperature, maximum wind gust, climatic water deficit, drought index, as well as the proportion of each circle containing conifer forest, hardwood forest, grassland, and shrubland (Table 1).

We fitted one model containing all 12 predictor variables at each spatial scale and for each of the two response variables, and compared the relative importance of each variable by computing the increase in the percent mean squared error when the model was re-fitted without including the focal variable. Then, we examined partial dependence plots of a subset of variables with high relative importance to interpret the form and direction of the relationship between the predictor and the response variables. We conducted the random forest model fitting using

Table 2
Model performance metrics from the landscape-scale random forest analysis.

		Scale			
Response variable	Metric	500 m	1000 m	2000 m	4000 m
High-severity fire	*Variance explained (R^2)*	0.606	0.698	0.812	0.915
	Mean out-of-bag error	0.0019	0.0012	0.0006	0.0002
Moderate/high-severity fire	*Variance explained (R^2)*	0.656	0.734	0.824	0.903
	Mean out-of-bag error	0.0105	0.0070	0.0039	0.0017

the R package 'randomForest' version 4.7–1.1 (Liaw and Wiener, 2002) and examined partial dependence plots using the R package 'pdp' version 0.8.1 (Greenwell, 2022).

2.4. Fine-scale progression analysis

To understand how fire severity changes when an advancing fire encounters a previously treated area, we conducted a fine-scale fire progression analysis. We generated radial lines from the fire origin to the fire perimeter separated by 1° using ArcGIS Pro (Lydersen et al., 2017). Along each line, we randomly generated 120 transects beginning in each of the three burn severity classes (120 in low, 120 in moderate, and 120 in high). In each burn severity class, we generated 60 'treatment' and 60 'control' transects. Treatment transects consisted of 10 sequential points separated by 50 m occurring in the direction of fire spread, with the first 5 points occurring outside of a treated area and the second 5 points occurring inside of a treated area. Control transects were similar, consisting of 10 sequential points occurring in the direction of fire spread, except they never intersected a previously treated area. We visually assessed each transect to ensure that it occurred along the direction of fire spread as estimated from fire progression maps provided by the USDA Forest Service Southwestern Region (Fig. 1).

We developed a generalized linear mixed-effects model to analyze the fire progression dataset. The model was of the form:

$$y_{ik} = \beta_0 + \beta_1 Type_{ik} + \beta_2 Treated_{ik} + \tau_k$$

where y_{ik} was the value of the Poisson-distributed response variable at a given point i along transect k. We selected a Poisson distribution with a log-link because the response variable, burn severity, was measured as RdNBR that took on discrete integer values from 0 to 842; β_0 was the model intercept; β_1 was the coefficient for the variable $Type_{ik}$, which took on a value of 1 for all points along treatment transects, and a value of 0 for all points along control transects; β_2 was the coefficient for the variable $Treated_{ik}$, which took a value of 1 for points along treatment transects that actually occurred within a treatment (i.e., the second 5 points along the transect) and 0 for all other points in both treatment and control transects; finally, τ_k was a random effect for transect to account for spatial dependence. We fitted separate models for each burn severity class using the R package 'lme4' version 1.1–35.5 (Bates et al. 2015) and used package 'segmented' version 2.1–0 (Muggeo, 2024) to identify possible break points in partial dependence plots.

3. Results

In the landscape-scale analysis, previously treated area was consistently a top predictor across the four spatial scales examined. Previously treated areas were the most important predictor of high-severity fire across all scales (Fig. 2a). Partial dependence plots indicated that the predicted proportion of area burned at high-severity decreased by an average of 51 % (from 0.053 to 0.026) as the proportion of an area treated increased from 0 to 1, with strong non-linearity in this effect (Fig. 2b). Break point analysis suggested that the strongest decreases in fire severity occurred once the treated proportion reached a value of 0.57, 0.50, 0.38, and 0.42 for the 500 m, 1000 m, 2000 m, and 4000 m scales, respectively (Fig. 2b). The random forest models fit relatively well to the data, with the variance explained (R^2) ranging from 0.606 to 0.915 depending on the severity and scale examined, with R^2 generally increasing at larger spatial scales (Table 2).

When predicting the proportion burned at either moderate or high-severity, previous treated area was the most important predictor at the 500 m and 1000 m spatial scales, and was the third most important predictor at the 2000 m and 4000 m spatial scales (behind relative humidity and drought index; Fig. 2c). Partial dependence plots indicated that the predicted proportion of area burned at moderate- and high-severity decreased by an average of 35 % (from 0.23 to 0.15) as the proportion of an area treated increased from 0 to 1 (Fig. 2d). As with the high-severity model, non-linearity was apparent, and break point analysis suggested that the strongest decreases in fire severity occurred once the treated proportion reached a value of 0.56, 0.47, 0.35, and 0.39 for the 500 m, 1000 m, 2000 m, and 4000 m scales, respectively (Fig. 2d).

In the fine-scale progression analysis, fire severity decreased significantly when transects encountered previously treated areas, regardless of the initial severity (Fig. 3, Fig. 4). Burn severity tended to be slightly

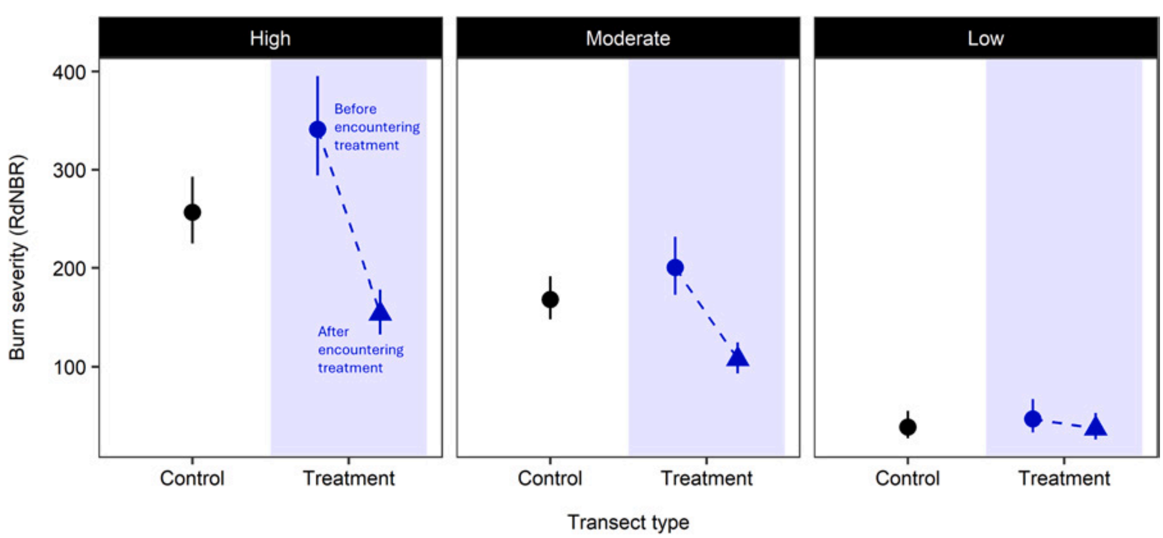

Fig. 3. Predicted burn severity (RdNBR) across treatment and control transects. Each panel shows the results from models where the transects began in different burn severities (high, moderate, and low).

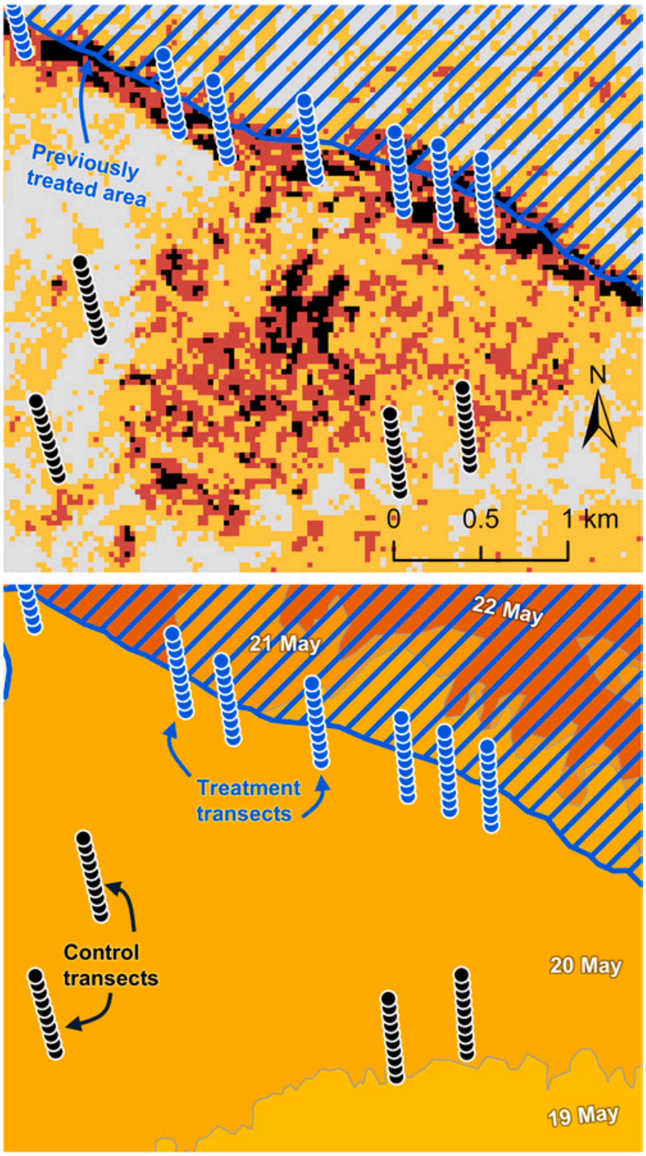

Fig. 4. Example of the fine-scale progression transects, showing treatment transects (blue dots) encountering a previously treated area (blue hatched area). In the top panel, the reduction in burn severity is apparent after the transects intersect with previously treated areas. The bottom panel shows the transects in relation to the burn progression map. The burn severity color gradient in this figure is the same as that shown in Fig. 1.

Table 3
Model coefficients and uncertainty from the fine-scale fire progression analysis. SE = standard error; LCL = lower 95% confidence limit; UCL = upper 95% confidence limit.

	Coefficient	SE	LCL	UCL
High severity				
Intercept	5.547	0.067	5.413	5.682
Transect type	0.284	0.101	0.083	0.486
Treated	−0.796	0.008	−0.812	−0.780
Moderate severity				
Intercept	5.127	0.065	4.997	5.256
Transect type	0.173	0.099	−0.023	0.369
Treated	−0.621	0.009	−0.638	−0.603
Low severity				
Intercept	3.651	0.183	3.290	4.011
Transect type	0.196	0.258	−0.313	0.703
Treated	−0.235	0.007	−0.250	−0.220

higher in treatment transects compared to control transects across all severities (β_1; Table 3). However, within treatment transects, burn severity decreased by 21–55 % when a transect encountered a previously treated area, depending on the initial severity (Table 3). When a transect started in high-severity, mean RdNBR decreased by 55 % (from 395 to 178) once it encountered treatment ($\beta_{2,\ high} = -0.796$, 95 % confidence interval [−0.812, −0.780]). When a transect started in moderate-severity, mean RdNBR decreased by 46 % (from 232 to 125) once it encountered a treatment ($\beta_{2,\ moderate} = -0.621$, [−0.638, −0.603]). Finally, when a transect started in low-severity, mean RdNBR decreased by 21 % (from 67 to 53) once it encountered a treatment ($\beta_{2,\ low} = -0.235$, [−0.250, −0.220]).

4. Discussion

We showed that fire-treated areas – areas experiencing prescribed fire, wildfire managed for resource benefit, and other wildfires – were effective in reducing observed burn severity in a real, large fire event, the 2022 Black Fire, in the southwestern United States. The range of fuel conditions that existed on the landscape prior to the Black Fire, produced by many previous fires, made such a positive outcome possible. At a landscape scale, patterns of both moderate and high severity fire were most strongly controlled by previously treated area, having stronger influence than a suite of fire weather and vegetation predictors. At a fine scale, when the fire front encountered a previously treated area, the observed burn severity decreased, regardless of whether the fire was burning at high, moderate, or low intensity at the time of encounter. As government agencies in the United States continue to invest billions of dollars in an attempt to increase the pace and scale of forest restoration and fuels reduction treatments in vulnerable forests (USDA Forest Service, 2022), our findings provide further support for the effectiveness of such treatments in real, large landscape fire events.

Although relatively rare, other studies have documented effectiveness of fuels reduction and forest restoration in real, large fire events, and our results align with previous findings quite well in dry conifer forest systems. Lydersen et al. (2017) examined the extent to which previous mechanical thinning and prescribed fire prescriptions influenced the severity of the 2013 Rim Fire (104,131 ha) in the central Sierra Nevada, CA, USA. Like our study, Lydersen et al. (2017) showed that previous treatments were an important driver of landscape-scale burn severity and that treatment effects were scale-dependent in a similar manner that we showed in Fig. 2b. In our study, treatments remained the most important predictor of burn severity across all scales (Fig. 2a), whereas Lydersen et al. (2017) showed that fire-line intensity outweighed previously treated areas in terms of predictive importance at smaller scales. Moreover, Lydersen et al. (2017) showed that burn severity was reduced when the fire encountered a previously treated area in a progression analysis like ours. In the North Cascades, USA, Prichard and Kennedy (2014) showed that even under extreme weather conditions experienced during the 2006 Tripod Complex fires (70, 894 ha), fuels reduction treatments – and particularly those that included burning of surface fuels – were effective in reducing observed burn severity. In Arizona, USA, Waltz et al. (2014) showed that burn severity in the 2011 Wallow Fire (217,740 ha) was significantly lower in treated areas, and high-severity patch sizes exceeded those observed in historical reference conditions in untreated forest stands. In the 2014 San Juan Fire in Arizona, the distance that high-severity effects persisted into treated areas varied as a function of post-treatment canopy cover (Johnson et al., 2019). Numerous other examples have been summarized elsewhere (Prichard et al., 2020).

Fuels reduction and forest restoration treatments are effective in dry conifer forest systems because these systems were historically fuel limited (Krawchuk and Moritz, 2011). While planned fuels reduction activities can act to limit available fuels, wildfires were the primary disturbance that limited available fuels historically and continue to play a primary role in the self-regulation of these systems (Parks et al., 2015;

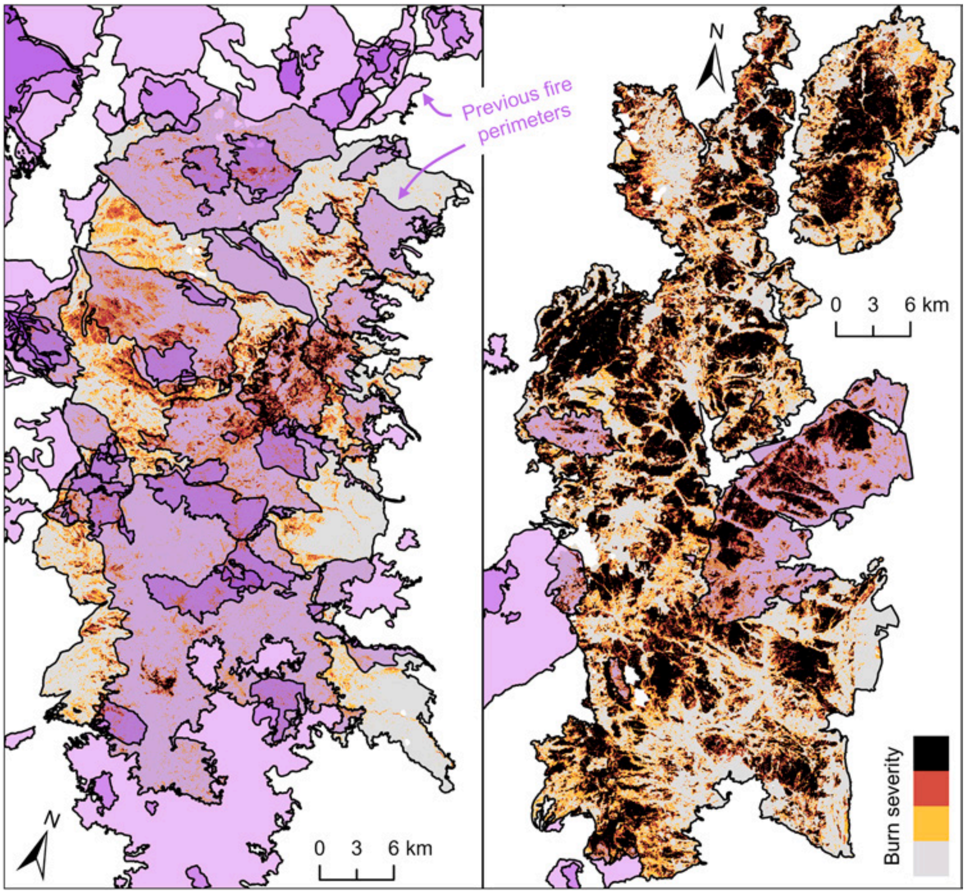

Fig. 5. Comparison of the 2022 Black Fire (left) and the 2022 Hermit's Peak/Calf Canyon (HPCC) fires. The area that eventually burned in the Black Fire had experienced at least 48 previous fires (including both unmanaged wildfire and wildfire managed for resource benefit) since 1984, likely resulting in lower fuel accumulation and, ultimately, lower overall burn severity. In contrast, the area that eventually burned in the HPCC fire had experienced only 9 previous fires over the same time period. The burn severity color gradient in this figure is the same as that shown in Fig. 1.

Cansler et al., 2022). For example, Parks et al. (2014) showed that in two large United States wilderness areas, including the Aldo Leopold Wilderness (coinciding with a portion of our study area), fires that burned through previously burned areas tended to experience lower fire severity. Previous fires are likely one reason why the 2022 Black Fire experienced such spatially limited high-severity fire (only ~4 % of the total burned area, or just over ~5000 ha). According to data from the USDA Forest Service Southwestern Region and the Monitoring Trends in Burn Severity program, at least 48 fires of at least 400 ha in size burned within the Black Fire perimeter between 1984 and 2021, which likely acted to limit fuels and curb high-severity fire extent (Fig. 5a). Compare this with the similarly sized 2022 Hermit's Peak/Calf Canyon (HPCC) complex, which burned in northern New Mexico at the same time as the Black Fire, also under extreme weather conditions. The HPCC complex experienced only 9 fires over this same period, and only a handful of small fuels reduction treatments, and it burned predominately at high-severity (Fig. 5b). Further analysis is necessary to understand drivers of burn severity in the HPCC complex, but it appears that lack of previous fires may be one potential driver of increased burn severity.

Our study comes with two primary caveats that readers should consider when interpreting our results. First, we pooled all treatment types including prescribed burns and managed wildfire into a single 'treatment' category, and thus we could not estimate the effectiveness of each treatment type individually. Our rationale for doing this was that some individual treatment types were too rare on the landscape to obtain reliable estimates of their individual effects, so pooling them at least allowed us to estimate an overall effect. Second, we did not make any efforts to quantify a potential time-since-treatment effect. The effectiveness of fuels reduction treatments has been shown to decline over time as vegetation recovers (Finney et al., 2007; Holden et al., 2010; Parks et al., 2014), and thus older treatments may be less effective at reducing subsequent burn severity compared to newer ones. However, we pooled all previous treatments into a single treatment group for similar reasons as we described above for treatment type; estimating different effects for time-since-treatment may have resulted in weakened inference because of smaller group sample sizes and inherent uncertainty in treatment dates in our database.

There are several management implications for forest restoration and fuels reduction in the southwestern United States that emerge from our study. First, application of prescribed fire and wildland fire for resource benefit across large and heterogenous combinations of time and space can reduce observed burn severity and create landscapes that are more resilient to fire disturbance. Second, multiple fire treatments can reduce risk to forest, watershed, and other ecological values, and facilitate the ability of wildland fire to perform ecological functions within the historical range of variation. Third, prescribed fire treatments and wildfires managed for resource benefit are effective at reducing stand-replacing fire effects, even under extreme fire weather conditions. Finally, the scale of treatments (area treated) is important to reducing extreme fire behavior in extreme fire weather conditions; the larger the area that is treated, the larger the expected reductions in burn severity. Our results suggest that increasing the pace and scale of treatments in southwestern US dry forests is expected to reduce high severity patch size and subsequent undesirable social and ecological effects. Further understanding of fire-environment interactions (fuels, weather, topography) that lead to desirable outcomes, particularly those that involve mechanical treatments, in other large fire events will be critical for facilitating successful wildland fire management.

CRediT authorship contribution statement

Hurteau Matthew D.: Writing – review & editing, Methodology. **Chongpinitchai Angela:** Writing – review & editing. **Spannuth Alexander:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Jones Gavin M.:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

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

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Data availability

All data are publicly available

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