Efficacy of Recent Prescribed Burning and Land Management on Wildfire Burn Severity and Smoke Emissions in the Western United States

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Abstract

Prescribed fire is increasingly proposed as a policy strategy to reduce wildfire risks, but evidence of its effectiveness in lowering fire severity and smoke emissions remains limited in the western US. We empirically demonstrate that areas treated with prescribed fire and subsequently burned during California's extreme 2020 wildfire season showed a -14% net reduction in smoke emissions, though these treatments were less effective near populated areas. Our findings suggest that expanding prescribed fire use can meaningfully reduce smoke emissions, even when factoring in smoke from the prescribed fires themselves. The proposed policy of treating one million acres annually in California could reduce overall smoke emissions by 655,000 metric tons over the next five years—equivalent to 52% of the emissions from 2020 wildfires. Our results also suggest that broader application of prescribed fires can provide benefits in mitigating severe wildfire impacts and improve air quality in fire-prone regions worldwide.

Introduction

Due to a warming climate, a legacy of fire suppression, and population growth in the wildland-urban interface ("WUI"), the western United States has seen a recent rise in extreme wildfire seasons(*1–3*). Large wildfires can irreversibly alter ecosystems (*4*), destroy human-built environments (*5*), and cause poor air quality and health problems due to smoke particulate matter ($PM_{2.5}$) (*6*, *7*). Prescribed ("Rx") burning is increasingly proposed as a mitigation strategy to reduce the risk and intensity of future wildfires, including a national investment of nearly $2 billion toward the reduction of hazardous fuels using Rx burns and other treatments (H.R.5376) (*8*) and a California plan to treat one million acres annually by the end of 2025 (*9*). However, there is limited systematic, quantitative evidence of the efficacy of Rx burning in reducing fire severity and overall smoke emissions.

Despite the potential benefits of Rx fires to reduce future wildfire severity and smoke, their implementation in the western US remains limited (*10*). While indigenous practices and strategies across the US demonstrate the advantages of Rx fires for ecosystem management (*11–13*), public acceptance in the western US is hindered by concerns over smoke impacts and escaped fires (*14*). Additionally, climate warming has reduced the calendar windows for safe Rx burning, complicating efforts to manage wildland fire risks (*15*, *16*). The primary policy focus of Rx fire management in the western US has been to protect communities in the WUI, which presents issues ranging from efficacy to equity (*17*). The spread of homes into wildfire-prone areas (*18*) and rapidly rising vapor pressure deficit in the WUI (*3*) amplifies these risks. Wealth disparities mean that while wealthier homeowners may afford home-hardening measures, poorer districts struggle with the associated costs (*19*). Furthermore, although Rx fires generally produce less smoke and have higher combustion efficiency on average compared to wildfires (*20*, *21*), Rx fires can still negatively impact air quality and disproportionately affect vulnerable communities (*22*). In contrast to mechanical thinning—which primarily reduces canopy density and removes smaller ladder fuels that contribute to crown fire behavior—Rx fire consumes litter and understory shrubs, thereby reducing future fire intensity (*23*). Existing research lacks a clear method to quantify the trade-offs between Rx fires and future wildfire risk reduction, leaving a gap in understanding the overall benefits versus the potential public health costs.

Evidence on the net effects of Rx burning in the western US is limited and primarily derived from a small number of case studies conducted before the 2018 wildfire season. Globally, most studies on Rx fires take place in North America (*24*), with additional studies focusing on regions in Australia (*25*, *26*), the Mediterranean (*27*), and Africa (*28*). These works include characterizing Rx fire effects on wildfire smoke emissions (*29*) and severity (*30*), but none assess empirically the impact of Rx fires on burn severity and smoke emissions from subsequent wildfires. A recent meta-analysis by Davis et al. (2024) examines 40 publications evaluating wildfire severity in both Rx fire-treated areas and untreated controls for wildfires spanning from 1994-2016 and the Dixie Fire in 2021 in the western US (*30*). Using mixed severity metrics (e.g., crown scorch height, percent canopy cover change, burn severity derived from satellite imagery), they find that Rx burns reduced severity by 62% relative to untreated areas. Most of these experimental designs compared fire risks, severity, and intensity between areas treated with Rx fires and untreated areas, accounting for variations in fire weather, slope, topography, and land cover types. However, these studies do not include information about smoke emissions, treatment sizes, and other environmental covariates such as proximity to the WUI. The WUI, where human development and undeveloped wildland vegetation meet, is the area where fires pose the greatest risk to people due to the proximity of flammable vegetation (*31*). Most observational studies occur at the scale (~1000 m^2) of a forest canopy (e.g., (*32*)), with few results addressing $PM_{2.5}$ smoke during recent severe wildfire seasons.

Data on Rx fires are limited, so a variety of assumptions are made that lead to potential spatiotemporal discrepancies. Low-intensity fires are often used as proxies for Rx fire treatments (*33*), although these fires are frequently ignited by lightning as opposed to humans (*34*) and generally have different seasonal trends (*35*). Lightning-ignited fires tend to occur more frequently with convective events such as thunderstorms and over specific orographic features such as mountain ranges (*36*) but are relatively random with respect to proximity to the WUI (*37*). In contrast, Rx fire planning typically has specific at-risk communities in mind (*17*). In modeling Rx fires, few observational constraints exist, requiring studies to rely on historical projections of Rx fires (*38*) or to create hypothetical case studies (*39*, *40*). Moreover, most regional modeling efforts use resolutions greater than 10 km even though most Rx fires cover less than 100 acres (approximately 0.4 km^2), underscoring the need for high-resolution analysis.

Here, we empirically assess the effects of Rx fire treatments on burn severity in the western US and $PM_{2.5}$ emissions in California during the extreme 2020 wildfire season. We use high-resolution satellite data (upscaled to 30m) from Sentinel-2A and Landsat platforms, historical land management records from the National Fire Plan Operations and Reporting System (NFPORS), detailed wildfire emissions data from the Wildfire Burn Severity and Emissions Inventory (WBSE) (*41*) and Rx fire emissions data from a reclassified FINNv2.2 inventory (*21*). We develop a quasi-experimental design to compare Rx fire-treated areas with adjacent control areas defined in this study (Fig. 1). We define treated areas based on Rx fire records from Fall 2018 to Spring 2020, using 186 treatments in areas (average size of 55 acres) that subsequently burned in wildfires in 2020. We then create buffers around point locations to represent treated areas, with buffer size equal to reported treated acreage, and designate "control areas" using concentric buffers outside the treated zones, of equal acreage to the treated area. We then quantify whether subsequent burn severity (measured at the pixel level using the differenced Normalized Burn Ratio, dNBR) and $PM_{2.5}$ smoke emissions during 2020 wildfires differed between treated and control areas, using a regression approach that controls flexibly for land cover type, past fire activity, and whether sampled pixels were in the WUI (Materials and Methods). In essence, our approach assumes that absent treatment, a pixel treated with Rx fire would have had the same burn severity and $PM_{2.5}$ emissions as a nearby untreated pixel, conditional on the controls. Finally, we estimate the net effect on $PM_{2.5}$ emissions per acre burned by Rx fires in California – i.e. the tradeoff between additional emissions from Rx fire and reduced emissions from subsequent wildfires – along with the implications for a dramatic near-term scaling of Rx fire efforts, as is currently being proposed in the state.

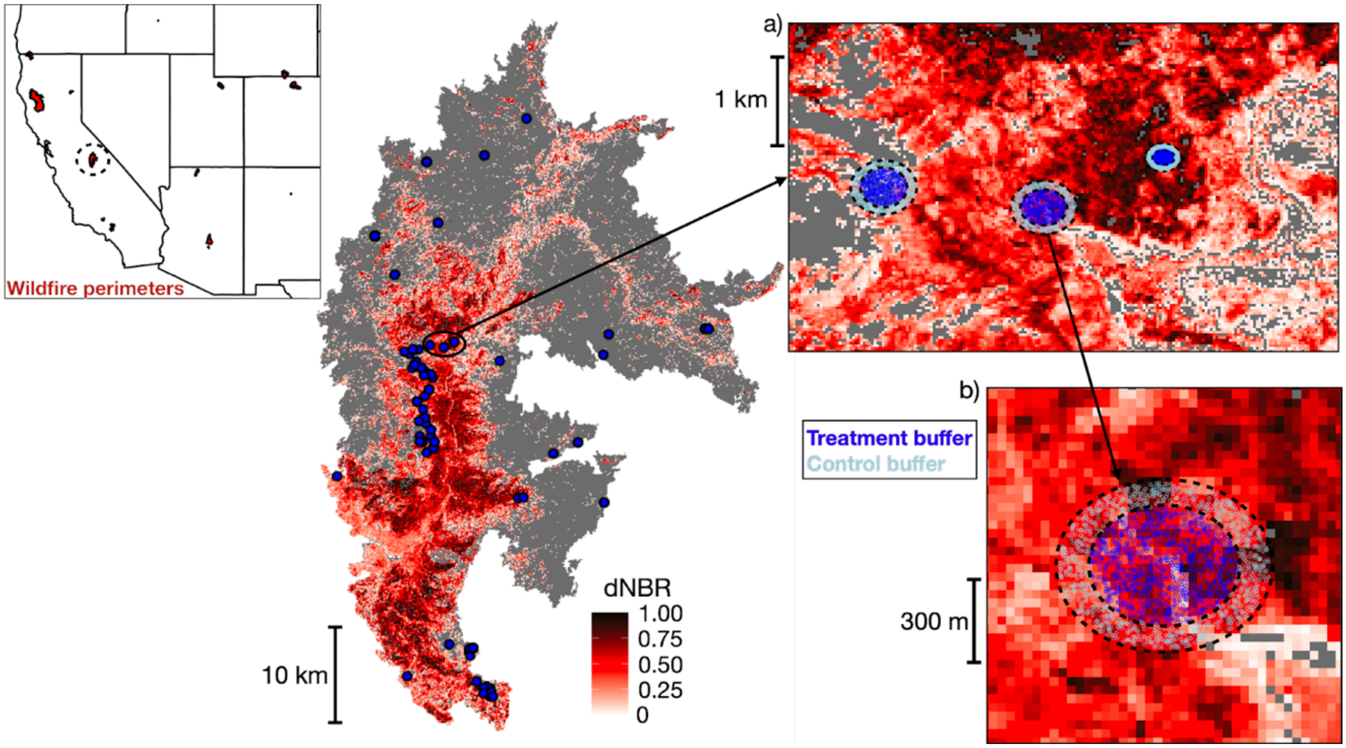
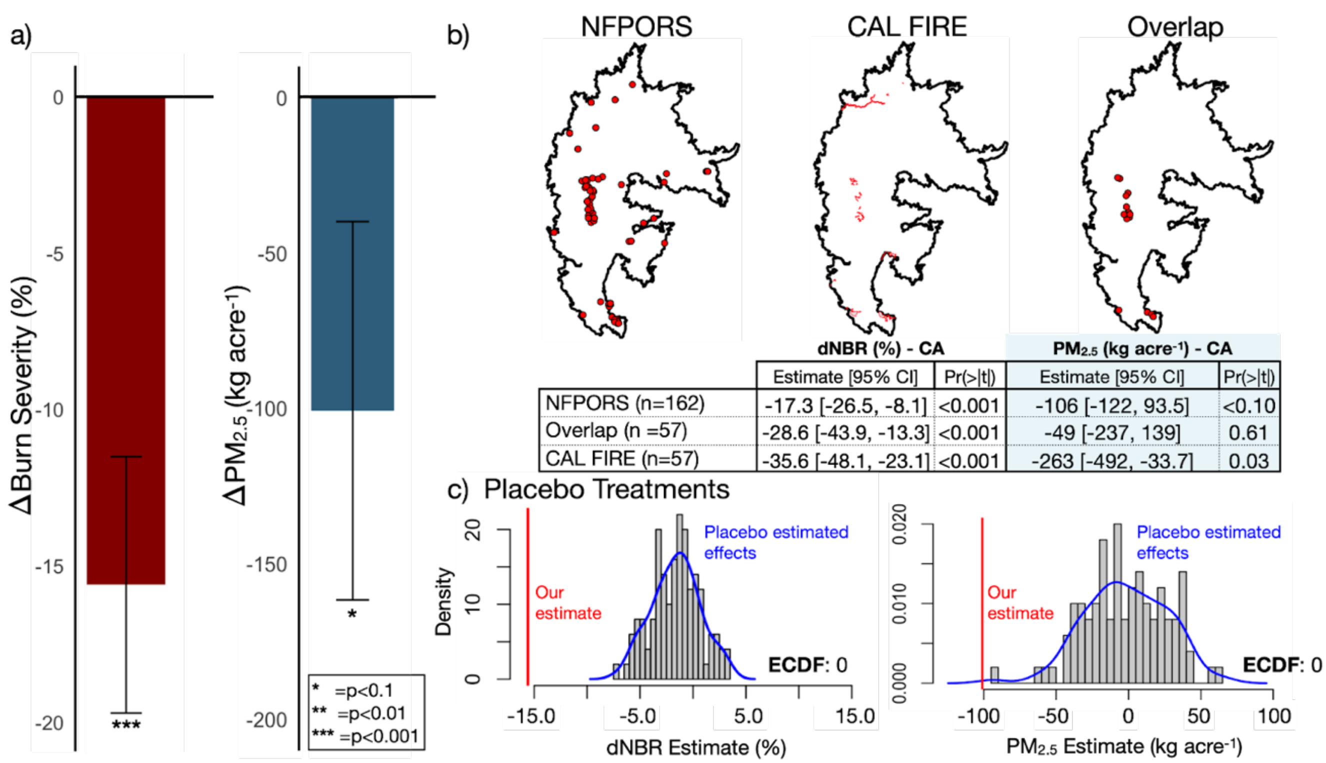


Fig 1. Approach to estimating the impact of Rx fire on burn severity, using the Creek Fire as an example. The Creek Fire perimeter contains 30m pixels of dNBR values from Sentinel-2 with higher values in dark red indicating more severe burns. Blue dots represent Rx fire treatment locations recorded by NFPORS (n=59) from October 2018 to May 2020. Insets (a, b) show zoomed-in views of our randomly generated, treatment buffers centered on the NFPORS coordinates (blue dots), and the surrounding control buffers (cyan dots) buffers.

Results

Efficacy of Rx burning in the western US

When investigating the 2020 wildfire season, we find that Rx fire treatments in the two years prior to a wildfire significantly reduced burn severity and smoke emissions (Fig. 2a). On average across the western US, Rx fire-treated areas show a reduction of -15.6 [-23.6, -7.6]% ($p<0.001$) in burn severity compared to control areas. In California, Rx fire treatments lead to a -101 [-220, 18.4] kg per acre ($p<0.1$) decrease in smoke $PM_{2.5}$ emissions, with similar reductions observed in burn severity (-17.0 [-25.8, -8.2]%, $p<0.001$) (Table S1). Increasing the circular buffer size around treatments and controls slightly reduces the magnitude of these estimates but does not alter their direction or statistical significance (Table S2).



	dNBR (%) - CA		$PM_{2.5}$ (kg acre^{-1}) - CA	
	Estimate [95% CI]	Pr(>|t|)	Estimate [95% CI]	Pr(>|t|)
NFPORS (n=162)	-17.3 [-26.5, -8.1]	<0.001	-106 [-122, 93.5]	<0.10
Overlap (n =57)	-28.6 [-43.9, -13.3]	<0.001	-49 [-237, 139]	0.61
CAL FIRE (n=57)	-35.6 [-48.1, -23.1]	<0.001	-263 [-492, -33.7]	0.03

Fig 2. Impact of Rx fire treatments on burn severity and smoke emissions. (a) All sample estimates of burn severity and smoke $PM_{2.5}$ emissions reduction in Rx fire-treated areas compared to control areas during the 2020 wildfire season. (b) Comparison of estimates using NFPORS (treatment and control circular buffers), CAL FIRE (treatment perimeters, control circular buffers), and the "overlap" (treatment and control circular buffers) subset of NFPORS inside CAL FIRE perimeters. Maps show overlaps for a single fire (Creek Fire), and the table of estimates shows pooled treatment effect estimates across all fires for which we have data. (c) Results from 100 randomized placebo treatments demonstrate that our estimates of the treatment effect of Rx fires are extremely unlikely to occur by chance ($p<0.001$). The blue line on the empirical cumulative distribution function (ECDF) plots outlines the distribution density and the red line corresponds to our estimates from (a).

We conduct a number of analyses to test the robustness of these primary results. Fig. 2b shows the comparison of our experimental sampling (Fig. 1) to more precise Rx fire perimeters from the California Department of Forestry and Fire Protection (CAL FIRE). Our sampling method creates Rx burn area polygons by generating a circular buffer around the geographic point location based on the reported burn area from NFPORS. This sampling strategy likely mischaracterizes the precise Rx treated area. To understand whether this mis-measurement matters, we use the more precise CAL FIRE perimeters for the more limited set of treatments in those data, constructing adjacent control buffers and estimating treatment effects in the same manner. For this more limited set of perimeters in California, we estimate a reduction in burn severity by -35.6 [-48.1, -23.1]% ($p<0.001$) and in smoke $PM_{2.5}$ emissions by -263 [-492, -33.7] kg per acre ($p<0.1$). If instead of using these precise perimeters we estimated Rx fire treatment effects using our circular buffers at the same locations as CAL FIRE, burn severity is reduced by -28.6 [-43.9, -13.3]% ($p<0.1$) while smoke $PM_{2.5}$ emissions decreased by -49 [-237, 139] kg per acre ($p=0.61$). The latter $PM_{2.5}$ estimate likely differs due to the smoothing effect of emission factors in the inventory, which reduces the ability to capture emission variability especially in severely burned areas where many CAL FIRE perimeters are located.

To further understand whether our measured differences in burn severity and $PM_{2.5}$ emissions between treated and adjacent control pixels could have occurred by chance, we run a set of placebo experiments in which, within the same fires, we estimate the "impact" of 100 placebo treatments and compare the distribution of these placebo estimates to our estimate of the true treatment effect of Rx fire (Materials and Methods). Fig. 2c displays our treatment effect estimate relative to the placebo distribution. For both burn severity and smoke emissions, our treatment effect estimate is entirely outside the distribution of placebo treatment effects, which are themselves centered on zero as expected – indicating that our estimated treatment effects are highly unlikely to happen by chance in our data.

Characterizing land treatments in the western US

Our findings reveal that Rx fire treatments are significantly more effective in reducing burn severity compared to mechanical thinning. Fig. 3a shows that across the western US, Rx fire treatments reduce burn severity by -27.4 [-44.0, -10.8]% ($p<0.001$), whereas mechanical thinning treatments only reduce burn severity by -7.7 [-18.2, 2.8]% ($p=0.15$). These results are consistent with Davis et al. (2024), which found mechanical thinning to be 35% less effective in reducing burn severity in subsequent wildfires than Rx fire treatments. Rx fire consumes a wide range of fuel types including fine fuels and larger woody debris, whereas mechanical thinning targets larger vegetation and thus often leaves behind smaller fuels (*42*).

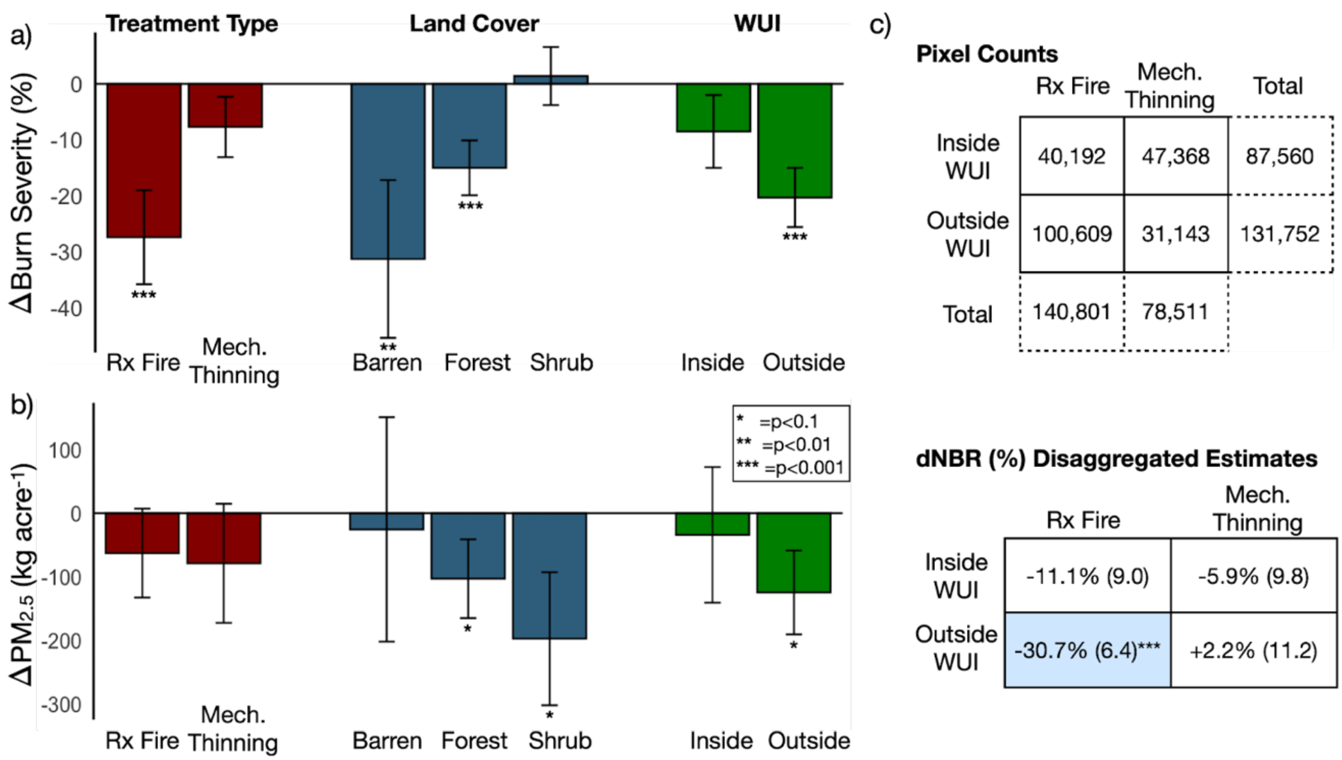


Fig 3. **Comparative efficacy of wildfire management strategies**. (a) Estimates of burn severity reduction in Rx fire-treated buffers compared to control buffers during the 2020 wildfire season, by treatment type, land cover, and whether the treated area was in the wildland-urban interface (WUI). (b) Same, for $PM_{2.5}$ emissions reduction. (c) Disaggregated statistics for treatment type (Rx fire vs. mechanical thinning) inside and outside of the WUI.

In forest ecosystems, land management treatments including Rx fire and mechanical thinning significantly reduce both burn severity and smoke emissions (Fig. 3a, b). Specifically, these treatments reduce burn severity by -15.0 [-24.7, -5.3]% ($p<0.001$) and smoke $PM_{2.5}$ emissions by -103 [-224, 17.9] kg per acre ($p=0.09$). In barren areas where vegetation accounts for less than 15% of total cover, treatments significantly reduce burn severity by -31.3 [-58.0, -4.6]% ($p=0.03$) but the effect on smoke $PM_{2.5}$ emissions is minimal (-26 [-373, 321] kg per acre, $p=0.89$). In shrublands, the impact of treatments on burn severity is not significant (1.4 [-8.8, 11.6]%, p=0.79) but there is a significant reduction in smoke $PM_{2.5}$ emissions (-198 [-405, 8.7] kg per acre, p=0.06).

We find that Rx fire treatments are less effective within the WUI compared to outside it (Fig. 3a-c). Treatments inside the WUI reduce burn severity by -8.5 [-21.1, 4.1]% (p=0.19) and reduce smoke $PM_{2.5}$ emissions by -34 [-244, 176] kg per acre (p=0.75). In contrast, treatments outside the WUI significantly reduce burn severity by -20.3 [-30.6, -10.0]% (p<0.001) and reduce smoke $PM_{2.5}$ emissions by -125 [-255, 4.7] kg per acre (p=0.06). On average, the number of acres treated is larger inside than outside the WUI (p<0.001, Fig. S1). Fig. 3c indicates that most treatments outside the WUI use Rx fire, while treatments inside the WUI predominantly use mechanical thinning. Statistical tests confirm that Rx fire outside the WUI significantly reduces burn severity, whereas other combinations of WUI designation and treatment type do not.

Net Rx burning effects and future projections

We quantify the net impact of Rx fire treatments on smoke emissions, considering both the emissions from Rx fires themselves and subsequent prevented smoke from future wildfires (Materials and Methods). Emissions from Rx fires are derived from a reclassified FINNv2.2 source-specific inventory of daily $PM_{2.5}$ emissions and emissions from wildfires are from the WBSE inventory. We use these data and our results to calculate three quantities: (quantity 1) the ratio of emissions from an average acre of Rx fire versus an average acre of wildfire; (quantity 2) the per-acre reduction in emissions during a wildfire resulting from having done a previous Rx treatment in an area that subsequently burned; these estimates are used to calculate the emissions benefits of a dramatic near-term scaling of Rx fire efforts that is currently being considered in California (*9*); and (quantity 3) the ratio of total emissions from conducting an Rx burn to total emissions had that burn not happened, accounting for emissions from the Rx burn itself, and the probabilistic benefits that burn has on subsequent wildfire emissions. This last ratio is our preferred estimate of the expected net benefits from implementing Rx fire.

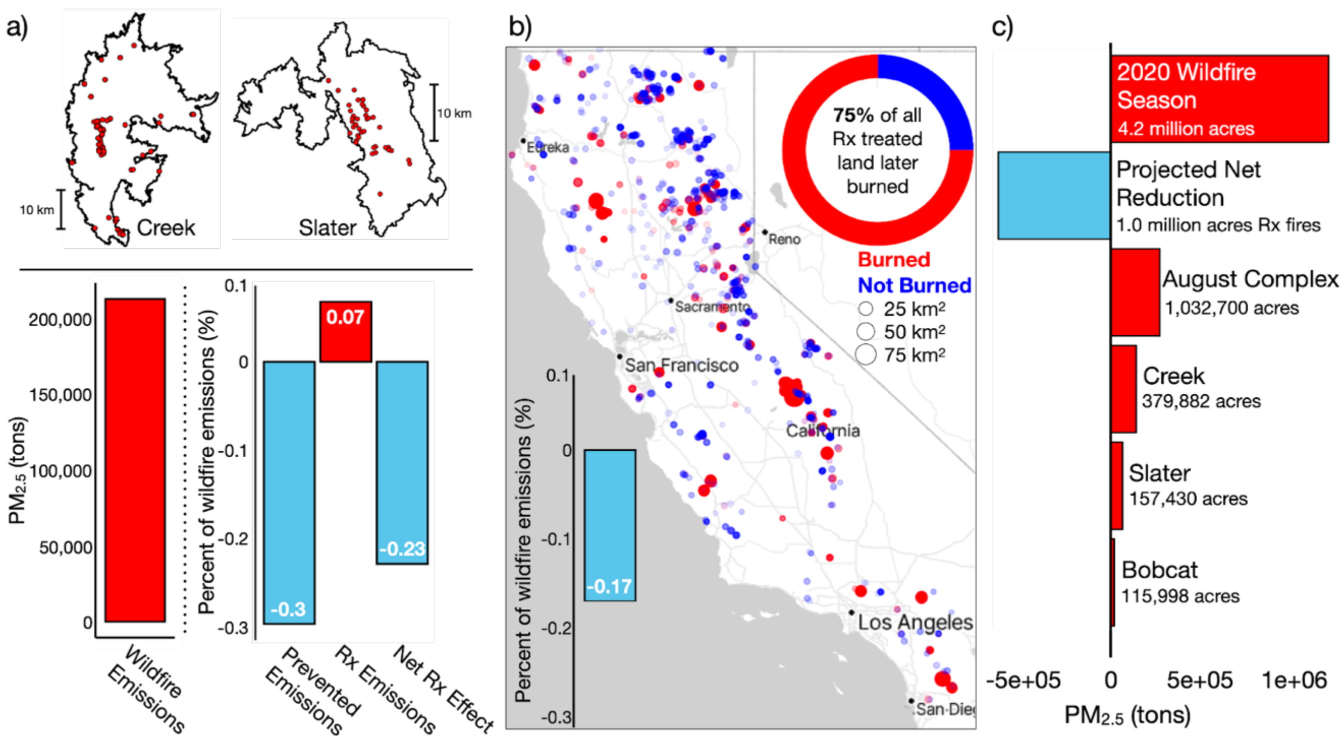


Fig 4. **Net effects and projections of Rx fire treatments on smoke emissions in California**. (a) The net smoke $PM_{2.5}$ effects from prior Rx fire treatments in the Creek and Slater Fires in terms of both $PM_{2.5}$ emitted from these Rx burns and potential $PM_{2.5}$ saved during these wildfires. (b) The proportion of treated land that subsequently burned in wildfires from a reclassified FINNv2.2 emissions inventory from 2012-2020, with an adjusted net smoke $PM_{2.5}$ savings estimate incorporating that, on average, 75% of Rx fire treatments eventually burn. (c) Projecting the potential $PM_{2.5}$ emission reductions if Rx fire treatments are scaled up to one million acres in California by CAL FIRE as mandated by the Governor's Wildfire and Forest Resilience Task Force, with emissions comparisons to other large wildfires during 2020.

We find that the net effects of Rx fires result in overall emission savings, though estimated total savings from observed Rx fires are small, given their limited implementation. The Creek and Slater Fires in California contain 66% of all NFPORS treatments in this study and align most closely with observations from the reclassified FINNv2.2 emissions, while other wildfires in California had too few Rx fire observations that overlapped between the datasets. We calculate the fire-specific effect of Rx fire treatments on smoke emissions estimates and observed decreases in both the Creek (-246 kg per acre, $p=0.07$) and Slater (-293 kg per acre, $p=0.08$) Fires. Fig. 4a shows that the Creek and Slater Fires emitted 213,000 tons of $PM_{2.5}$ smoke. We estimate that the 122 NFPORS treatments occurring prior to these two fires reduced smoke emissions by 630 tons. Inventory estimates suggest the Rx fires at these locations emitted 144 tons of smoke, yielding a net savings of 486 tons of smoke emissions. Although this subset of treatments yields a net smoke savings, the scale of the treatments is much less than even 1% of the total wildfire emissions.

By design, our study considers Rx fires that subsequently burned in a wildfire. Estimating the net emissions effect of future Rx fires, however, requires accounting for the fact that not all Rx-burned locations will subsequently burn in a wildfire, at least in the near term. We calculate that on average 75%

of the land treated by Rx fire burns in a wildfire within the next eight years (Fig. 4b, Fig. S2). We use this value to adjust our estimate of the net emissions savings from Rx fire (Fig. 4a). Using this adjustment, we find that Rx fires yield a net savings of 364 tons. Rx fire smoke only constitutes 17% of the smoke emissions from a wildfire in the same areas (quantity 1). We calculate a -33.7% reduction in wildfire emissions due to an earlier Rx fire (quantity 2, Materials and Methods Eq. 6). Compared to a counterfactual scenario where no Rx fire treatments are applied (quantity 3, Materials and Methods Eq. 4), the application of Rx fire (quantity 3, Materials and Methods Eq. 3) results in a net -14% reduction in overall $PM_{2.5}$ smoke emissions (quantity 3, Materials and Methods Eq. 5).

By scaling our net effect of Rx fire treatments per acre, we estimate that treating one million acres of land in California, as mandated by the Governor's Wildfire and Forest Resilience Task Force, would result in 288,000 tons of emissions from the Rx fires themselves. Over the next five years—reflecting a balanced timeframe between our Rx fire burn window (three years; 2018-2020) and our calculation of reburn potential (eight years; 2012-2020)—these treatments would reduce emissions in subsequent wildfires by 943,000 tons, resulting in a net reduction of 655,000 tons of $PM_{2.5}$ smoke emissions. We base this projection on a treatment year comparable to 2018, reflecting accumulated fuel loads and moderate to high wildfire activity. These reductions are substantial relative to total emissions in extreme wildfire years like 2020. Fig. 4c shows that scaling our net Rx fire effect estimates to one million acres would save more smoke than the emissions from four Creek Fires and two August Complex Fires, the latter of which burned over a million acres. This projected net reduction includes both the smoke emitted and the smoke saved by Rx fires. The wildfire smoke saved from doing these Rx fires constitute 52% of the total emissions from the 2020 wildfire season.

Discussion

Using data on 186 recent Rx fire treatments across the western US, we find that Rx fire treatments effectively reduced burn severity and future smoke emissions from wildfires during the historically active 2020 wildfire season. Our estimates are not driven by differences in land cover or previous fire history between Rx fire-treated areas and adjacent controls, and a placebo exercise indicates our treatment effects are highly unlikely to arise by chance.

There are at least three reasons why our main estimates could be a lower bound on the benefits of Rx fire on subsequent burn severity and emissions. First, our comparison of NFPORS data and a smaller set of more precise CAL FIRE perimeters (Fig. 2b) suggests a more substantial reduction in burn severity and smoke emissions where Rx fire treatments are estimated precisely. However, we cannot rule out the possibility that CAL FIRE treatments differ in some important way from treatments in other locations or jurisdictions. Second, our approach to estimating the treatment effects of Rx fire within subsequently burned wildfire perimeters could underestimate beneficial spillovers from treated areas to neighboring untreated areas, either because treatments reduced severity or emissions in nearby "control" regions that we constructed, or because treatments limited the spatial extent of the wildfire itself. In either case, our approach of comparing treated pixels to neighboring untreated pixels – designed to ensure that these pixels are otherwise similar absent treatment – could lead us to understate the benefits of Rx fire. Finally, to estimate the benefits of substantially scaled Rx fire treatments across California, we account for the fact that not all Rx fire-treated areas subsequently burn in wildfires. However, our calculation of the percentage of Rx fire-treated areas that subsequently burn is based on a limited (eight-year) temporal sample and likely underestimates the true probability of near-term reburn. Higher estimates of reburn probability would lead to higher estimated benefits from Rx fire and our calculation of the net reduction in overall smoke emissions are specific to two large, representative wildfires (Creek, Slater) with a sufficient number of reported Rx fire treatments. While our results indicate a net savings in smoke emissions from Rx fires, it should be noted that Rx fires release smoke that can adversely affect human health and disproportionately affect vulnerable communities as highlighted in prior studies (e.g., Afrin and Garcia-Menendez, 2021).

The relatively greater effectiveness of Rx fire in reducing burn severity, compared to mechanical thinning, aligns with previous findings (*30*). This effectiveness is attributed to Rx fire's ability to address a wider range of fuel types and disrupt fuel continuity across landscapes, creating patches of burned and unburned areas that may reduce the spread and intensity of future fires (Fig. 3a). In contrast, mechanical thinning primarily targets larger vegetation such as trees and shrubs, often leaving smaller fuels on the ground. While it may reduce vegetation density, mechanical thinning may not create the same level of fuel discontinuity as Rx fire (*43*). We find that land management treatments are more effective in reducing burn severity in forest ecosystems likely due to the heavier fuel loads in forests, which typically generate more smoke and heightened burn severity. The effects in barren areas are minimal due to the limited availability of combustible fuel, while shrublands are likely significant in reducing smoke emissions due to the combustion of smaller and more easily ignitable fuels. Our study does not account for weather variables at the time of treatment, nor does it differentiate between types of vegetation within land cover categories.

The reduced effectiveness of Rx fire within versus outside the WUI highlights the challenges of implementing effective Rx fire in areas with dense human populations and infrastructure. There may be several factors related to the WUI that are not fully understood or captured here, which could limit the impact of Rx fires in these areas. These factors might include the application of Rx fire mixed with other methods such as thinning, weather conditions at the time of ignition, and National Environmental Policy Act (NEPA) mitigation requirements. Moreover, the need to adopt extremely cautious approaches—due to factors concerning community smoke exposure, the risk of escaped Rx fires, and the higher density of structures—could further reduce the treatment's overall effectiveness in the WUI.

The net effects of Rx fire treatments estimated in our analyses indicate potential emission savings, accounting for both smoke emissions of Rx fire and prevented smoke from future wildfires (Fig. 4). While the current scale of Rx fire treatments in the western US is relatively small, California plans to scale up to treating 400,000 acres annually using Rx fire by 2025. This goal, shared among state, federal, tribal, and local entities, is part of a broader objective to treat one million acres annually across California (*9*). Meeting this goal may be challenging, as CAL FIRE treated on average only 30,000 acres annually with Rx fire from 2018 to 2023 (https://www.fire.ca.gov/our-impact/statistics, last access: 27 August 2024)—just 7.5% of its 400,000 acres goal. However, if met, the smoke savings are likely to be substantial: Not only do our analysis suggest that such a program is likely to reduce a large fraction of the smoke emissions in California (Fig. 4), but the smoke savings achieved in California may also represent a significant reduction in wildfire smoke exposure across the western US, given the importance of California as a source of wildfire smoke for other regions (*10*, *44*).

Materials and Methods

Rx Fire and Land Management Datasets

The National Fire Plan Operations and Reporting System (NFPORS) fuels treatment database is maintained by the US Department of the Interior (DOI) collaboratively with the US Department of Agriculture (DOA). NFPORS reports Rx fires with a resolution as fine as 1 acre (~0.004 km²). It records whether a treatment is accomplished in the WUI, the size of the treatment in acres, the category of treatment (e.g., Rx fire, mechanical thinning), along with unique treatment IDs. Our analysis is focused on the 2020 extreme wildfire season. We use historical records of Rx burn locations from October 2018, when comprehensive geolocated data on Rx burned areas first became available, through May 2020, using Rx burns that overlap with subsequent wildfires during the 2020 wildfire season (July-November). Starting in 2018, these data are available as point data and an accompanying acreage (but do not contain treatment polygons). To map wildfire perimeters, we use the Monitoring Trends in Burn Severity (MTBS) (*45*) database, which uses 30m Landsat imagery to define the final fire (polygon) perimeters and assess burn severity for all fires over 1,000 acres (~4 km²) in the western US (*46*). We find that 255 NFPORS treatments intersect with 14 wildfires, with 6 of these wildfires located in California (Table 1). After removing overlapping treatment locations in space, we have 186 unique NFPORS treatments.

Table 1. Characteristics of 2020 Wildfires Overlapping with NFPORS Treatments.

Wildfire (State)	State	Ignition date	Acres burned	NFPORS acres treated (number of treatments)
August Complex	CA	2020-08-17	1,032,648	1,716 (73)
Bobcat	CA	2020-09-06	115,997	217 (5)
Bush	AZ	2020-06-13	193,455	534 (1)
Cameron Peak	CO	2020-08-13	208,663	738 (20)
Creek	CA	2020-09-05	379,895	1,519 (81)
East Fork	UT	2020-08-21	89,568	1,909 (10)
Lake	CA	2020-08-12	31,089	8 (1)
Mangum	AZ	2020-06-08	71,450	7,814 (6)
Medio	NM	2020-08-17	3,775	43 (1)
Mullen	WY	2020-09-17	176,878	342 (5)
Phillips Creek	ID	2020-08-05	2,112	552 (1)
Sheep	CA	2020-08-17	29,570	668 (7)
Slater	CA/OR	2020-09-08	157,220	872 (41)
Superstition	AZ	2020-08-20	9,539	183 (3)

NFPORS did not report geolocated information on burned areas before the fall of 2018 and only provided longitude and latitude information without final treatment perimeters. As a result, we construct random sampling strategies (detailed in a following section) to estimate the effects of land management treatment in the absence of provided perimeter information. Additionally, we compare our data to the Rx fire perimeters dataset (https://map.dfg.ca.gov/metadata/ds0397.html) from CAL FIRE. The CAL FIRE dataset includes perimeters from multiple agencies and provides associated data such as project number, start date, and acres reported. However, the CAL FIRE dataset reports a fraction of the treatments done by the DOI and DOA. For example, NFPORS reports 115 unique treatments within the Creek Fire perimeter between 2018 and May 2020, while CAL FIRE reports only 36 treatment perimeters, despite all treatments being conducted by or in collaboration with the DOA. The NFPORS dataset reports general treatment types (e.g., Fire vs. Mechanical) as well as subtypes for specific land management techniques: machine pile burn, broadcast burn, biomass removal, thinning, crushing, fire use, lop-and-scatter, and chemical treatments. While these treatment subtypes are important for understanding which techniques result in more effective reductions in fire severity and smoke emissions, we focus on general treatment types due to greater statistical power and balanced sample sizes. Nevertheless, we provide coefficient estimates for these specific techniques, divided into areas inside and outside the WUI, in Table S3. The Rx fire treatments we report here may include mixed methods, such as mechanical thinning followed by burning (e.g., pile burning), whereas the mechanical treatments exclusively omit the use of fire.

Satellite Datasets

We employ a burn severity gridded dataset derived from the Sentinel-2A satellite. We use the Google Earth Engine (GEE) cloud computing platform (*47*), which hosts Sentinel-2 Level 2A data containing 13 spectral bands with spatial resolutions ranging from 10 to 60m. We retrieve imagery from two weeks before and two weeks after a wildfire occurrence, as determined by MTBS perimeters and ignition dates. We exclude pixels with a greater than 65% probability of being obscured by cloud cover using the Sentinel-2 cloud probability 10m dataset on GEE. For each pre- and post-fire image, we calculate the Normalized Burn Ratio (NBR), a common spectral index for fire severity that approximates the burn effects by dividing the difference between the near-infrared (NIR; 835.1-833 nm) and shortwave infrared (SWIR; 2202.4-2185.7 nm) bands by their sum (*48*). We then calculate the differenced Normalized Burn Ratio (dNBR), which quantifies the fire-induced changes in vegetation greenness and landscape moisture content, by subtracting the post-fire NBR from the pre-fire NBR:

$$dNBR = \left(\frac{NIR_{pre-fire} - SWIR_{pre-fire}}{NIR_{pre-fire} + SWIR_{pre-fire}}\right) - \left(\frac{NIR_{post-fire} - SWIR_{post-fire}}{NIR_{post-fire} + SWIR_{post-fire}}\right) \quad \text{Eq. 1}$$

The final dataset resolution is reduced to 30m to match the resolution of the other datasets used in this work. A negative dNBR value or value of 0 indicates no fire effect on vegetation, while increasingly positive dNBR values suggest higher burn severity. All dNBR values less than 0 were excluded from this analysis.

For land cover classifications, we use the 2019 National Land Cover Database (NLCD), which is a Landsat-based dataset that uses digital change detection methods to identify changes in land cover, impervious cover, and forest canopy cover across the US (*49*). The data resolution is at 30m for the year 2019, and we focus on three broad land cover types: forest, shrub, and barren.

For elevation data, we use the NASA Digital Elevation Model (NASADEM), which is also at 30m resolution (*50*) and is a reprocessed version of Shuttle Radar Topography Mission data from 2000, with improved height accuracy and filled missing elevation data. Both NLCD and NASADEM data were retrieved and processed in GEE using MTBS perimeters.

Fire Emissions Datasets

To estimate $PM_{2.5}$ emissions from wildfire smoke, we use the Wildfire Burn Severity and Emissions Inventory (WBSE) . WBSE is a severity-based emissions inventory that uses Landsat imagery to calculate burn severity through dNBR. The Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) active fire detections, with spatial resolutions of 1 km and 375 m respectively, are used to determine the day of burning for each pixel. Vegetation types and emission factors are informed by California-specific field studies to calculate smoke emissions. WBSE provides a 30m resolution for event-based emissions in California, covering the six California fires listed in Table 1. Although WBSE is limited to California, it offers the highest resolution $PM_{2.5}$ smoke emissions data with a strong correlation to burn severity metrics.

To estimate $PM_{2.5}$ emissions from Rx fire smoke, we use a reclassified FINNv2.2 source-specific inventory of daily $PM_{2.5}$ emissions from Rx fire across California (*21*). Schollaert et al. reclassified the FINN emissions inventory (*51*) data by spatially matching it with fire-type information from national and state-level fire and fuel treatment databases, including from CAL FIRE. The Rx fire emissions are provided at a daily 1 km resolution and have been validated using county-level estimates from the EPA's National Emissions Inventory.

Quasi-Experimental Design Sampling Strategy

To evaluate the effects of Rx fire treatments on burn severity and $PM_{2.5}$ emissions during the 2020 wildfire season, we employ a quasi-experimental sampling design using location data from NFPORS. Our analysis aims to estimate these Rx fire impacts conditional on a wildfire occurring. We identify overlaps between land management areas treated in NFPORS from October 2018 to May 2020 and MTBS wildfire perimeters during the 2020 wildfire season. Based on these intersections, we develop a random sampling strategy to create treatment and control buffers around each set of coordinates, each buffer corresponding to the total acreage treated.

We define the treatment area as a circular buffer centered on an NFPORS coordinate. We then define the control area as a concentric circle completely enclosing the treatment buffer, with its area equal to the treatment acreage but excluding the enclosed treatment buffer area. This design ensures that the control buffer captures areas directly outside the treatment zone while maintaining an equivalent acreage. (See Fig. 1 for a schematic illustration, and below for further details.)

We generate 1000 random points within both the treatment and control buffers to capture the impact inside and outside each Rx fire treatment (Text S1). For each random point, we extract dNBR values from Sentinel-2A data, $PM_{2.5}$ emissions from WBSE, and covariate information (land cover, elevation). The random points are seeded to ensure that the burn severity and air quality impacts at each sampling location are consistent. If there are multiple NFPORS treatments in the same location over time, we report the statistics of the largest treatment in terms of acreage. We did not observe multiple treatments in the same location with different methods of treatments over time (e.g., Rx fire treatment and then later mechanical thinning).

To test for robustness, we increase the size of the treatment and control buffers. We recognize that the control area might still be indirectly affected by the treatment, particularly if the treated area impacts nearby vegetation or other environmental variables. To account for potential spillover effects, we expand the area of both the treatment and control buffers by one-third. Such an adjustment can help to ensure that any treatment effects are distinguished from changes in the control areas. Additionally, to confirm that our method of assigning treated areas by buffering points is reasonable, we use CAL FIRE Rx fire perimeter data to compare treated and control areas within observed Rx fire perimeters.

Causal Inference of Rx Fire Treatments

We use regression analysis to evaluate the impact of Rx fire treatments on dNBR for all locations and $PM_{2.5}$ emissions for all California fires listed in Table 1. We estimate the following regression:

$$y_{id} = \beta D_{id} + \lambda X_{id} + \alpha_d + \varepsilon_{id} \qquad \text{Eq. 2}$$

where y represents either of our outcomes (dNBR or $PM_{2.5}$ emission) measured at pixel i across our 186 treatment locations d. D_{id} represents a dummy variable for whether a given pixel was treated by an Rx fire treatment, X_{id} is our vector of control variables, which includes indicator variables for whether a given pixel was in the WUI, its land cover type, and whether it had burned in a previous fire, ε is the error term, and α is a vector of dummy variables (separate intercepts, or "fixed effects") for each "treated area" d, which includes both the Rx fire treated area as well as the surrounding control buffer for a single treatment. The inclusion of treated-area fixed effects ensures that we are only comparing directly adjacent treated and control pixels to one another and not comparing a treated pixel in one location to a distant control pixel. For each regression we report the 95% confidence interval, where standard errors are clustered at the treatment level. Furthermore, we identify areas treated with Rx fire between October 2018 and May 2020 that previously experienced wildfires between 2001 and 2015. We found five wildfire perimeters (Santiago Fire 2007, Station Fire 2009, Aspen Fire 2013, French Fire 2014, Pickett Fire 2015) that intersected with 38 land management treatments found in NFPORS. For wildfires before 2015, we use Landsat 7 dNBR imagery. Performing similar treatment-control analyses with these buffers indicates that treated areas had a 12.5% increase ($p<0.001$) in burn severity compared to adjacent controls. To account for past fire history and isolate the effects of Rx fire treatments from legacy impacts, we control for these 38 treatment locations in the above regression.

To test for whether Rx fire treatments have different effects inside or outside the WUI, we first limit our sample to either Rx fire or mechanical thinning treatments and then interact our treatment with an indicator (dummy variable) for whether the treatment was inside the WUI as designated by NFPORS. The coefficient and statistical significance of the estimate on the interaction tell us whether the treatment was larger in the WUI for a given type of treatment; these coefficients are reported in Fig 3c.

To ensure the robustness of our sampling strategy, we perform several additional statistical checks and historical comparisons. We assess the distribution of covariates between treated and control pixels, examining variables such as elevation and land cover types. We conduct t-tests for differences in means and pixel-level regressions to identify significant differences. Covariates showing imbalance between groups are included as controls in the main regression estimates (Fig. S3, Tables S4, S5).

To help ensure that our approach to estimating the impact of Rx fire treatments is actually recovering the impact of treatment rather than random differences in burn severity or emissions that occur within a wildfire burn scar, we implement placebo tests. For each fire, we create 100 random hypothetical treatment locations with accompanying control buffers and compare the distribution of estimated "treatment effects" in these placebo treatment areas to our estimate of the impact of treatment in the true treated area(s) in that same fire. By comparing outcomes ($PM_{2.5}$ and dNBR) of these placebo-treated pixels with actual treated pixels, we can assess whether our observed treatment effects might be attributed to random chance.

To assess the net impact of Rx fire treatments on smoke emissions in California, we use estimates derived from our regression analysis. These estimates allow us to quantify the overall per-acre reduction in smoke $PM_{2.5}$ attributed to Rx fire treatments by accounting for the Rx fire emissions themselves from the reclassified FINNv2.2 inventory from 2012 to 2020. We also identify grid cells where Rx fire emissions occurred in a given year and calculate if they overlapped with any wildfire emission grid cells at a subsequent timestep within a 5 km distance threshold. We then compute the percentage of Rx fire-treated areas that remained unburned. We assume an emissions base year of 2018, which reflects moderate to high wildfire activity. In addition, we compute the total emissions with Rx burning, E_{Rx}:

$$E_{Rx} = (1-a)x + a(x + (1-b)y) \qquad \text{Eq. 3}$$

total emissions without Rx burning, E_{NoRx}:

$$E_{NoRx} = ay \qquad \text{Eq. 4}$$

and, the percent reduction in overall smoke emissions by conducting Rx fires:

$$\frac{E_{NoRx} - E_{Rx}}{E_{NoRx}} \qquad \text{Eq. 5}$$

Here, the *x* variable is the average emissions from an acre of Rx fire calculated by dividing the total emissions from the FINNv2.2 inventory divided by the acres burned by these fires. The *y* variable is the average emissions from an acre of wildfire burned, which we calculate by dividing the total emissions from our wildfire case studies (here, the Creek and Slater Fires) by the acres burned in Table 1 for these fires. The *a* variable is the proportion of Rx fire-treated areas that later reburned described above. The percent reduction in wildfire emissions due to an Rx fire, *b*, is calculated as follows:

$$b = \frac{y - z}{y} \qquad \text{Eq. 6}$$

where *z* is the fire-specific effect of Rx fire treatments on smoke emissions estimates and observed decreases for both the Creek and Slater Fires chosen due to data availability. Because Rx fire treatments in these two fires produced different estimates, we take the weighted average based on acres treated in NFPORS for Creek (1519 acres) and Slater (872 acres). The $a(1-b)y$ term describes the overlap of Rx fire and wildfire emissions, accounting for the fact that if an area reburns it will emit a reduced amount of wildfire smoke because Rx fire treatment had already occurred. If Eq. 5 is less than 1, Rx fires result in a net savings of smoke emissions, whereas a value greater than 1 indicates that the Rx fires contribute more to smoke emissions than they mitigate during subsequent wildfires. Finally, we scale up these per-acre emission reductions to align with the target treatment of 1 million acres mandated by California's Wildfire and Forest Resilience Task Force.

References

1. J. T. Abatzoglou, D. E. Rupp, L. W. O'Neill, M. Sadegh, Compound Extremes Drive the Western Oregon Wildfires of September 2020. *Geophysical Research Letters* **48**, e2021GL092520 (2021).
2. W. R. L. Anderegg, O. S. Chegwidden, G. Badgley, A. T. Trugman, D. Cullenward, J. T. Abatzoglou, J. A. Hicke, J. Freeman, J. J. Hamman, Future climate risks from stress, insects and fire across US forests. *Ecology Letters* **25**, 1510–1520 (2022).
3. K. Rao, A. P. Williams, N. S. Diffenbaugh, M. Yebra, A. G. Konings, Plant-water sensitivity regulates wildfire vulnerability. *Nat Ecol Evol* **6**, 332–339 (2022).
4. C. S. Stevens-Rumann, K. B. Kemp, P. E. Higuera, B. J. Harvey, M. T. Rother, D. C. Donato, P. Morgan, T. T. Veblen, Evidence for declining forest resilience to wildfires under climate change. *Ecology Letters* **21**, 243–252 (2018).
5. L. A. St. Denis, K. C. Short, K. McConnell, M. C. Cook, N. P. Mietkiewicz, M. Buckland, J. K. Balch, All-hazards dataset mined from the US National Incident Management System 1999–2020. *Sci Data* **10**, 112 (2023).
6. M. Burke, M. L. Childs, B. de la Cuesta, M. Qiu, J. Li, C. F. Gould, S. Heft-Neal, M. Wara, The contribution of wildfire to PM2.5 trends in the USA. *Nature* **622**, 761–766 (2023).
7. X. Zhou, K. Josey, L. Kamareddine, M. C. Caine, T. Liu, L. J. Mickley, M. Cooper, F. Dominici, Excess of COVID-19 cases and deaths due to fine particulate matter exposure during the 2020 wildfires in the United States. *Science Advances* **7**, eabi8789 (2021).
8. J. A. [D-K.-3 Rep. Yarmuth, H.R.5376 - 117th Congress (2021-2022): Inflation Reduction Act of 2022 (2022). https://www.congress.gov/bill/117th-congress/house-bill/5376.
9. California's Wildfire and Forest Resilience Action Plan: Recommendations of the Governor's Forest Management Task Force (2021). https://wildfiretaskforce.org/wp-content/uploads/2022/04/californiawildfireandforestresilienceactionplan.pdf.
10. M. M. Kelp, M. C. Carroll, T. Liu, R. M. Yantosca, H. E. Hockenberry, L. J. Mickley, Prescribed Burns as a Tool to Mitigate Future Wildfire Smoke Exposure: Lessons for States and Rural Environmental Justice Communities. *Earth's Future* **11**, e2022EF003468 (2023).
11. C. Adlam, D. Almendariz, R. W. Goode, D. J. Martinez, B. R. Middleton, Keepers of the Flame: Supporting the Revitalization of Indigenous Cultural Burning. *Society & Natural Resources* **35**, 575–590 (2022).
12. R. El Asmar, Z. Li, D. J. Tanner, Y. Hu, S. O'Neill, L. G. Huey, M. T. Odman, R. J. Weber, A Multi-site Passive Approach for Studying the Emissions and Evolution of Smoke from Prescribed Fires. *EGUsphere*, 1–40 (2024).
13. F. K. Lake, A. C. Christianson, Indigenous fire stewardship. *Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires*, doi: 10.1007/978-3-319-51727-8_225-1 (2019).
14. C. A. Kolden, We're Not Doing Enough Prescribed Fire in the Western United States to Mitigate Wildfire Risk. *Fire* **2**, 30 (2019).
15. A. Jonko, J. Oliveto, T. Beaty, A. Atchley, M. A. Battaglia, M. B. Dickinson, M. R. Gallagher, A. Gilbert, D. Godwin, J. A. Kupfer, J. K. Hiers, C. Hoffman, M. North, J. Restaino, C. Sieg, N.

Skowronski, How will future climate change impact prescribed fire across the contiguous United States? *npj Clim Atmos Sci* **7**, 1–10 (2024).
16. D. L. Swain, J. T. Abatzoglou, C. Kolden, K. Shive, D. A. Kalashnikov, D. Singh, E. Smith, Climate change is narrowing and shifting prescribed fire windows in western United States. *Commun Earth Environ* **4**, 1–14 (2023).
17. R. B. Keiter, Wildfire Policy, Climate Change, and the Law Wildfire Law Edition. *Tex. A&M J. Prop. L.* **1**, 87–108 (2012).
18. United States Government Accountability Office, Wildland fire: federal agencies' efforts to reduce wildland fuels and lower risk to communities and ecosystems (2019). https://www.gao.gov/assets/710/703470.pdf.
19. M. R. Auer, Considering equity in wildfire protection. *Sustain Sci* **16**, 2163–2169 (2021).
20. A. Marsavin, R. van Gageldonk, N. Bernays, N. W. May, D. A. Jaffe, J. L. Fry, Optical properties of biomass burning aerosol during the 2021 Oregon fire season: comparison between wild and prescribed fires. *Environmental Science: Atmospheres*, doi: 10.1039/D2EA00118G (2023).
21. C. L. Schollaert, M. E. Marlier, T. M. Busch Isaksen, Development of a source-specific biomass burning emissions inventory for Washington, Oregon, and California. *Atmospheric Environment* **319**, 120283 (2024).
22. S. Afrin, F. Garcia-Menendez, Potential impacts of prescribed fire smoke on public health and socially vulnerable populations in a Southeastern U.S. state. *Science of The Total Environment* **794**, 148712 (2021).
23. E. G. Brodie, E. E. Knapp, W. R. Brooks, S. A. Drury, M. W. Ritchie, Forest thinning and prescribed burning treatments reduce wildfire severity and buffer the impacts of severe fire weather. *Fire Ecology* **20**, 17 (2024).
24. S. Fuhlendorf, R. Limb, D. Engle, R. Miller, Assessment of Prescribed Fire as a Conservation Practice (2011). https://www.researchgate.net/profile/Samuel-Fuhlendorf/publication/265000863_Assessment_of_Prescribed_Fire_as_a_Conservation_Practice/links/53fde1290cf22f21c2f85b70/Assessment-of-Prescribed-Fire-as-a-Conservation-Practice.pdf.
25. M. M. Boer, R. J. Sadler, R. S. Wittkuhn, L. McCaw, P. F. Grierson, Long-term impacts of prescribed burning on regional extent and incidence of wildfires—Evidence from 50 years of active fire management in SW Australian forests. *Forest Ecology and Management* **259**, 132–142 (2009).
26. L. Collins, R. Trouvé, P. J. Baker, B. Cirulus, C. R. Nitschke, R. H. Nolan, L. Smith, T. D. Penman, Fuel reduction burning reduces wildfire severity during extreme fire events in south-eastern Australia. *Journal of Environmental Management* **343**, 118171 (2023).
27. J. M. Fernández-Guisuraga, P. M. Fernandes, Prescribed burning mitigates the severity of subsequent wildfires in Mediterranean shrublands. *Fire Ecology* **20**, 4 (2024).
28. M. Sow, C. Hély, C. Mbow, B. Sambou, Fuel and fire behavior analysis for early-season prescribed fire planning in Sudanian and Sahelian savannas. *Journal of Arid Environments* **89**, 84–93 (2013).
29. M. E. Hunter, M. D. Robles, Tamm review: The effects of prescribed fire on wildfire regimes and impacts: A framework for comparison. *Forest Ecology and Management* **475**, 118435 (2020).
30. K. T. Davis, J. Peeler, J. Fargione, R. D. Haugo, K. L. Metlen, M. D. Robles, T. Woolley, 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**, 121885 (2024).
31. V. C. Radeloff, D. P. Helmers, H. A. Kramer, M. H. Mockrin, P. M. Alexandre, A. Bar-Massada, V. Butsic, T. J. Hawbaker, S. Martinuzzi, A. D. Syphard, S. I. Stewart, Rapid growth of the US

wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences* **115**, 3314–3319 (2018).

32. N. M. Vaillant, J. A. Fites-Kaufman, S. L. Stephens, Effectiveness of prescribed fire as a fuel treatment in Californian coniferous forests. *Int. J. Wildland Fire* **18**, 165 (2009).

33. X. Wu, E. Sverdrup, M. D. Mastrandrea, M. W. Wara, S. Wager, Low-intensity fires mitigate the risk of high-intensity wildfires in California's forests. *Science Advances* **9**, eadi4123 (2023).

34. K. Rao, A. P. Williams, N. S. Diffenbaugh, M. Yebra, C. Bryant, A. G. Konings, Dry Live Fuels Increase the Likelihood of Lightning-Caused Fires. *Geophysical Research Letters* **50**, e2022GL100975 (2023).

35. S. C. P. Coogan, X. Cai, P. Jain, M. D. Flannigan, Seasonality and trends in human- and lightning-caused wildfires ≥ 2 ha in Canada, 1959–2018. *Int. J. Wildland Fire* **29**, 473–485 (2020).

36. A. Soler, N. Pineda, H. S. Segundo, J. Bech, J. Montanyà, Characterisation of thunderstorms that caused lightning-ignited wildfires. *Int. J. Wildland Fire* **30**, 954–970 (2021).

37. A. Dorph, E. Marshall, K. A. Parkins, T. D. Penman, Modelling ignition probability for human- and lightning-caused wildfires in Victoria, Australia. *Natural Hazards and Earth System Sciences* **22**, 3487–3499 (2022).

38. A. L. Kramer, J. Liu, L. Li, R. Connolly, M. Barbato, Y. Zhu, Environmental justice analysis of wildfire-related PM2.5 exposure using low-cost sensors in California. *Science of The Total Environment* **856**, 159218 (2023).

39. L. Kiely, S. E. Neyestani, S. Binte-Shahid, R. A. York, W. C. Porter, K. C. Barsanti, California Case Study of Wildfires and Prescribed Burns: PM2.5 Emissions, Concentrations, and Implications for Human Health. *Environ. Sci. Technol.* **58**, 5210–5219 (2024).

40. A. Rosenberg, S. Hoshiko, J. R. Buckman, K. R. Yeomans, T. Hayashi, S. J. Kramer, S. Huang, N. H. F. French, A. G. Rappold, Health Impacts of Future Prescribed Fire Smoke: Considerations From an Exposure Scenario in California. *Earth's Future* **12**, e2023EF003778 (2024).

41. Q. Xu, A. L. Westerling, A. Notohamiprodjo, C. Wiedinmyer, J. J. Picotte, S. A. Parks, M. D. Hurteau, M. E. Marlier, C. A. Kolden, J. A. Sam, W. J. Baldwin, C. Ade, Wildfire burn severity and emissions inventory: an example implementation over California. *Environ. Res. Lett.* **17**, 085008 (2022).

42. S. L. Stephens, J. J. Moghaddas, Experimental fuel treatment impacts on forest structure, potential fire behavior, and predicted tree mortality in a California mixed conifer forest. *Forest Ecology and Management* **215**, 21–36 (2005).

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

44. J. Wen, S. Heft-Neal, P. Baylis, J. Boomhower, M. Burke, Quantifying fire-specific smoke exposure and health impacts. *Proceedings of the National Academy of Sciences* **120**, e2309325120 (2023).

45. J. Eidenshink, B. Schwind, K. Brewer, Z.-L. Zhu, B. Quayle, S. Howard, A Project for Monitoring Trends in Burn Severity. *fire ecol* **3**, 3–21 (2007).

46. J. J. Picotte, K. Bhattarai, D. Howard, J. Lecker, J. Epting, B. Quayle, N. Benson, K. Nelson, Changes to the Monitoring Trends in Burn Severity program mapping production procedures and data products. *Fire Ecology* **16**, 16 (2020).

47. N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, R. Moore, Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* **202**, 18–27 (2017).

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

49. S. Jin, J. Dewitz, C. Li, D. Sorenson, Z. Zhu, M. R. I. Shogib, P. Danielson, B. Granneman, C. Costello, A. Case, L. Gass, National Land Cover Database 2019: A Comprehensive Strategy for Creating the 1986–2019 Forest Disturbance Product. *Journal of Remote Sensing* **3**, 0021 (2023).
50. R. Crippen, S. Buckley, P. Agram, E. Belz, E. Gurrola, S. Hensley, M. Kobrick, M. Lavalle, J. Martin, M. Neumann, Q. Nguyen, P. Rosen, J. Shimada, M. Simard, W. Tung, NASADEM GLOBAL ELEVATION MODEL: METHODS AND PROGRESS. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* **XLI-B4**, 125–128 (2016).
51. C. Wiedinmyer, Y. Kimura, E. C. McDonald-Buller, L. K. Emmons, R. R. Buchholz, W. Tang, K. Seto, M. B. Joseph, K. C. Barsanti, A. G. Carlton, R. Yokelson, The Fire Inventory from NCAR version 2.5: an updated global fire emissions model for climate and chemistry applications. *Geoscientific Model Development* **16**, 3873–3891 (2023).

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Supporting Information Text

Text S1. We establish buffer zones around the treated coordinate for sampling. We convert the reported treatment acreage a into square meters (1 acre = 4046.86 m²) and calculate the buffer radius r with the formula:

$$r = \sqrt{\frac{a}{\pi}} \qquad \text{Eq. 1}$$

We then design a larger control buffer $r * \sqrt{2}$ (approximately ~141% of the original radius). This control buffer is constructed around the convex hull of each treatment area and then the treatment buffer is subtracted from the control buffer, resulting in a set of points located outside the immediate treatment zone.

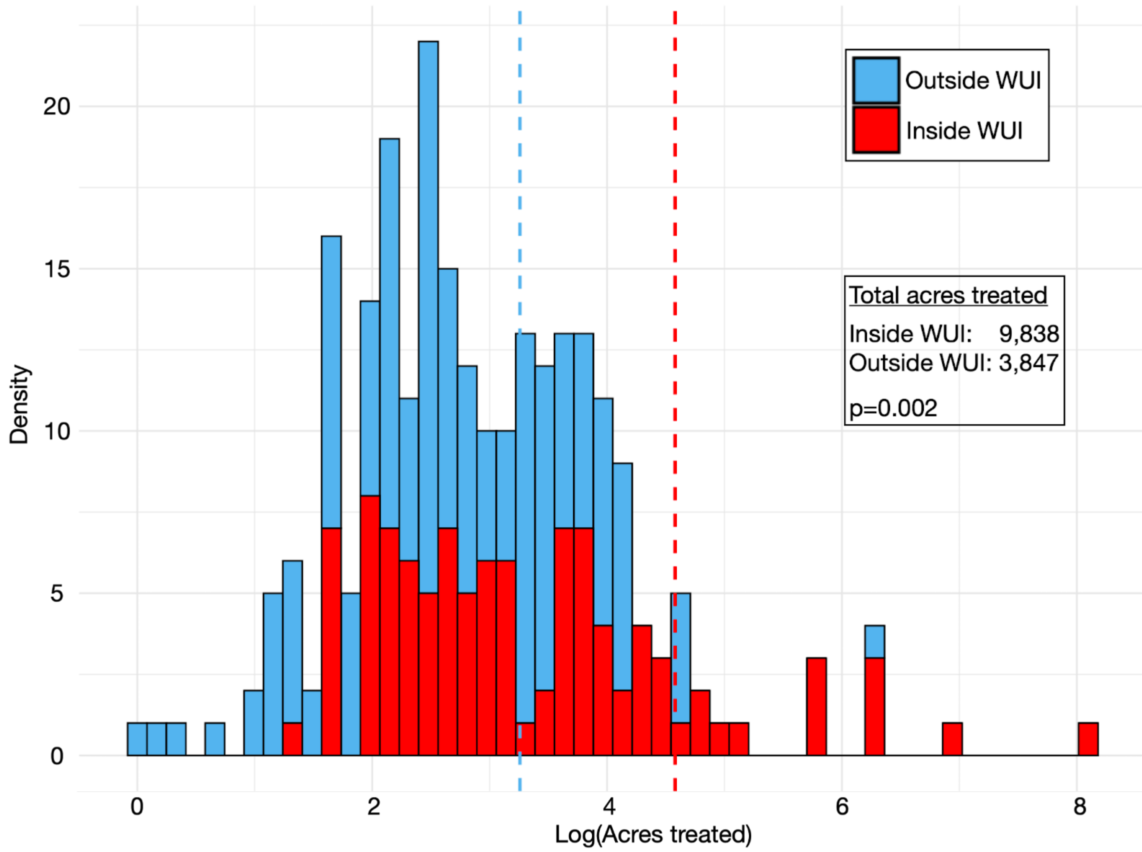

Fig. S1. Log distribution of acres treated inside the WUI and outside. Mean acreage sizes are reported as vertical lines.

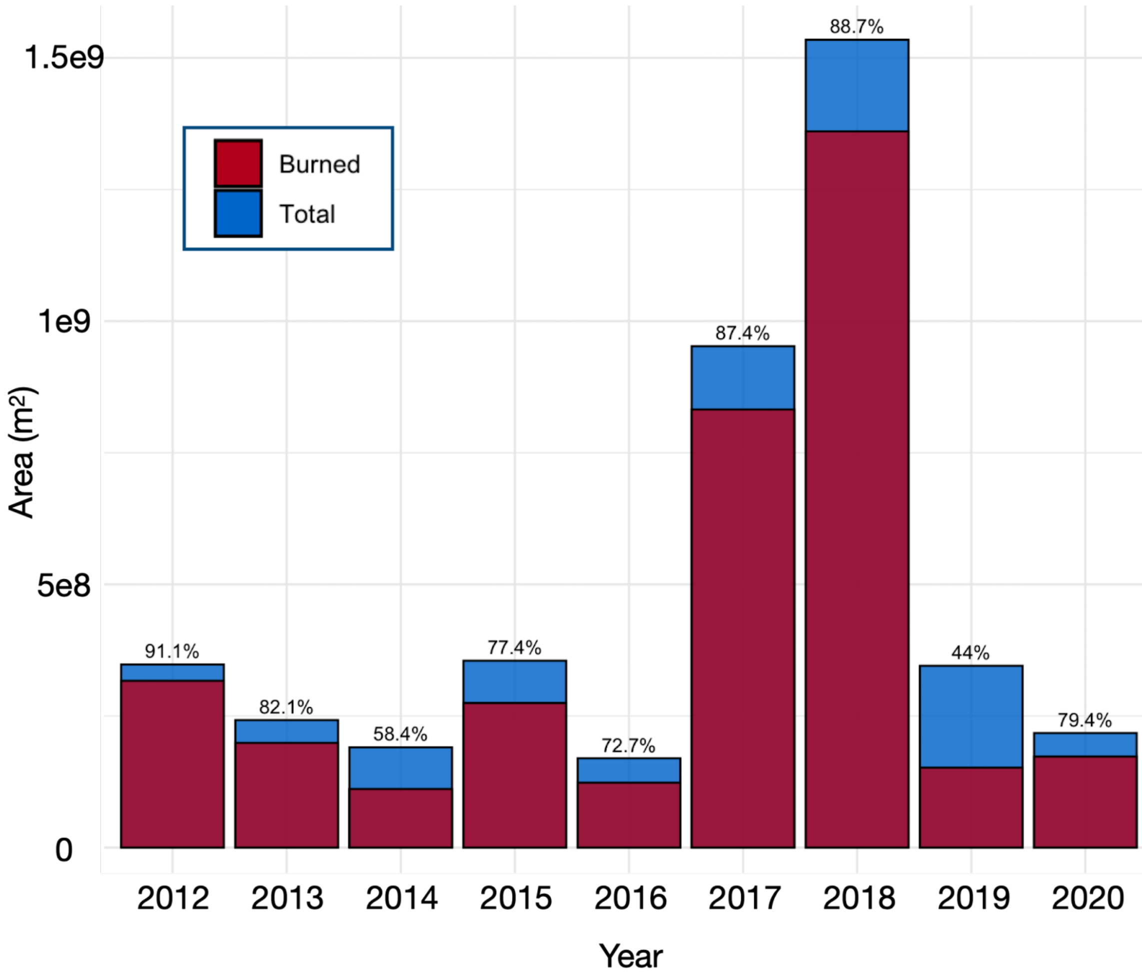

Fig. S2. Total area burned by Rx fires in California according to the reclassified FINNv2.2 inventory (1) and the proportion later reburned within the same timeframe.

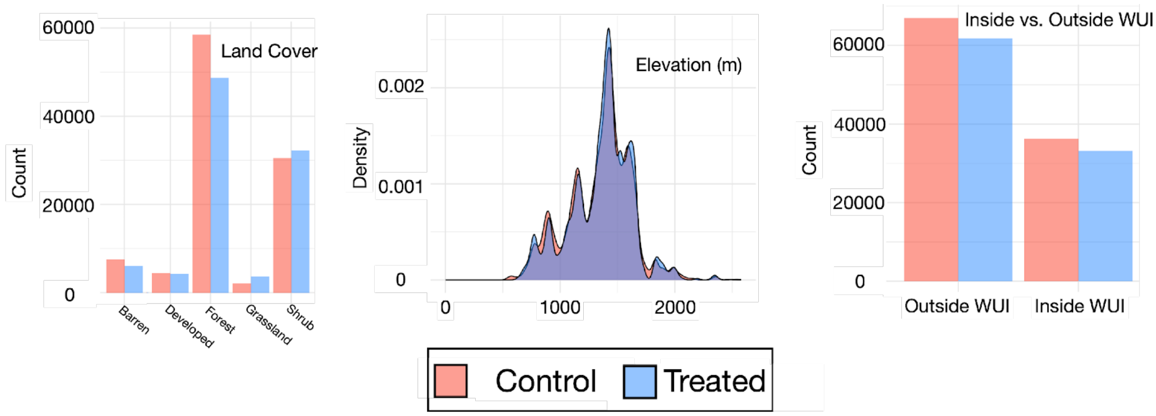

Fig. S3. Distribution imbalances in covariates between treated and control groups. Land cover, elevation, and WUI designation are subsequently added as controls in all regressions.

Table S1. Coefficient estimates for burn severity and smoke emissions.

	dNBR - All (%)		**dNBR - CA (%)**		**$PM_{2.5}$ - CA (kg acre^{-1})**	
	Estimate [95% CI]	Pr(>|t|)	Estimate [95% CI]	Pr(>|t|)	Estimate [95% CI]	Pr(>|t|)
Pooled Estimate	-15.6 [-23.6, -7.6]	<0.001	-17.0 [-25.8, -8.2]	<0.001	-101 [-220, 18.4]	<0.10
Rx fire	-27.4 [-44.0, -10.8]	<0.001	-27.9 [-39.7, -16.1]	<0.01	-31 [-168, 106]	0.37
Mechanical Thinning	-7.7 [-18.2, 2.8]	0.15	-2.3 [-16.6, 12.0]	0.76	-79 [-263, 105]	0.40
Barren	-31.3 [-58.0, -4.6]	0.03	-32.1 [-60.0, -4.2]	0.03	-26 [-373, 321]	0.89
Developed	-39.6 [-58.0, -21.2]	<0.001	-39.5 [-58.5, -20.5]	<0.001	232 [-156, 620]	0.24
Forest	-15.0 [-24.7, -5.3]	<0.001	-16.6 [-27.4, -5.8]	<0.01	-103 [-224, 17.9]	0.09
Grassland	-9.4 [-27.2, 8.4]	0.31	-13.1 [-32.2, 6.0]	0.19	-189 [-489, 111]	0.23
Shrub	1.4 [-8.8, 11.6]	0.79	0.3 [-10.9, 11.5]	0.97	-198 [-405, 8.7]	0.06
Inside WUI	-8.5 [-21.1, 4.1]	0.19	-10.3 [-24.7, 4.1]	0.17	-34 [-244, 176]	0.75
Outside WUI	-20.3 [-30.6, -10.0]	<0.001	-20.5 [-31.7, -9.3]	<0.001	-125 [-255, 4.7]	0.06

Table S2. Coefficient estimates for burn severity and smoke emissions for larger treatment and control buffer definitions.

	dNBR - All (%)		**dNBR - CA (%)**		**$PM_{2.5}$ - CA (kg acre^{-1})**	
	Estimate [95% CI]	Pr(>|t|)	Estimate [95% CI]	Pr(>|t|)	Estimate [95% CI]	Pr(>|t|)
Pooled Estimate	-11.5 [-17.6, -5.4]	<0.001	-12.9 [-19.7, -6.1]	<0.001	-84 [-159, -9.4]	0.03
Rx fire	-17.6 [-25.0, -10.2]	<0.001	-20.7 [-29.1, -12.3]	<0.01	-75 [-167, 16.6]	0.12
Mechanical Thinning	-2.5 [-14.3, 9.3]	0.67	-3.1 [-15.5, 9.3]	0.63	-35 [-155, 84.8]	0.57
Barren	-24.9 [-41.2, -8.6]	<0.001	-25.2 [-41.7, -8.7]	<0.01	-126 [-240, -12.4]	0.03
Developed	-27.0 [-43.3, -10.7]	<0.001	-27.1 [-42.7, -11.5]	<0.001	-130 [-265, 5.2]	0.06
Forest	-11.8 [-19.0, -4.6]	<0.001	-13.2 [-13.3, -13.1]	<0.01	-43 [-121, 35.2]	0.28
Grassland	-5.7 [-18.8, 7.4]	0.40	-11.4 [-24.4, 1.6]	<0.10	-5.0 [-198, 188]	0.96
Shrub	1.5 [-6.5, 9.5]	0.72	2.2 [-6.6, 11.0]	0.62	-154 [-295, -12.8]	0.04
Inside WUI	-5.6 [-15.6, 4.4]	0.27	-8.1 [-19.7, 3.5]	0.17	-70 [-218, 77.6]	0.35
Outside WUI	-15.3 [-23.2, -7.4]	<0.001	-15.5 [-23.9, -7.1]	<0.001	-91 [-174, -8.4]	0.03

Table S3. Coefficient estimates for burn severity for NFPORS subtypes for all of the western US.

Subtype	**dNBR - All (%)**			**dNBR - Inside WUI (%)**			**dNBR - Outside WUI (%)**		
	n [acreage]	Estimate [95% CI]	Pr(>|t|)	n [acreage]	Estimate [95% CI]	Pr(>|t|)	n [acreage]	Estimate [95% CI]	Pr(>|t|)
Pile Burn	114 [3184]	-24.1 [-34.9, -13.4]	<0.001	38 [1549]	-12.9 [-32.6, 6.7]	0.21	79 [1699]	-28.3 [-40.1, -15.7]	<0.001
Broadcast Burn	3 [3746]	-18.1 [-37.9, 74.0]	0.59	2 [3636]	6.3 [1.9,10.7]	0.22	1 [110]	-114 [-131, -97.3]	<0.001
Biomass Removal	5 [687]	-1.7 [-24.2, 20.8]	0.89	2 [589]	-19.7 [-19.8, -19.5]	<0.001	3 [89]	9.3 [4.0, 14.6]	0.07
Thinning	39 [2443]	17.8 [-12.6, 17.8]	0.74	24 [2182]	4.7 [-22.2, 12.8]	0.60	18 [281]	18.9 [-4.4, 42.1]	0.13
Machine Pile	9 [433]	-41.5 [-57.6, -25.5]	<0.001	6 [414]	-28.6 [-60.0, 2.8]	0.13	3 [19]	-41.4 [-72.2, -10.6]	0.12
Crushing	3 [56.5]	-14.6 [-81.6, 52.5]	0.72	3 [56.5]	-14.6 [-81.6, 52.5]	0.72			
Fire Use	3 [558]	-26.1 [-38.7, -13.5]	0.06				3 [558]	-26.1 [-38.7, -13.5]	0.06
Lop and Scatter	7 [101]	27.4 [-24.8, 79.6]	0.34	3 [27.3]	72.4 [6.8, 138]	0.16	4 [74]	-7.1 [-26.8, 12.5]	0.53
Chemical	13 [242]	3.3 [-22.6, 16.0]	0.74	5 [78.9]	-14.5 [-53.4, 24.5]	0.51	8 [163]	3.2 [-18.1, 24.5]	0.78

Table S4. T-tests for differences in dNBR means for land cover types across the western US.

Land Cover	Estimate	Estimate1	Estimate2	Statistic	P value	Parameter	95% CI
Barren	0.00929	0.0645	0.0552	9.41	4.97e-21	230310	0.00736, 0.0112
Developed	-0.00076	0.0381	0.0389	-0.940	3.47e-1	229347	-0.00233, 0.000818
Forest	0.0403	0.587	0.546	19.5	8.96e-85	229300	0.0362, 0.0443
Grassland	-0.0182	0.0211	0.0393	-25.5	9.18e-143	205501	-0.0196, -0.0168
Shrub	-0.0308	0.288	0.319	-16.1	4.60e-58	228680	-0.0345, -0.0270

Table S5. T-tests for differences in dNBR means for land cover types in California

Land Cover	Estimate	Estimate1	Estimate2	Statistic	P value	Parameter	95% CI
Barren	0.00932	0.0731	0.0638	8.22	1.98e-16	198174	0.00715, 0.0115
Developed	-0.00170	0.0431	0.0448	-1.85	6.50e-2	196246	-0.00351, 0.000106
Forest	0.0543	0.567	0.512	24.3	4.72e-130	196611	0.0500, 0.0587
Grassland	-0.0184	0.0204	0.0388	-24.0	4.05e-127	173199	-0.0199, -0.0169
Shrub	-0.0436	0.296	0.339	-20.8	3.07e-96	195467	-0.0477, -0.0395