



CLIMATOLOGY

Low-intensity fires mitigate the risk of high-intensity wildfires in California's forests

Xiao Wu^{1*}, Erik Sverdrup², Michael D. Mastrandrea³, Michael W. Wara^{3*}, Stefan Wager^{2*}

The increasing frequency of severe wildfires demands a shift in landscape management to mitigate their consequences. The role of managed, low-intensity fire as a driver of beneficial fuel treatment in fire-adapted ecosystems has drawn interest in both scientific and policy venues. Using a synthetic control approach to analyze 20 years of satellite-based fire activity data across 124,186 square kilometers of forests in California, we provide evidence that low-intensity fires substantially reduce the risk of future high-intensity fires. In conifer forests, the risk of high-intensity fire is reduced by 64.0% [95% confidence interval (CI): 41.2 to 77.9%] in areas recently burned at low intensity relative to comparable unburned areas, and protective effects last for at least 6 years (lower bound of one-sided 95% CI: 6 years). These findings support a policy transition from fire suppression to restoration, through increased use of prescribed fire, cultural burning, and managed wildfire, of a presuppression and precolonial fire regime in California.

INTRODUCTION

Wildfires have emerged as a critical climate adaptation and public safety issue in a number of regions, including the western United States, as the human and economic costs due to wildfires and the area burned at high severity have substantially increased over the past decades (1). These changes have coincided with large increases in loss of life, structure loss (2), and human health impacts due to wildfire smoke (3). Causes for these increased impacts include changes in the western hydroclimate (4), changes in the duration of wildfire season and the probability of fire weather (5), and the history and legacy of landscape management in California (6). Proxy reconstructions of precolonial fire activity—a combination of wildfire and cultural burning by Native Americans—indicate a much greater extent and frequency of low-intensity wildfire than during the last century (7, 8). Increased wildfire impacts have led to a much greater focus by state and federal land managers, fire services, utilities, and private landowners on reducing wildfire risks for both landscapes and communities (9–11). Policymakers broadly agree that a fundamental shift in landscape management approach will be required to reduce the consequences of wildfires (9, 10).

The consensus on how to address the growing societal impacts of wildfire focuses on fuel treatments with mechanical thinning, prescribed fire, and managed wildfire as principal components (9, 10). Legal, operational, and cost constraints limit the applicability of mechanical thinning treatments to specific contexts while approaches involving the reintroduction of fire to landscapes may have wider applicability (12). However, despite the preeminent role of prescribed and low-intensity fire in current wildfire management policy and planning, their beneficial effects on limiting the likelihood of future high-intensity fires have only been demonstrated in a small number of studies with a highly localized focus.

Fighting fire with fire

Multiple case studies indicate that the resilience of western North American forests depends critically on the presence of fire at intervals and at intensities that approximate presuppression and precolonial conditions that existed prior to the extirpation of Native Americans from ancestral territories in California in the 1850–1870 period (6). A watershed in Yosemite National Park where naturally ignited wildfires have been allowed to burn without suppression exhibited increased landscape heterogeneity, improved resilience to fire and drought-related disturbance, and increases in soil moisture and runoff (13). Precolonial forests in the Klamath region were ecologically stabilized because of a combination of indigenous cultural burning (i.e., the intentional application of fire to land by Native American tribes, tribal organizations, or cultural fire practitioners to achieve cultural goals or objectives, including subsistence, ceremonial activities, biodiversity, or other benefits) and lightning ignitions up to colonization (6). Fire behaviors in the Gila-Aldo Leopold Wilderness Complex in New Mexico and the Frank Church - River of No Return Wilderness in Idaho have been shown to be shaped by the presence or absence of prior wildfires (14). Evidence from the 2021 Dixie Fire, the largest single fire to date in California history at 3900 km² of burned areas, indicates strong controls on undesirable fire from past fires that had burned within its footprint (12). Additional regional studies have shown evidence for the legacy effect of disturbance processes, including the use of wildfire and prescribed fire, on enhancing fire resilience, under moderate fire weather conditions (15–17); however, these studies have been limited to specific geographic subregions and small numbers of wildfires and have not quantified the magnitude and duration of the protective effect of such fire.

The goal of this paper is to provide a unified analysis of fire dynamics across California's forests, based on 20 years of continuous, satellite-based monitoring of wildfires. We consider data from all fires detected by satellite monitoring in California's conifer and hardwood forests during our study period. Using these data, we seek to measure whether areas that burn at low intensity are less likely to experience high-intensity wildfire in the future—and how long any such protective effect lasts. Operationally, we collect

¹Department of Biostatistics, Columbia University, New York, NY, USA. ²Graduate School of Business, Stanford University, Stanford, CA, USA. ³Woods Institute for the Environment, Stanford University, Stanford, CA, USA.

*Corresponding author. Email: xw2892@cumc.columbia.edu (X.W.); mwara@stanford.edu (M.W.W.); swager@stanford.edu (S.W.)

and harmonize satellite data from various public geospatial data sources, including Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Products Collection 6.1 (MCD14ML) (18), Daymet Daily Surface Weather Data V4 data products (19), California's Disturbance Agents and Fractional Vegetation Cover Database (20), and Global Multi-resolution Terrain Elevation Data (GMTED2010) (21). We categorize every detectable fire based on its fire intensity, which refers to the energy release of each fire, and use a physical measurement directly estimated from MODIS. Fire intensity correlates with, but differs from, fire severity, which primarily measures above-ground biomass disruptions (see the Material and Methods for details). We then conduct a counterfactual analysis using the synthetic control approach, a modern, interpretable quasi-experimental design for causal inference (22).

We emphasize that our study measures the overall protective effect of any low-intensity fires, not just prescribed fires. During our study period, only 9.5% of wildfires in forests were recorded as prescribed fires (23), and thus, only considering the effects of recorded prescribed fires would not have given us sufficient statistical power to measure meaningful effects. The relevance of our study in informing policy regarding prescribed fire relies on an assumption that low-intensity wildfire and prescribed fire have similar effects on forest ecosystems. This assumption has support in the literature: For example, Taylor *et al.* (12) find that low-severity wildfires and prescribed fires have similar effects in reducing surface fuels, modifying the age structure of a forest, and maintaining separation of the tree canopy from fires with low flame lengths that remain close to the ground and thus create similar beneficial ecological and fuel treatment effects.

The purpose of fuel treatments is not to exclude all future fires, but rather to increase the likelihood that, upon the inception of a fire within a designated area, the fire remains low to moderate intensity and exhibits a reduced rate of spread. This mitigation strategy provides windows of opportunity for control through the allocation of additional suppression resources and reduces the potential for the fire to develop into a high-intensity fire (24). Low- to moderate-intensity fire has beneficial ecosystem effects and is much easier to manage for the protection of communities and critical

infrastructure. Under the most extreme conditions, even the best fuel treatments may fail to prevent high-intensity fires with the potential for substantial impacts on both the ecosystem and human welfare; however, they can increase the chance that fire services are able to manage their impacts (24). Our purpose here is to quantify the magnitude and duration of potential beneficial impacts of low-intensity fires in protecting against future high-intensity fires.

RESULTS

To quantify the effect of fire that burned at low intensity on landscapes in a given year, we need to assess how these landscapes might have evolved had they not burned in that same year and compare these counterfactuals to their actual evolution. Prior work has done this using specific examples, e.g., by examining the effect of past prescribed fires on a subsequent large wildfire in the southern Cascade Range in California (25), but has not attempted to synthesize evidence across time, multiple geographies, and fuel types. To facilitate the counterfactual comparisons, we tailor the well-established synthetic control method to create a weighted set of unexposed areas (i.e., synthetic controls) that maintain similar historic trajectories on fire behaviors and topography, meteorological, disturbance, and vegetation conditions as the exposed area (22, 26, 27).

Figure 1 illustrates the quasi-experimental design under the synthetic control method, in which we divide the time horizons of each area into three periods: (i) pre-focal period, in which we use pre-exposure covariate trajectories to construct synthetic controls; (ii) focal period, in which we define exposed and unexposed units based on fire status during this period; and (iii) evaluation period, in which we evaluate the impact of fire exposure evolving over years. We produce the synthetic controls via a covariate balancing weighting algorithm, which is computationally efficient enough to be able to accommodate large-scale satellite-based data (28–30). We require a minimal 8-year pre-focal period to allow synthetic controls to be sufficiently comparable to exposed units in relatively long historic trajectories, which is why the first focal year starts in 2008.

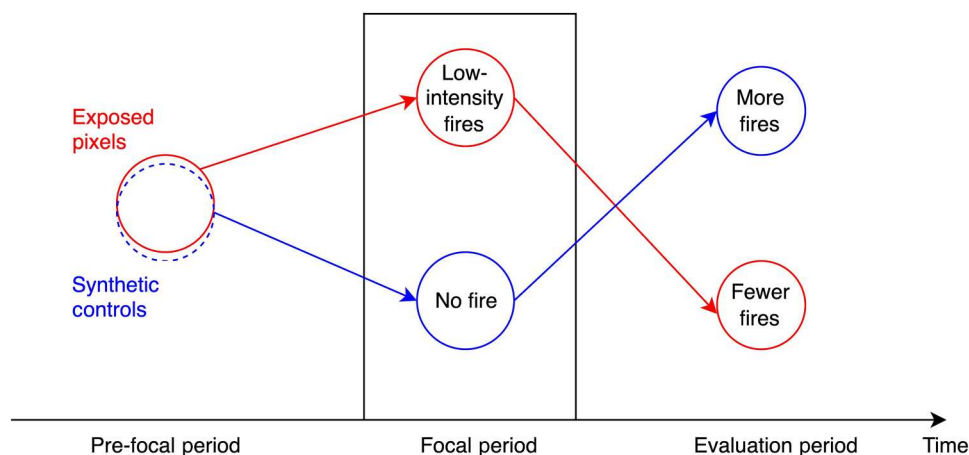


Fig. 1. Overview of the quasi-experimental design. Exposed and unexposed units are defined by fire status within a focal period. We create synthetic controls as a weighted set of unexposed pixels that maintain similar trajectories on fire behaviors and topography, meteorological, disturbance, and vegetation conditions, as the exposed pixel set during the pre-focal period. These synthetic controls are then used as counterfactuals in the evaluation period to estimate the effects of low-intensity fires on future fire frequency and intensity.

Results on the magnitude and duration of fire risk reduction

For the focal period 2008–2020, we found substantial and statistically significant reductions in high-intensity fire risks following low-intensity fires, although the effect magnitude varies across land cover type and fire outcome class.

In conifer forests, areas that have recently burned at low intensity are 64.0% [95% confidence interval (CI): 41.2 to 77.9%] less likely to burn at high intensity in the following year relative to unburned synthetic control areas. This protective effect against high-intensity fires persists for at least 6 years (lower bound of one-sided 95% CI: 6 years). The construction of CIs is described in the Supplementary Materials. Our findings are robust to whether we consider high-intensity fire events only or combine moderate- to high-intensity fire events together as the outcomes of interest. On the other hand, the effect of low-intensity fire in reducing all future fires (of any intensity) is much more muted. In conifer forests, we find a smaller (yet still statistically significant) 16.4% (95% CI: 2.4 to 28.3%) reduction in the risk of any fire following low-intensity burn relative to unburned synthetic control areas, and this effect persists for at least 5 years (lower bound of one-sided 95% CI: 5 years).

Our findings in hardwood forests are comparable to those in conifer forests, except with weaker statistical significance (partially due to a smaller sample size). We again find that areas burned at low intensity 1 year earlier are approximately half as likely to burn at high or moderate-to-high intensity than unburned synthetic control areas, although (likely due to sample size issues) the result is not statistically significant for the high-intensity fire outcome. We are not able to detect any protective effect of low-intensity fires on overall future fires in hardwood forests.

Figure 2 shows the estimated trajectories of fire risk reductions up to 9 years following low-intensity fires, stratified by land cover type and fire outcome class. In the Supplementary Materials, we show that the effects are robust under sensitivity analyses that change focal year spans, alter classification schemes for fire intensity, and compare different definitions of fire intensity and severity.

In summary, our finding that low-intensity fire offers years of protection against future high-intensity fire—but does not necessarily prevent all future fire—is well in line with our knowledge of the climate and ecosystems in California. It is well understood that the low-elevation pine and mixed conifer forests in California can burn at low intensity even just one growing season postfire—and the ecosystem is well adapted for such frequent, low-intensity fires (31–33). On the other hand, high-intensity fires happen when an overgrown understory enables the fire to climb into the crowns of mature trees (6); and, in this context, our results suggest that low-intensity fires help, on average across California, control the amount of available fuels in a way that persists (and protects against high-intensity fires) for many years.

Policy outlook

Our approach illustrates, in the context of California's forest ecosystems, the benefits of using prescribed fires and managed wildfires that burn at low intensity as tools to mitigate the risks from high-intensity wildfires, i.e., fires of the type that have led to increasingly adverse impacts on both the ecosystem and human welfare in California and other jurisdictions. Our results allow accurate quantification of the risk mitigation value and duration of investments in prescribed fire and managed wildfire. We find that the protective

effects of low-intensity fire are strong but decay over the course of a decade, consistent with existing studies (34–36), implying that prescribed fire treatments are better thought of as periodic maintenance rather than a one-time intervention for forests that are adjacent to communities or critical infrastructure. To be effective, investments in restoring low-intensity fire to forest ecosystems in California need to be structured to recur on a periodic and ongoing basis.

The findings of this study have important policy implications related to land management and utility planning. At present, the U.S. Congress is working on the reauthorization of the U.S. Department of Agriculture programs through the Farm Bill (37). A crucial aspect of this undertaking involves examining improvements to the U.S. Forest Service programs governing fuel treatments, and the U.S. Forest Service has proposed treating nearly 200,000 km² over the upcoming decade through a mixture of fuel treatment strategies (9). Our study provides a quantification of the potential benefit that increased investment in fuel treatments could yield at a scale of geography as large as California. The results of our study provide a foundation for future evaluation of wildland fuel treatments by comparing the quantified benefits to potential costs and risks associated with its implementation. It not only illustrates how the intentional reintroduction of low-intensity fire via prescription, cultural burning, and managed wildfire could potentially lead to a substantial reduction in the occurrence of high-intensity wildfires, improving health, societal, and ecological outcomes for people, communities, and ecosystems across the western United States but also illustrates the potential limitations of such a policy if not sustained over time.

Likewise, California has proposed a substantial expansion of treated areas, increasing to 2000 km² annually on state and private lands (10). Assuming that all such areas were treated with prescribed fire and that, as suggested by our results, the protective effects last for at least 5 to 6 years, this implies the state could achieve ongoing protective effects on the order of 10,000 km² of forest lands if the program was sustained. However, given that there are roughly 125,000 km² of forests in California, of which half are state or privately owned, the risk mitigation benefit of this intervention will depend heavily on careful selection and targeting of the intervention to provide maximum protection for people, communities, and ecosystems.

Our results, by quantifying both the magnitude and duration of the protective effect of low-intensity wildfire on future high-intensity wildfires, also pave the way for comparing wildland fuel treatments with other forms of wildfire mitigation, such as home hardening, shaded fuel breaks, or utility ignition avoidance in terms of both hazard reduction, risk mitigation, and cost-effectiveness. On the basis of our findings, and assuming that low-intensity fire is a reasonable proxy for prescribed fire, our results suggest a considerable hazard and risk mitigation effect through the regular use of prescribed fire. Furthermore, our results indicate a future direction for the evaluation of prescribed fire interventions and a comparison with other approaches aimed at improving future wildfire outcomes.

While our results highlight the potential benefit of prescribed fire in mitigating future high-intensity wildfires, they do not capture the full risk-benefit assessment of prescribed fire. Prescribed fires do occasionally escape prescription and cause widespread losses, as evidenced by recent examples like the Calif

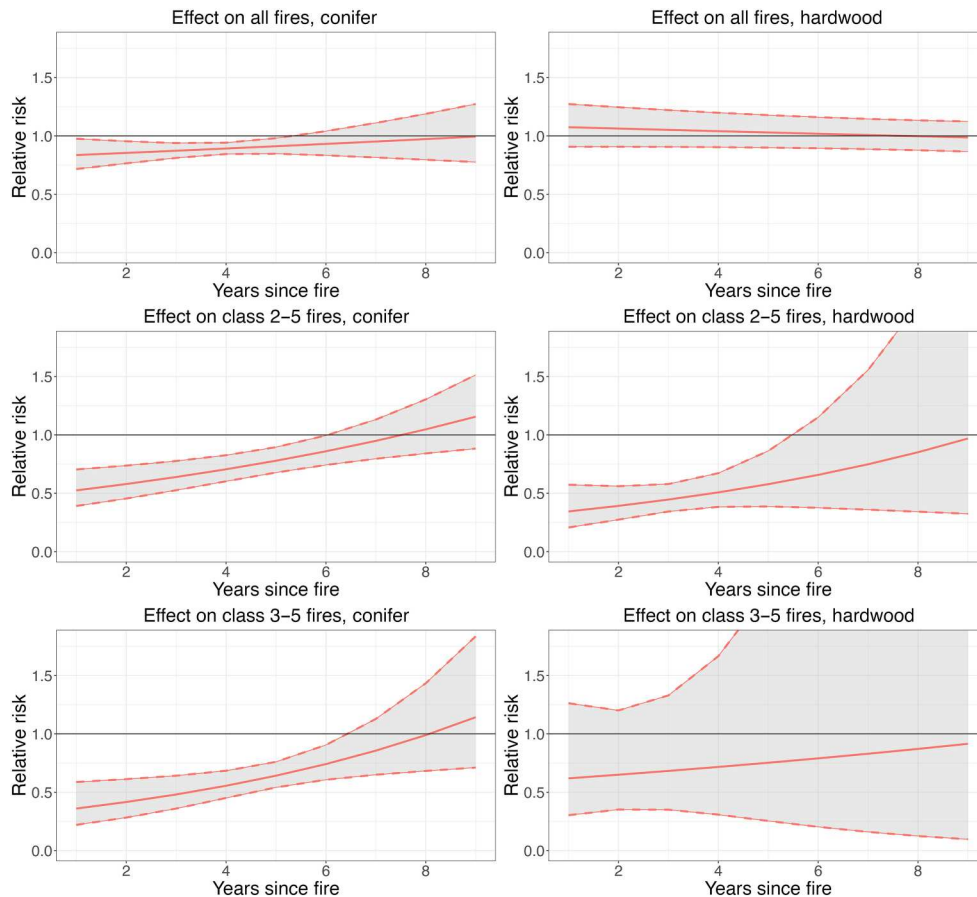


Fig. 2. Effects of low-intensity fires on the subsequent fire frequency and intensity up to nine-year lags, grouped by land cover types and fire outcome classes, pooled across focal years 2008–2020. Two-sided 95% CIs are presented.

Canyon and Hemet’s Peak fires in New Mexico (38). In addition, just like unmanaged wildfires, prescribed fires emit smoke that can subsequently result in adverse human health effects, both in the short and long term (39–41); however, the amount of smoke produced may be less than what would be produced by a high-intensity wildfire in the same area (42). Given the growing contribution of wildfire smoke to overall air pollution in the western United States (43), further examination of air quality trade-offs and public health concerns at landscape scales, resulting from substantial increases in prescribed fire usage, is needed (44).

DISCUSSION

This study deployed modern data science tools to quantify the protective effect of low-intensity fire against future high-intensity fire using unified, large-scale satellite-based data of California’s forests. We estimate the effects of low-intensity fires via counterfactual comparisons of areas recently burned at low intensity with unburned synthetic control regions whose past attributes match those of the burned regions as closely as possible. We find that low-intensity fires substantially reduce the risk of future high-intensity fires in California conifer and hardwood forests and that this risk reduction persists for at least 5 to 6 years. This work confirms,

at a large temporal and spatial scale, earlier results from studies of smaller numbers of wildfires.

This study has several strengths. We collected and harmonized comprehensive large-scale spatial-temporal data derived from publicly available satellite remote sensing data and we made all code for processing and analysis of data publicly accessible to ensure reproducibility and transparency of our results. We deployed a synthetic control methodology to achieve desirable covariate balance for long-time horizons of covariate trajectories. These methods are considered a quasi-experimental design that can be used to measure causal effects from observational data (22). To increase our confidence in the results, we ran sensitivity analyses using multiple data and model choices. Overall, our study shows how synthetic control methods can be used to leverage large-scale spatial-temporal data in climate and sustainability research.

Our study also has limitations. First, as discussed above, we did not restrict our analysis to the effects of prescribed fire alone; rather, we used low-intensity fires as a proxy exposure, which we believe reasonable since research has shown that prescribed fire mimics the effects on fuels and ecosystem structure of low-intensity wildfire (45). In the Supplementary Materials, we also demonstrate that low-intensity wildfires and prescribed fires have similar fire-intensity distributions. In the future, once we have access to more observations of prescribed fires, it would be interesting to repeat our

analysis to measure the effect of prescribed fires alone. Second, our quasi-experimental design measured the protective effect of low-intensity fire at a location-by-location level and did not consider spillover effects between neighboring locations. The fact that we use a relatively large grid size (1 km²) in our analysis partially mitigates concerns about spillovers; for example, Taylor *et al.* (16) and Harris *et al.* (46) argued that using grids that are at >800 m helps to reduce the influence of spatial autocorrelation when studying wildfires. That being said, in future work, it would still be interesting to refine the analysis using a spatial model that incorporates how fire propagates across neighboring areas in a landscape. The goal of improving spatial modeling efforts by incorporating variables representing neighborhoods was also discussed in Parks *et al.* (14), Taylor *et al.* (47), and Estes *et al.* (48).

Overall, our study demonstrates that judicious use of prescribed fire and managed wildfire can offer considerable benefits in protection against future high-intensity wildfires. This finding supports greater analysis of and investment in the use of prescribed fire and managed wildfire to alleviate the escalating wildfire crisis in the western United States. It also contributes to the underlying benefit quantification needed to estimate risk buydown and cost-effectiveness of reintroduction of fire in California forests, an important area of future research.

MATERIALS AND METHODS

We use satellite imagery to assemble a unified fire information dataset in California 2000–2021. The unit of analysis is a 1-km² pixel. We define as forests all pixels categorized as either forestlands or woodlands by the California Department of Forestry and Fire Protection (CAL FIRE) Fire and Resource Assessment Program (FRAP) (49), resulting in 124,186 km² worth of data (we do not disambiguate between forestlands or woodlands in our analysis, as CAL FIRE separates these landscape types based on land-use rather than ecological considerations). We further stratify our analysis by vegetation type and separately consider conifer- and hardwood-dominated forests [again as specified in CAL FIRE-FRAP (49)]; this results in 91,335 km² of conifer forests and 32,851 km² of hardwood forests. We do not include grasslands or shrublands because of their rapid growth after a wildfire.

For each pixel, we obtain a daily estimate of fire radiative power (FRP) from NASA's MODIS (50). FRP can be used to quantify fire intensity; we adapt a classification system that uses FRP to categorize fire intensity into classes 1 to 5 proposed by Ichoku *et al.* (51). We denote that a pixel has burned in a given year if its FRP ever exceeds 0. We denote that a pixel has burned at high intensity if its maximal FRP in that year exceeds 500 MW (class 3 to 5 fire), moderate intensity if its maximal FRP exceeds 100 MW but not 500 MW (class 2 fire), and low intensity if its maximal FRP does not exceed 100 MW (class 1 fire). Table 1 displays the relative frequency of these fire types in California during our study period.

We additionally obtain topography, meteorological, disturbance, and vegetation from various satellite-based data sources (see the Supplementary Materials for details) (19, 20, 52). Five meteorological covariates, including minimum air temperature, maximum air temperatures, precipitation, snow water equivalent, and water vapor pressure, were chosen as monthly averages to capture the seasonal variations of meteorological conditions within a year. Other covariates were chosen as the annual averages. Therefore, the analyses

account for up to $d = 1383$ pre-exposure covariates, including fire behavior history, topography, meteorological, disturbance, and vegetation variables, to control the potential confounders changing over time and ensure the representativeness of our constructed synthetic controls.

A synthetic control study

For each focal year (2008–2020) and forest land cover type (conifer and hardwood forests), we define an exposed region consisting of all pixels dominated by that land cover type and that burned at low intensity (class 1 fire) in the given focal year. Pixels that burned at moderate to high intensity, i.e., with classes 2 to 5 fire, during the focal year are excluded from the analysis. We then use pixels from the same land cover type that did not burn in the focal year to form a synthetic control region, i.e., creating a weighted set of unburned pixels that, outside of their fire experience in the focal year, look as similar as possible to the exposed region in terms of historic trajectories—including fire behaviors and topography, meteorological, disturbance, and vegetation conditions. Last, we can assess the protective effect of low-intensity fire in the focal year by comparing the evolution of the areas burned at low intensity in the focal year with their synthetic control region.

The validity of our approach hinges on the synthetic controls being representative of the exposed region. The key assumption

Table 1. Annual burned area (in square kilometers) by fire intensity classes, land cover types, and years. The fire intensity is quantified by FRP estimated from NASA's MODIS Active Fire Products Collection 6.1 (MCD14ML). The land cover type is defined by CAL FIRE-FRAP.

	Conifer			Hardwood		
	Class 1	Class 2	Classes 3–5	Class 1	Class 2	Classes 3–5
2001	376	66	6	102	29	6
2002	608	119	23	121	30	11
2003	601	123	17	218	99	29
2004	477	91	13	222	49	22
2005	532	87	16	112	14	3
2006	978	245	72	151	42	12
2007	644	232	81	212	109	32
2008	2854	631	104	475	138	35
2009	642	154	31	151	43	17
2010	316	34	1	70	9	1
2011	414	82	8	92	8	0
2012	937	384	92	169	58	9
2013	927	477	142	193	77	19
2014	1133	434	142	157	44	15
2015	1500	447	110	282	137	42
2016	555	166	37	292	126	29
2017	1515	478	94	514	258	80
2018	1835	813	259	670	322	81
2019	451	121	39	139	43	12
2020	3720	2559	1044	1417	735	196

underlying the causal validity of this synthetic control design is that, had the exposed regions not burned in the focal year, their average future fire behavior would have matched that of the synthetic control region—and thus, any future divergence in fire behavior for the exposed versus synthetic control regions is due to low-intensity fire in the focal year. The validity of this assumption depends on, first, the availability of adequate unexposed units for building the synthetic control region that can steadily track the historic trajectories of the exposed region before the intervention (53) and,

second, there being no unobserved confounders that would lead to future divergence in the fire behavior between exposed and unexposed synthetic control regions.

For the first point, we assess the quality of the synthetic control design via covariate balance to check the degree to which the distributions of pre-exposure covariate trajectories are similar across exposure and synthetic control regions (54). Figure 3 displays one of these covariate balance checks for the focal year 2008; checks for other years and individual covariates are given in the

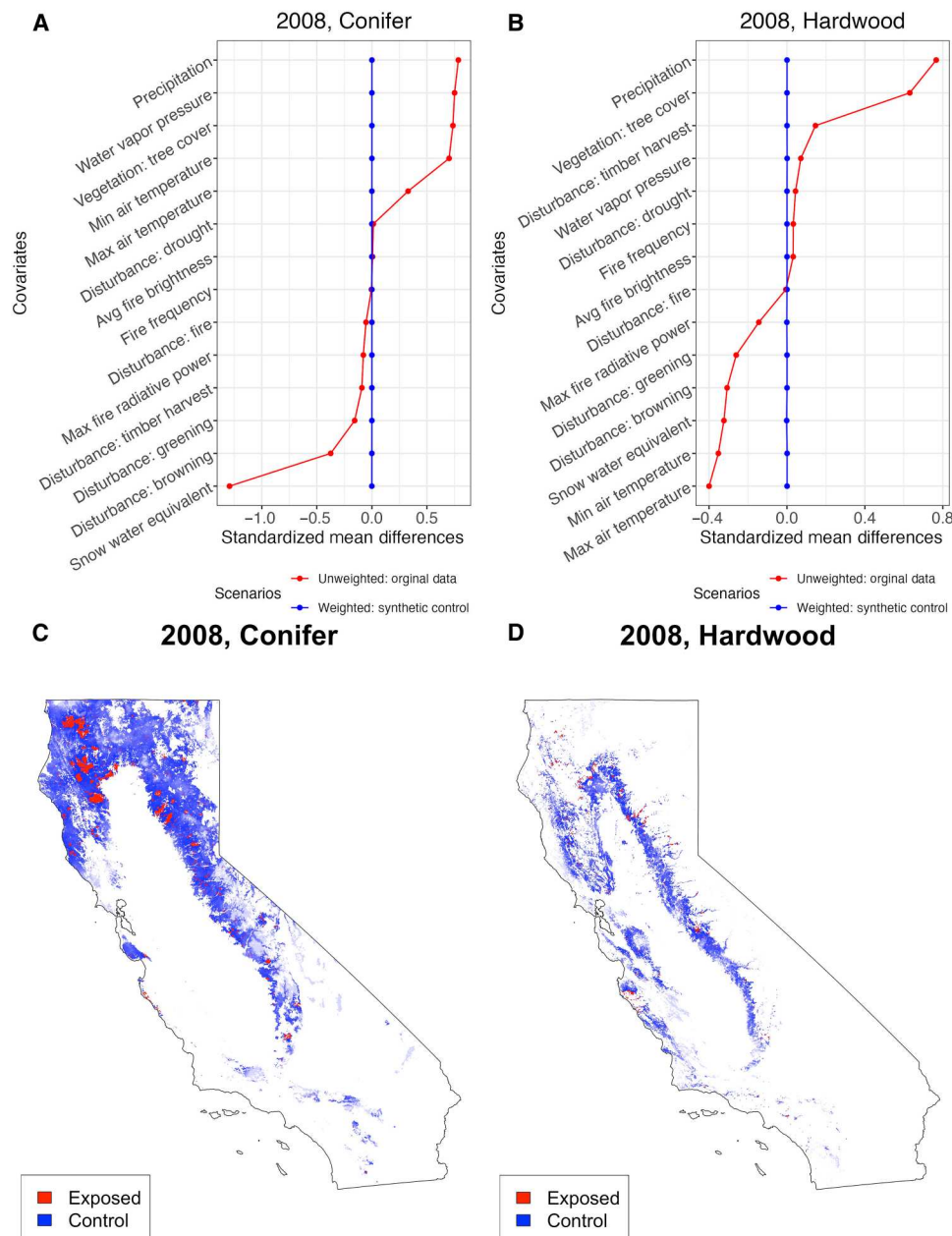


Fig. 3. Covariate balance and exposure distribution under the synthetic control quasi-experimental design for the focal year 2008 in different land cover types (conifer and hardwood). (A and B) show the standardized mean differences of covariate trajectories in the pre-focal period between exposed pixels and synthetic controls, measuring their degree of covariate balance. The covariate balance is substantially improved after implementing synthetic control approaches. (C and D) show the geographic location of exposed (red) and unexposed pixels (blue) that were used to create synthetic controls. The transparency of the blue color represents the synthetic control weights for each unexposed pixel. Results including additional focal years are shown in the Supplementary Materials.

Supplementary Materials. We see that, before weighting, the unburned pixel set (control) looks different from those that burn (exposed) in terms of pre-exposure covariate trajectories. However, our synthetic control approach eliminates these covariate imbalances across a wide variety of attributes for every focal year from 2008 to 2020.

The second point cannot be directly validated from data. However, we examine the robustness of our results to unmeasured confounding by calculating E values. The E value for an effect is the minimal strength of an association, on the relative risk scale, that an unmeasured confounder would need to have with both the exposure and outcome, conditional on the covariates already included in the model, to fully explain the observed association under the null (55). As discussed in the Supplementary Materials, our main findings appear to be reasonably robust to unobserved confounding according to this metric.

Last, our analysis also implicitly depends on an assumption that the only difference in treatment between exposed and unexposed synthetic control regions is from the exposed regions burning at low intensity. This assumption could be threatened if California already had extensive fire mitigation programs in place such that, e.g., regions that did not burn recently would be prioritized for prescribed burning in the next few years. However, given that prescribed burns are still relatively rare within our data, it is unlikely this is a major source of bias for our study.

Comparing the fire risks at the post-exposure evaluation period between exposed units and synthetic controls allows us to assess the impact of low-intensity fire on subsequent fire behaviors. To investigate long-term effects, we examine a range of evaluation periods, spanning from 1 to 9 years following the focal year, enabling us to study the persisting effect of the low-intensity fire exposure for up to 9-year lags. Last, we pool the estimated fire risks at the same lag from different focal years. We build Wald-type CIs based on standard errors estimated via a Jackknife variance estimator clustered at the outcome-year level (56); see the Supplementary Materials for details.

Fire intensity versus fire severity

In our analysis, we categorize wildfires by the intensity of energy release as quantified by FRP. The FRP measurement is subject to measurement uncertainty and errors (57), although we show that our analysis results are robust to alternate classification schemes for fire intensity in the Supplementary Materials. Furthermore, in some settings, it may be more natural to focus on high-severity wildfires that have transformative ecological impact rather than high-intensity wildfires with high energy release. In the Supplementary Materials, we apply our proposed method using an ecological rather than physical categorization of wildfire types. We consider wildfires assessed as low, moderate, or high severity by the Monitoring Trends in Burn Severity (MTBS) program (42). These assessments capture the degree to which a site has been altered or disrupted by fire (42). We then seek to measure the extent to which low-severity fires help prevent future high-severity fires. While this fire severity definition differs from the fire intensity definition used in this study (and results in a meaningfully different classification of fires), the high-level finding that prescribed fire has the potential to prevent future fires with potentially substantial impacts persists. Notably, the magnitudes of resulting protective

effect assessed under the MTBS fire severity categorization are more pronounced.

Supplementary Materials

This PDF file includes:

Supplementary Text
Figs. S1 to S22
Tables S1 to S4
References

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Xiao Wu, Erik Sverdrup, Michael D. Mastrandrea, Michael W. Wara, and Stefan Wager

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