**Title**
Do fuel reduction treatments alter forest fire severity and carbon stability in California forests?



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**Publication Date**
2023

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Santa Barbara

# Do vegetation fuel reduction treatments alter forest fire severity and carbon stability in California forests?

A Thesis submitted in partial satisfaction of the

requirements for the degree Master of Arts

in Geography

by

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June 2023

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April 2023

**Acknowledgements**

This research was made possible by extensive support from my research collaborators Winslow D. Hansen (Cary Institute of Ecosystem Studies, Millbrook, NY), Jacob Gellman and Andrew Plantinga (Bren School of Environmental Science & Management, University of California, Santa Barbara, CA), and Charles Jones (Department of Geography, University of California, Santa Barbara, CA). Thanks also to Joe McFadden (Department of Geography, University of California, Santa Barbara, CA), who provided advice, moral support, and excellent feedback as a committee member. Above all, this research would not have been possible without the expert council, thoughtful guidance, and unending patience of my advisor Anna Trugman. Thank you, Anna.

ABSTRACT

Do fuel reduction treatments alter forest fire severity and carbon stability in California forests?

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Forest fire frequency, extent, and severity have rapidly increased in recent decades across the western United States (US) due to climate change and suppression-oriented wildfire management. Fuels reduction treatments are an increasingly popular management tool, as evidenced by California's plan to treat one million acres annually by 2050. However, the aggregate efficacy of fuels treatments in dry forests at regional and multi-decadal scales is unknown. We develop a novel fuels treatment module within a coupled dynamic vegetation and fire model to study the effects of dead biomass removal from forests in the Sierra Nevada region of California. We ask how annual areal treatment extent, stand-level treatment intensiveness, and spatial treatment placement alter fire severity and live carbon loss. We find that a ~30% reduction in stand-replacing fire was achieved under our baseline treatment scenario of 1000 $km^2$ $year^{-1}$ after a 100-year treatment period. Prioritizing the most fuel-heavy stands based on precise fuel distributions yielded cumulative reductions in pyrogenic stand-replacement of up to 50%. Both removing constraints on treatment location due to remoteness, topography, and management jurisdiction and prioritizing the most fuel-heavy stands yielded the highest stand-replacement rate reduction of ~90%. Even treatments that succeeded in lowering aggregate fire severity often took multiple decades to yield measurable effects, and avoided live carbon loss remained negligible across scenarios. Our results suggest that strategically placed fuels treatments are a promising tool for controlling forest fire severity at regional, multi-decadal scales, but may be less effective for mitigating live carbon losses.

## 1. Introduction

Fire is a critical part of the Earth system, facilitating essential biogeochemical and ecological processes including nutrient cycling and secondary succession in forests (Pausas and Keeley 2019; Scott L Stephens et al. 2021; Safford et al. 2022; Walker et al. 2020). However, in the past several decades forest fire frequency, annual area burned, and severity have rapidly increased in western North America (Abatzoglou and Williams 2016; Dennison et al. 2014; Kasischke and Turetsky 2006; R. Kelly et al. 2013; Westerling et al. 2006). For example, annual burned forest area in the western United States (US) has increased by 1,200 percent since 1984 due to a confluence of drought and fire weather resulting from climate change (Williams et al. 2022; Williams et al. 2019; Abatzoglou and Williams 2016; Abatzoglou et al. 2021). Additionally, in some forest types (Stephens et al. 2013; Schoennagel et al. 2017), large fuel-burdens from a century of fire exclusion have contributed to wildfire trends in the 21st century (Kolden 2019; Stephens and Ruth 2005; Vaillant and Reinhardt 2017). In the state of California, eighteen of the twenty largest recorded fires have occurred since the year 2000, including during the historic 2020 fire season in which 17,000 km$^2$ burned, resulting in over $19 billion USD in economic losses (Safford et al. 2022). Further, an increasing number of people are being affected by wildfire due to the expanding wildland-urban interface (WUI), where homes are interspersed with wildland vegetation (Radeloff et al. 2018), compounded by the fact that atmospheric dryness (or vapor pressure deficit) that affects fuel moisture and wildfire risk varies spatially and has risen most rapidly in seasonally temperate areas where WUI expansion is most notable (Rao et al. 2022).

High-severity wildfires strongly affect biodiversity (Kelly et al. 2020), water quality and quantity (Williams et al. 2022), forest carbon sequestration (Anderegg et al. 2022), and human health and safety (Radeloff et al. 2018). In the future, there is strong potential for wildfire severity and area burned to increase manyfold with continued anthropogenic climate change, even as fuels become more limiting than they are at present (Abatzoglou et al. 2021; Anderegg et al. 2022; Balch et al. 2022). However, some research suggests that although fire severity has increased in recent decades, mean annual burned area across North America is still lower than in the era preceding Euro-American settlement (Safford et al. 2022; Swetnam et al. 2016; O'Connor et al. 2014). Forest management practices that reduce overall fire severity while allowing wildfires to burn may therefore offer a strategic compromise between limiting risk to human lives and livelihoods while promoting vital ecosystem services.

In recent years, fuels reduction treatments (Agee and Skinner 2005; Hessburg et al. 2016; Prichard et al. 2021; North et al. 2021) have gained attention among policymakers as a wildfire severity mitigation tool. For example, in 2021, California more than doubled its annual budget for forest management projects to $536 million after a devastating fire season in 2020 burned more than four percent of the state, destroyed 10,500 buildings, and killed 33 people (Porter, Crowfoot, and Newsom 2020). The California Wildfire and Forest Resilience Action Plan (Blumenfeld, Porter, and Crowfoot 2021), the Forest Carbon Plan (Johnston 2018), and activities by numerous county and local California management agencies (Gilles et al. 2018) highlight the rapid expansion of fuels reduction treatments as a tool for wildfire mitigation. In 2022, California Governor Newsom also pledged to fund "beneficial fire" and "cultural burning" on 400,000 acres (1619 $km^2$) in a partnership between state, tribal, local, and federal agencies, adding to previous commitments to fund fuel reduction treatments across one million acres (4,047 $km^2$) of CA lands per year by 2050. At the national level, the 2021 Infrastructure Investment and Jobs Act (IIJA) and the 2022 Inflation Reduction Act (IRA) allocated an additional \$2.56 billion and \$2.87 billion USD respectively for fuels reduction treatments, and \$2.14 billion and \$2.22 billion USD respectively for prescribed fire (Yarmouth 2022; DeFazio 2021). In light of the magnitude of expenditure and millions of vegetated acres targeted by fuel treatment policies, it is important to understand their mitigation potential and long-term ecological consequences.

Studies of watershed-scale fuels reduction treatments have shown near-term reductions in severity of subsequent wildfires (Kolden 2019; Burger 2009; North and Hurteau 2011). However, to understand how new state and federal fuels reductions policies may factor in future wildfire mitigation and adaptation, it is critical to constrain how the overall treatment strategy will affect fire severity and ecological impacts across tens of thousands of square kilometers and multiple decades into the future. A key determinant of fuels management policy outcome will be the interaction of political and technical factors controlling spatial allocation of fuels reduction treatments across a region, including land ownership and jurisdiction, road access, terrain ruggedness, and the availability of quality information about fuel distributions.

Process-based vegetation models are useful tools for understanding how fuels reduction interventions influence the coupled vegetation-wildfire system at large spatial and long temporal scales through the incorporation of scalable hypotheses for how vegetation fuel prevalence and type influence wildfire impacts (Hansen et al. 2022; Seidl et al. 2020). However, few vegetation models are suitable for assessing state or federal fuels management policies, as vegetation models are either too computationally-intensive to apply at scales larger than watersheds (Burke et al. 2021; Albrich et al. 2020; Hansen et al. 2022; Hurteau et al. 2019; Seidl, Rammer, and Spies 2014; Serra-Diaz et al. 2018), or they operate at very coarse scales (~100 $km^2$) and do not include sufficient mechanistic detail of wildfire-vegetation interactions to inform the efficacy of region-specific management interventions (Sanderson and Fisher 2020; Hantson et al. 2020; Fisher et al. 2018; S.S. Rabin, Gérard, and Arneth 2022).

To address these challenges, we use the DYNAmic Temperate and Boreal Fire and FORest-EcosySTem simulator (DYNAFFOREST) (Hansen et al 2022), a dynamic vegetation model equipped with a probabilistic fire module. DYNAFFOREST is well suited to model how fuels reductions protocols impact fire severity and forest dynamics at medium to large spatial and temporal extents for the following reasons. First, DYNAFFOREST is purposefully designed to operate at an intermediate degree of computational complexity, allowing for rigorous but computationally tractable modeling of regional- and centennial-scale ecological processes. Second, DYNAFFOREST explicitly simulates the impacts of climate and seed bank composition on secondary succession and how these factors subsequently determine post-fire forest trajectories, fuel accumulation, and flammability. Third, the relationship between fuels and fire dynamics, including fire size and severity, has been extensively benchmarked in DYNAFFOREST using historical fire databases (Hansen et al. 2022). Finally, the probabilistic nature of model outcomes allows for a rigorous quantification of uncertainties across different management interventions due to stochasticity in wildfire occurrences and post-fire seedling recruitment.

We pose the following questions. First, how does the areal extensiveness and intensiveness of fuels reduction treatment, such as the fraction of biomass removed, affect fire severity and subsequent forest dynamics? Second, do spatial constraints imposed by land jurisdiction hamper treatment coordination efforts and decrease treatment efficacy? Third, how important are physical restrictions such as topography and road access for treatment efficacy? Lastly, how much can a detailed spatial knowledge of regional fuels distributions increase treatment efficacy?

## 1. Methods

### *2.1 Model Overview*

Our study uses DYNAFFOREST, a cohort-based spatially-explicit dynamic vegetation and fire model that includes a stochastic representation of forest fire and vegetation recruitment following disturbance (Hansen et al 2022). DYNAFFOREST includes 12 vegetation plant functional types (PFTs) that are representative of the major forest types in the western US. Heterogeneity in vegetation size classes and functional type is simulated at a 1-km$^2$ resolution, enabling the model to capture heterogeneity in fuels in topographically complex landscapes. The spatial resolution of fire characteristics and their responsiveness to climate operates at a 12-km$^2$ grid scale.

The DYNAFFOREST model attributes offer a significant advantage to understand the feedbacks between fire and vegetation fuels compared to Earth system models that operate at course spatial resolutions without demographic processes, and often do not include fire (Sanderson and Fisher 2020; Hantson et al. 2020; Rabin et al. 2017). At fine spatial scales, several models have been developed to represent both wildfire and vegetation demographic processes, but all are too computationally intensive to be used to study vegetation-wildfire dynamics, and anthropogenic modification of vegetation fuels, at broad spatial domains (Albrich et al. 2020; Hansen et al. 2022; Hurteau et al. 2019; Seidl, Rammer, and Spies 2014; Serra-Diaz et al. 2018). One such domain is the ~77,000-km$^2$ Sierra Nevada Mountains in California, a region of major concern for wildfire risk under changing climatic conditions (Kennedy et al. 2021; Vachula, Russell, and Huang 2019). DYNAFFOREST's parsimonious representation of vegetation processes allows for sufficient computational efficiency to both simulate broad spatial domains of forested area in the western US and provide a nuanced map of evolving forest structure and fuels. These combined attributes make DYNAFFOREST uniquely capable of capturing how fires can alter forests, how fuels feedback to impact forest fire spread and burn severity, and how management interventions modify this dynamic feedback loop at scales relevant to recent politically-mandated fuels treatment interventions.

*2.2 Model Technical Details*

Here we summarize several key components of the DYNAFFOREST model (Fig. 1). A full model description, including model functionalities and benchmarking, is available in Hansen et al. 2022. Vegetation and fire dynamics in DYNAFFOREST operate on an annual timestep. Each 1-km$^2$ vegetation grid cell comprises an even-aged cohort of one of 12 possible forest PFTs or a grassland PFT. Cohorts grow and reallocate biomass annually according to PFT-specific allometric growth-curves derived from the USDA Forest Inventory and Analysis Program (Bechtold and Patterson, 2005). Biomass is added to the system through three live biomass pools (leaves, branches, and stems), and cycles into three dead biomass pools (litter, coarse woody debris, and snags) at PFT-specific rates, or as a result of drought or fire mortality. Dead biomass pools decompose at pool-specific decomposition rates, or are removed through combustion. Crown-kill within a 1-km grid cell is simulated for cells experiencing fire, and is proportional to available fuel loads. Here, we define fire severity as a statistic scaled between zero and one that is equivalent to modeled percent crown-kill, a common fire severity metric (Keeley 2009). Pyrogenic stand-replacement is defined an instance in which fire results in 100% crown kill within a given 1 $km^2$ grid cell, initiating a renewed cycle of recruitment and regrowth. In this study, a quantity of stand-replacement "events" denotes the number of 1 $km^2$ grid cells that experienced pyrogenic stand-replacement within a given period. Seed availability in DYNAFFOREST is determined by age- and PFT-specific fecundity and dispersal rates from neighboring cells, while recruitment success following stand-replacement is determined probabilistically based on PFT-specific climate tolerances. If tree recruitment fails, grassland can establish within a grid cell, which lowers the probability of future forest recruitment over time.

Fire ignition occurs probabilistically within a 12-$km^2$ fire grid according to observed lightning strike frequency, observed mean aridity (defined as the ratio of total annual precipitation to potential evapotranspiration), modeled forest connectivity between 1-$km^2$ vegetation grid cells, modeled live and dead fuel loading, and observed terrain slope. A maximum attainable fire size is selected pseudo-randomly from a database of observed fires between 1985-1994 that includes perimeters from the Monitoring Trends in Burn Severity (MTBS) database for fires > 400 ha and the point locations of fires smaller than 400 ha (Juang et al. 2022). This representation allows fire size to be implicitly constrained by factors not represented in prognostic model processes, including anthropogenic and meteorological suppression, even when fuel geography might allow for further growth. If sufficient vegetation fuels exist, fires can reach their maximum size, which can exceed the 12-km$^2$ fire grid cell. However, model-predicted fire extent may not reach maximum predicted size if there are insufficient connected forest grid cells to burn due to grass recruitment. In practice, complex model-simulated fire perimeters emerge due to grass-dominated vegetation grid cells across the model domain that increase in prevalence following stand-replacement events. Importantly, the current parameterization of the fire module within DYNAFFOREST does not allow for understanding how fire dynamics are expected to evolve under future climate conditions expected with anthropogenic climate change, or even the increasingly severe conditions experienced in the western US after 2000. However, the model has been benchmarked for its representation of fuels accumulation and fuels effects on fire size, perimeter complexity, area burned, and percent stand-replacement (Hansen et al. 2022), making DYNAFFOREST an ideal tool to understand how vegetation management affects forest fire and the forested landscape.

*2.3 New Fuels Management Module*

In this study, we developed a fuels treatment module to simulate controlled burning by removing a user-specified fraction of litter, downed coarse wood, and snags in each 1-km$^2$ forest tiles selected for fuels management (Fig. 1). In the fuels reduction module, forest cells are inventoried at each 1-year time step for non-static eligibility factors (live and dead biomass loading, fuels connectivity, and minimum re-treatment interval) from a pool of cells pre-constrained by static eligibility factors (land management jurisdiction, proximity to roads, proximity to homes, hillslope, forest type, stand age, lightning strike frequency, and aridity). We test 19 scenarios. In each scenario, a cell's treatment eligibility, as well as the parameters for the model, were informed by conversations with forest managers, model sensitivity tests, and a literature review (Fig. S1). “Treatment Base” represents a realistic baseline treatment protocol that is moderately ambitious with respect to existing political and technical challenges; treatment locations are constrained by slope, road access, and public land ownership, and are prioritized using relatively coarse spatial knowledge of downed woody fuels, capturing the fact that in practice managers have limited knowledge of dead fuels distributions at the kilometer scale (Fig. 2). When a larger number of cells is eligible for treatment than meets the annual treatment extent target, locations are chosen pseudo-randomly from the pool of eligible cells unless a factor is chosen as a sorting factor (detailed below in the different model experimental scenarios). In this case, the pool of available cells is sorted hierarchically with respect to that factor and the highest ranking cells are selected up to the treatment areal target. We compare all treatment scenarios to a “Control” scenario of no vegetation treatment.

*2.3 Experimental Overview*

We simulated a ~77,000-km$^2$ area in California’s Sierra Nevada region, where aggressive vegetation management strategies have been legislated in order to mitigate rapidly increasing fire risk (Wang et al. 2022; Gilles et al. 2018; Hazelhurst 2020). Following the protocol in Hansen et al. (2022), vegetation in the model was initialized with a gridded PFT map (Buotte et al. 2019), remotely-sensed stand age (Pan et al. 2011), and information on fuel loads based on PFT (Prichard et al. 2019). The dynamic vegetation module was forced with 1965–1994 downscaled 1 km$^2$ mean daily temperature observations (Oyler et al. 2015) to calculate tree-seedling germination and establishment thresholds and average growing season volumetric soil moisture in the rooting zone (0- to 100-cm depth) (Park Williams et al. 2017), fire severity, PFT-specific regeneration probability, and drought mortality (Hansen et al. 2022). Fire module forcings include 1984–2019 climatological mean annual aridity (ratio of total annual precipitation to total annual potential evapotranspiration) for each 12-$km^2$ grid cell (Williams et al. 2020), topography (Hastings and Dunbar, n.d.), and 1987–2019 mean lightning strike density, which influences ignition probability (Cummins, Krider, and Malone 1998).

Fuel loads at model initialization reflect forest type distributions but lack disturbance-driven heterogeneity. Thus, we ran the model for 250 years without simulated management to allow the coupled vegetation-fire response in the study region to generate initial fuel conditions. We used year 250 from this simulation as the common origin ("spin-up") for all model experiments (Hansen et al. 2022). In total, we ran a total of 500 x100-year model simulations across 19 different treatment scenarios in which we systematically varied annual areal treatment extent, stand-level treatment intensiveness, and treatment site selection parameters across two feasibility axes representing political and technical constraints, respectively (Fig. S1). Several processes in the model are probabilistic (stochastic) including fire ignition, stand mortality (due to fire or senescence), and tree recruitment. Thus, each model experiment includes 25 replicate ensemble members to account for stochastic variability. Ensemble size (replicate count) was chosen by calculating the intra-ensemble variance of representative model diagnostics (including pyrogenic stand-replacement rate, live C loss, and forest coverage) for $n$ pseudo-randomly selected simulations at 100 years from within a 50-member replicate ensemble ($n$ = 1:50). Where the variance of these diagnostics among $n$ members approached asymptotic stability, we selected $n$ = 25 as our standard experimental replicate size. All experimental scenarios shared a common control (no-treatment) ensemble and “Treatment Base” ensemble to account for residual stochastic variability and provide a common point of comparison.

To understand model sensitivity to fuels reduction treatment areal extent and treatment intensiveness, we conducted two sensitivity tests. First, we systematically varied treatment areal extent within a range of possible values mandated in 2020 by the state of California that could be allocated to the Sierra Nevada Mountains within California (Hazelhurst 2020). Specifically, we ran simulations with varying annual areal fuels reduction treatment extent set to 100 $km^2$ $year^{-1}$, 500 $km^2$ $year^{-1}$, 1000 $km^2$ $year^{-1}$, 1,500 $km^2$ $year^{-1}$, and 2000 $km^2$ $year^{-1}$, keeping all other parameters the same as our “Treatment Base” experiment (see Fig. 2 for “Treatment Base” description). Second, we held areal extent and all other parameters constant at 1,000 $km^2$ $year^{-1}$ and varied the fraction of dead fuels removed during simulated fuels reduction treatments. In these two experiments, scenarios treating 1000 $km^2$ $year^{-1}$ and removing 90% of dead biomass respectively were therefore equivalent with “Treatment Base”.

Following model sensitivity tests to treatment area and dead fuel removal intensiveness, we performed a set of model experiments designed to understand the sensitivity of our results to treatment placement, measured through reductions in stand-replacement events and overall fire severity (quantified according to crown kill fraction, see Methods), forest cover changes, and reductions in live carbon (C) lost to fire. In this set of model experiments, we varied treatment placement (for a fixed annual treatment area and fractional fuels reduction) according to factors constraining real-world treatment allocation, including: 1) land management agency constraints, where treatments were subject to the majority of the "Treatment Base" parameters but constrained to US Forest Service and Bureau of Land Management Land ("Agency Low"), versus both public and private lands ("Agency High"); 2) landscape accessibility factors, where treatments were subject to the majority of the "Treatment Base" parameters but were either tightly constrained by access factors including hill slope and proximity to roads ("Access Low"), versus unconstrained by slope or road access ("Access High"); 3) stand-level knowledge of regional fuel-load distribution, where treatments were subject to the majority of the "Treatment Base" parameters but eligible cells were sorted based on dead fuels loading ("Knowledge High") versus an experiment where dead fuels loading was not used to inform treatment location ("Knowledge Low"); and 4) combined effects of criteria 1-3 for our "Synergy Low" and "Synergy High" model experiments (Fig. 2). For all scenarios, we analyzed both transient (captured by our Time of Emergence statistic) and equilibrium treatment responses (model outcomes at year 100 and mean fourth quarter-century values). We hope that this will provide treatment evaluations on both policy-relevant time scales (on the order of a decade), and long-term forest ecological outcomes (on the order of a century).

*2.4 Analysis*

We calculated model diagnostics for each timestep on a 1-km vegetation cell-by-cell basis. During post-processing, grid cell values were summed or averaged annually for each ensemble member within each treatment scenario. Ensemble annual mean or cumulative values were calculated, and quantile values for each annual distribution were extracted. We considered several key modeled response variables with relevance both to human policy goals and safety, as well as forest ecosystem composition and structure. Diagnostics included rates of pyrogenic stand-replacement and overall fire severity (see section 2.2), forest cover change, and quantity of live C lost (combusted or moved to dead C pools). Responses in each model experiment are shown as a median, interquartile, and full range of ensemble member values, depending on the visualization. Hereafter, any statistic not otherwise specified refers to the loess-smoothed (see below) ensemble mean value at year 100 of the simulation for a given scenario.

For some figures and decadal statistics, we employed a loess (span = 0.2) smoothing function from R's "stats" package (R Core Team 2022) on annualized model output to remove the influence of stochastic noise. We also averaged time series data for each ensemble. Inter-decadal values summarized in box plots were calculated as a distribution of the mean ensemble values for each scenario during all years. Compact letter display indicates a set of pairwise comparisons with an analysis of variance and subsequent Tukey honest significant difference (HSD) test using the functions "aov" and "TukeyHSD" from R's "stats" package (R Core Team 2022). Within each simulation we used Time of Emergence (ToE) (Gaetani et al. 2020; Turk et al. 2019; Maraun 2013) to quantify the point at which treatment diagnostics become statistically distinct from a no-treatment control scenario for regionally summed values. We defined ToE as the fifth year in a ten year moving window whose decadal median value for a given response variable fell outside of the control scenario's IQR for that variable for the same period. If a simulation's median value overlapped with the control scenario's IQR for over ten consecutive years after achieving ToE, any ToE observations before this period were disqualified.

Model code and all analyses were performed in R version 4.2.1 (2022-06-23).

## 2. Results

Throughout the description of results, we refer to ensemble mean values relative to the no-treatment control ensemble mean over the 100-year simulations.

### *3.1 Systematically varying treatment extent*

Increasing annual treatment area from 100 $km^2$ $yr^{-1}$ to 2000 $km^2$ $yr^{-1}$ within the 77,000 $km^2$ Sierra Nevada model domain decreased rates of pyrogenic stand-replacement, fire severity, and total live C lost to fire, and decreased the ToE for significant treatment effects by several decades. However, diminishing returns per acre treated occurred at >1000 $km^2$ $yr^{-1}$ (Fig. 3). For example, stand-replacement rate, total forest coverage, and live C loss exhibited no statistically significant difference during the last quarter-century for treatment extents over 1000 $km^2$ $yr^{-1}$ (Fig. 3). When we examined cumulative values over the 100-year simulation, we found that increasing annual treated area from 0 to 500 $km^2$ $yr^{-1}$ yielded a 16.5% (351 $km^2$) reduction in total stand-replacement events over 100 years relative to the no-treatment control scenario (2,132 $km^2$), and that doubling the annual treated area to 1,000 $km^2$ $yr^{-1}$ yielded a further 12.7% reduction (622 $km^2$, or 29.2% below the no-treatment rate). However, a second doubling of treated area to 2,000 $km^2$ $yr^{-1}$ yielded only a further 9% reduction (813 $km^2$, or 38% below the no-treatment rate). Similar decreasing returns per $km^2$ treated were observed over the 100 year simulation with respect to cumulative avoided live C loss, where 500 $km^2$ $yr^{-1}$ treated yielded a 13.6% (1,466 MT C) reduction relative to control experiment (10,788 MT C) and each successive doubling of treated area (1,000 $km^2$ $yr^{-1}$ and 2,000 $km^2$ $yr^{-1}$) only yielded additional reductions of 8.7% (2,404 MT C total) and a further 5.3% (2,978 MT C total), respectively.

ToE was also impacted by treatment extent and varied with the response diagnostic of interest. For example, although ensemble mean distributions for stand replacement events showed no statistical difference between scenarios treating more than 1,000 $km^2$ $yr^{-1}$ over years 75-100 (Fig. 3b), increasing treated area from 1,000 $km^2$ $yr^{-1}$ to 1,500 $km^2$ $yr^{-1}$ decreased the observed ToE from year 75 to year 40, and treating an additional 500 $km^2$ $yr^{-1}$ (2,000 $km^2$ $yr^{-1}$ total) yielded an observed ToE at year 24 (Fig. 3a). In contrast, model-predicted median annual fire severity displayed more rapidly diminishing returns: a 100% increase in treated area from 500 $km^2$ $yr^{-1}$ to 1,000 $km^2$ $yr^{-1}$ yielded an 18 year reduction in ToE (from 29 to 11 years), while a further doubling of treated area (1,000 $km^2$ $yr^{-1}$ to 2000 $km^2$ $yr^{-1}$) yielded a further ToE reduction of only 5 years (from year 11 to year 6) (Fig. 3c). In some cases where treatments were not significantly different from one another, ToE was not consistent with overall treatment trends. For example, we observed the earliest ToE (year 15) for the 1,000 $km^2$ $yr^{-1}$ treatment scenario when measuring changes in overall forest cover change, while treating 2,000 $km^2$ $yr^{-1}$ resulted in a ToE 7 years later (year 22) (Fig. 3e). This illustrates that ToE depends strongly on the response variable of interest, and that some variables exhibit more measurable decreases in effective returns per additional $km^2$ treated than others.

*3.2 Systematically varying fractional biomass reduction*

Next, we systematically increased the fraction of dead biomass removed as part of fuels treatment for the same areal treatment extent of 1000 $km^2$ $yr^{-1}$. With respect to some diagnostics, treatment impact on cumulative values scaled roughly linearly (Fig. 4). For example, a 30% increase in dead biomass removed per treated $km^2$ from (30% to 60%)

yielded an 11.3% reduction (from 9.1% to 20.4%) in total stand replacement events relative to the control scenario over 100 years, and an additional 30% increase in percent biomass removal (from 60% to 90%) reduced that figure by a further 8.8% (from 20.4% to 29.2%) at the end of the 100 year simulation. Other diagnostics, notably changes in total forest cover, suggested a threshold response to increasing treatment intensity. For example, treatments removing 10% and 30% of dead biomass per treated $km^2$ did not show statistically significant changes in total forest cover with respect to the no-treatment scenario across the fourth quarter-century, while treatments removing 60%, 90%, and 100% of dead biomass from treated stands were statistically insignificant with respect to one another, but were all significantly different from the control for that period. For the latter group, however, increased treatment intensity did accelerate ToE, with a 50 year decrease in ToE observed between the 60% reduction scenario and the 90% reduction scenario. Putting these figures in perspective, the maximum achieved increase in total forest extent achieved by fuels treatments (100% dead biomass removal) was 155 $km^2$ by the end of the century (0.2% of the model domain). Total avoided stand replacement events over 100 years for the same scenario reached 621 $km^2$ (0.8% of the model domain).

### *3.3 Technical and political restrictions on spatial treatment allocation*

Next, we held both annual treated area and fractional fuels reduction constant (1000 $km^2$ $yr^{-1}$ and 90% removal, respectively) (Fig. 2; Fig. S1) and tested how spatial constraints on regional treatment allocation associated with land management jurisdiction and ownership ("Agency High" and "Agency Low" scenarios), infrastructural and technical access ("Access High" and "Access Low" scenarios), degree of prioritization placed on of fuel-loading

("Knowledge High" and "Knowledge Low"), and the combined effects of the three ("Synergy High" and "Synergy Low") impacted treatment efficacy (Fig. 5). We found that the most appreciable reductions in fire severity and pyrogenic stand-replacement rate (Fig. 5a-d) occurred in simulations that highly prioritized treatment placement according to dead biomass-loading ("Knowledge High", "Synergy High"; 1,104 $km^2$ and 1,984 $km^2$ cumulative avoided pyrogenic stand-replacement events relative to the total figure of 2,132 $km^2$ for the no-treatment control scenario, respectively). In treatments where fuel loading was not highly prioritized, such that all stands above the 20$^{th}$ percentile for dead biomass loading qualified for treatment (e.g. "Agency High", "Agency Low", "Access High", and "Access Low"), few significant differences in response variables were notable, even as constraints related to topography and road access ("Access High"), and multi-jurisdictional cooperation ("Agency High") were eliminated. This result suggests that prioritizing more spatially homogeneous (extensive) treatment allocation is less effective than spatially heterogeneous (intensive) retreatment of stands known to exhibit high rates of fuel accumulation (Fig. 6). Decreased efficacy resulting from lower fuel loading prioritization (as in "Agency High", "Agency Low", "Access High", "Access Low", and "Synergy Low") can be partially compensated for by increasing annual treated area above 1,000 $km^2$ $yr^{-1}$ (Fig. 3). However, a doubling of annual treated area (from 1,000 $km^2$ $yr^{-1}$ to 2,000 $km^2$ $yr^{-1}$) was required to achieve similar fire severity reductions similar to those observed in experiments where fuel-loading was highly prioritized (e.g. "Knowledge High").

Including high prioritization of fuel loading ("Knowledge High"), releasing infrastructural and technical access constraints to remote and rugged areas ("Access High"), and allowing for multi-jurisdictional cooperation in treatment application ("Agency High"), resulted in similar 100-year treatment outcomes with respect to cumulative avoided pyrogenic live C loss (either combusted or moved to the dead C pool; 2,714 MT, 2,993 MT, and 2,330 MT, respectively). "Synergy High" also yielded a relatively large increase in 100-year cumulative avoided live C loss—a total reduction of 4,857 MT C relative to no-treatment (a 81.3% increase from 2,679 MT C, the mean of the constituent three scenarios: "Agency High", "Access High", and "Knowledge High").

Efficacy of a particular treatment scenario and ToE strongly depended on the 'outcome' (or response variables of interest). While all nine scenarios achieved ToE with respect to forest cover by mid-century (Fig. 5e), only four scenarios ("Synergy High", "Knowledge High", "Agency High", and "Access High") achieved ToE with respect to pyrogenic stand-replacement rate during that period, with three more ("Knowledge Low", "Treatment Base", and "Agency Low") only exhibiting ToE around the outset of the final 4$^{th}$ quarter-century (Fig. 5a).

The spatial patterns of deployed treatments reflect technical and political constraints associated with infrastructure and land ownership (Fig. S2), and the natural vegetation type distribution (Fig. S3), which affects fuel loading. Collectively, the constraints and prioritizations associated with different treatment scenarios resulted in intensive treatment regimes in both highly restrictive scenarios (e.g. "Synergy Low"), and the scenarios targeting vegetation cells with high fuel-loads (e.g. "Synergy High") (Figs. 6,S4). In spatially restrictive scenarios characterized by access or land ownership constraints, treatments clustered and manifested lower re-treatment intervals due to the limited number of cells eligible for treatment in the model domain. By contrast, in scenarios targeting higher fuel-loads, treatments clustered in forest types that were associated with the most rapid fuel accumulation (notably Hemlock/Cedar, in higher elevation portions of the mid-latitude Sierra Nevada). Net quantity of dead biomass removal by fuels treatments (Fig. S5) varied by scenario and was closely correlated with treatment efficacy across a number of model diagnostics.

## 3. Discussion

Vegetation fuels reduction treatments are increasingly being legislated as a means to mitigate accelerating wildfire risk in the western US (Gilles et al. 2018; Hazelhurst 2020). In this study, we developed a new fuels management module within the coupled vegetation-fire model DYNAFFOREST. We applied DYNAFFOREST to the California Sierra Nevada Mountains, a region where vegetation management is legislated to increase sharply over the coming decade. We evaluated treatment outcomes with respect to pyrogenic stand-replacement rates, fire severity (crown kill fraction), forest coverage change (with respect to nonforest landcover types), and live C loss to fire to understand how fuels reduction treatments impacted the magnitude and earliest measurable achievement (ToE) of treatment effects. Specifically, we tested how annual treatment area, stand-level intensiveness of dead biomass removal, land ownership constraints, landscape accessibility factors, and detailed knowledge of spatial fuels distribution influence subsequent forest fire severity and ecological impacts.

We found that the most appreciable treatment effects occurred in simulations that prioritized treatment allocation based on fuel-loading. Lower treatment efficacy occurred when overall area eligible for treatment was constrained by political or technical limitations, or when knowledge of fuel loading was a lower priority. Decreased priority on fuel-loading could be compensated for by increasing annual treated area, however in some cases a doubling of annual treated area was required to achieve similar measured reductions in fire severity or live C loss.

*4.1 Impacts of management on fire severity*

All of the nine simulated treatment scenarios that varied fuel placement according to different land constraints and fuel loading priorities showed statistically significant reductions in fire severity during the final 4$^{th}$ quarter-century (Fig. 5d), and all eight scenarios that achieved ToE ("Synergy High", "Knowledge High", "Access High", "Agency High", "Treatment Base", "Knowledge Low", "Agency Low", and "Access Low") did so before mid-century, with all but "Access Low" occurring by year 12 (Fig. 5c). The scenarios that yielded the largest reductions in pyrogenic stand-replacement events, percent crown kill, and live C loss ("Synergy High" and "Knowledge High") achieved ToE with respect to stand mortality reduction after only 6 years of simulation. Because DYNAFFOREST does not currently simulate fire suppression or rate of spread, reductions in fire intensity did not translate into reductions in overall fire size in our results. However, observational studies link reduced fire severity (ecological outcomes from fire) to reduced intensity (total combustive energy output), in turn suggesting reduced rates of spread and increased suppressibility (Wagner 1977), reducing the damage potential to homes and infrastructure (Kramer et al. 2019). Thus, our results indicate that coordinated fuels treatments at a regional scale, particularly those that prioritize forest patches with high fuel-loads, have the potential to reduce some economic losses and human health and safety impacts, other factors held equal.

*4.2 Impact of management on forest extent and carbon balance*

We found statistically significant differences with respect to the no-treatment control scenario over the final fourth quarter-century for all but one simulated treatment ("Synergy Low") when measuring changes in forest cover, and for all simulated treatments when measuring differences in live C loss (Fig. 5f, h). The treatment scenario with no spatial constraints that prioritized grid cells with high dead fuel loads ("Synergy High") achieved ToE with respect to cumulative live C loss in 25 years, while only one other scenario ("Access High") reached ToE in the 100-year simulation period (at year 70). In all cases, the overall avoided C loss was small compared to regional C budgets. For example, in "Synergy High", where we allow precise prioritization of dead fuel-loading and assumed no spatial constraints on treatments, cumulative avoided live C loss amounted to 4,857 MT C over 100 years, relative to no treatment. In this case, total avoided loss is equivalent to the annual C footprints of ~1.5 typical upper-income (or ~4 typical low-income) US residents (Feng, Hubacek, and Song 2021), and would offset just a small fraction (0.0012%) of California's C emissions from the year 2020 (annual) (California Air Resources Board 2022).

While the removal of dead biomass during treatments also acts in and of itself to decrease total C loss during forest fires (by removing dead biomass that would otherwise burn), cleared dead biomass is typically stacked and burned on-site during fuels treatments, meaning net C flux and C stabilization is not typically reduced through dead biomass removal, except where burn conditions during treatment differ significantly from those in uncontrolled fire (Belcher et al. 2018). Moreover, not all biomass removed during fuels treatments would otherwise burn in forest fires (Campbell, Harmon, and Mitchell 2012). Thus, a substantial fraction of treated fuels are diverted away from heterotrophic respiration and abiotic weathering processes rather than uncontrolled combustion. Since combustion and decomposition of treatable fuels both reallocate C from dead biomass pools to the atmosphere, we consider these fates as functionally equivalent for the purposes of this study, and do not consider differences in the composition of greenhouse gas species released in these distinct processes. This still leaves the C impact of fuels treatment implementation itself, which typically involves the extensive use of internal combustion engines for transportation, gathering fuels, sawing, mastication, and other mechanical processes (Stephens et al. 2009), and would imply net positive C fluxes not accounted for in this study. While opportunities exist for the stabilization of cleared biomass through its integration into novel forestry products (Cabiyo et al. 2021), these technologies are still nascent and are not usually employed in conjunction with fuels treatment protocols. As a result, we conclude that while fuels-reduction treatments may decrease combustive C loss, they will not necessarily increase standing forest C storage, or result in a net negative C balance, a result that is in line with a number of observational studies (Stephens et al. 2009).

*4.3 The importance of treatment strategy on forest fire outcomes*

We found wide variation in fuels reduction treatment efficacy across all diagnostics including stand kill events, crown kill fraction, live C loss, and forest extent change, depending on how treatment location was prioritized. Model experiments that leveraged hierarchical prioritization based on a detailed knowledge of fuels across the landscape, even with some restrictions to access, reduced fire impacts, mediated forest transitions to grassland (Hill et al. 2023), and achieved a larger treatment effect across other diagnostics compared with simulations with less emphasis on fuel loading. This speaks to the importance of (i) further developing and maintaining updated fuels maps and (ii) employing coordinated treatments informed by known fuel-loading geography.

Current vegetation management strategies can be subject to strong path dependencies depending on when funding is allocated, the source of the funding, and the availability of wildland firefighters to oversee treatments, which can often delay management by several years when intense wildfire seasons require resources to be devoted elsewhere. Our treatment scenarios indicate that management strategies that are subject to these constraints may be operating well below than their maximum potential. Further, our results show the importance of prioritizing fuel-heavy stands, emphasizing the relevance of ongoing fuel-mapping and modeling efforts to identify candidate stands for intensive treatments. Finally, though we do find potential for management to mitigate forest fire impacts, significant treatment effects may take a decade or more to manifest at a regional fire-regime scale, depending on the outcome variable of interest. In a policy environment where projects and funding frequently operate on 2- to 4-year time scales commensurate with the standard election cycle, and are typically legislated and evaluated at regional scales, these results highlight the importance of sustained forest management policies that operate on ecological as opposed to political timescales.

*4.4 Future work to determine management outcomes across broad spatial and long temporal scales*

The effects of fuels reduction treatments have implications for a wide variety of domains such as nature-based C management or insurance risks for housing in the wildland urban interface. However, most empirical studies, due to costs and practicality constraints, occur at the stand scale (Moreau et al. 2022). Process-based models that are benchmarked for key processes like prognostic fuels accumulation and fire-fuels sensitivities are one of the only tools available for understanding the sensitivity of wildfire regimes to fuels reduction treatments across large spatial scales and at long temporal scales. Remote sensing data on a number of wildfire diagnostics such as fire severity, subcanopy fuels, and C combusted from wildfire have the potential to be leveraged to further understand how fuels reduction protocols influence outcomes of interest and improve model benchmarking. Presently, many of these desired remote sensing capabilities are limiting, but provide an exciting opportunity for future research (Gale et al. 2021).

## 4. Conclusion

Vegetation fuels treatments are emerging as a key strategy to mitigate rapidly increasing wildfire risk in the western US. We found that treatment scenarios that strongly prioritize stands based on the regional fuel distribution were most successful at controlling fire severity and secondarily at reducing live C loss. However, we also found that extensive inter-jurisdictional participation across public and private lands, as well as ambitious treatment of remote and rugged areas can compensate for lowered prioritization of the regional fuel distribution. Even treatments with substantial spatial constraints that strongly prioritized stands according to regional fuel distributions yielded statistically significant results across all measured response variables, but these effects did not become measurable until several decades later than less spatially constrained scenarios with the same fuels distribution information. Though the best performing scenario yielded impressive reductions in fire severity, stand-replacement events, and forest cover loss, the cumulative quantity of avoided live C loss to fire relative to the control scenario was relatively small (up to 4,857 MT C over one century for extremely intensive treatment scenarios) in the context of California's overall carbon budget (equivalent to 0.0012% of annual statewide emissions in 2020) (California Air Resources Board 2022).

While further research is needed to understand the efficacy of fuels management as a strategy for C emissions reduction, our results suggest that fuels treatments may not represent an efficient strategy for limiting statewide C emissions or increasing naturally sequestered C. More relevant gains are represented by the overall control on fire severity achieved by fuels reduction treatments. Research suggests that low-severity wildfire can promote important ecosystem functions, including elevated soil C sequestration, the maintenance of higher floral biodiversity, and increased stream water quality. In our treatment protocols that were most effective at reducing fire severity, fire severity was maintained below stand-killing thresholds almost universally across the region. Although this result may be unattainable in practice due to practical limitations on treatment allocation and intensiveness, our work suggests that fire severity-mitigation through fuels treatments may help promote a fire regime characterized by lower severity, more containable, and less ecologically deleterious forest fires. However, these ameliorating effects may only manifest after several decades of coordinated fuels treatments across the region.

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## Figures

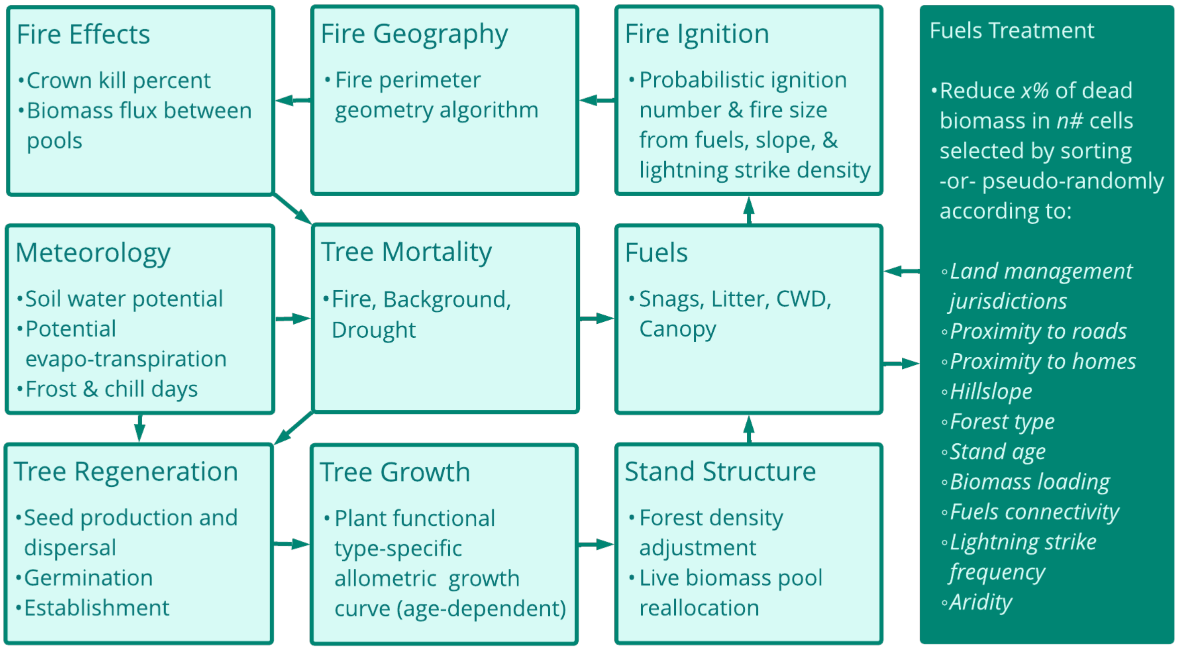



**Figure 1.** Schematic illustrating DYNAFFOREST model processes including the model described fully in Hansen et al. 2022 (light green) and the new fuels treatment module developed in this study (right in dark green).

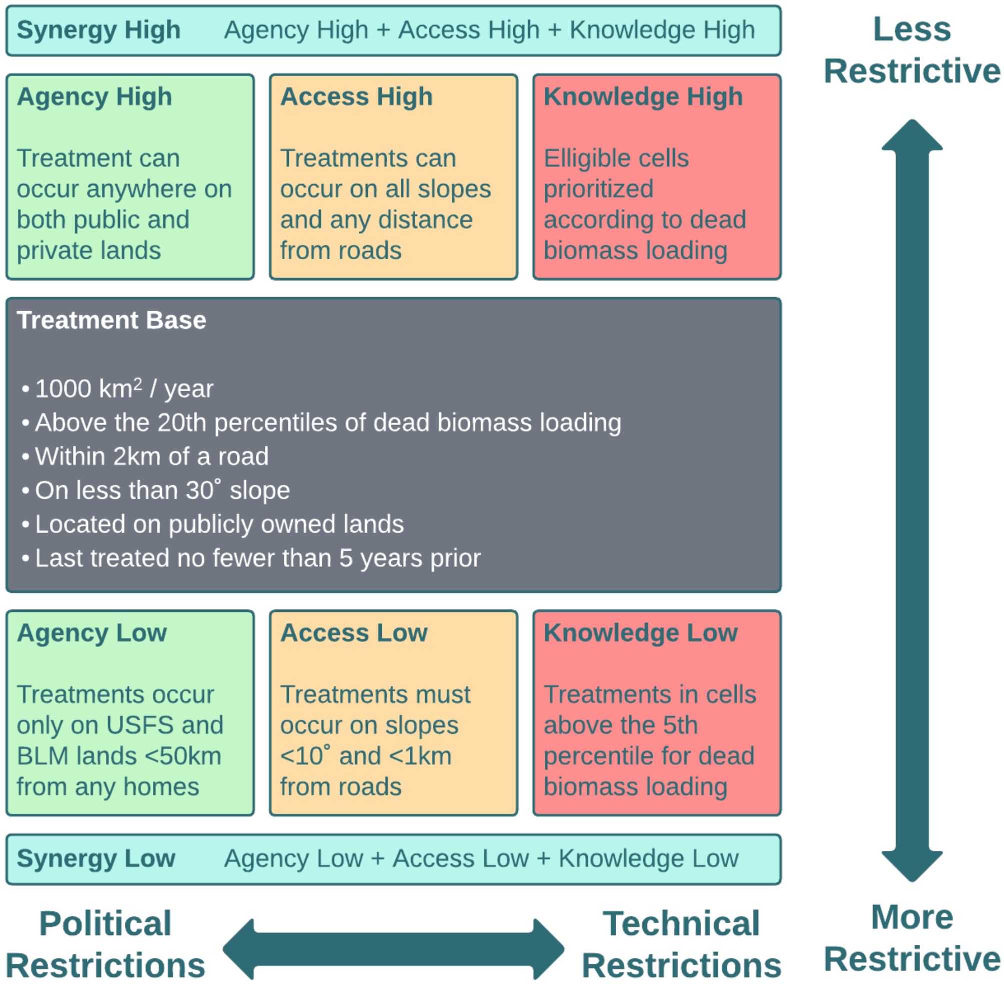
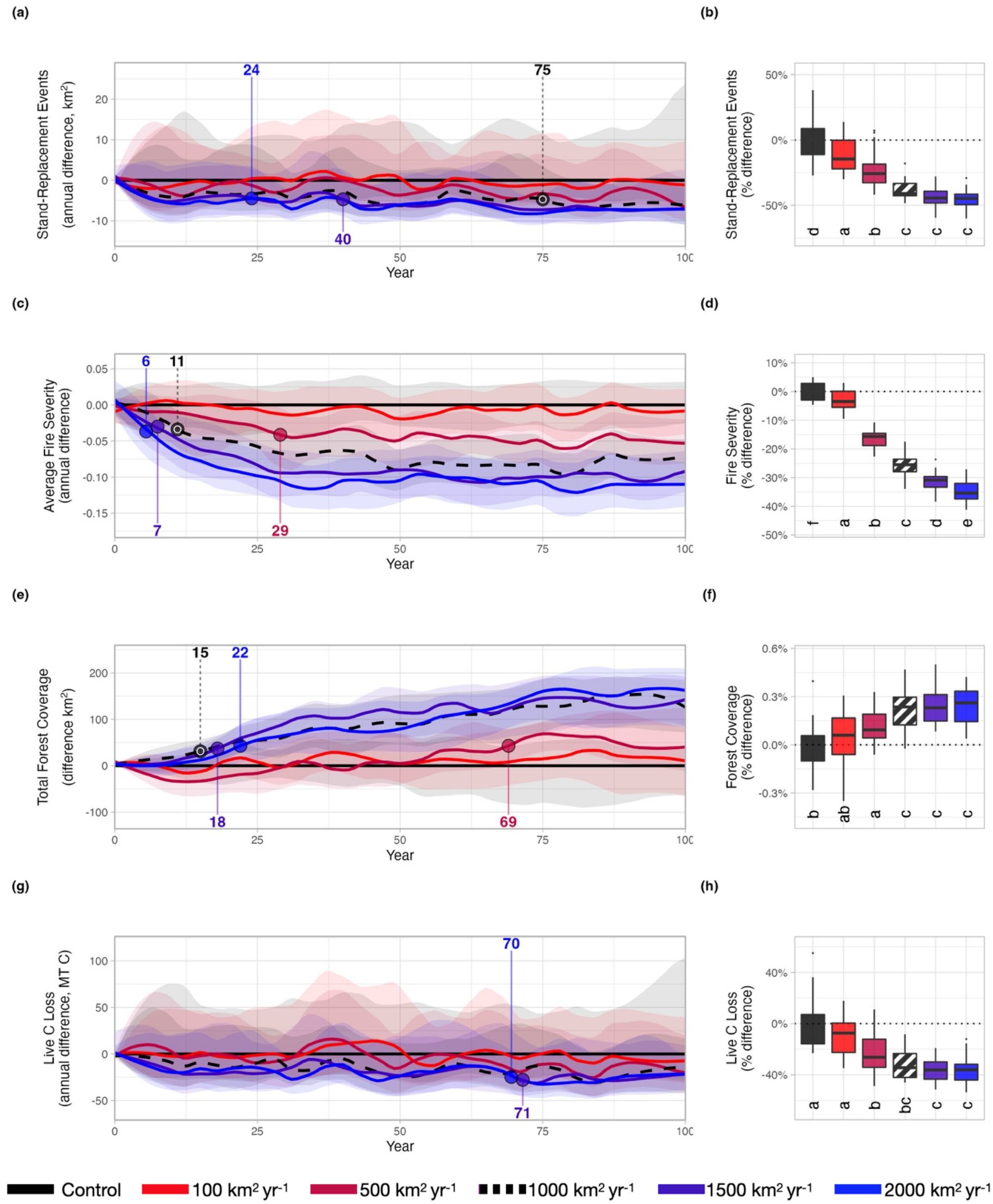
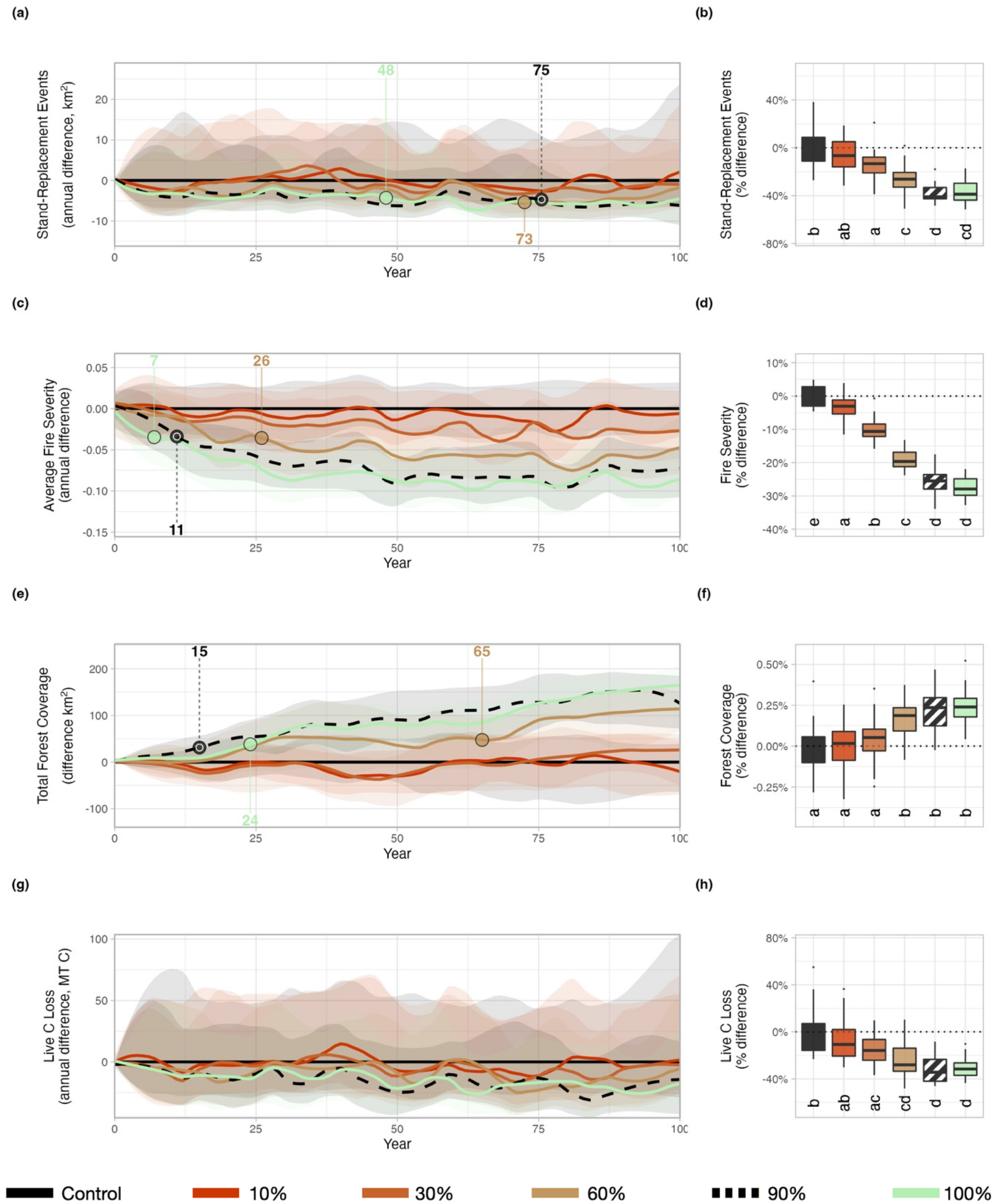



**Figure 2.** Experimental design showing our standard treatment scenario in the center (black), and four pairs (eight total) of modified treatment scenarios. More spatially restrictive scenarios due to political or technical constraints (left versus right columns) shown in the bottom rows and scenarios with larger eligible treatment areas are in the top rows. All scenarios share our standard (base) treatment's parameters except where noted.



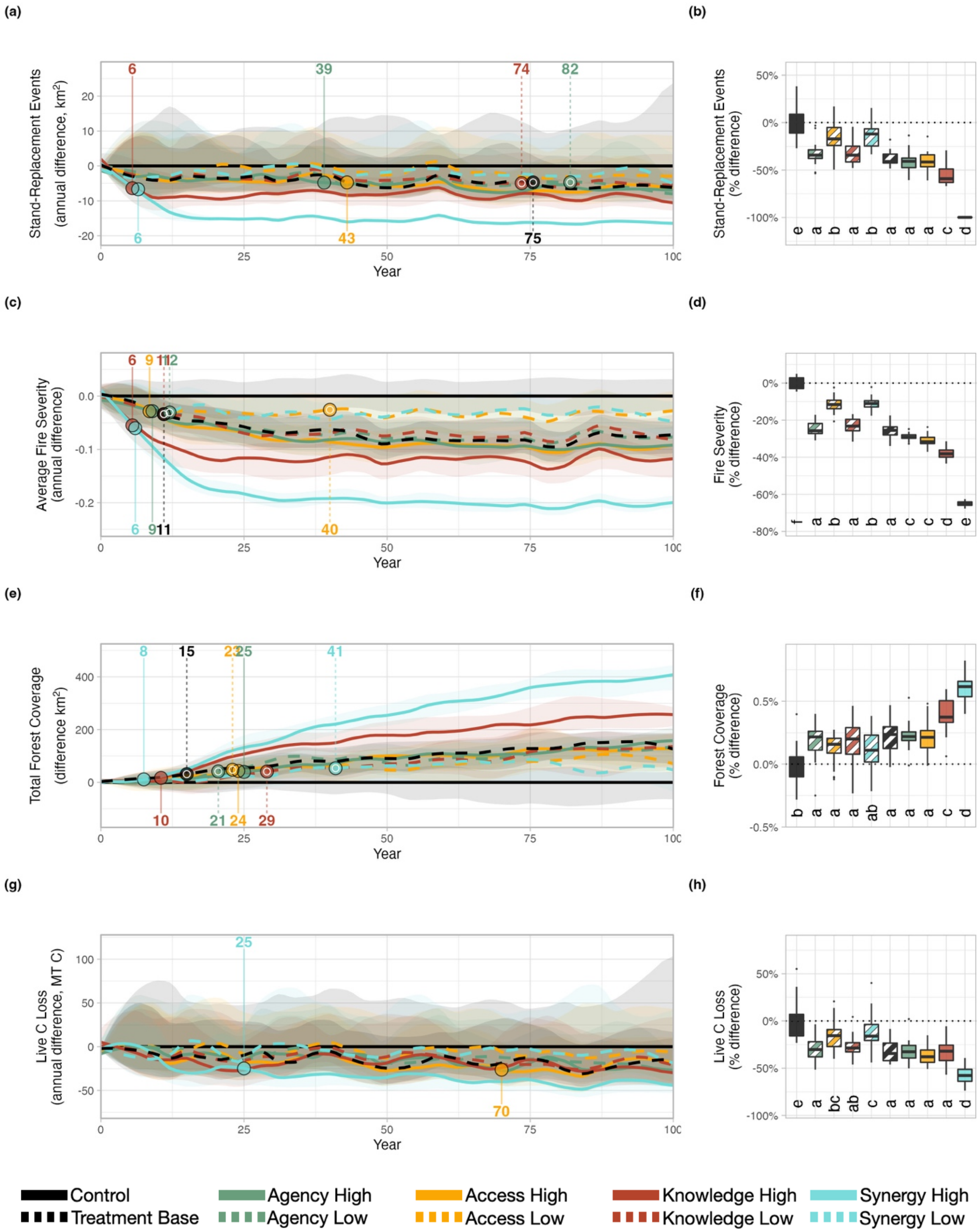
(a)
(b)
Stand-Replacement Events (annual difference, km²)
24
75
40
Year
Stand-Replacement Events (% difference)
50%
0%
-50%
d a b c c c
(c)
(d)
Average Fire Severity (annual difference)
6
11
7
29
Fire Severity (% difference)
f a b c d e
(e)
(f)
Total Forest Coverage (difference km²)
15
22
18
69
Forest Coverage (% difference)
b ab a c c c
(g)
(h)
Live C Loss (annual difference, MT C)
70
71
Live C Loss (% difference)
a a b bc c c
Control
100 km² yr⁻¹
500 km² yr⁻¹
1000 km² yr⁻¹
1500 km² yr⁻¹
2000 km² yr⁻¹

**Figure 3.** Increased annual fuels treatment extent decreases pyrogenic stand-replacement rates, wildfire severity, forest conversion to grassland, and live carbon loss rates, and results in an earlier time of emergence (ToE) for treatment effects. All values are plotted relative to the annual ensemble median value of the no-treatment control scenario. (a) Time series of relative areal differences in pyrogenic stand-replacement events ($km^2$) and (b) percent difference in 50-year ensemble mean values for pyrogenic stand-replacement events relative to the control scenario in the second half-century. Negative values correspond to a reduction in stand mortality events. (c) Time series of relative differences in annual mean fire severity for cells affected by fire and (d) percent difference in 50-year ensemble mean values for fire severity relative to the control scenario in the second half-century. Negative values correspond to a reduction in fire severity. (e) Time series of relative differences in overall forest coverage and (f) percent difference in 50-year ensemble mean values for overall forest coverage relative to the control scenario in the second half-century. Positive values correspond to an increase in forest coverage. (g) Time series of relative difference in live carbon (metric tons C) lost to wildfire and (h) percent difference in 50-year ensemble mean values for live carbon loss relative to the control scenario in the second half-century. Negative values correspond to a decrease in live C loss. For time series plots, the solid line is the ensemble median ($50^{th}$ percentile) relative to the control ensemble median, and ribboning indicates the IQR ($25^{th}$-$75^{th}$ percentile range). For the box whiskers plots, the horizontal black line at center denotes the median of the ensemble distribution; the boxes denote the IQR; whiskers denote the range between the IQR and the end-members of the distribution, or 1.5 times the IQR if outliers are present; outliers are denoted by black dots above or below the whiskers; compact letter display indicates significant differences in ensemble means derived from a pairwise ANOVA test (see methods section 2.4).



(a)
(b)
Stand-Replacement Events
(annual difference, km²)
Year
48
75
73
Stand-Replacement Events
(% difference)
b
ab
a
c
d
cd
(c)
(d)
Average Fire Severity
(annual difference)
7
26
11
Fire Severity
(% difference)
e
a
b
c
d
d
(e)
(f)
Total Forest Coverage
(difference km²)
15
65
24
Forest Coverage
(% difference)
a
a
a
b
b
b
(g)
(h)
Live C Loss
(annual difference, MT C)
Live C Loss
(% difference)
b
ab
ac
cd
d
d
Control
10%
30%
60%
90%
100%

**Figure 4.** Increased stand-level treatment intensiveness (percent reduction of dead biomass fuels during treatment) decreases wildfire severity, forest conversion to grassland, and live carbon loss rates, and results in an earlier time of emergence (ToE) for treatment effects. All values are plotted relative to the annual ensemble median value of the no-treatment control scenario. (a) Time series of relative areal differences in pyrogenic stand-replacement events ($km^2$) and (b) percent difference in ensemble mean values for pyrogenic stand-replacement events relative to the control scenario over years 75-100. Negative values correspond to a reduction in stand mortality events. (c) Time series of relative differences in annual mean fire severity for cells affected by fire and (d) percent difference in ensemble mean values for fire severity relative to the control scenario over years 75-100. Negative values correspond to a reduction in fire severity. (e) Time series of relative differences in overall forest coverage and (f) percent difference in ensemble mean values for overall forest coverage relative to the control scenario over years 75-100. Positive values correspond to an increase in forest coverage. (g) Time series of relative difference in live carbon (MT C) lost to wildfire and (h) percent difference in ensemble mean values for live carbon loss relative to the control scenario over years 75-100. Negative values correspond to a decrease in live C loss. For time series plots, the solid line is the ensemble median (50th percentile) relative to the control ensemble median, and ribboning indicates the IQR ($25^{\mathbf{th}}$-$75^{\mathbf{th}}$ percentile range). For the box whiskers plots, the horizontal black line at center denotes the median of the ensemble distribution; the boxes denote the IQR; whiskers denote the range between the IQR and the end-members of the distribution, or 1.5 times the IQR if outliers are present; outliers are denoted by black dots above or below the whiskers; compact letter display indicates significant differences in ensemble means derived from a pairwise ANOVA test (see methods section 2.4).



(a)
(b)
Stand-Replacement Events
(annual difference, km²)
Year
Stand-Replacement Events
(% difference)
(c)
(d)
Average Fire Severity
(annual difference)
Fire Severity
(% difference)
(e)
(f)
Total Forest Coverage
(difference km²)
Forest Coverage
(% difference)
(g)
(h)
Live C Loss
(annual difference, MT C)
Live C Loss
(% difference)
Control
Treatment Base
Agency High
Agency Low
Access High
Access Low
Knowledge High
Knowledge Low
Synergy High
Synergy Low

**Figure 5.** Multiple scenarios representing combinations of political and technical factors limiting spatial treatment allocation (Fig. S1) show relative success in severity reduction for scenarios utilizing precise knowledge of annual fuels distributions to prioritize treatment location. All values are plotted relative to the annual ensemble median value of the no-treatment control scenario. (a) Time series of relative areal differences in pyrogenic stand-replacement events ($km^2$) and (b) percent difference in ensemble mean values for pyrogenic stand-replacement events relative to the control scenario over years 75-100. Negative values correspond to a reduction in stand mortality events. (c) Time series of relative differences in annual mean fire severity for cells affected by fire and (d) percent difference in ensemble mean values for fire severity relative to the control scenario over years 75-100. Negative values correspond to a reduction in fire severity. (e) Time series of relative differences in overall forest coverage and (f) percent difference in ensemble mean values for overall forest coverage relative to the control scenario over years 75-100. Positive values correspond to an increase in forest coverage. (g) Time series of relative difference in live carbon (MT C) lost to wildfire and (h) percent difference in ensemble mean values for live carbon loss relative to the control scenario over years 75-100. Negative values correspond to a decrease in live C loss. For time series plots, the solid line is the ensemble median (50th percentile) relative to the control ensemble median, and ribboning indicates the IQR ($25^{th}$-$75^{th}$ percentile range). For the box whiskers plots, the horizontal black line at center denotes the median of the ensemble distribution; the boxes denote the IQR; whiskers denote the range between the IQR and the end-members of the distribution, or 1.5 times the IQR if outliers are present; outliers are denoted by black dots above or below the whiskers; compact letter display indicates significant differences in ensemble means derived from a pairwise ANOVA test (see methods section 2.4).

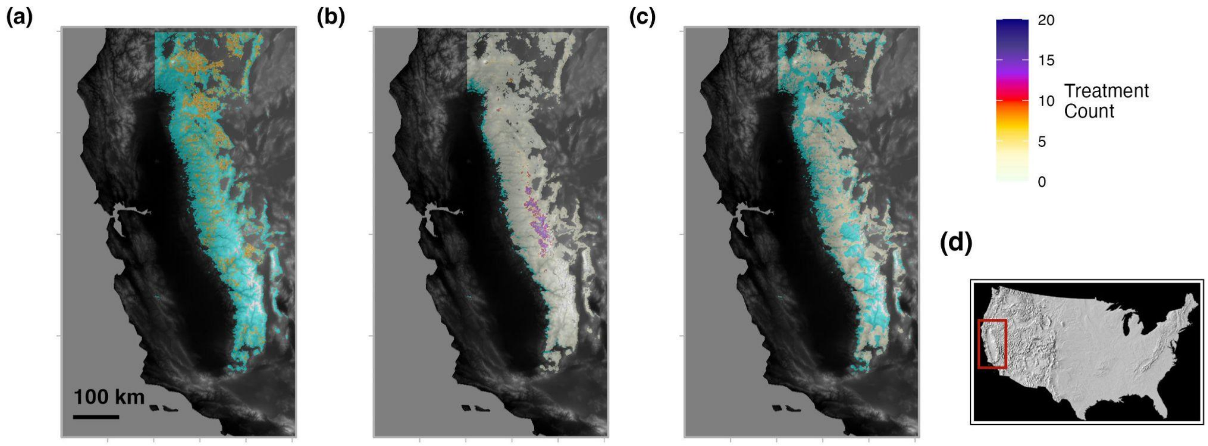



**Figure 6.** High retreatment frequency of select stands occur in both very spatially restrictive scenarios shown in (a) which shows treatment distributions for model experiment "Synergy Low", and more spatially unrestricted scenarios that prioritize treatment of the most fuel-heavy stands shown in (b) which shows treatment distributions for model experiment "Synergy High"). Evenly distributed, lower-intensity treatments are emergent in treatment scenarios with intermediate spatial constraints and fuel-mapping information shown in (c) which shows treatment distributions for model experiment "Treatment Base". Color legend shows the mean ensemble retreatment counts over a 100-year simulation. Untreated areas within the model domain are shown in cyan. Panel (d) indicates the map domain within the larger continental United States.

## Supplemental Figures

| Experiment | Scenario | Dead biomass filtering | Proximity to Roads | Maximum Treatable Slope | Participating Land Jurisdictions | Proximity to WUI/ Homes | Annual Treated Area | Precent Dead Fuels Removal |
|---|---|---|---|---|---|---|---|---|
| **Restriction** | **Treatment Base** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 90% |
| **Restriction** | **Agency Low** | > 20th percentile | < 3 km | 30˚ | USFS & BLM | < 50 km | 1000 km$^2$ | 90% |
| **Restriction** | **Agency High** | > 20th percentile | < 3 km | 30˚ | All Public & Private Lands | Any | 1000 km$^2$ | 90% |
| **Restriction** | **Access Low** | > 20th percentile | < 1 km | 10˚ | All Public Lands | Any | 1000 km$^2$ | 90% |
| **Restriction** | **Access High** | > 20th percentile | Any | Any | All Public Lands | Any | 1000 km$^2$ | 90% |
| **Restriction** | **Knowledge Low** | > 5th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 90% |
| **Restriction** | **Knowledge High** | Hierarchy | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 90% |
| **Restriction** | **Synergy Low** | > 5th percentile | < 1 km | 10˚ | USFS & BLM | < 50 km | 1000 km$^2$ | 90% |
| **Restriction** | **Synergy High** | Hierarchy | Any | Any | All Public & Private Lands | Any | 1000 km$^2$ | 90% |
| **Area** | **100** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 100 km$^2$ | 90% |
| **Area** | **500** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 500 km$^2$ | 90% |
| **Area** | **1000** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 90% |
| **Area** | **1500** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1500 km$^2$ | 90% |
| **Area** | **2000** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 2000 km$^2$ | 90% |
| **Biomass** | **10%** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 10% |
| **Biomass** | **30%** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 30% |
| **Biomass** | **60%** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 60% |
| **Biomass** | **90%** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 90% |
| **Biomass** | **100%** | > 20th percentile | < 3 km | 30˚ | All Public Lands | Any | 1000 km$^2$ | 100% |

**Figure S1.** Parameterization of treatment factors for each model experiment.

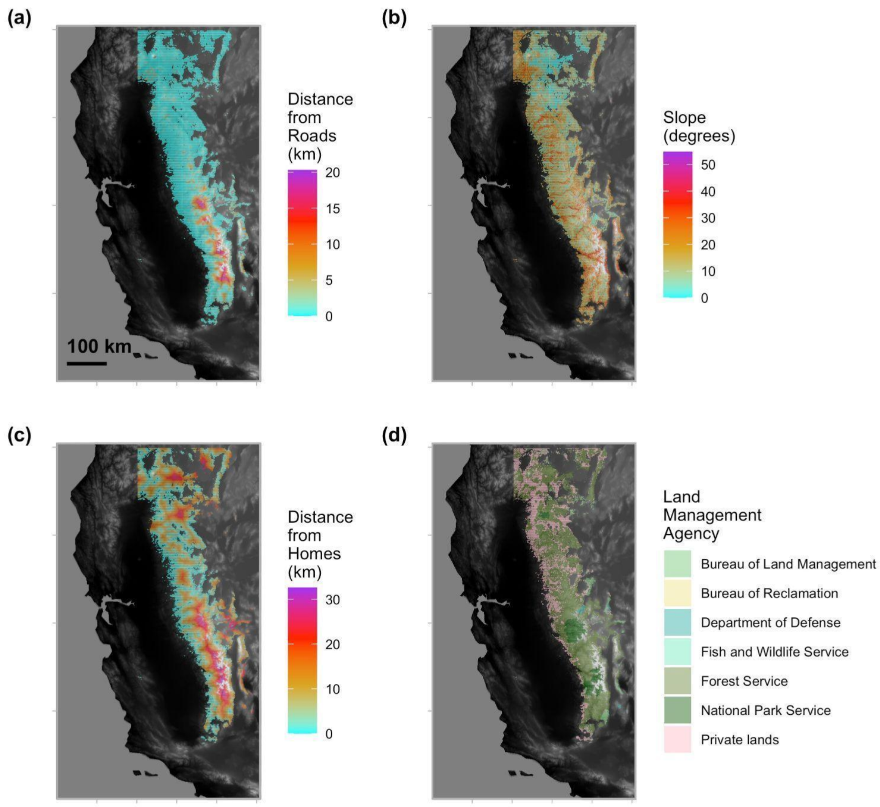



**Figure S2** Topographical, technical, and political factors influencing treatment distribution, clockwise from top left: a) Distance from roads by grid-cell, b) slope angle by grid-cell, c) distance from homes by grid-cell, and d) land management agency or stakeholder jurisdiction by grid-cell.

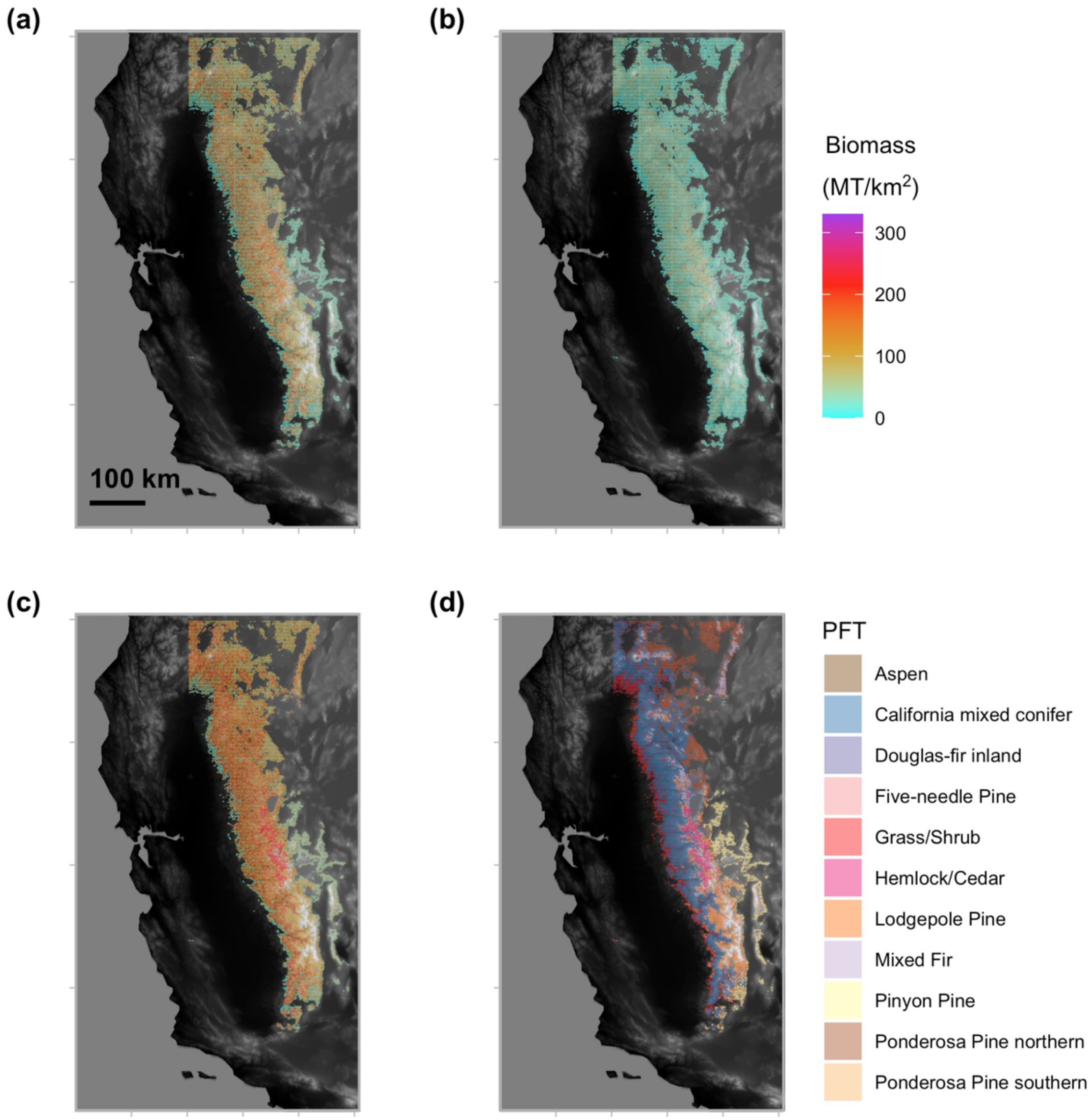



**Figure S3** Biomass loading at year 0 after a 250 year spin up shows how pretreatment biomass distributions vary as a result of climate and forest type. (a) Live biomass, (b) Dead biomass, (c) Total biomass, (d) plant functional type (PFT).

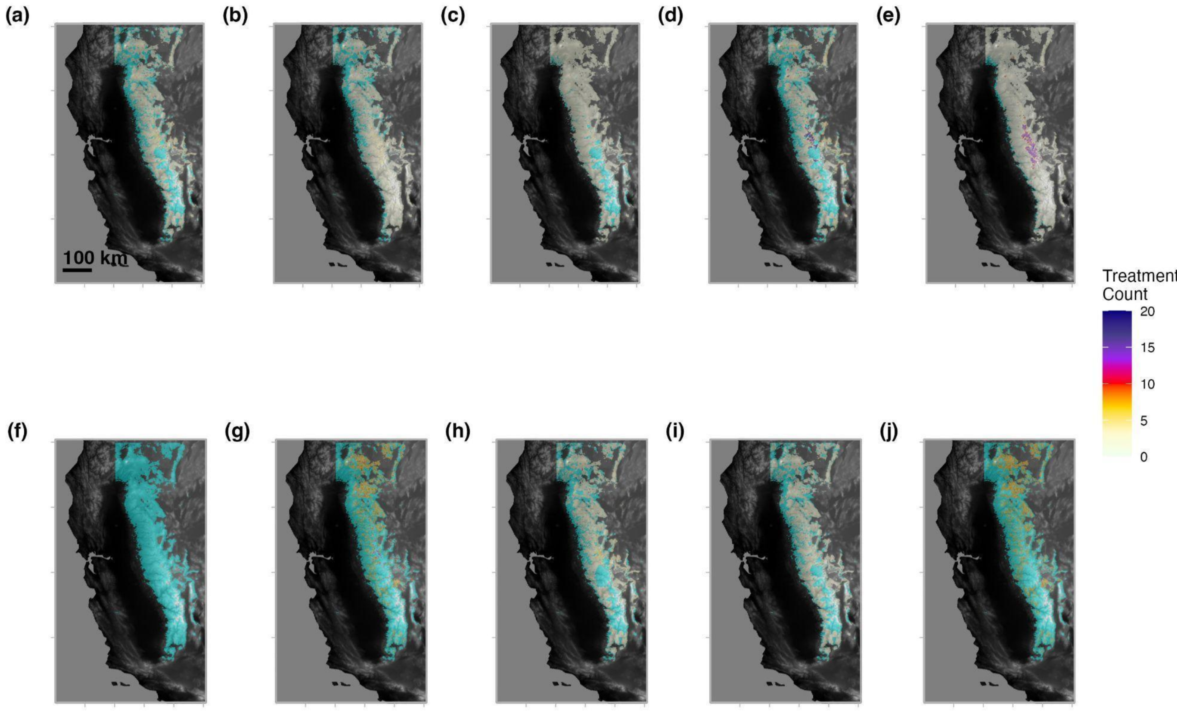



**Figure S4** Retreatment counts for each simulated scenario (untreated areas displayed in turquoise): (a) Treatment Base, (b) Access High, (c) Agency High, (d) Knowledge High, (e) Synergy High, (f) Control (no treatment), (g) Access Low, (h) Agency Low, (i) Knowledge Low, (j) Synergy Low

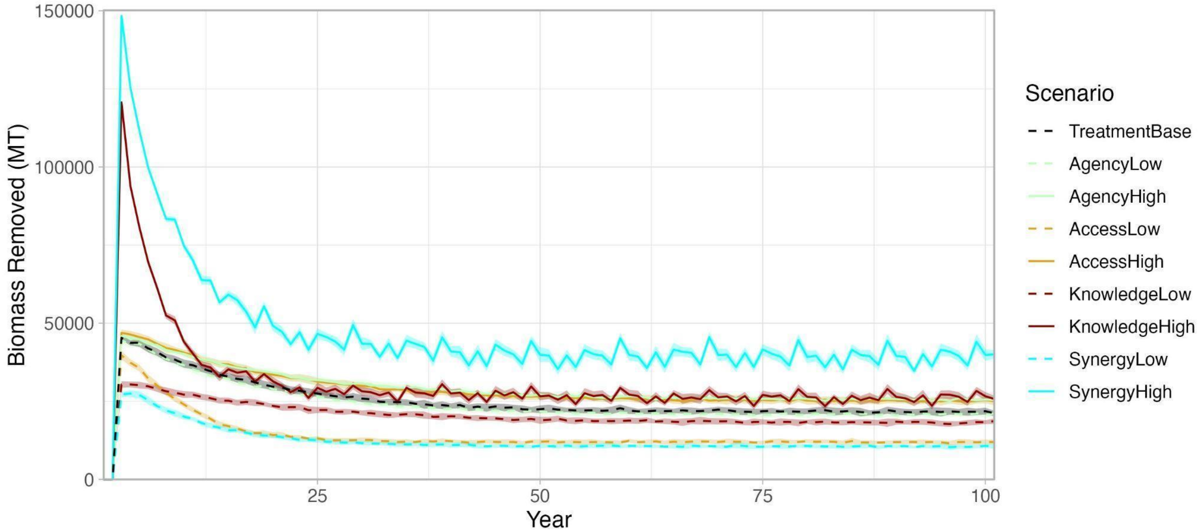



**Figure S5** Mean annual dead biomass removed (plotted in metric tons) during fuels treatments for each scenario was closely correlated with treatment success. Shaded regions indicate standard deviation.