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Prioritizing forest fuels treatments based on the probability of high-severity fire restores adaptive capacity in Sierran forests

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Abstract

In frequent fire forests of the western United States, a legacy of fire suppression coupled with increases in fire weather severity have altered fire regimes and vegetation dynamics. When coupled with projected climate change, these conditions have the potential to lead to vegetation type change and altered carbon (C) dynamics. In the Sierra Nevada, fuels reduction approaches that include mechanical thinning followed by regular prescribed fire are one approach to restore the ability of the ecosystem to tolerate episodic fire and still sequester C. Yet, the spatial extent of the area requiring treatment makes widespread treatment implementation unlikely. We sought to determine if a priori knowledge of where uncharacteristic wildfire is most probable could be used to optimize the placement of fuels treatments in a Sierra Nevada watershed. We developed two treatment placement strategies: the naive strategy, based on treating all operationally available area and the optimized strategy, which only treated areas where crown-killing fires were most probable. We ran forecast simulations using projected climate data through 2,100 to determine how the treatments differed in terms of C sequestration, fire severity, and C emissions relative to a no-management scenario. We found that in both the short (20 years) and long (100 years) term, both management scenarios increased C stability, reduced burn severity, and consequently emitted less C as a result of wildfires than no-management. Across all metrics, both scenarios performed the same, but the optimized treatment required significantly less C removal (naive=0.42 Tg C, optimized=0.25 Tg C) to achieve the same treatment efficacy. Given the extent of western forests in need of fire restoration, efficiently allocating treatments is a critical task if we are going to restore adaptive capacity in frequent-fire forests.

KEYWORDS
adaptive capacity, fire weather, forest carbon, fuels management, treatment optimization, wildfire

1 | INTRODUCTION

Forests are a substantial contributor to the terrestrial carbon (C) sink, but this ecosystem service is jeopardized globally by the increasing frequency and intensity of disturbances associated with rapid climatic change (Bellassen & Luyssaert, 2014). This is especially true for the frequent-fire adapted forests of the western United States, where fire suppression-caused biomass build-up and changing climate are causing larger, hotter wildfires that are threatening the ability of these systems to sequester and store C (Liang, Hurteau, &

Westerling, 2017a,b; Miller & Safford, 2012; Miller, Safford, Crimmins, & Thode, 2009; Westerling, 2016). Identifying the adaptive capacity of different forest ecosystems to deal with these changes and evaluating the potential for management intervention to increase adaptive capacity are central to sustaining functioning forest ecosystems in the presence of changing climate and disturbance regimes (Millar & Stephenson, 2015; Lindner et al., 2010; Brandt et al., 2017.).

A primary impediment to establishing adaptive capacity in western US forests is the result of a legacy of fire exclusion across the region. Fire exclusion has resulted in an increase in biomass, both in terms of surface fuels and tree density, which has pushed the attributes of fire events in many ecosystems beyond their natural range of variability (Collins, 2014; Hurteau, Westerling, Wiedinmyer & Bryant, 2014; North, Collins, & Stephens, 2012). The altered amounts and distributions of biomass, coupled with recent increases in fire weather severity and duration of the fire season are driving increased wildfire size, severity, and frequency (Miller et al., 2009; Westerling, 2016). These altered fire regime attributes and the direct and indirect risks they pose to society present challenges to land management agencies that are likely to be further exacerbated by projected climate change (Liang et al., 2017b).

Restoring forest structure and fire regimes, however, poses a complex multivariate problem, with socioeconomic and ecological factors often presenting opposing objectives (North et al., 2015). Removing fuels across the landscape and restoring fire regimes to historic frequencies in western forests requires the combination of mechanical thinning and prescribed fire, both of which reduce carbon stocks and increase C emissions to the atmosphere. These activities have the short-term effect of degrading air quality and reducing the capacity of the ecosystem to sequester carbon (North, Hurteau, & Innes, 2009; Wiechmann, Hurteau, North, Koch, & Jerabkova, 2015). This short-term detriment, however, can yield long-term benefits in terms of avoided future emissions of C from wildfire and increased capability of the forest to sequester C, increasing the capacity of the ecosystem to tolerate changing climate and fire weather regimes with minimal loss of function (Hurteau, 2017).

In the Sierra Nevada, complex topography, land ownership patterns, and at-risk species have contributed to a back-log of forest area requiring restoration (North et al., 2012). Coupled with proposed accelerated treatment rates (North et al., 2012), restoration implementation must be designed with a strategy that maximizes treatment benefits while minimizing the associated costs of management (Chung, 2015). Previous work has demonstrated that optimizing treatment placement can be handled in a variety of ways, often, however, management treatment targets or timber production are fixed requirements of the optimization process (e.g., Finney, 2001, 2007; Vaillant, 2008). It follows that by simplifying the multivariate management problem, the spatial allocation of treatments can be designed such that their efficacy is maximized, with optimal placement resulting in reduced high-severity wildfire risk, smaller net removals of C, and at a reduced cost due to a smaller fraction of the landscape being treated.

We sought to compare the impacts of forest restoration treatments in the Dinkey Creek watershed in the Sierra Nevada using two management strategies: treatment restricted only by operational limitations (e.g., steep slopes, wilderness or riparian areas, etc.; hereafter naive, indicating a priori information was not used to inform treatment placement), and treatment placement governed by both operational limitations and a high-severity fire risk model (hereafter optimized). Specifically, we asked the question: Can an optimized treatment approach to placement perform as well as a naive placement approach in terms of high-severity wildfire risk reduction at a significantly reduced C cost? We hypothesized that (i) short- (<20 years) and long-term (20–100 years) aboveground C accumulation would be similar in both naive and optimized treatment placement strategies; (ii) patterns of mean fire severity across the landscape would be similar between the naive and optimized placement strategies; and contingent on hypotheses 1 and 2, (iii) the similar treatment efficacy, coupled with the reduced biomass removal associated with optimizing treatment placement, would result in greater net C storage in the optimized scenario than in the naive scenario.

2 | MATERIALS AND METHODS

We conducted landscape simulations of vegetation growth and disturbance within the Dinkey Creek watershed, an 87,500 ha area in the southern Sierra Nevada, CA that is part of a Collaborative Forest Landscape Restoration Project (CFLRP). This study leveraged our previous work, which evaluated the efficacy of forest restoration treatments under severe fire weather in the Dinkey Creek CFLRP (Krofcheck, Hurteau, Scheller, & Loudermilk, 2017). The watershed spans roughly 2,700 meters in elevation (300 to 3,000 m), with a precipitation gradient of 50–100 cm/year and variability in mean daily minimum temperatures from -3 to 10°C and mean daily maximum temperatures from 12 to 25°C (DAYMET, Thornton et al., 2012). This edaphic and climatic variability results in vegetation that ranges from mixtures of oak (*Quercus spp.*) and shrubs at the lowest elevations to ponderosa pine (*Pinus ponderosa*) and mixed-conifer forests at mid-elevations, and subalpine forest types at the highest elevations.

2.1 | Model description and parameterization

We modeled landscape scale disturbance and succession using LANDIS-II (v6.0), which simulates the growth and mortality of age and species-specific cohorts of trees and shrubs across a spatially explicit landscape (Scheller et al., 2007). In each grid cell, each cohort undergoes growth, disturbance, and dispersal. Species are defined with individual parameters that govern growth and dispersal, whereas broader plant traits are parameterized in the model using plant functional groups. Similarly, the landscape is divided into ecoregions, fire regions, and management regions, each with a unique set of parameters that govern how the landscape interacts with climate and disturbance to govern landscape scale carbon balance. LANDIS-II uses community developed extensions to build additional model functionality into the simulation framework. We used the Century Succession (v4.0.1) extension to track landscape C dynamics, the Dynamic Fire and Fuels System (DFFS, v2.0.5) and the Dynamic Fuels Leaf Biomass (v2.0) extensions to simulate stochastic fire and changes to forest fuels across the landscape, and the Leaf Biomass Harvest extension (v2.0.3) to simulate management scenarios.

LANDIS-II requires that the landscape be split into edaphically and climatically similar ecoregions, which are parameterized with an independent set of soil properties and climate drivers. Similarly, the Dynamic Fire and Fuels extension requires the generation of fire regions, each with an independent set of fire probabilities and parameters. The creation of the ecoregions and fire regions used in this study is described by Krofcheck et al. (2017).

We ran the model using climate projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5) collection of models. Specifically, we chose the Localized Constructed Analogs (LOCA) statistically downscaled climate projections (Pierce, Cayan, & Thrasher, 2014), a daily, 1/16th degree resolution downscaled product that has been shown to track local variability in precipitation better than the coarser resolution parent models. We chose four general circulation models that bracket the precipitation and temperature envelope as represented by the CMIP5 family of models for the region: CCSM4 (CCSM4_r6i1p1_rcp85), CNRM-CM5 (CNRM-CM5_r1i1p1_rcp85), FGOALS-g2 (FGOALS-g2_r1i1p1_rcp85), and MIROC-ESM (MIROC-ESM_r1i1p1_rcp85), each run under Representative Concentration Pathway (RCP) 8.5. The projections include data from 1950 to 2100, and we used data from 1950 to 2000 for model spin-up. We downloaded the data using the USGS Geo Data Portal (http://cida.usgs.gov/gdp/, Thornton et al., 2012), and computed weighted area grid statistics on a per-ecoregion basis using the export service in the data portal.

The Dynamic Fire and Fuels extension requires fire weather data separate from the climate inputs to the Century extension. To better link how changing climate would interact with management and wildfire regimes, we generated decadal distributions of fire weather from the four climate model projections and updated the fire weather in the model every decade. Wind gust velocity was the only fire weather variable not present in the LOCA climate data, and to account for this we took the measurement record of local RAWS stations used in previous work in this area (Krofcheck et al., 2017) and generated a distribution of wind gusts by fire region, starting at the 50th percentile, and increasing by increments of 5% of the distribution per decade. At each increment, we calculated the cumulative distribution function of wind gusts for that percentile, and randomly drew from a normal distribution centered on the percentile mean and variance. Ultimately, this resulted in moving toward but never exceeding measured values recorded during the 2013 Rim fire, corresponding to the 95th percentile of wind gust velocity. We generated these data on a per fire region basis, the result of which is shown in Figure 1.

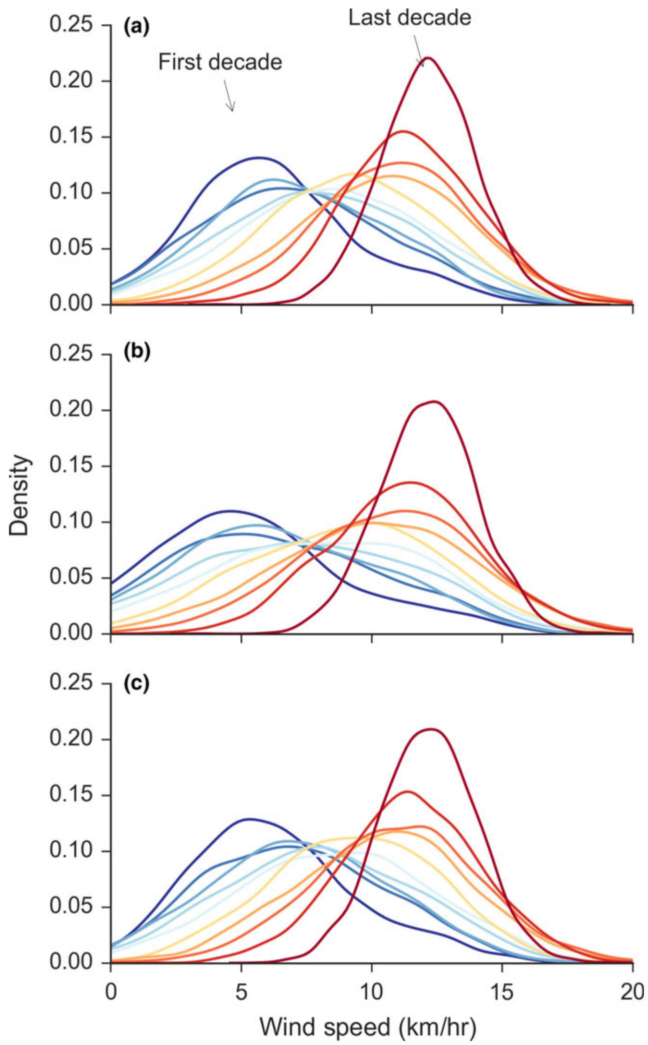

FIGURE 1 Probability density functions of wind speed used to generate the wind component of the projected fire weather. Measurements in local fire region 1 (a), 2 (b), and 3 (c) were used to create ten decadal PDFs, increasing from blue (early century) to red (late century)

The Dynamic Fire and Fuels extension determines the fuels class of each grid cell as a function of the species and ages present, using a set of equations adapted from the Canadian Fire Behavior and Prediction System (Sturtevant, Scheller, Miranda, Shinneman, & Syphard, 2009). The model also allows the modification of all fuels characteristics as a function of time since treatment or time since disturbance (e.g., wildfire). At each time-step, cells in each fire region are randomly selected for attempted ignition. Fire occurrence in a given cell with attempted ignition is a probabilistic function of fire weather and fuels characteristics. Maximum fire size is a function of the size drawn from the fire size distribution and the realized fire size is a function of fire weather, topography, and the fuel characteristics of adjacent grid cells. The model assigns a severity class to each grid cell within each fire, based on the percent of the crown that burned in each grid cell. Fire severity ranges from surface fire with no crown mortality (severity 1) to 95% or greater crown mortality (severity 5). Management treatments that reduce the number of cohorts and increase the mean cohort age do not affect the rate of fire spread, but do increase the canopy base height and can result in decreased fire severity. In this study, we retained the fire and fuels parameterization used in Krofcheck et al. (2017). In the previous work, the number of attempted ignitions per fire region was adjusted such that the number of fires that resulted in the model matched historical data for the surrounding region. Per our previous work, we adapted fuels parameterizations from Syphard et al. (2011) and Loudermilk et al. (2014) to represent the local conditions inside our study area.

2.2 | Scenario description

We developed three scenarios: no-management, naive placement, and optimized placement. Both management scenarios employed combinations of mechanical thinning and prescribed burning. The naive placement scenario aimed to simulate mechanical thinning from below and prescribed fire to all forest types that have experienced a fuels load departure from their historic condition due to fire exclusion. Within each forest type that received mechanical thinning, thinning was constrained based on operational limits (slope>30%, which totaled 22,436 ha available for mechanical thinning). The optimized placement scenario further constrained the area that received mechanical thinning by limiting thinning to areas that also had a high probability of mixed- and high-severity wildfire.

The optimization process was based on 50 replicate simulations resulting from previous work (Krofcheck et al., 2017), wherein we simulated wildfire across the watershed using a distribution of fire weather from the extreme tail of the distribution over a 100-year period. The first step in our optimization was to use the output from these previous simulations and calculate average total number of fires per grid cell (Figure 2a). Next, we calculated the number fires per grid cell that resulted in some crown mortality (fires≥severity class 3 in the model, Figure 2b). Finally, we divided the number of crown-killing fires by the total number of fires in each grid cell (Figure 2c). The resulting probability surface described the likelihood of crown-killing fire across the watershed, in aggregate under the most extreme fire weather events captured in the contemporary record. We used this surface to prioritize areas for treatment and excluded areas available to treat that had a low probability of severe fire, resulting in a total of 7,266 ha identified for mechanical thinning. This approach accounts for the influences of fuel type, canopy base height, slope, and fire weather on the probability of severe wildfire. Table 1 describes the forest type rates and total for the biomass removal that resulted from the species and age combinations removed under each management scenario.

In both treatment scenarios, stands identified for mechanical treatment were thinned from below, removing roughly one-third of the live tree biomass over the first decade of the simulation. Stands selected for mechanical thinning were only thinned once in the simulations, and all thinning was completed within the first decade. We used the mean historic fire return interval for each forest type to simulate prescribed fire frequency and applied prescribed fire to all forest types where more frequent fire is ecologically appropriate. Using this approach, many grid cells received prescribed fire more than once during the simulations, as a function of the historic fire return interval and the disturbance regime experienced by the grid cell.

We ran 50 replicate 100-year simulations for each climate projection and management scenario, resulting in 200 replicates within each management scenario. We leveraged the stochastic nature of vegetation establishment and wildfire ignition and propagation afforded by this replication as a means of describing the range of potential outcomes in our simulation environment.

We used analysis of variance and Tukey's honestly significant difference for mean separation following Bartlett's test for homoscedasticity. For comparisons where data were heteroscedastic, we employed Kruskal–Wallis tests with post hoc Dunn's comparisons. We conducted all model parameterization and output analyses, as well as figure generation using Python (Python Software Foundation, version 2.7. http://www.python.org).

3 | RESULTS

We hypothesized that patterns of landscape aboveground carbon (AGC) accumulation would be similar in both treatment scenarios

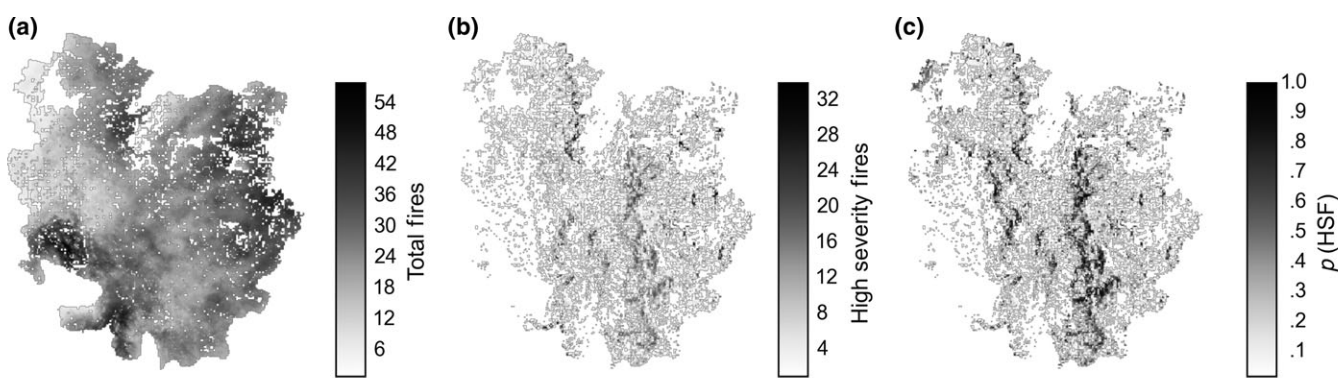

FIGURE 2 Total fires simulated in 50 replicates simulations (from Krofcheck et al., 2017) by grid cell (a), fires with mean severity≥3 (b), and the resulting probability of high-severity fire p(HSF) used to govern the optimized treatment placement (c)

TABLE 1 Treatment areas and rates by forest type and treatment. Areas that received thinning were only thinned once

Optimized treatment	Thin area (ha)	Thin rate (ha/year)	Prescribed fire area (ha)	Prescribed fire rate (ha/year)
Ponderosa pine	532	106	7,508	417
Mixed conifer-pine	3,644	728	12,474	623
Mixed conifer-fir	3,431	686	9,087	363
Red fir	-	-	5,921	148
Naive treatment	**Thin area (ha)**	**Thin rate (ha/year)**	**Prescribed fire area (ha)**	**Prescribed fire rate (ha/year)**
Ponderosa pine	4,558	651	7,508	417
Mixed conifer-pine	8,150	1,164	12,474	623
Mixed conifer-fir	6,767	966	9,087	363
Red fir	-	-	5,921	148

over both the short- (<20 years) and long-term (20-100 years). The range of AGC across replicates and climate projections for each scenario are shown in Figure 3. The no-management scenario showed a wide range of potential outcomes, from 90.5 to 121.2 Mg C ha^{-1} in the short-term and 139.4 to 185.6 Mg C ha^{-1} in the long term. Both management scenarios showed significantly smaller variances in AGC relative to no management, with the naive scenario ranging from 98.7 to 115.4 Mg C ha^{-1} and the optimized scenario ranging from 100.6 to 118.3 Mg C ha^{-1} (Table 2).

The maximum AGC is the maximum value for a given year from the 200 replicate simulations for a given scenario. The initial treatment costs associated with mechanical thinning are most apparent in the comparison of maximum AGC, where treatment scenarios have lower maximum AGC than the no-management scenario during the first decade when thinning treatments are implemented. However, this difference diminishes over the full 100 years of simulation (Figure 4a). Short-term reductions in maximum AGC relative to no management were 5.7 Mg C ha^{-1} for naive placement and 2.9 Mg C ha^{-1} for optimized, with long-term reductions of 2.6 Mg C ha^{-1} for naive and 1.6 Mg C ha^{-1} for optimized placement.

The minimum AGC is the minimum value for a given year from the 200 replicate simulations for a given scenario. Therefore, the difference in minimum landscape AGC between treatments and the no-management scenario (Figure 4b) represents the gains in worst-case AGC that result from treatment. The naive scenario had minimum AGC values that were greater than the no-management minimum throughout the simulation period. The 67% reduction in thinned area in the optimized scenario yielded lower minimum AGC values than the naive scenario over the majority of the simulation period and had lower minimum values than the no-management scenario in the short-term (Figure 4b). The lower minimum values in the short-term are a function of the occurrence of a large wildfire in one replicate simulation early in the simulation, before the initial prescribed fire treatments had all been implemented.

The lower 95th percentile of AGC represents the collection of highest disturbance affected simulation years from the 200 replicate simulations for each scenario. When we compared the difference in the lower 95th percentile AGC between the treatment scenarios and the no-management scenario, both treatment scenarios were lower than the no-management scenario in the short-term (Figure 4c). However, the lower 95th percentile of AGC for the optimized scenario surpassed the no-management scenario in year 31 and in year 36 for the naive scenario. While both the naive and optimized treatment placement scenarios underwent mechanical thinning and prescribed fire over the same time intervals, substantially less biomass was removed annually via mechanical thinning across the landscape in the optimized scenario (Figure 4d).

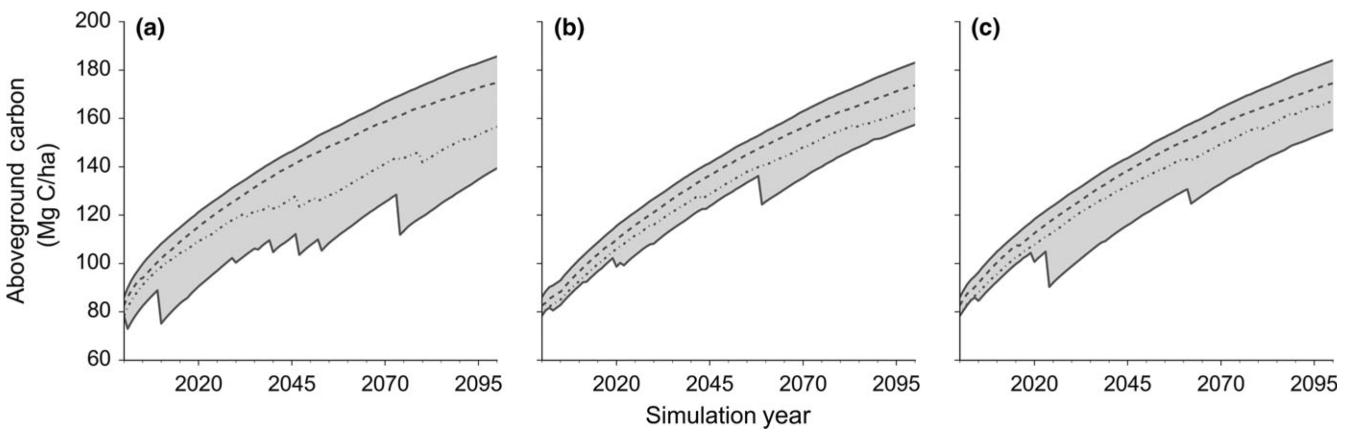

FIGURE 3 Above ground carbon (AGC) for the no-management scenario (a), the naive placement scenario (b), and the optimized scenario (c). Each subplot shows the absolute minimum, maximum, mean (dashed) and lowest 95th percentile (dotted) of AGC for each year across 200 total simulations

TABLE 2 Mean above ground carbon for the short- and long-term from each scenario and the corresponding standard deviation across the 200 replicate simulations. Variances that are significantly different ($p < .001$) from one another are denoted with different letters

	Year 20		Year 100	
Scenario	Mean (Mg C ha)	σ	Mean (Mg C ha)	σ
No management	116.0	5.1 a	173.1	8.3 a
Naive	111.1	3.9 b	174.4	5.0 b
Optimized	113.6	4.1 b	175.0	4.8 b

The end-of-simulation mean fire severity for all three scenarios is shown in Figure 5a-c. In all three scenarios, the greatest burn severity occurred in areas dominated by ponderosa pine and pine-dominated mixed-conifer forests. Consistent with our hypothesis, the impact of treatment in both management scenarios was lower mean fire severity relative to the no-management scenario. In both management scenarios mean severity was significantly reduced, with a mean reduction of 16.1% for the naive placement, and 18.4% for the optimized placement scenario ($p < .001$; Figure 5d-e).

Cumulative wildfire carbon emissions in both the naive (7.0 ± 8.5 Mg C ha^{-1}) and optimized (6.8 ± 8.0 Mg C ha^{-1}) treatment scenarios were significantly lower ($p < .001$) than the no-management scenario (15.2 ± 17.7 Mg C ha^{-1}). The increased area thinned in the naive scenario resulted in significantly higher cumulative C removals from thinning (0.31 Tg C) than the optimized scenario (0.14 Tg C; $p < .001$). In spite of the greater area prescribed burned without first being thinned in the optimized scenario, the optimized scenario cumulative prescribed fire emissions (0.12 Tg C) were not significantly different than the prescribed fire emissions from the naive scenario (0.11 Tg C). When we accumulated the C losses from the landscape by summing C efflux from wildfires and C removal from management, the end of simulation C losses from the optimized scenario were significantly lower than both the no-management and naive placement scenarios ($p < .001$, Figure 6).

4 | DISCUSSION

The concept of optimization is inherently context dependent, as it implies maximizing one process while minimizing another, and consequently we acknowledge that optimum treatment placement is a moving target. Previous studies have sought to optimize treatment location to minimize fire spread, via fuels treatment placement that reduces the rate of fire progression (e.g., Finney, 2007). This approach has been widely used in the fire management literature as a component of wildfire management frameworks (e.g., Ager, Vaillant, & Finney, 2011), and is designed to minimize fire size. Here, we specifically aimed to maximize the reduction in wildfire severity across the landscape, while minimizing the area mechanically thinned, and so we chose to use the probability of high-severity wildfire as the sole metric to govern differences in our management treatment design. This approach forgoes the socioeconomic system considerations that often complicate management decision making (Agee & Skinner, 2005; Ager, Vaillant, & Finney, 2010; Prichard, Peterson, & Jacobson, 2010), and consequently seeks only to maximize the potential treatment effect of fuels reduction across the landscape. Furthermore, by forgoing any efforts to reduce fire size or percent of the landscape burned, our process-based approach permits large, low severity wildfires which managers may choose to manage for resource benefit, facilitating the often difficult to achieve targets for hectares burned per year in these landscapes. This approach is broadly applicable to historically frequent-fire ecosystems, or systems which have transitioned away from a low severity and fuel limited fire regime to one characterized by high-severity fires. Such transitions often occur as a result of fire suppression as is

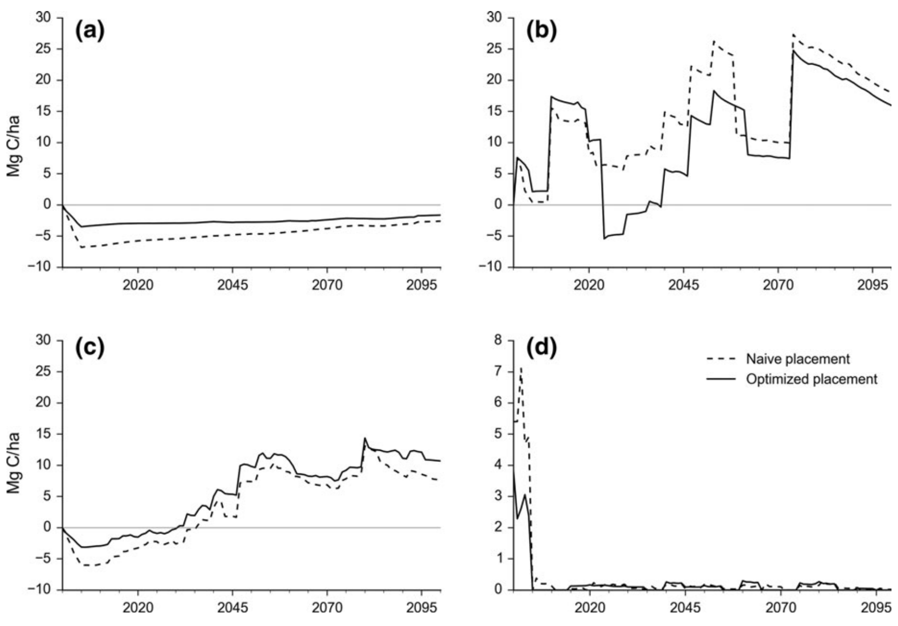

FIGURE 4 Relative differences in above ground carbon (AGC) between the naive placement (dashed), optimized placement (solid), and the no-management scenarios (zero line). Differences between the maximum (a), minimum (b), lowest 95th percentile (c), and the AGC removed during management (d) are shown for each year of the simulation across 200 replicates

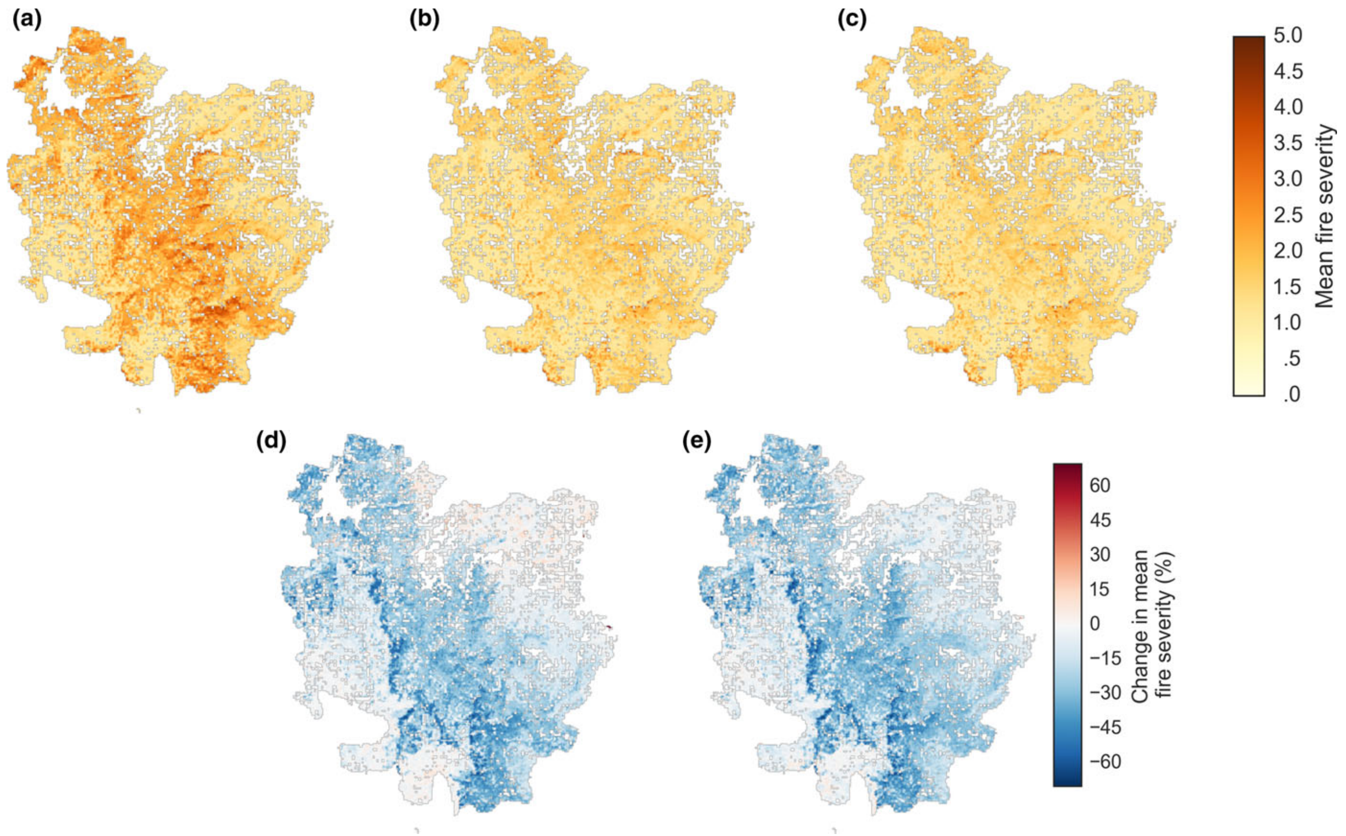

FIGURE 5 Mean fire severity for the no management (a), naive placement (b), and optimized placement (c) scenarios, and the resulting percent change in fire severity relative to the no-management scenario caused by the naive (d) and optimized (e) treatments

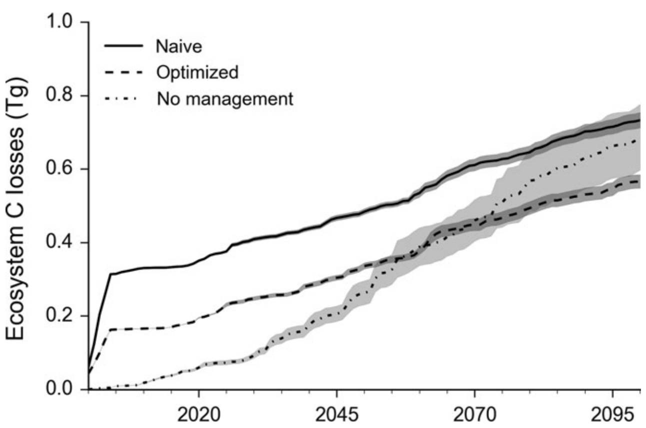

FIGURE 6 Total losses of C from the landscape represented as means of the 200 replicate simulations for the no management (dotted), naive placement (solid), and optimized (dashed) simulations. Shaded regions represent the 95% confidence interval about the mean

the case in the broader western United States, where the interannual variability in large fire size is well described as a function of fire-year climate and vegetation type (Keyser & Westerling, 2017). This approach has applications in other regions around the globe as well, where shifts in land use and land occupancy have reshaped the fuels structure and subsequently the fire regime of forests and woodlands, for example, across landscapes in the Mediterranean (e.g., Pausas & Fernandez-Munoz, 2012) and northern Australia (e.g., Russell-Smith et al., 2003).

In our simulation environment, wildfire is stochastic and probabilistic across the landscape, and by designing our optimized treatment placement scenario based on the probability of high-severity wildfire, we were able to identify and subsequently apply treatments to the high-risk portions of the landscape with a finer granularity than in the naive placement. This fundamental difference resulted in a much more targeted mechanical thinning prescription, treating all of the high fire risk areas with significantly fewer resources. Furthermore, the optimized scenario assumes that placing treatments to reduce the probability of high-severity fire achieves adequate 'anchors' (Ager et al., 2010; North et al., 2015) for widespread application of prescribed fire, which is an integral piece of the management strategy in both the naïve and optimized scenarios.

The cumulative C costs incurred by management resulted in a mean landscape reduction in 0.42 Tg C for the naive scenario and 0.25 Tg C for the optimized scenario, yet the treatment efficacy of both scenarios in terms of reductions in burn severity (Figure 5b) and changes in AGC accumulation (Figure 3) was very similar. However, forest fuels management decision making generally operates with the aim of mitigating disturbances from all but the extreme tail of the distribution, which in the case of wildfire is commonly represented by the 95th percentile of weather events. In our simulations, both treatment scenarios resulted in the same treatment efficacy in terms of avoided wildfire emissions and reduced landscape burn severity while continuing to accumulate carbon even under the increasingly extreme fire weather. While both treatments therefore restored adaptive capacity to the landscape, the optimized placement scenario did so at a considerably reduced C cost.

Understanding the short- and long-term implications of the C costs and benefits of treatment was one of our research objectives. The treatment efficacy relative to the C removed by management in both treatments in the short-term was fairly similar, resulting in a landscape carbon deficit at the lower 95th percentile level well into the second decade of simulation (Figure 4c). We attribute this to lower intensity fire weather that resulted from the milder first two decades of projected climate. Once the number of extreme fire weather events began to increase, the avoided C losses from wildfire also increased, and because burn severity reduction in our treatment simulations were not significantly different (Figure 5b), the benefit of the optimized treatment placement scenario was realized primarily as a reduction in carbon losses from the ecosystem (Figure 6). The C benefit of treatment was also realized under the most extreme disturbance conditions, at the lower 95th percentile AGC, where both treatment scenarios resulted in an increase across the landscape of 5–15 Mg C ha.

The total losses of C from the landscape were heavily governed by management decision making until mid-century, when the increases in fire weather severity began to result in significant C loss in the no-management scenario (Figure 6). Because both treatments remove a significant portion of the C from the system in the first decade of simulation with mechanical thinning, the actual C loss to the atmosphere due to management is considerably lower than the apparent C loss due to treatment. Roughly 60% of the C removed by mechanical thinning can be stored in long-lived wood products (North et al., 2009), and subsequently further offsets the landscape C loss for the treatment scenarios by approximately 0.18 Tg C for the naive scenario and 0.08 Tg C for the optimized placement scenario.

In both management scenarios, building the adaptive capacity to store C under projected climate and more extreme fire weather was contingent on restoring surface fire to the system and front loading the mechanical thinning to reduce the standing fuel load. Without the regular use of prescribed fire to reduce surface fuel accumulation, the potential for high-severity fire would likely have been significantly greater (Krofcheck et al., 2017). The similar treatment efficacies achieved by both the naive and optimized management scenarios, is indicative of the fact that an a priori understanding of high-severity wildfire risk in a given landscape can be used to more efficiently allocate management resources (Ager et al., 2011; Chung, Jones, Krueger, Bramel, & Contreras, 2013; Finney, 2007). This optimization benefit is especially poignant given that the Sierra Nevada on the whole has a massive backlog of nearly one million ha of untreated forest (North et al., 2012), and an increase in the efficiency of management decision making that affords even a 10% reduction in area mechanically treated may have large implications at the landscape scale.

Our approach to determining the optimum placement of fuels treatments required a predecision making set of simulations with a large number of replicates, and consequently opportunities for wildfire to occur. The probability of high-severity fire layer we generated for the watershed then served as a relatively simple means of determining optimum placement, in a post hoc, treat the highest probabilities first framework. This approach did not require an iterative simulation approach, and yielded a comparable treatment efficacy to the naive approach with fewer management inputs. Furthermore, by optimizing treatment placement, the lower 95th percentile of AGC surpassed that of the no-management scenario 5 years earlier in the optimized simulation than in the naive scenario. This finding suggests that efficiently allocating resources, in this case thinning, and using thinned areas to restore surface fire in the short-term, can yield long-term C storage gains because this approach takes advantage of less extreme early century fire weather to restore adaptive capacity for more extreme late-century fire weather.

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