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Evaluating the potential of forest fuel treatments to reduce future wildfire emissions

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ABSTRACT

Background. Effective forest fuel reduction treatments reduce hazardous fuel conditions, wildfire behavior and severity. It has been suggested and partially quantitatively analyzed that these treatments may also reduce future wildfire emissions, but this potential is debated. We apply a previously published, encompassing modeling approach to assess the potential of forest fuel reduction treatments to reduce future wildfire emissions. **Aims.** Evaluate the effectiveness of four fuel treatment types at reducing future wildfire greenhouse gas (GHG) emissions across a range of forest types and initial fire hazard levels. **Methods.** Forest growth, fire behavior, fire spread and emissions models were used to simulate fuel treatments and their potential impacts. **Key results.** The 'underburn only' and 'thin from below + pile burn' treatments had a minimum annual fire probability (AFP) 5–35% lower than other treatment types to achieve reduced GHG emissions. When AFP was high, the 'stand density index (SDI) thin + underburn' treatment reduced GHG emissions 13–54% more than the next best treatment. **Conclusions.** AFP, forest type and initial hazard level should be primary considerations when selecting a fuel treatment type for reducing future GHG emissions. **Implications.** These results provide decision support when selecting a fuel treatment type for reducing future GHG emissions.

Keywords: Douglas-fir, forest thinning, FVS modeling, fuel treatments, mixed conifer, Monte Carlo wildfire modeling, ponderosa pine, prescribed fire, white fir, wildfire emissions.

Introduction

Forests are an important component to the global carbon cycle as the largest terrestrial carbon sink for carbon dioxide (CO_2) (Canadell and Raupach 2008). Forests can also become a carbon source for CO_2 when they burn in wildfires (Hurteau 2021; Zhao *et al.* 2021; Bartowitz *et al.* 2022). It has been suggested that forest fuel reduction treatments (hereafter referred to as 'fuel treatments'), when applied strategically to the landscape, can mitigate carbon stock loss and greenhouse gas (GHG) emissions from future wildfires (Hurteau and North 2009; North and Hurteau 2011; Stephens *et al.* 2012; Restaino and Peterson 2013; Buchholz *et al.* 2022). Effective fuel treatments reduce future wildfire severity and improve wildfire suppression efficiency ultimately resulting in smaller wildfires (Moghaddas and Craggs 2007; Cochrane *et al.* 2012). Less severe wildfire effects generally correspond to reduced tree mortality and thus less carbon stock loss compared to a scenario with higher severity. Smaller wildfires generally correspond to relatively less carbon stock loss and fewer GHG emissions simply because less area, and thus less biomass, burns. Quantification of this concept, that fuel treatments reduce future wildfire GHG emissions, has been partially discussed and assessed in the literature (Hurteau and North 2009; North and Hurteau 2011; Stephens *et al.* 2012; Restaino and Peterson 2013). However, an analysis has not been done that accounts for all emission and carbon stock components, nor considers spatial or landscape impacts of fuel treatments. A modeling approach, the Avoided Wildfire Emissions (AWE) methodology, that accounts for all

Collection: Fire Behaviour and Fuels Conference emission and carbon stock components and considers landscape scale impacts of fuel treatments, has been suggested for assessing the potential of fuel treatments at reducing future wildfire GHG emissions, but it has not yet been applied in any published analyses (Buchholz *et al.* 2022).

Other analyses have estimated fuel treatment effects on GHG emissions from observed pre- and post-wildfire carbon stocks, or relied on the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) (Rebain *et al.* 2022; Dixon 2024) or the First Order Fire Effects Model (FOFEM) (Keane and Lutes 2020). These studies unanimously concluded that treated areas produced less wildfire emissions than untreated areas, but these reductions did not overcome the carbon stock losses caused by the treatment (Hurteau and North 2009; North and Hurteau 2011; Campbell *et al.* 2012; Stephens *et al.* 2012; Restaino and Peterson 2013). Several of these analyses also found that wildfire-induced tree mortality was much higher in untreated areas compared to treated areas (Hurteau and North 2009; North and Hurteau 2011; Restaino and Peterson 2013). Greater tree mortality can cause untreated forest stands to become carbon sources for a period of time post-wildfire when the amount of emissions from decaying wood is greater than the carbon sequestration potential of the surviving trees – this dynamic was discussed in some papers but not fully evaluated (Hurteau and North 2009; Campbell *et al.* 2012). One paper also suggests that lower intensity fuel treatment prescriptions that minimally reduce live tree carbon and emphasize surface fuel reduction may be optimal for net reducing GHG emissions; this idea is supported by a case study analysis that found over 70% of wildfire emissions to come from the combustion of surface fuels (Campbell *et al.* 2007; Stephens *et al.* 2012). These studies lay the foundational understanding that fuel treatments reduce initial forest carbon stocks and reduce subsequent wildfire emissions and wildfire-induced tree mortality.

However, these previous studies do not fully analyze the carbon sequestration potential of untreated vs treated forests, consider wildfire probability, or account for the secondary landscape effects a fuel treatment may have on fire behavior or effects. Thinned forest stands are known to experience increased incremental diameter growth (and therefore increased carbon sequestration) over comparable forest stands that have not been thinned (Tappeiner *et al.* 2022). The optimal fuel treatment type and placement to minimize reductions in carbon stocks and maximize wildfire hazard reduction is known to vary with wildfire probability (Salis *et al.* 2016; Krofcheck *et al.* 2018). Effective fuel treatments are known to have landscape-scale impacts on wildfire occurrence and size (McKinney *et al.* 2022; Ott *et al.* 2023). Thus, it is imperative that an analysis seeking to complete an encompassing evaluation of the potential impacts a fuel treatment may have on carbon stocks and future wildfire emissions incorporate evaluation of the carbon sequestration potential with and without treatment, the influence of wildfire probability and the potential impacts on landscape-scale wildfire behavior and effects. The AWE methodology proposed in Buchholz *et al.* (2022) builds on previous studies and is an improvement in that these three components are evaluated.

In this study, we employ the AWE methodology (Buchholz *et al.* 2022) to evaluate the potential for four different fuel treatments to produce net reduced future wildfire GHG emissions in four forest types and three initial wildfire hazard conditions. The AWE methodology is a modeling framework for quantification of net GHG emissions from potential future wildfires in a landscape with and without fuel treatments; the details of this framework and specific model parameterizations for this study are discussed in the methods section of this paper. Our findings will be useful to land managers when deciding what type of fuel treatment may be most effective for their project area when the objective is net reduced GHG emissions from future wildfires.

Materials and methods

We applied the AWE methodology to evaluate effects of four fuel treatment prescriptions on future wildfire GHG emissions in 12 synthetic landscapes. The AWE methodology consists of three modeling and three accounting (i.e. data summarization) components. Potential GHG emissions are modeled and quantified over a project duration of 40 years and account for carbon in standing live trees, shrubs and herbaceous understory; standing dead trees; dead surface fuels (woody debris, litter and duff); harvested wood products; biomass combustion emissions from fires (prescribed and wildfire); mobile combustion emissions; biogenic emissions from decomposition of forest products; and delayed reforestation. In computing the net GHG emissions with the AWE methodology the following carbon and GHG exchanges are considered: carbon stocks lost due to the fuel treatment, mobile combustion emissions from the equipment used to implement the fuel treatment, GHG emissions from underburn or pile burn (if part of the fuel treatment), potential changes in tree growth (carbon acquisition) due to changes in stand structure post-fuel treatment, GHG emissions from future wildfires (discounted based on annual fire probability (AFP) and conditional burn probability), GHG emissions from decaying wood (both woody debris and forest products) and foregone carbon acquisition due to tree mortality and delayed reforestation post-high severity wildfire. The four unique fuel treatment prescriptions are consistent with commonly implemented fuel treatments across western US forests. The synthetic landscapes consist of flattened topography and forest inventory data from the northern Sierra Nevada region of California, but are not meant to represent any specific location in the region. Detailed explanation of each component of the methodology, our specific parameterizations, the four fuel treatment prescriptions and the creation of the synthetic landscapes follow.

Synthetic landscapes

Twelve synthetic landscapes were created to control the influence of variability in topography, forest type and initial fire hazard in estimated emissions. Zero slope, elevation and aspect were used for all synthetic landscapes. Forest inventory data for the synthetic landscapes were derived from the TreeMap v2016 dataset (Riley *et al.* 2022).

The synthetic landscapes created for this study do not represent a given area in real space but had to be tied somewhat to a real geographic area due to the geographic dependence of the forest growth and yield equations implemented in the Forest Vegetation Simulator (FVS) (Dixon 2024). The northern Sierra Nevada subregion of California was selected for this purpose due to its fire history and need for fuel treatments. The northern Sierra Nevada sub-region is the area represented by the Western Sierra FVS variant and that fell within the extent of the northern half of the United States Geological Survey (USGS) level-3 ecoregion 'Sierra Nevada'. The northern Sierra Nevada is a fire-prone subregion; historical fire return interval has been estimated as 5–15 years in mixed conifer and ponderosa pine forest types, 10–25 years in Douglas-fir forest types and less than 50 years in white fir forest types (Skinner *et al.* 1996; Moody *et al.* 2006; Beaty and Taylor 2008). Fuel treatments are common across the northern Sierra Nevada (California Wildfire & Forest Resilience Task Force 2024), and much of the northern Sierra Nevada landscape has been identified as a priority in the western US for increasing the pace and scale of forest fuel treatments over the next decade (USDA Forest Service 2022).

The forest inventory stands assigned to each unique synthetic landscape pertained to a unique combination of one of the four most dominant forest types and initial fire hazard present in the northern Sierra Nevada sub-region. The four dominant forest types were California mixed conifer, Douglas-fir (*Pseudotsuga menziesii*), ponderosa pine (*Pinus ponderosa*) and white fir. The California mixed conifer forest type in the Sierra Nevada is typified by a mix of Douglas-fir, ponderosa pine, white fir, sugar pine (*Pinus lambertiana*), incense-cedar (*Calocedrus decurrens*) and California black oak (*Quercus kelloggii*) (Tappeiner 1980).

To establish initial fire hazard, each TreeMap v2016 stand within the dominant forest types was input to the FFE-FVS, grown to 2024, and then potential fire behavior was modeled under 97th percentile weather conditions (Rebain *et al.* 2022; Dixon 2024). The 97th percentile weather conditions represent extreme wildfire conditions and were computed from historical weather data for the region and represent extreme potential wildfire conditions (Table 1). Each stand was assigned a wildfire hazard category based on the FFE-FVS estimated flame length and percent basal area mortality (Fig. 1). A synthetic landscape was created for each forest type-hazard level combination (e.g. white fir-high hazard) by randomly distributing corresponding TreeMap2016 stands across a 24,500-ha landscape.

Table 1. Fire weather parameters used to simulate wildfire and determine wildfire hazard category under 97th percentile fire weather conditions in the Fire and Fuels Extension to the Forest Vegetation Simulator and GridFire.

Parameter	Value
Temperature	32°C
6-m wind speed	32 km/h
1-h fuel moisture content	3%
10-h fuel moisture content	4%
100-h fuel moisture content	5%
1000-h fuel moisture content	10%
Duff fuel moisture content	15%
Live woody fuel moisture content	70%
Live herbaceous fuel moisture content	70%
Season	Fall

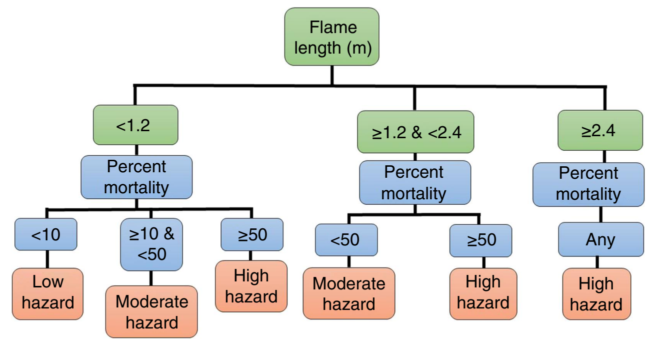

Fig. 1. Flowchart showing how each TreeMap2016 forest stand was assigned a hazard level based on simulated fire behavior and effects outputs from the Fire and Fuels Extension to the Forest Vegetation Simulator.

Each fuel treatment prescription was modeled as if implemented on 22% of the synthetic landscape with 110 individual units (~49 ha each) arranged in an overlapping louvered pattern (Fig. 2). This pattern is more effective at disrupting simulated wildfire spread compared to other landscape fuel treatment patterns and was chosen to minimize pattern bias in assessing fuel treatment effectiveness at reducing GHG emissions (Finney 2001; Schmidt *et al.* 2008).

Fuel treatment prescriptions

Four fuel treatment prescriptions that are commonly implemented in forests across the western US were simulated and compared in this study (Table 2). The 'stand density index (SDI) thin + underburn' (STU) prescription consisted of cutting trees up to 76 cm diameter at breast height (DBH)

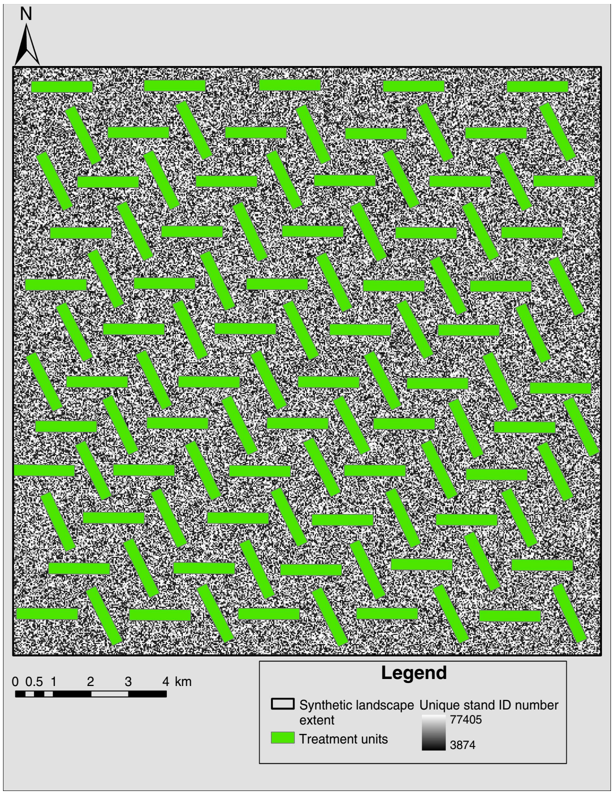

Fig. 2. Simulated treatment pattern on a synthetic landscape comprised of stands from TreeMap2016. Each treatment unit is ~49 ha and the total treated area is about 22% of the total area.

to achieve a SDI equal to 35% of maximum SDI, removing bole wood off-site, followed by a prescribed fire across the entire treatment unit. The 'thin from below + pile burn' (TBP) treatment consisted of cutting 90% of trees <25 cm DBH, leaving all cut material on-site, and pile burning 70% of the woody debris. The 'mastication' (MA) treatment consisted of masticating 90% of trees <25 cm DBH, 70% of the woody debris and 75% of the height of live shrubs. The 'underburn only' (UB) treatment consisted of a prescribed fire across the entire treatment unit.

Modeling workflow 1: forest growth and yield

For the project (with fuel treatment) scenarios, forest inventory data for each unique stand in a given synthetic landscape were grown from 2016 to 2024 in FVS, the fuel treatment was simulated in 2024, and then the stands continued to be grown in FVS until 2064. For the baseline (without fuel treatment) scenarios, forest inventory data for each unique stand in a given synthetic landscape were grown from 2016 to 2064 in FVS. The analysis period for the AWE methodology was applied for years 2024–2064 (a 40-year period). Nine iterations of each the project and baseline scenario simulations occurred, each with a wildfire being simulated via FFE-FVS at a different 5-year time step (e.g. simulation 1 had a wildfire simulated in year 2024,

Table 2. The four selected fuel treatments for simulation.

Fuel treatment	Thinning specifications	Pile burn	Underburn	Mastication
Stand density index (SDI) thin + underburn	Thin from below, ≤76 cm diameter at breast height (DBH), to a residual 35% of max SDI	–	Mild, early spring	–
Thin from below + pile burn	Thin 90% of trees ≤25 cm DBH	Pile and burn 70% of surface fuels	–	–
Mastication	Thin 90% of trees ≤25 cm DBH	–	–	Transfer 70% of fuels >7.5 cm diameter into the 2.5–7.5 cm diameter size class
Underburn only	–	–	Mild, early spring	–

simulation 2 had a wildfire simulated in year 2029, and so on). The simulated wildfires were parameterized with the same 97th percentile weather and fuel moisture conditions mentioned previously and were not varied over the duration of the simulation (i.e. potential impacts of climate change on 97th percentile weather were not considered) (Table 1).

Within an FVS simulation, modeled dynamics and metrics include tree growth, mortality, harvested wood volume and dead wood decay (Dixon 2024). FVS uses a collection of distance-independent, individual tree growth models to estimate growth through time. Growth models are dependent upon species, tree DBH, height, stand site index and stand basal area (BA). FVS uses a collection of mortality models to estimate individual tree mortality in a given time frame. Mortality models are dependent upon species, DBH, stand BA and site index. Wildfire-induced mortality is also modeled in FFE-FVS when a wildfire is simulated and varies with tree species (Rebain *et al.* 2022; Abrahamson 2024). FVS estimates harvested wood volume by computing the volume of merchantable wood cut when it is simulated as being removed from the stand. In the Western Sierra variant of FVS, merchantable cubic foot volume is computed for trees with a minimum DBH of 17.8 cm as saw-logs with a minimum small-end diameter of 11.4 cm and a length of 4.9 m. Dead wood decay is estimated within the FFE-FVS and is dependent on species and diameter.

Modeling workflow 2: Monte Carlo wildfire spread simulation

Monte Carlo wildfire spread simulations were completed for each iteration and each 5-year time step of the baseline and project scenarios in the GridFire wildfire spread model (pyregence/gridfire 2024). The 97th percentile weather and fuel moisture values discussed previously (Table 1) were held constant across time steps for the Monte Carlo simulations. Fire behavior fuel models assigned by FFE-FVS, as well as canopy base height, canopy bulk density, canopy cover and canopy height estimated by FVS were rasterized and used for the surface and canopy fuel inputs to GridFire. Each Monte Carlo simulation consisted of 10,000 iterations, and each iteration was initialized with a randomly placed ignition point and allowed to 'burn' for 8 simulation hours. Conditional burn probability was computed from each Monte Carlo simulation for each time step and scenario.

Modeling workflow 3: fire emissions

Potential wildfire GHG emissions for each forest stand, iteration, time step of each project and baseline scenarios were modeled using the FOFEM (Keane and Lutes 2020). Potential wildfire GHG emissions were estimated under the same 97th percentile weather conditions previously discussed (Table 1). Project scenario potential wildfire GHG emissions were discounted by multiplying each stand's potential wildfire GHG emissions by the ratio of project conditional burn probability to baseline conditional burn probability. Potential wildfire GHG emissions were summed across each landscape for each project and baseline scenario. Prescribed fire GHG emissions were also modeled in FOFEM when the project fuel treatment included prescribed fire, and those emissions were added to the corresponding project scenario's summed GHG emissions.

Accounting workflow 1: carbon

Forest carbon stocks for each iteration-scenario were calculated for the 40-year time period from FVS estimations of carbon in each stand (Dixon 2024). These carbon stock estimations accounted for carbon in standing live trees, shrubs and herbaceous understory; standing dead trees; dead surface fuels (woody debris, litter and duff); harvested wood products; and biogenic emissions from decomposition of forest products.

Accounting workflow 2: delayed reforestation

Delayed reforestation refers to when a forest stand experiences stand-replacing wildfire severity and subsequently undergoes a risk of, at least, temporarily forgone carbon sequestration potential from tree growth (Davis *et al.* 2019; Coop *et al.* 2020; Steel *et al.* 2023). The modeled fire behavior from the FFE-FVS simulated wildfires was used to identify forest stands that could potentially experience delayed reforestation. Delayed reforestation was assumed if FFE-FVS estimated flame length >1.22 m. If delayed reforestation was assumed for a given forest stand then a literature-based, forest type-specific scaling factor was used to estimate the percentage of the stand that would experience mortality and therefore delayed reforestation (Roccaforte *et al.* 2012; Van Wagtendonk *et al.* 2012; Collins and Roller 2013; Coppoletta *et al.* 2016; Rother and Veblen 2016; Welch *et al.* 2016; Tubbesing *et al.* 2019). The proportional carbon stock loss from delayed reforestation due to high-severity wildfire was accounted for as GHG emissions for the corresponding scenario.

Accounting workflow 3: net GHG emissions

Total cumulative emissions (scaled by the AFP) and total cumulative carbon stocks were each calculated for the baseline and project scenarios. We computed total cumulative emissions scaled by a range of AFP values, 0 up to 0.055, in steps of 0.005. This AFP range was selected to capture the minimum AFP at which each treatment type net reduced GHG emissions. Net GHG emissions for a scenario were computed by calculating net GHG emissions for each baseline and project time-step iteration (total emissions minus total carbon), subtracting project net GHG emissions from baseline net GHG emissions, and then summing across time-step iterations.

This selected AFP range was relatively consistent with the AFP range (0–0.059) estimated for the Northern Sierra Nevada subregion (Kearns et al. 2022). In context, Kearns et al. (2022) provides comparatively low AFP estimates compared to other regional datasets (e.g. CalAdapt decadal fire probability (https://v2.cal-adapt.org/tools/wildfire/) (Dale et al. 2018; Westerling 2018), and CalFire's annual fire probability for carbon accounting (https://egis.fire.ca.gov/FireProbability/) (Mann et al. 2016)). AFP estimations can vary widely based on key attributes and assumptions such as length of historic wildfire history, future climate scenarios, or future housing density and data reporting such as static vs dynamic wildfire probabilities over the applicable (future) timeframe.

Comparative analysis

Quantification of net GHG emissions was completed for AFP values 0.0–0.055, in steps of 0.005, for each forest type-hazard level-fuel treatment combination to identify minimum AFP required to net reduced GHG emissions and trends as AFP increased. Intermediate outputs pertaining to forest carbon stocks and emissions were explored to understand drivers of differences between fuel treatments within and between forest types and fire hazard levels.

Results

Three elements stood out: (1) low intensity prescriptions were more effective compared to other prescriptions at producing net reduced GHG emissions when AFP was lower (Table 3), (2) higher intensity prescriptions were more effective compared to other prescriptions when AFP was higher (Figs 3–6), and (3) underburn frequently performed well independent of AFP (Figs 3–6). Net reduced GHG emissions results are realized when potential GHG emissions were reduced beyond any loss in carbon stocks, but carbon stock losses from any treatment type were relatively small compared to potential GHG emission reductions (Figs 7–10).

Reducing GHG emissions when AFP is low

The lowest minimum AFP at which a treatment net reduced GHG emissions was associated with the UB treatment in 58% of scenarios, the TBP treatment in 50% of scenarios and the STU treatment in 8% of scenarios (Table 3). The second lowest AFP at which a treatment net reduced GHG emissions was associated with the STU treatment in 50% of scenarios, the UB treatment in 33% of scenarios and the TBP treatment in 16% of scenarios. The second lowest minimum AFP was 5–35% higher than that of the treatment with the lowest minimum AFP in the same forest type-hazard level scenario (Table 3). Within each forest type-hazard level scenario, the minimum AFP to net reduced GHG emissions tended to be relatively close between TBP, UB and STU treatments. The MA fuel treatment minimum AFP was 53–147% higher than the lowest minimum AFP in the same forest type-hazard level and consistently had the highest minimum AFP of all the treatments within the same forest type-hazard level scenario (Table 3).

Table 3. Minimum annual fire probability (as percent) that yielded net reduced greenhouse gas emissions for each of the selected fuel treatments in each forest type-hazard level combination.

Forest type	Fuel treatment	Low hazard	Moderate hazard	High hazard
California mixed conifer	Stand density index (SDI) thin + underburn	0.0112	0.0088	0.0079
	Thin from below + pile burn	0.0086*	0.0069*	0.0083
	Mastication	0.0150	0.0134	0.0181
	Underburn only	0.0086*	0.0076	0.0075*
Douglas-fir	SDI thin + underburn	0.0088	0.0081	0.0114
	Thin from below + pile burn	0.0100	0.0041*	0.0099*
	Mastication	0.0167	0.0275	0.0238
	Underburn only	0.0077*	0.0053	0.0108
Ponderosa pine	SDI thin + underburn	0.0149	0.0105	0.0111
	Thin from below + pile burn	0.0223	0.0089	0.0140
	Mastication	0.0398	0.0147	0.0518
	Underburn only	0.0120*	0.0067*	0.0103*
White fir	SDI thin + underburn	0.0170*	0.0109	0.0132
	Thin from below + pile burn	0.0181	0.0061*	0.0107*
	Mastication	0.0315	0.0111	0.0266
	Underburn only	0.0170*	0.0088	0.0133

An asterisk (*) indicates the treatment with the lowest annual fire probability for the forest type-hazard level combination.

Reducing GHG emissions when AFP is high

As AFP increased in a given scenario, the STU treatment was able to net reduce the most GHG emissions followed by the UB treatment in second and the TBP treatment in third in every forest type-hazard level scenario (Figs 3–6). The UB treatment reduced 13–54% fewer GHG emissions at the maximum AFP tested for each scenario than the STU treatment, except in the white fir-high hazard scenario in which it was only 1% lower (Figs 3–6). The TBP treatment reduced 36–101% fewer GHG emissions at the maximum AFP tested

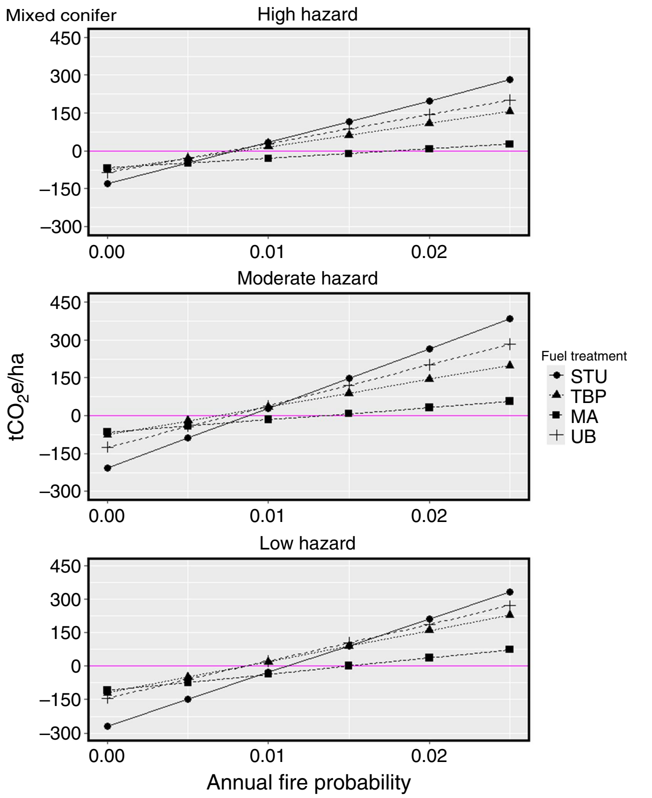

Fig. 3. Estimated net reduced greenhouse gas emissions per hectare as annual fire probability increases for the California mixed conifer forest type for low-, moderate-, and high-initial wildfire hazard levels. STU, stand density index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

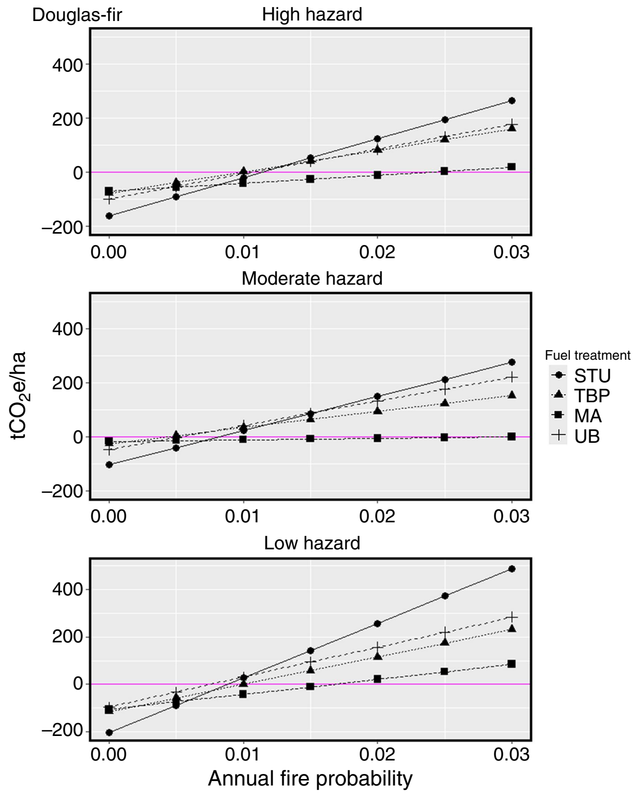

Fig. 4. Estimated net reduced greenhouse gas emissions per hectare as annual fire probability increases for the Douglas-fir forest type for low-, moderate- and high-initial wildfire hazard levels. STU, stand density index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

for each scenario than the STU treatment, except in the white fir-high hazard scenario in which it was only 13% lower (Figs 3–6). The TBP treatment reduced 5–56% fewer GHG emissions at the maximum AFP tested for each scenario than the UB treatment (Figs 3–6). The MA treatment reduced 118–195% fewer GHG emissions at the maximum AFP tested for each scenario than the STU treatment (Figs 3–6).

Reducing GHG emissions in each forest type

In the California mixed conifer landscape, in high- and moderate-hazard landscapes when AFP is less than or equal to 0.015 and in low-hazard landscapes when AFP is less than or equal to 0.02, the relative difference between fuel treatment performance is relatively small except for the MA fuel treatment that had minimal to no net reduced GHG emissions at those AFP levels (Fig. 3). The net reduced GHG emissions per hectare remained similar between the TBP and UB fuel treatments at higher AFP in the high- and low-hazard landscapes (Fig. 3).

In the Douglas-fir landscape, when AFP is less than or equal to 0.02 in high-hazard landscapes, 0.025 in moderate-hazard landscapes and 0.015 in low-hazard landscapes, the relative difference between fuel treatment performance is relatively small except for the MA fuel treatment that had minimal to no net reduced GHG emissions at those AFP (Fig. 4). The net reduced GHG emissions per hectare remained similar between the TBP and UB fuel treatments at higher AFP in the high- and low-hazard landscapes (Fig. 4).

In the ponderosa pine landscape, when AFP is less than or equal to 0.03 in any hazard landscape, the relative difference between fuel treatment performance is relatively small except for the MA fuel treatment that had minimal to no net reduced GHG emissions at those AFP (Fig. 5). The general trend of STU being the 'best' fuel treatment at higher AFP followed by UB, TBP and MA respectively holds true in the high- and moderate-hazard landscapes (Fig. 5). In the low-hazard landscape the trend changes above AFP = 0.055 when the UB and TBP fuel treatments converge and the TBP fuel treatment net reduces more GHG emissions per hectare at higher AFP (Fig. 5).

In the white fir landscape, the net reduced GHG emissions per hectare was relatively similar for STU, TBP and UB fuel treatments at all AFP modeled in the high- and low-hazard landscapes (Fig. 6). Fuel treatments in the moderate-hazard landscape showed trends similar to other forest type-hazard level combinations with the differences between fuel

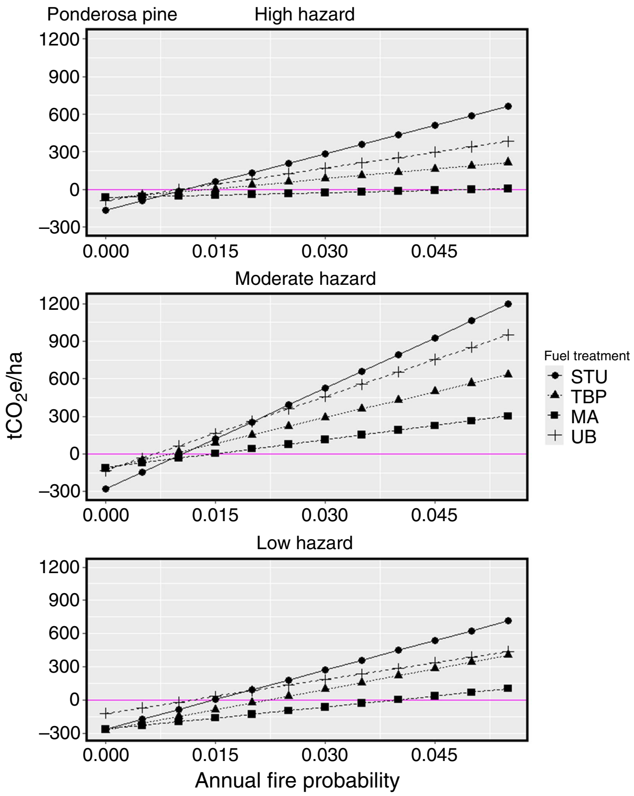

Fig. 5. Estimated net reduced greenhouse gas emissions per hectare as annual fire probability increases for the ponderosa pine forest type for low-, moderate-, and high-initial wildfire hazard levels. STU, stand density index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

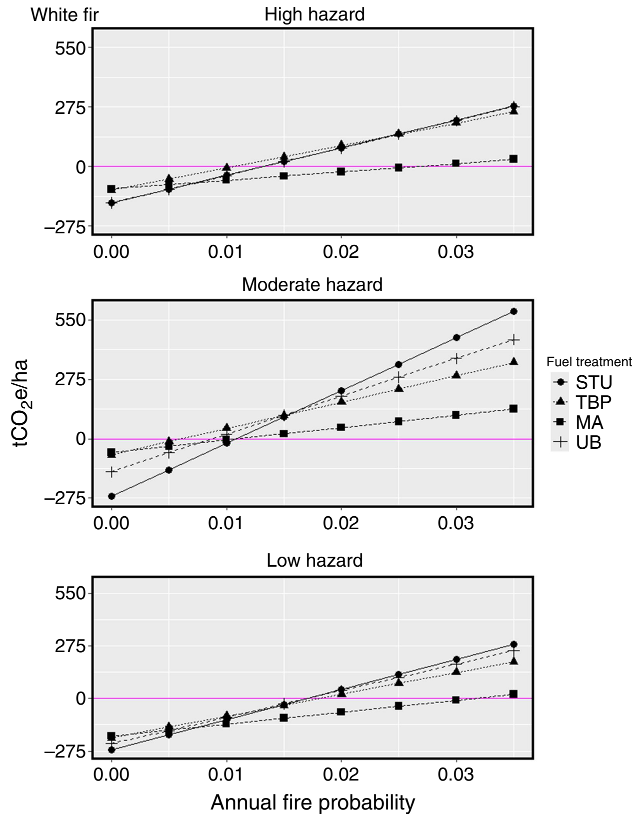

Fig. 6. Estimated net reduced greenhouse gas emissions per hectare as annual fire probability increases for the white fir forest type for low-, moderate-, and high-initial wildfire hazard levels. STU, stand denisty index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

treatments being relatively small below an AFP threshold (~0.025), while above that threshold the STU fuel treatment proved to be the 'best' fuel treatment (Fig. 6).

Reducing GHG emissions in each hazard level

When the initial fire hazard level was low, the UB treatment had the lowest minimum AFP at which it net reduced GHG emissions in all four forest types, the TBP treatment had an equally low minimum AFP in the California mixed-conifer forest type and the STU treatment had an equally low minimum AFP in the white fir forest type (Table 3). When the initial fire hazard level was moderate, the TBP treatment had the lowest minimum AFP at which it net reduced GHG emissions in three out of the four forest types, and the UB treatment had the lowest minimum AFP at which it net reduced GHG emissions in the ponderosa pine forest type (Table 3). When the initial fire hazard level was high, the TBP treatment had the lowest minimum AFP at which it net reduced GHG emissions in the Douglas-fir and white fir forest types, and the UB treatment had the lowest minimum AFP at which it net reduced GHG emissions in the California mixed-conifer and ponderosa pine forest types (Table 3).

Comparing emission reductions to carbon stock losses

Carbon stock losses from any treatment type were relatively small compared to potential GHG emission reductions. As expected, the largest reduction in carbon stocks was associated with the STU fuel treatment as it was inherently designed to remove the largest, and potentially greatest number of trees compared to the other modeled fuel treatments (Figs 7–10). However, the reduction in carbon stocks for any fuel treatment across forest type-hazard level combinations was minuscule compared to the potential reductions in GHG emissions (Figs 7–10). The STU and UB fuel treatments generally had much higher unadjusted potential reductions in GHG emissions across forest type-hazard level combinations compared to the TBP or MA fuel treatments (Figs 7–10).

Discussion

This modeling analysis considered two metrics for evaluating fuel treatments. The first was the minimum AFP value at which a treatment net reduced GHG emissions under the

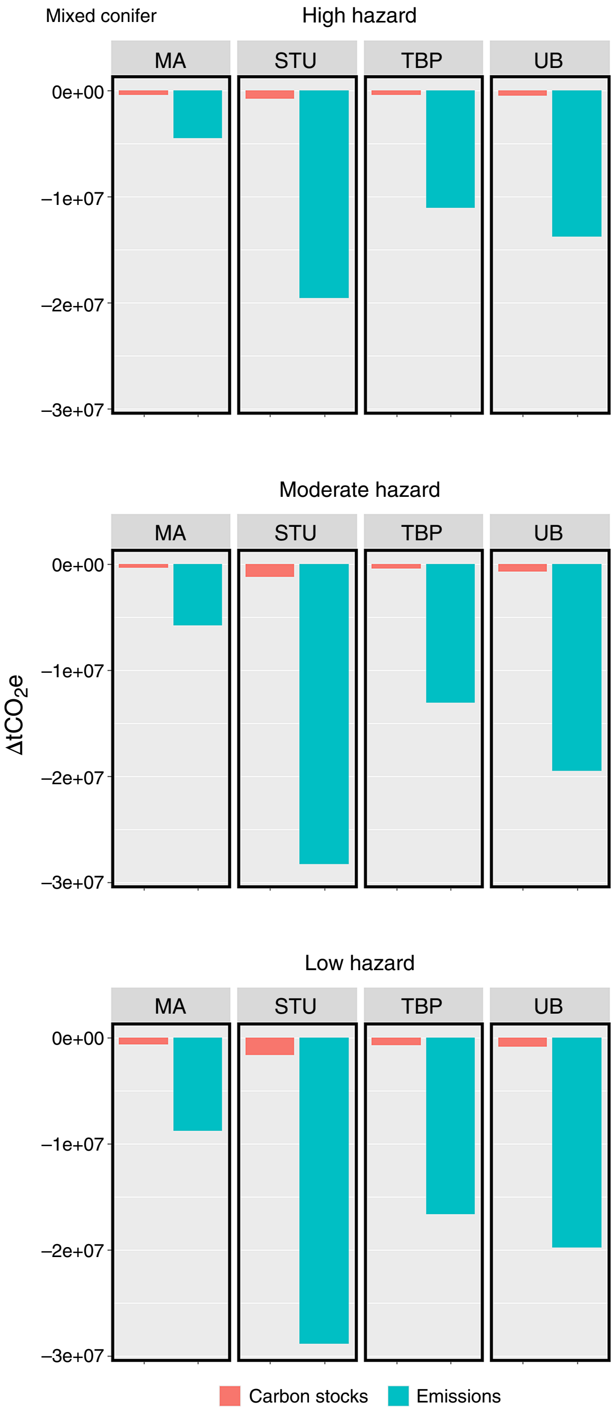

Fig. 7. Cumulative, differenced (Project – Baseline) carbon stocks and emissions for the California mixed conifer forest type. These values are not adjusted for annual fire probability. Carbon stocks are reduced with treatment but emission reductions tend to be far greater. STU, stand density index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

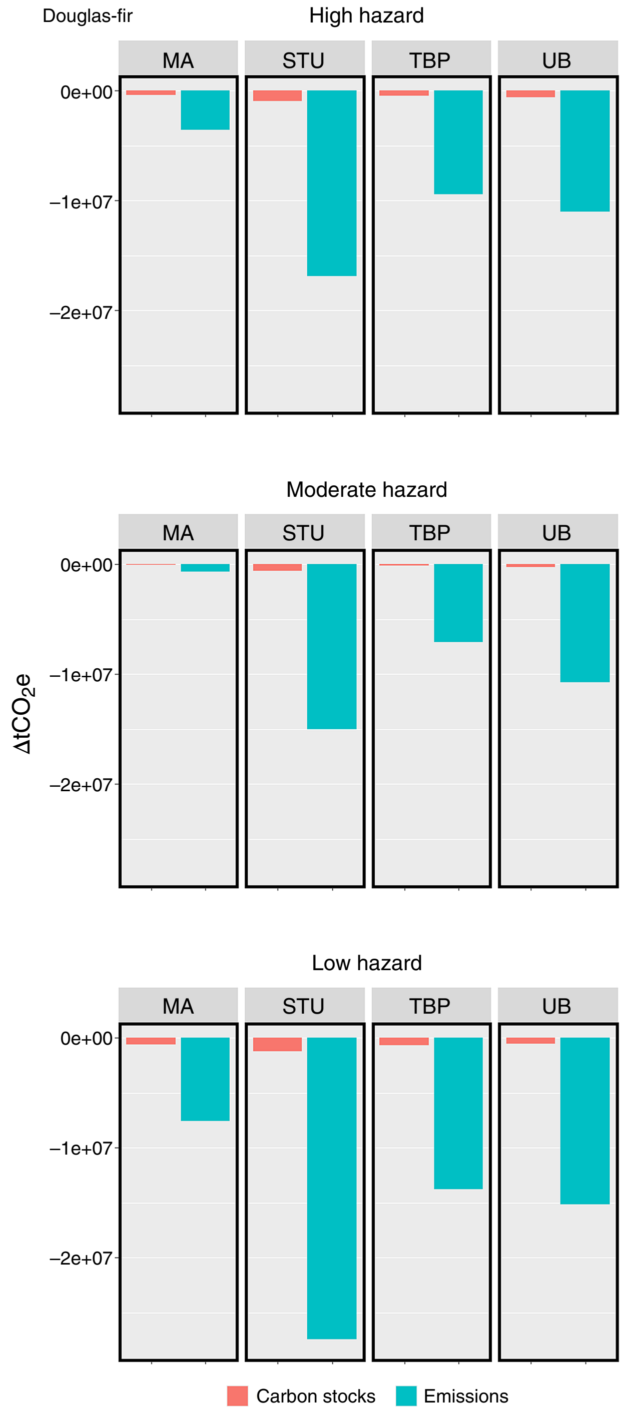

Fig. 8. Cumulative, differenced (Project – Baseline) carbon stocks and emissions for the Douglas-fir forest type. These values are not adjusted for annual fire probability. Carbon stocks are reduced with treatment but emission reductions tend to be far greater. STU, stand density index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

AWE methodology. By this criterion, the treatments that involved understory thinning followed by pile burning surface fuels (TBP), or just UB, yielded GHG benefits starting at lower AFPs; i.e. they were superior from a climate perspective. This indicates that when AFP is lower, a less intensive treatment that emphasizes the reduction of ladder fuels (via thinning or underburning) and surface fuels (via pile burning or underburning) may be the most effective at net reducing GHG

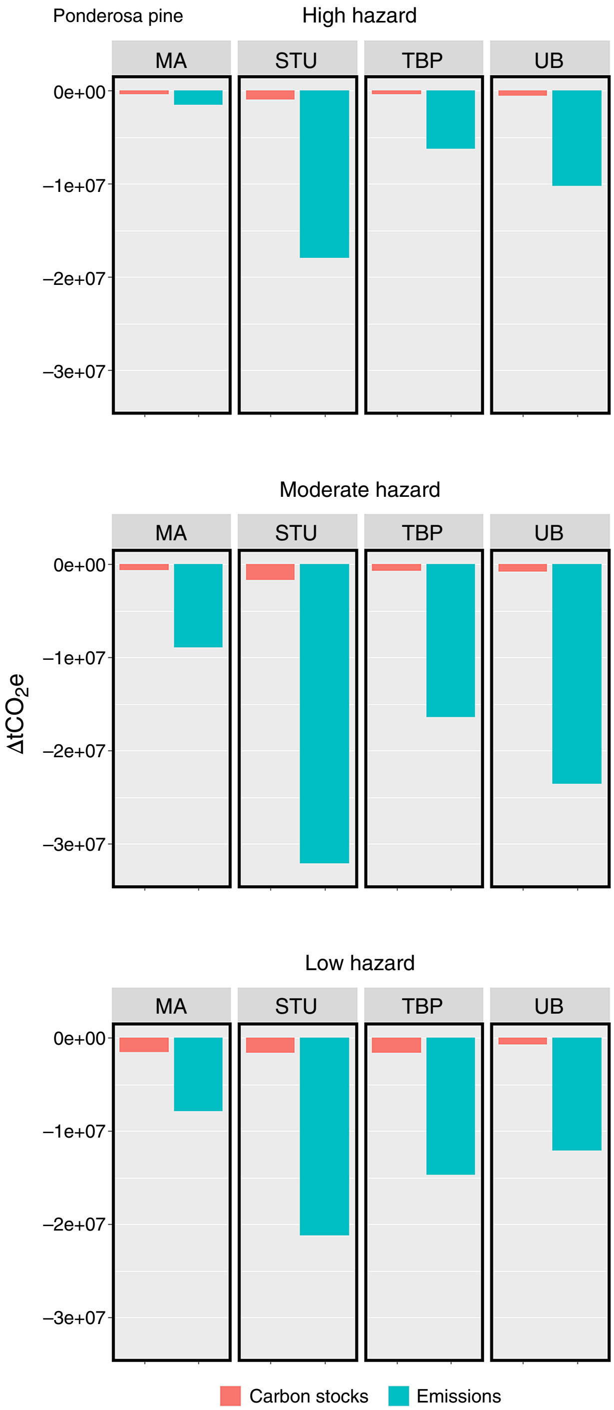

Fig. 9. Cumulative, differenced (Project – Baseline) carbon stocks and emissions for the ponderosa pine forest type. These values are not adjusted for annual fire probability. Carbon stocks are reduced with treatment but emission reductions tend to be far greater. STU, stand density index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

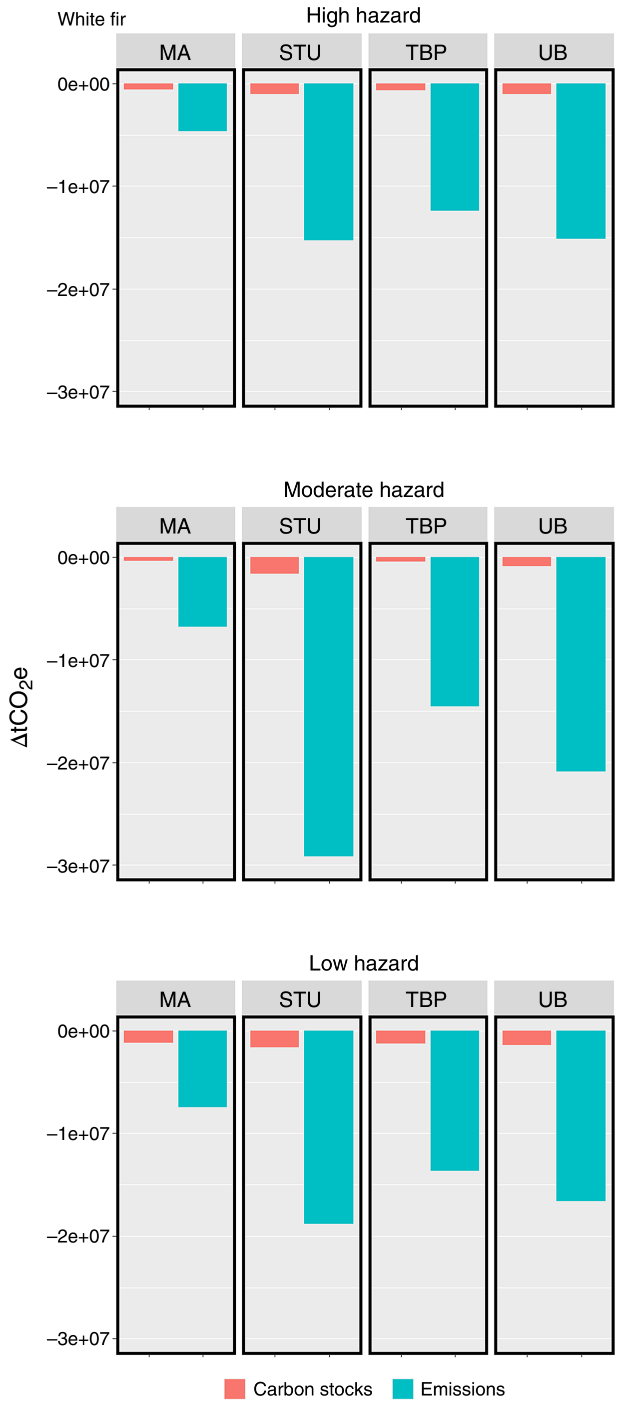

Fig. 10. Cumulative, differenced (Project – Baseline) carbon stocks and emissions for the white fir forest type. These values are not adjusted for annual fire probability. Carbon stocks are reduced with treatment but emission reductions tend to be far greater. STU, stand denisty index (SDI) thin + underburn; TBP, thin from below + pile burn; MA, mastication; UB, underburn only.

emissions from potential future wildfires. This finding is in agreement with a previous analysis that suggested lower intensity prescriptions, especially those that emphasize surface fuel reduction (like via pile burning or underburning), may be optimal for net GHG emission reductions (Stephens *et al.* 2012).

The other criterion was the net reduced GHG emissions as AFP increased. By this criterion, the more intensive treatment

(STU) was superior. This indicates that when AFP is higher, a more intensive fuel treatment that emphasizes reducing overstory canopy fuels as well as surface fuel load may be the most beneficial at reducing net GHG emissions from potential future wildfires. We expect that this result is because reducing canopy and crown fire probability by reducing canopy continuity and canopy bulk density becomes more important to reducing GHG emissions as the AFP of extreme wildfire increases.

The MA treatment fared poorly by both criteria, with relatively high minimum AFP values and reducing relatively little GHG emissions even at the highest modeled AFP values. MA treatments reduce ladder fuels but translate all the biomass to the surface fuel load. Thus, we were unsurprised by the poor performance of the MA fuel treatment since research suggests that the increased surface fuel loading caused by mastication treatments increases subsequent wildfire severity (Stephens and Moghaddas 2005; Safford *et al.* 2009). This further highlights the importance of implementing fuel treatments that emphasize surface fuel load reduction to mitigate GHG emissions from potential future wildfires.

Many studies of fuel treatment effectiveness in Sierra Nevada forest types have shown that some form of mechanical thinning followed by prescribed fire reduces subsequent wildfire intensity and wildfire severity, often better than mechanical thinning alone (Knapp *et al.* 2004; Stephens and Moghaddas 2005; Moghaddas and Craggs 2007; Moghaddas *et al.* 2010; North *et al.* 2012; Stevens *et al.* 2016; York *et al.* 2021; Stephens *et al.* 2024). Under the assumption that lower wildfire intensity and severity correlate to lower GHG emissions, these findings are consistent with the results of this simulation study, indicating the AWE methodology yields results that are reflective of reality. Thus, fuel treatment types that are understood to be the most effective at reducing subsequent wildfire behavior and severity are also those that have the most potential to reduce future wildfire GHG emissions.

In conclusion, lower intensity fuel treatments are potentially more effective at reducing GHG emissions from future wildfires when the AFP is lower and higher intensity fuel treatments are potentially more effective when the AFP is higher. Underburning without any additional thinning treatments can be an effective treatment for reducing GHG emissions from future wildfires, regardless of forest type and initial fire hazard level. This study was applied on synthetic landscapes to assess the effects of fuel treatments independent of other variables; due to this design, the results are not directly applicable to any real location in space. However, these findings (within the examined Sierra Nevada forest types) and our approach can be useful in decision support when planning forest fuel treatments with the objective of reducing potential future wildfire emissions. Further research into this topic may include identifying where on real landscapes each fuel treatment type may be most effective at reducing GHG emissions, what percentage of a landscape needs to be treated for each fuel treatment type to be effective, improving the models upon which this methodology is based and evaluating economic trade-offs of fuel treatment types.

References

Abrahamson I (2024) Fire Effects Information System (FEIS). Available at https://www.feis-crs.org/feis/

Bartowitz KJ, Walsh ES, Stenzel JE, Kolden CA, Hudiburg TW (2022) Forest carbon emission sources are not equal: putting fire, harvest, and fossil fuel emissions in context. *Frontiers in Forests and Global Change* **5**, 867112. doi:10.3389/ffgc.2022.867112

Beaty RM, Taylor AH (2008) Fire history and the structure and dynamics of a mixed conifer forest landscape in the northern Sierra Nevada, Lake Tahoe Basin, California, USA. *Forest Ecology and Management* **255**(3–4), 707–719. doi:10.1016/j.foreco.2007.09.044

Buchholz T, Gunn J, Springsteen B, Marland G, Moritz M, Saah D (2022) Probability-based accounting for carbon in forests to consider wildfire and other stochastic events: synchronizing science, policy, and carbon offsets. *Mitigation and Adaptation Strategies for Global Change* **27**(1), 4. doi:10.1007/s11027-021-09983-0

California Wildfire & Forest Resilience Task Force (2024) Interagency Fuel Treatment Tracking System. Available at https://interagencytrackingsystem.org/

Campbell J, Donato D, Azuma D, Law B (2007) Pyrogenic carbon emission from a large wildfire in Oregon, United States. *Journal of Geophysical Research: Biogeosciences* **112**(G4), G04014. doi:10.1029/2007JG000451

Campbell JL, Harmon ME, Mitchell SR (2012) Can fuel-reduction treatments really increase forest carbon storage in the western US by reducing future fire emissions? *Frontiers in Ecology and the Environment* **10**(2), 83–90. doi:10.1890/110057

Canadell JG, Raupach MR (2008) Managing forests for climate change mitigation. *Science* **320**(5882), 1456–1457. doi:10.1126/science.1155458

Cochrane MA, Moran CJ, Wimberly MC, Baer AD, Finney MA, Beckendorf KL, Eidenshink J, Zhu Z (2012) Estimation of wildfire size and risk changes due to fuels treatments. *International Journal of Wildland Fire* **21**(4), 357–367. doi:10.1071/WF11079

Collins BM, Roller GB (2013) Early forest dynamics in stand-replacing fire patches in the northern Sierra Nevada, California, USA. *Landscape Ecology* **28**(9), 1801–1813. doi:10.1007/s10980-013-9923-8

Coop JD, Parks SA, Stevens-Rumann CS, Crausbay SD, Higuera PE, Hurteau MD, Tepley A, Whitman E, Assal T, Collins BM, Davis KT, Dobrowski S, Falk DA, Fornwalt PJ, Fulé PZ, Harvey BJ, Kane VR, Littlefield CE, Margolis EQ, North M, Parisien M-A, Prichard S, Rodman KC (2020) Wildfire-driven forest conversion in western North American landscapes. *BioScience* **70**(8), 659–673. doi:10.1093/biosci/biaa061

Coppoletta M, Merriam KE, Collins BM (2016) Post-fire vegetation and fuel development influences fire severity patterns in reburns. *Ecological Applications* **26**(3), 686–699. doi:10.1890/15-0225

Dale L, Carnall M, Wei M, Fitts G, Lewis McDonald S (2018) Assessing the impact of wildfires on the California electricity grid. Available at https://www.energy.ca.gov/sites/default/files/2019-11/Energy_CCCA4-CEC-2018-002_ADA.pdf

Davis KT, Dobrowski SZ, Higuera PE, Holden ZA, Veblen TT, Rother MT, Parks SA, Sala A, Maneta MP (2019) Wildfires and climate change push low-elevation forests across a critical climate threshold for tree regeneration. *Proceedings of the National Academy of Sciences* **116**(13), 6193–6198. doi:10.1073/pnas.1815107116

Dixon GE (2024) 'A User's Guide to the Forest Vegetation Simulator.' (USDA Forest Service)

Finney MA (2001) Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. *Forest Science* **47**(2), 219–228. doi:10.1093/forestscience/47.2.219

Hurteau MD (2021) The role of forests in the carbon cycle and in climate change. In 'Climate Change'. (Ed. TM Letcher) pp. 561–579. (Elsevier)

Hurteau M, North M (2009) Fuel treatment effects on tree-based forest carbon storage and emissions under modeled wildfire scenarios. *Frontiers in Ecology and the Environment* **7**(8), 409–414. doi:10.1890/080049

Keane RE, Lutes D (2020) 'First-Order Fire Effects Model (FOFEM) User Guide V6.7.' p. 92 (Intermountain Forest and Range Experiment Station, Forest Service, US Department of Agriculture)

Kearns EJ, Saah D, Levine CR, Lautenberger C, Doherty OM, Porter JR, Amodeo M, Rudeen C, Woodward KD, Johnson GW, Markert K, Shu E, Freeman N, Bauer M, Lai K, Hsieh H, Wilson B, McClenny B, McMahon A, Chishtie F (2022) The construction of probabilistic wildfire risk estimates for individual real estate parcels for the contiguous United States. *Fire* **5**(4), 117. doi:10.3390/fire5040117

Knapp EE, Stephens SL, McIver JD, Moghaddas JJ, Keeley JE (2004) Fire and Fire Surrogate Study in the Sierra Nevada: Evaluating Restoration Treatments at Blodgett Forest and Sequoia National Park. In 'Proceedings of the Sierra Nevada Science Symposium'. Gen. Tech. Rep. PSW-GTR-193. Vol. 193, pp. 79–85. (Pacific Southwest Research Station, Forest Service, US Department of Agriculture: Albany, CA)

Krofcheck DJ, Hurteau MD, Scheller RM, Loudermilk EL (2018) Prioritizing forest fuels treatments based on the probability of high-severity fire restores adaptive capacity in Sierran forests. *Global Change Biology* **24**(2), 729–737. doi:10.1111/gcb.13913

Mann ML, Batllori E, Moritz MA, Waller EK, Berck P, Flint AL, Flint LE, Dolfi E (2016) Incorporating anthropogenic influences into fire probability models: effects of human activity and climate change on fire activity in California. *PLoS One* **11**(4), e0153589. doi:10.1371/journal.pone.0153589

McKinney ST, Abrahamson I, Jain T, Anderson N (2022) A systematic review of empirical evidence for landscape-level fuel treatment effectiveness. *Fire Ecology* **18**(1), 21. doi:10.1186/s42408-022-00146-3

Moghaddas JJ, Craggs L (2007) A fuel treatment reduces fire severity and increases suppression efficiency in a mixed conifer forest. *International Journal of Wildland Fire* **16**(6), 673–678. doi:10.1071/WF06066

Moghaddas JJ, Collins BM, Menning K, Moghaddas EEY, Stephens SL (2010) Fuel treatment effects on modeled landscape-level fire behavior in the northern Sierra Nevada. *Canadian Journal of Forest Research* **40**(9), 1751–1765. doi:10.1139/X10-118

Moody TJ, Fites-Kaufman J, Stephens SL (2006) Fire history and climate influences from forests in the Northern Sierra Nevada, USA. *Fire Ecology* **2**(1), 115–141. doi:10.4996/fireecology.0201115

North MP, Hurteau MD (2011) High-severity wildfire effects on carbon stocks and emissions in fuels treated and untreated forest. *Forest Ecology and Management* **261**(6), 1115–1120. doi:10.1016/j.foreco.2010.12.039

North M, Collins BM, Stephens S (2012) Using fire to increase the scale, benefits, and future maintenance of fuels treatments. *Journal of Forestry* **110**(7), 392–401. doi:10.5849/jof.12-021

Ott JE, Kilkenny FF, Jain TB (2023) Fuel treatment effectiveness at the landscape scale: a systematic review of simulation studies comparing treatment scenarios in North America. *Fire Ecology* **19**(1), 10. doi:10.1186/s42408-022-00163-2

pyregence/gridfire (2024) pyregence.org. Available at https://github.com/pyregence/gridfire

Rebain SA, Reinhardt ED, Crookston NL, Beukema SJ, Kurz WA, Greenough JA, Robinson DCE, Lutes DC (2022) 'The Fire and Fuels Extension to the Forest Vegetation Simulator: Updated Model Documentation.' (USDA Forest Service)

Restaino JC, Peterson DL (2013) Wildfire and fuel treatment effects on forest carbon dynamics in the western United States. *Forest Ecology and Management* **303**, 46–60. doi:10.1016/j.foreco.2013.03.043

Riley KL, Grenfell IC, Shaw JD, Finney MA (2022) TreeMap 2016 dataset generates CONUS-wide maps of forest characteristics including live basal area, aboveground carbon, and number of trees per acre. *Journal of Forestry* **120**(6), 607–632. doi:10.1093/jofore/fvac022

Roccaforte JP, Fulé PZ, Chancellor WW, Laughlin DC (2012) Woody debris and tree regeneration dynamics following severe wildfires in Arizona ponderosa pine forests. *Canadian Journal of Forest Research* **42**(3), 593–604. doi:10.1139/x2012-010

Rother MT, Veblen TT (2016) Limited conifer regeneration following wildfires in dry ponderosa pine forests of the Colorado Front Range. *Ecosphere* **7**(12), e01594. doi:10.1002/ecs2.1594

Safford HD, Schmidt DA, Carlson CH (2009) Effects of fuel treatments on fire severity in an area of wildland–urban interface, Angora Fire, Lake Tahoe Basin, California. *Forest Ecology and Management* **258**(5), 773–787. doi:10.1016/j.foreco.2009.05.024

Salis M, Laconi M, Ager AA, Alcasena FJ, Arca B, Lozano O, Fernandes De Oliveira A, Spano D (2016) Evaluating alternative fuel treatment strategies to reduce wildfire losses in a Mediterranean area. *Forest Ecology and Management* **368**, 207–221. doi:10.1016/j.foreco.2016.03.009

Schmidt DA, Taylor AH, Skinner CN (2008) The influence of fuels treatment and landscape arrangement on simulated fire behavior, Southern Cascade range, California. *Forest Ecology and Management* **255**(8–9), 3170–3184. doi:10.1016/j.foreco.2008.01.023

Skinner CN, Chang C, Et-man DC, Husari SJ, Parsons DJ, van Wagtendonk JW, Weatherspoon CP (1996) An Overview of Fire in the Sierra Nevada. In 'Sierra Nevada Ecosystem Project, Final Report to Congress, Vol. II, Assessments and Scientific Basis for Management Options'. Report No. 37. pp. 1033–1040. (University of California, Centers for Water and Wildland Resources: Davis, CA, USA)

Steel ZL, Jones GM, Collins BM, Green R, Koltunov A, Purcell KL, Sawyer SC, Slaton MR, Stephens SL, Stine P, Thompson C (2023) Mega-disturbances cause rapid decline of mature conifer forest habitat in California. *Ecological Applications* **33**(2), e2763. doi:10.1002/eap.2763

Stephens SL, Moghaddas JJ (2005) Experimental fuel treatment impacts on forest structure, potential fire behavior, and predicted tree mortality in a California mixed conifer forest. *Forest Ecology and Management* **215**(1–3), 21–36. doi:10.1016/j.foreco.2005.03.070

Stephens SL, Boerner REJ, Moghaddas JJ, Moghaddas EEY, Collins BM, Dow CB, Edminster C, Fiedler CE, Fry DL, Hartsough BR, Keeley JE, Knapp EE, McIver JD, Skinner CN, Youngblood A (2012) Fuel treatment impacts on estimated wildfire carbon loss from forests in Montana, Oregon, California, and Arizona. *Ecosphere* **3**(5), 1–17. doi:10.1890/ES11-00289.1

Stephens SL, Foster DE, Battles JJ, Bernal AA, Collins BM, Hedges R, Moghaddas JJ, Roughton AT, York RA (2024) Forest restoration and fuels reduction work: different pathways for achieving success in the Sierra Nevada. *Ecological Applications* **34**(2), e2932. doi:10.1002/eap.2932

Stevens JT, Collins BM, Long JW, North MP, Prichard SJ, Tarnay LW, White AM (2016) Evaluating potential trade-offs among fuel treatment strategies in mixed-conifer forests of the Sierra Nevada. *Ecosphere* **7**(9), e01445. doi:10.1002/ecs2.1445

Tappeiner JC (1980) Sierra Nevada mixed conifer. In 'Forest cover types of the United States and Canada'. (Ed. FH Eyre) pp. 118–119, 243. (Society of American Foresters: Washington, DC, USA)

Tappeiner J, Adams D, Montgomery C, Maguire D (2022) Growth of managed older douglas-fir stands: implications of the Black Rock Thinning Trial in the Coast Range of Western Oregon. *Journal of Forestry* **120**(3), 282–288. doi:10.1093/jofore/fvab063

Tubbesing CL, Fry DL, Roller GB, Collins BM, Fedorova VA, Stephens SL, Battles JJ (2019) Strategically placed landscape fuel treatments decrease fire severity and promote recovery in the northern Sierra Nevada. *Forest Ecology and Management* **436**, 45–55. doi:10.1016/j.foreco.2019.01.010

USDA Forest Service (2022) Confronting the Wildfire Crisis: A Strategy for Protecting Communities and Improving Resilience in America's Forests. FS-1187a. Available at https://www.fs.usda.gov/sites/default/files/Confronting-Wildfire-Crisis.pdf

Van Wagtendonk JW, Van Wagtendonk KA, Thode AE (2012) Factors associated with the severity of intersecting fires in Yosemite National Park, California, USA. *Fire Ecology* **8**(1), 11–31. doi:10.4996/fireecology.0801011

Welch KR, Safford HD, Young TP (2016) Predicting conifer establishment post wildfire in mixed conifer forests of the North American

Mediterranean-climate zone. *Ecosphere* **7**(12), e01609. doi:10.1002/ecs2.1609

Westerling AL (2018) Wildfire simulations for California's fourth climate change assessment: projecting changes in extreme wildfire events with a warming climate. A Report for California's Fourth Climate Change Assessment. p. 57. (California Energy Commission: Sacramento, CA, USA) https://www.energy.ca.gov/sites/default/files/2019-11/Statewide_Reports-SUM-CCCA4-2018-013_Statewide_Summary_Report_ADA.pdf

York RA, Noble H, Quinn-Davidson LN, Battles JJ (2021) Pyrosilviculture: combining prescribed fire with gap-based silviculture in mixed-conifer forests of the Sierra Nevada. *Canadian Journal of Forest Research* **51**(6), 781–791. doi:10.1139/cjfr-2020-0337

Zhao B, Zhuang Q, Shurpali N, Köster K, Berninger F, Pumpanen J (2021) North American boreal forests are a large carbon source due to wildfires from 1986 to 2016. *Scientific Reports* **11**(1), 7723. doi:10.1038/s41598-021-87343-3

Data availability. The data that support this study will be shared upon reasonable request to the corresponding author.

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