GREENHOUSE GAS EMISSIONS AND FIRE BEHAVIOR IMPACTS FOLLOWING CALIFORNIA FUEL TREATMENTS

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ABSTRACT

Greenhouse Gas Emissions and Fire Behavior Impacts Following California Fuel Treatments

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Fuel treatments are being increasingly applied across California landscapes as communities struggle to recover from wildfire disasters nationwide. Increased funding for treatments stems from grants under CARB's Greenhouse Gas Reduction Fund and funding requires reports accounting the yielded benefits from these fuel treatments. Using data from real-world local scale fuel treatments, I used the forest simulation model FVS-FEE and fire behavior software IFTDSS to quantify GHG emission benefits and fire behavior impacts 70 years after treatment. Results suggest that fuel treatments do not yield significant GHG benefits, and fire behavior impacts (conditional flame length) are minimal but overall show slight reductions in the impact area's burn severity. However, treatment outcomes may vary on the localized landscapes, size of treatment, and unique parameters applied to each treatment simulation.

Keywords: Fuel treatments, wildfire, carbon emissions, fire behavior, simulation modeling, FVS

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1. INTRODUCTION

Greenhouse Gas (GHG) emissions continue to be released in Earth's atmosphere at an accelerating rate and strongly correlate with rising global atmospheric temperatures (IPCC, 2023). The overall warming of our planet increases risks associated with frequent natural disasters, food disparity, and freshwater access. The IPCC accentuates clear guidelines for reducing GHG emissions so global temperatures won't exceed the 1.5°C limit predicted to create compounding climate hazards to our ecosystems and aggregate health (IPCC, 2023). Understanding the sources of GHG emissions is paramount for identifying economic sectors where emissions can be reduced with the largest impact. Carbon dioxide is the primary GHG associated with global warming, and the key emission derived from wildfires (Larkin et al., 2014; Sommers et al., 2014). Forests act as large carbon sinks (areas where carbon is captured and stored) storing about 45% of terrestrial carbon (Malmsheimer et al., 2011). Unmanaged wildlands have the potential to emit massive amounts of carbon dioxide, and other greenhouse gases, into the atmosphere through the burning of fuels (M. Hurteau & North, 2009; Lorenzo-Sáez et al., 2021). Fuels are defined by fire managers as living and dead plant material that may ignite during a wildfire.

Previous studies have found that fuel treatments (like prescribed fire, thinning, and mastication treatments) can be used to reduce wildfire severity and therefore mitigate emissions in the event of disastrous wildfires (Defossé et al., 2011; North et al., 2021; Tubbesing et al., 2019). Fuel treatment effectiveness is largely dependent on scope of landscape, weather patterns, and time treated (Fernandes, 2015; Price et al., 2012). Modeling simulations, satellite imagery, and historical wildfire observations have been used to calculate the consumption of fuels and impacts of specific fuel treatments (Ager et al., 2006; Urza et al., 2023; Volkova et al., 2017; Wimberly et al., 2009). Modeled simulations showed that wide-scale prescribed fires were predicted to reduce carbon dioxide emissions by 18-25% in the western United States (Wiedinmyer & Hurteau, 2010). Defossé et al. did a case study simulating fuel treatment effectiveness in Argentina found that prescribed burning reduced carbon emissions by 44% compared to the simulation that did not employ prescribed burning. Moreover, the carbon stores in these forested regions may act as offsets for the forestry and land management sectors (Lorenzo-Sáez et al., 2021).

However, conflicting research also shows scenarios where fuel treatments have resulted in no affect and even negative effects on the burned area after simulated wildfires (Rabin et al., 2022). Analyzing effects of fuel treatments creates room for improvement towards increased landscape resilience and reduced wildfire emissions.

Fuel treatment effectiveness is widely studied; however, many papers suggest difficulties in evaluating fuel treatment effectiveness with empirical results due to a lack in quantitative tools like carbon calculators that can account for a multitude of unique, dependent variables (Agee & Skinner, 2005; Duane et al., 2019). Fire emission predictions also require modeling software that simulates fuel treatments, but even software similar in methodology may produce different results (Larkin et al., 2014). Disagreements about which type of modeling software provides the most reliable results cause differences in applicable data and methods. Fuel treatment planning is also constrained by unique landscape characteristics that can dictate fire severity and GHG emission levels. Each landscape may differ in fuel type, local weather pattern, scope, and more (McKinney et al., 2022). Overall, research into landscape-level fuel treatment effectiveness is lacking the substantial empirical evidence needed for guiding improved management designs and policy (McKinney et al., 2022).

Our objective was to add to the quantitative data pool informing GHG emissions benefits achieved after applied fuel treatments. Provided with Cal Fire data, this project will use modeling systems, like the Forest Vegetation Simulator (FVS) and ArcGIS, to quantify the GHG emission benefits through Cal Fire's fuel treatment programs and identify potential fire behavior within the treatment areas and impacts within the buffer zone of these fuel reduction treatments. The general quantification methodology for this project has already been set up by Cal Fire and the California Air Resources Board (Forest Restoration and Management QM). However, the methodology required specific steps to carry out quantitative research.

The primary goal of this project is to provide quantitative results as deliverables to Cal Fire using the general CARB methodology and improved methodology redeveloped by the team's research. Secondary goals include identifying general trends of treatment effectiveness mitigating GHG emissions and impact area burn severity. The GHG and fire behavior impact area benefits will be measured in terms of MTCO2e. The MTCO2e (metric tonne of carbon dioxide equivalent) is the standardized metric used to measure the contribution of GHGs to global warming (Gohar & Shine, 2007). The results will be useful in determining treatment effectiveness, accessing potential impact areas of future wildfires, and developing accessible methodology to help inform future environmental policy and fire management practices.

2. LITERATURE REVIEW

In this chapter, I will briefly review the current issues surrounding wildfire severity, associated impact on GHG emissions and the importance of forested systems. I will then discuss the current fuel treatments used to reduce hazards and emissions, such as prescribed burns, vegetation thinning, and mastication. I incorporate reliable methods related to the quantification of GHG emissions benefits following wildfire fuel treatments which include modeling software like Forest Vegetation Simulator (FVS) and fuel treatment decision support software. Finally, I will introduce Cal Fire and its commitment to reducing GHG emissions and promoting landscape resilience through effective fuel management practices.

2.1 Wildfire Environmental Impacts

Wildfires remain a growing danger as global warming exacerbates drier landscapes (Williams et al., 2019). Current climate projections estimate that temperate forest regions will have increases in productivity offset by carbon loss to fire (Kim et al., 2017). Shifting climate conditions in the western United States, like an earlier spring snowmelt, correlates with increasing fire scope and frequency (Wiedinmyer & Hurteau, 2010). Current scientific research exploring the relationship between fire and climate indicates that a warming climate will induce more frequent fires in the western United States (Wiedinmyer & Hurteau, 2010). Fuel consumption is believed to impact atmospheric temperature, carbon stocks, and land surface reflectance, all of which create instability in the connected ecosystems (Ottmar, 2014).

Assorted studies use climate models that suggest wildfires will continue to increase in both severity and frequency due to rising GHG emissions, in addition to longer fire seasons (Fried et al., 2004; Jolly et al., 2015; Schoennagel et al., 2017; Westerling et al., 2006). With the predicted trajectory of global warming, wildfires constitute a growing problem especially in Mediterranean climates (Vilén & Fernandes, 2011), and more specifically, the western United States (Abatzoglou & Williams, 2016; M. D. Hurteau et al., 2014; Westerling et al., 2006). Forest fires contribute substantial amounts of carbon dioxide, nitrogen oxides, particulate matter, and other emissions into the atmosphere, adding to the accelerating global atmospheric temperatures (M. D. Hurteau et al., 2014). Wildfires are estimated to account for GHG emissions from accumulated biomass burns that produce climate feedback that further progress to warmer atmospheric temperatures where wildfires are most prevalent. Studies estimate that anthropogenic climate change is responsible for about 55% of fuel aridity from 1955-2015 in western United States forest systems (Abatzoglou & Williams, 2016).

Westerling et al. (2006) studied the western United States forest fire activity, and the influence warming climate has on wildfire frequency. Compiling data on large wildfires since 1970 showed a spike in wildfire activity increasing in frequency, duration, and season around the mid-1980s. A comparison of the wildfire data to hydroclimate and land surface data provided results indicating that wildfire activity is influenced by the changing climate causing arid vegetation induced by dry spring and summer seasons. These conditions create a high-risk environment for severe and recurrent wildfires that endanger urban and forested areas in addition to increasing the overall atmospheric carbon dioxide emissions (Westerling et al., 2006).

2.2 Forest Carbon

Forests act as large carbon sinks (Lorenzo-Sáez et al., 2021; Pacheco & Claro, 2021; Vaillant et al., 2013); carbon is stored within trees and surface biomass (M. Hurteau & North, 2009). Increasing CO_2 removal strategies in forest sectors, while maintaining current carbon stores, remains the largest challenge amongst land managers (Hudiburg et al., 2019). The carbon sequestered through reforestation efforts can serve as a carbon offset in other sectors that generate emissions (Hurteau & North, 2009). For example, western United States forests are estimated to be responsible for 20-40% of total U.S. carbon sequestration (Westerling et al., 2006). However, carbon that has taken decades to build up in the forest's biomass can rapidly burn down, causing an instant loss in sequestered carbon and potentially releasing a massive amount of carbon emissions (Breshears & Allen, 2002; Hurteau & North, 2009).

Preserving forests in the western United States that have a medium to high potential for carbon sequestration is estimated to mitigate approximately eight years of fossil fuel emissions and promote forest resilience and biodiversity (Buotte et al., 2020). Lorenzo-Sáez et al. (2021) identified three main causes of wildfire risk increase in Mediterranean climates: number of years with increased fire risks, season length with severe weather and extreme events during summer or drought seasons increasing. Results showed their tested methodologies to be successful in quantifying carbon fixation in living plant biomass and then applied to calculate the emission offsets. Sustainably managed forest systems may produce enough carbon storage to be considered as offsets and monetized as an economic incentive for countries (Lorenzo-Sáez et al., 2021).

Lorenzo-Saez et al. (2021) estimated the potential offsets created by sustainable forest management were between 1.2% and 5.6% of total diffuse GHG emissions.

For now, carbon sequestration in the western United States forests is a positive net balance even with the carbon lost during harvesting and wildfire. However, Hudiburg et al. (2019) explains that a century of wood usage is “reducing the potential annual sink by an average of 21%”. They showed federal reporting to be underestimated by 25%-55% and lacking in accuracy when it comes to measuring the state total of CO_2 emissions.

Forest’s large carbon storage can be preserved through preventing deforestation caused by either natural occurrences (e.g. insect disturbances) or human activities (Binkley et al., 2002). Natural forest disasters, primarily wildfires, emit 9 Gt of Carbon per year worldwide, which is 30% more than emissions caused by fossil fuels (Binkley et al., 2002). Deforestation (via mainly land conversion and harvesting) has been responsible for 10%-20% of global GHG emissions between 1980 and 2000 (Binkley et al., 2002). Increased action surrounding management in carbon sequestration is recommended, while also performing treatments that reduce fire severity in high-risk zones (Sommers et al., 2014).

2.3 GHG Emissions as Wildfire Byproduct

Forest fire emissions primarily consist of CO_2, but wildfire smoke is a complex mixture often including black carbon, fine particulate matter, CO, and other aerosols into the atmosphere (Hodshire et al., 2019; S. Urbanski, 2014; S. P. Urbanski et al., 2008). Emissions have a negative effect on atmospheric temperatures and air quality, therefore making emission reduction a top concern for safeguarding public health and the integrity of shared ecosystems (Reid et al., 2016; S. P. Urbanski et al., 2008).

While 95% of carbon is released as CO_2 (~ 90%), CO (~9%), and CH4 (~1%), CO_2 is considered the most “long-lived” GHG emission (French et al., 2011; Sommers et al., 2014; S. Urbanski, 2014). In general, calculating GHG emission from forest fires requires estimating landscape biomass including live or standing dead trees, and any other forest biomass that may ignite during a wildfire (Korísteková et al., 2020). Pyrogenic emission estimates are most generally quantified using burned area, fuel loads, and fraction of fuels consumed data sets (French et al., 2011).

Clinton et al. (2006) investigated the quantification of emissions produced during Southern California wildfires that occurred in October 2003, resulting in an estimation of 10 pollutant types, including micro particulates between 10 and 2.5μm, CO, CO_2, CH_4, were derived from 10 fuel categories. Models showed that of the over 5 million metric tons of pollutants created in the span of a few days, most of the emissions were CO, CO_2 and particulates. The top fuel by mass contributing to these emissions calculations came from the shrub and duff categories, indicating the importance of developing effective strategies in these chaparral ecosystems to minimize pollution risks (Clinton et al., 2006). Location and time of fire are deemed to be especially important factors when modeling air pollution (Larkin et al., 2014). Topography affects solar radiation and fuel moisture, so drier vegetation constitutes a higher ignition probability. For example, fuels on a southern facing slope during peak sunlight will have more ignition risk than on a north facing slope during the evening when atmospheric moisture is increased.

Substantial differences in emission production can occur between the various combustion phases (Korísteková et al., 2020). Higher levels of CO and CH4 were created during the smoldering phase of combustion, as opposed to CO2, which was normally split between the smoldering and flaming phases (Korísteková et al., 2020). Emission behaviors can depend on seasonality. For example, years with a high emission estimation synchronizes with droughts (Wiedinmyer & Neff, 2007). Fuel and weather data are integral factors to be considered while estimating wildfire emissions (de Groot, 2006). Detailed accounting for pyrogenic emissions and carbon sinks continues to be a challenging task for researchers attempting to quantify GHG benefits due to the lack of direct measurements informing emission estimates, and even at local scales (Bela et al., 2022; Gately & Hutyra, 2017; Marland & Schlamadinger, 1995)

2.4 Fuel Treatment Application and Efficacy

Since the late 1800s, fire suppression has been the long held policy in managing United States forest landscapes, which has attributed to the vast increase in stand density, high fuel loads, and overall risk to devastating wildfires (M. D. Hurteau et al., 2008). Overaccumulation of understory fuels also increases the risk of wildfires transforming into crown fires, which accelerate the speed of spread in continuous canopies (Schoennagel et al., 2004). Historical timber harvesting, in addition to fire suppression, has significantly altered the composition of tree species, resulting in stands less conducive to resisting fire effects (Hagmann et al., 2021). In pre-Colonial America, Indigenous people freely utilized fire to promote beneficial ecological processes (Klimaszewski-Patterson & Mensing, 2020). Traditional knowledge and application of fire to forest landscapes helped tribes control the quality and quantity of natural resources, as well as clearing land, but have varied across the North American landscape (Lake et al., 2017; Long et al., 2021). Contemporary forest and fuels management has shifted towards applying proactive fuels treatments on both a local and landscape scale to reduce probability and spread of wildfire to at-risk, high severity areas, with a focus on WUI locations (Tubbesing et al., 2019). The types of fuel treatment applied can vary based on topography, fuels, and community needs or ability. As seen from the acquired fuels reduction program data from Cal Fire, dominant fuel treatments being done throughout California typically include prescribed fire, thinning, thin & pile burn, and mastication.

2.4.1 Prescribed Fire

Wildfires are managed through the treatment of forest vegetation, and this may be accomplished through a variety of fuel treatments based on a landscape's characteristics. Prescribed fire is one of the most common wildfire management practices used to limit fuels in landscapes at risk for wildfires. The Clean Development Mechanism in the Kyoto protocol articulates the potential prescribed fires have to mitigate carbon emissions caused by wildfires that encroach upon untreated landscapes (Cirulis et al., 2019; Defossé et al., 2011). A multitude of studies have been conducted to test the efficacy prescribed burning has as a means of fire suppression and decreasing high intensity fires, however many have only produced qualitative results (Duane et al., 2019; Safford et al., 2009). Collectively, fuel treatments are known to be effective in decreasing fire severity (Agee

& Skinner, 2005), yet few studies approach their effectiveness in mitigating GHG emissions (Campbell et al., 2012).

Calculating prescribed fire effects on limiting GHG emissions remains a relatively new topic in forestry operation due to the lack of standardized methodology that produces accurate results (Herbert et al., 2023). Defossé et al. (2011) sought to study the effect prescribed burn treatments had on GHG emissions in Argentinian forest landscapes. Potential CO2 emissions caused by wildfires were simulated with 2 scenarios: one simulation showed the emissions released by a fire on lands previously treated with a prescribed burn and the other scenario showed the emissions resulting from lands not treated with prescribed fire. Data considered while running the simulations included accumulated biomass, downed dead wood, and litter (loose, dead biomass on the forest floor). Simulation outcomes showed that prescribed burning was successful in reducing carbon dioxide emissions by 44% compared to the simulation without prescribed burn treatment. However, the prescribed burn scenario itself contributed 12% of the total emissions. Including extra biomass growth of trees saved by avoided wildfires in the prescribed burn scenario, the treatment granted an additional 78% GHG emission mitigation. In the case of landscapes in Patagonia, Argentina, prescribed burns served as an effective treatment in both reducing fire severity and GHG emissions (Defossé et al., 2011). Additionally, fire management programs in Australia investigated landscape effects on prescribed burn treated lands completed in early dry seasons to reduce GHG emissions and fire severity in the late dry season when fires generally peak (Price et al., 2012).

Mediterranean countries utilize prescribed fire as a means of fire prevention; in terms of emission reduction, prescribed burn is not effective unless it is successful in minimizing the wildfire burn area (Vilén & Fernandes, 2011). In a study, landscapes with increased levels of litter had a bigger reduction in emissions post prescribed fire, as opposed to shrub-dominated landscapes (Vilén & Fernandes, 2011).

Simulations conducted in the Rocky Mountains, by Reinhardt and Holsinger (2010), found that a significant portion of emissions resulting from wildfires are due to consumption of dead downed wood, litter, and duff, not living biomass. Furthermore, their simulated fuel treatments showed that while the fuel treatments reduced carbon emissions from following wildfires, it did not increase the site's post-wildfire carbon storage. Additionally, tree mortality was lower, resulting in higher site carbon storage due to the presence of larger trees that sequester more carbon. Sites left untreated resulted in higher wildfire emissions and carbon storage (E. Reinhardt & Holsinger, 2010). While prescribed burns may initially result in a loss of carbon storage, long term sequestration may increase through avoiding burning of long-lived trees (Rabin et al., 2022).

Degree of effectiveness of prescribed burns depends heavily on the landscape, weather, area treated, and duration of burn (Duane et al., 2019). The frequency of applied treatments on a landscape is important in providing enduring landscape resilience. Current research suggests that prescribed burn effectiveness against unplanned fires can be minimal unless at least 5-10% of the landscape is treated annually (Duane et al., 2019). Simulations of forest lands in California showed potential wildfire carbon emissions before, and up to 8 years after prescribed burn treatments (Vaillant et al., 2013). The modeled wildfire events showed a 45% initial reduction in potential carbon emissions, followed by a 41% and 34% reduction in the following 2- and 8-years post treatment (Vaillant et al., 2013). Therefore, carbon emissions were reduced most effectively in the first year and declined in effectiveness as the post-treatment time increased.

Wiedinmyer and Hurteau (2010) used regional fire models to predict potential reductions in emissions following the applications of prescribed burnings in western United States forests between 2001-2008. The forests simulated were characterized as dry and temperate and were calculated as two scenarios: a default wildfire case without any applied treatment, and one in which a prescribed burn occurred before the wildfire. Daily CO2 estimations from fire emissions were spatially mapped using LANDSAT; emissions from the mixed-conifer forest type were the highest. Of the five forest types simulated, the average annual emissions were reduced by 52%-68% (with slight variations by year and state). Additionally, results showed a reduction in carbon emissions by 18 - 25% in the western U.S. and by 60% in more localized forest systems. An average of 71% of estimated fire emissions stemmed from federally controlled lands (Wiedinmyer & Hurteau, 2010).

Despite prescribed fires being operationally effective in reducing fuels, this method also releases carbon emissions and affects air quality. Most studies assume that emissions caused by fuels management are negligible, however each fuel treatment can produce a varying amount of GHG emissions (Reinhardt & Holsinger, 2010; Sonne, 2006). Sonne (2006) conducted a study of the emissions caused by forestry operations and found that pile and burn site preparation was the second largest contributor to GHG emissions, harvesting timber being the first. Sonne (2006) estimated that removing pile and burn operations in western Oregon and Washington would reduce GHG emissions by 67000 Mg $CO2eyr^{-1}$. Pierobon et al. (2022) examine the drawbacks of slash pile burns as a producer of emissions harmful to humans through simulating prescribed fires in Southwest Washington State. Through simulating the increased air pollutants level caused by a 30% increase in prescribed fires via slash pile burns, they found that during the 29 days burn period, that 438,591 more people were negatively affected by the resulting emissions (Pierobon et al., 2022).

Similarly, existing studies demonstrate that though fuel treatment reduced wildfire emissions, the fuel treatments also produced emissions of their own and the C cost of conducting treatments may sometimes surpass potential GHG benefits (Campbell & Ager, 2013; Chiono et al., 2017; Rabin et al., 2022). Chiono et al. (2017) found that all the simulated treatments, including prescribed burning, yielded higher C emission values than their control scenarios. Additionally, in a study by Rabin et al. (2022), the prescribed burns resulted in a higher burn area, but the fires burned have reduced severity and are more easily managed. In some cases, performing a prescribed burn produced more emissions than no treatment at all, but in other cases, a prescribed burn would mitigate emissions compared to landscapes left untreated (Rabin et al., 2022). Results have the potential to widely vary due to differing landscapes and unique characteristics. Applying a combination of fuel treatments (thinning followed by a prescribed burn) is suggested to be a more effective management approach to reducing carbon emissions (Rabin et al., 2022). Prescribed burns have also been linked to increased initial soil erosion (attributing prolonged post treatment recovery time), while other treatment like mastication does not share the same negative outcome (Karban et al., 2022).

Applying prescribed burn to landscapes can be a burden due to the many factors that limit the scope and ability to frequently manage the treatments. Forest management must operate within burn windows when conditions are deemed safe to conduct a prescribed burn (Striplin et al., 2020). When a site is chosen for prescribed burn treatment, it is usually deemed an area at risk of a high severity fire, but the site can only be treated when fire intensity is low (Rabin et al., 2022). Prepping the site takes time and energy to create fire breaks and slash and burn piles, if applicable (Striplin et al., 2020). Reburns are recommended to take place every 5-10 years, with a threshold of 15 years to allow for quantification of effects of prescribed burn in the short term (Agee & Lolley, 2006; Cansler et al., 2022). If a large duration of time has elapsed since a treatment, 10-15 or more years, then treatments are less effective in splitting up landscapes available fuel loads (Agee & Skinner, 2005; Cansler et al., 2022). Other fuel treatments do not have to depend on the same conditional criteria when planning and intervals can occur more frequently, as a result.

2.4.2 *Vegetation Thinning*

Thinning does not rely on the restricting criteria prescribed burns must follow before conducting their fuel treatment. Often, thinning treatments are paired with prescribed burn for decreased fire severity and risk (Cansler et al., 2022). Combining fuel have shown to produce the most beneficial outcomes in contrast to when treatments are applied separately (Cansler et al., 2022; Kalies & Yocom Kent, 2016). Additionally, conducting prescribed burns or thinning alone can yield either less effective or no effect when compared to untreated areas (Cram et al., 2015; Kalies & Yocom Kent, 2016).

However, thinning is an energy intensive process that requires the use of heavy machinery and many emission quantification models do not account for carbon emitted from fossil fuels used to prep sites and fertilize regrowth post wildfires (Markewitz, 2006). Still, thinning is a preferable method of reducing carbon emissions than allowing wildland fires to occur without any interference (Dore et al., 2010).

Carbon recovery rates were examined post thinning fuel treatments; overstory thinning created a large carbon deficit in the treated landscape because it involved the removal of larger trees known to store the most carbon annually which increases overall carbon stock recovery time (Hurteau & North, 2010). Thinning treatments that target the understory, there are initial carbon losses, but can quickly recover in these situations, if large, fire-resistant overstory trees are not removed (Hurteau & North, 2010).

2.4.3 Mastication

Mastication is a common fuel treatment that consists of grinding up fuels into smaller fragments that can either be transported to a biomass facility or redistributed on the surface. Heavy machinery, like masticators (and chippers) effectively break down surface fuels and reduce vertical continuity to transform the arrangement of fuels on site (D. Mitchell & Smidt, 2019). However, mastication treatments are less feasible on steep terrain because the heavy machinery requires more stable ground to safely traverse the landscape (D. Mitchell & Smidt, 2019). Fuel break maintenance and construction fall under the mastication treatment scope, as it typically requires quickly dispatching the small trees and shrubs along roads and bordering communities (Mitchell & Smidt, 2019).

Existing studies corroborate the effectiveness of reoccurring mastication treatment as a method to mitigate fire behavior (Low et al., 2023; Oliveira et al., 2016).

2.4.4 Fuel Treatments Tradeoffs

Removing fuels includes the removal of trees and affects carbon storage in the treated forest system. Campbell et al. (2012) argued that fuel treatments do not impact emission mitigation in a significant manner because the fuel treatments alter carbon storage. Carbon lost via fuel treatments typically exceed what ends up being protected from being ignited if the landscape burns (Campbell et al., 2012). About ten hectares, within even a fire prone forest, must be treated to influence fire behavior in one hectare (Campbell et al., 2012). So, "a regime of low-frequency, high severity fire stores more carbon over time than a regime of high-frequency, low-severity fire" (Campbell et al., 2012).

Hurteau, Stoddard, and Fulé (2011) examine effects on carbon size pre and post fire treatments (thinning) in a western United States forest (Fort Valley Experimental Forest) filled with ponderosa pine. Existing fuel treatments that reduce wildland fire severity called for a tradeoff between carbon stick size treatments and those that prioritize carbon stock stability through the presence of larger trees (Hurteau et al., 2011). Fire suppression efforts lead to a forest composition of smaller trees and less large trees (Fellows & Goulden, 2008). Large trees have a disproportionate amount of biomass, therefore attributing to elevated respiration and C storage (Fellows & Goulden, 2008). Removing large trees, and their accompanying carbon storage, is an ongoing tradeoff land managers make for strong fire suppression efforts (Fellows & Goulden, 2008). To protect larger trees, it is advised that future land managers plan to remove slash and fuel treatments surrounding particularly important trees or logs (Wales et al., 2007).

2.4.5 Alternative Treatment Management

Alternative treatment and management combinations are being explored to calculate GHG emission reduction. Graves et al. (2020) focused on sites in Oregon, U.S. studied natural climate solutions (NCS), or “changes in land management, ecosystem restoration, and conservation on natural and working lands as part of GHG reduction strategies” (Graves et al., 2020). NCS were separated into forest-based activities composed of three umbrella categories: conversion, land management, and restoration. Forest-based activity changes that showed the most potential in emission reductions included: postponing lumber harvesting, riparian reforestation, and replanting after wildfires. Results showed that NCS has the potential to reduce GHG emissions by 2.7 to 8.3 MMT CO_2e by 2035 and 2.9 to 9.8 MMT CO_2e by 2050, making it a potential option for future management implementation (Graves et al., 2020).

2.5 Forestry Simulation Modeling

Fuel consumption software has been designed for forestry operations to provide predictions on wildfire GHG emissions and aerosol inventories with the increased demand for understanding carbon pools (Hoover & Rebain, 2011; Ottmar, 2014). Fuel consumption models like First Order Fire Effects Model (FOFEM), CONSUME, CanFire and Forest Vegetation Simulator (FVS) used the most by researchers and land managers (Ottmar, 2014; Reinhardt & Dickinson, 2010). FOFEM and U.S. Forest Service’s

CONSUME model, used in quantifying fuel loads and total consumption both reach generally related results, but slight discrepancies are due to variations in site scope, vegetation type and fire weather (French et al., 2011).

French et al. (2014) tested the viability of modeling systems for the quantitative mapping of wildland fire emissions using the Wildland Fire Information System (WFEIS). This model utilizes data from a wide array of factors and prioritizes scale of landscape, fuels data and combines it with data collected from the U.S. geological services and the National Aeronautics and Space Administration (for fire location and timing). WFEIS proved to be consistent in its results and helpful in its ability to deal with so many diverse variables (French et al., 2014). The copious amount of software present in the field creates discrepancies amongst researchers, as different software, while similar in methodology may produce contrasting results (Larkin et al., 2014). Development of a more comprehensive program would prove beneficial in being able to provide duplicatable efforts as well as making it easier on users not having to learn so many software packages to conduct their landscape management simulations (Reinhardt & Dickinson, 2010).

2.5.1 FVS-FFE

FVS is a favored forest management program that has been accepted and utilized by the U.S. Forest Service for forest growth and yield modeling due to its ability to produce detailed forest stand outputs and requires a reasonable amount of initial data to begin simulations (Hoover & Rebain, 2011; Ray et al., 2009). Extensions of the FVS software have been created to calculate forest carbon stocks at regional scales to inform carbon emission inventories and mitigation tactics (Hoover & Rebain, 2011). The Fire and Fuels Extension (FFE) uses stand level carbon data to estimate effects of fuel treatments and intensity in the case of potential wildfires (Hoover & Rebain, 2011).

Like other simulation softwares, simplified default inputs are used to represent real world conditions. Fuel model inputs are used to depict the significant fuel loading amount and composition within the amongst the collection of fuel types (Scott, 2005). FVS-FFE simulates fire behavior by using all 53 fuel models which has been evaluated to be most effective at assessing fuel treatment effectiveness than using the limited 13 fuel models (Johnson et al., 2011; Noonan-Wright et al., 2014; Scott, 2005). It also requires a variant input, (a forest type that represent the general forest growth in that area) for modeling tree growth and fuel accretion over a designated amount of time (Vaillant et al., 2013). Beyond the variant type, users are encourage to calibrate growth measurements further to accurately characterize each local study site (Hoover & Rebain, 2011). Output validity is largely dependent on the inputs dictated by the user and accuracy of their own assumptions when creating simulation parameters (Herbert et al., 2023). The National Forestry Service, Cal Fire, and CARB all utilize the FVS software, but current methodologies only account for trees, not shrubs or grasses, when quantifying carbon stocks (Crookston & Dixon, 2005; Herbert et al., 2023). Though FVS has recently created a sub model for the inclusion of shrubs, it is not yet adopted into the FFE extension, nor is it compatible with the western Sierra variant frequently used in fuel treatment studies (Allen et al., 2023).

2.5.2 IFTDSS

As a web-based software, the Interagency Fuels Treatment Decision Support System (IFTDSS) integrates the processes of other fire behavior applications like FlamMap, Behave, FOFEM, and Consume to create a unified framework that encourages collaboration among scientists and fire managers (Drury et al., 2016; *Interagency Fuels Treatment Decision Support System (IFTDSS)*, 2021). The framework utilizes fuel parameters (1-hour, 10-hour, 100-hour, herbaceous and live fuel moisture levels) and weather inputs (wind speed, type, and direction) to conduct a comprehensive spatiotemporal wildfire analyses than builds upon the plethora of software previously developed (Nazemi & Dehghanian, 2022; Schmidt et al., 2022).

2.6 Quantification Barriers

Much of the research presented in current forestry discourse lacks quantitative evidence that supports the effectiveness of fuel treatments (McKinney et al., 2022). The scope of geographical area vastly differs between landscapes and creates challenges for land managers trying to create s treatments that apply to multiple scenarios (McKinney et al., 2022). There is a gap in understanding how to successfully distribute fuel treatments to maximize fire suppression efforts and favorable GHG emission benefits. Evidence speaking to the effectiveness of fuel treatments is lacking in quantity and overall consistency across the field (McKinney et al., 2022). Logistical barriers prove difficult to surpass, as simulations are hindered by cumbersome software and restrictions to conduct experiments in the field (McKinney et al., 2022). While prescribed burnings are suggested to reduce the quantity of CO_2 emissions from wildfires, an absence of regional-scale research compared with wildfire emissions continues to limit understanding of fuel treatment effectiveness (Cirulis et al., 2019; Wiedinmyer & Hurteau, 2010).

Despite the wide array of research into historical and simulated wildfires, quantitative data on fuel treatments and resulting GHG emission benefits remains incomplete. In the pursuit of expanding upon the scant collection of quantitative research, CAL FIRE provided my team with data on landscapes where fuel treatments were applied to expand research into calculating GHG emission benefits and identifying zones with increased fire severity. My research will address the lack of quantitative results in testing the efficacy of fuel treatments through applying Cal Fire's landscape data to FVS and GIS software to model GHG benefits following fuel treatments (if any). The results will be useful in determining treatment effectiveness, accessing potential impact areas of future wildland fires, and informing future environmental policy.

3. METHODS

3.1 Background

In pursuit of meeting climate goals around reducing greenhouse gas emissions, California has implemented legislation allocating funds towards the state's Greenhouse Gas Reduction Fund (GGRF). The funds are passed through the California Climate Investments (CCI), so they may be applied towards programs and projects related to the reduction of greenhouse gas emissions. Cal Fire has dispersed about $587 million towards CCI Fire Preventions, CCI Forest Health and CCI Urban and Community Forestry programs. Cal Fire CCI Fire Prevention (FP) program's purpose is to reduce the uncontrolled release of GHG emissions while mitigating wildfire risk to communities. Awardees of grants are required to submit data from their hazardous fuel reduction treatment projects for evaluation of GHG quantification. The treatment and fuels data used in this analysis were acquired from Cal Fire, who requested the data from awarded grant applicants.

Methods directly follow the California Air Resources Board's (CARB) procedures outlined in the Forest Restoration and Management Quantification Methodology (QM) modeling framework. The framework includes interfacing with applicant data, georeferencing in ArcGIS Pro, FVS, IFTDSS and other intermediate steps (Fig. 2). Evaluation of these projects include fire effects, impact area analysis, and forest regrowth to reach CO2 MT calculations. Measured model outputs from each fuel reduction project are entered into the official CARB CCI Forest Health Calculator tool for a final net GHG impact value in terms of metric tons CO2e (MT CO2e). The GHG benefit equations used within the CARB CCI Forest Health Calculator are derived from the original methodology. To reach a final GHG benefit value, we subtract the onsite carbon storage baseline value from the carbon storage and project emissions from the treated scenario (Appendix A). All relevant data used in calculations and results will be packaged for each completed project as deliverables and sent to Cal Fire FP program staff for review (Appendix B). This process was developed to better inform CARB's quantification methodology and the effectiveness fuels treatments have on reducing GHG emissions. For the purpose of this section, I will be reviewing CARB's methodology and explaining steps to acquire each net GHG impact value per project evaluated.

3.2 Study Scope

Vegetation treatment projects are dispersed over the entirety of California but are primarily located within Northern California and the Western Sierra Nevada, as these are locations where fire severity was deemed highest and where the carbon stocks are mostly trees. Regions with a majority of tree carbon stocks were necessary to run calculations through the Forest Vegetation Simulator. In FY 2017-18, the CCI Fire Preventions program awarded 142 grants; in FY 2018-19 it awarded 66 grants; in FY2019-20, the program awarded 41 grants; in FY 2020-21, it awarded 30 grants; in FY 2021-22, it awarded 35 grants. This project focuses on the 24 grant projects I individually completed which included grants from FY 2017-2018 and 2019-2020. Treatment areas studied include the following counties with the Cal Fire Unit abbreviation: AEU-Amador (1 site), BDU-Inyo (1 site), BEU-Monterey (1 site), BTU-Butte (3 sites), CZU-San Mateo (1 site), FKU-Fresno (5 sites), HUU- Humboldt (2 sites), KRN-Kern (1 site), LAC-Los Angeles (1 site), LMU-Plumas (1 site), LNU-Sonoma (1 site), TCU-Alpine/Calaveras (4 sites), TUU-Tulare (2 sites), (Fig. 1). Depending on the accuracy of polygons sent by applicants, some required georeferencing with information utilized from the project's scope of work and provided maps of treatment zones.

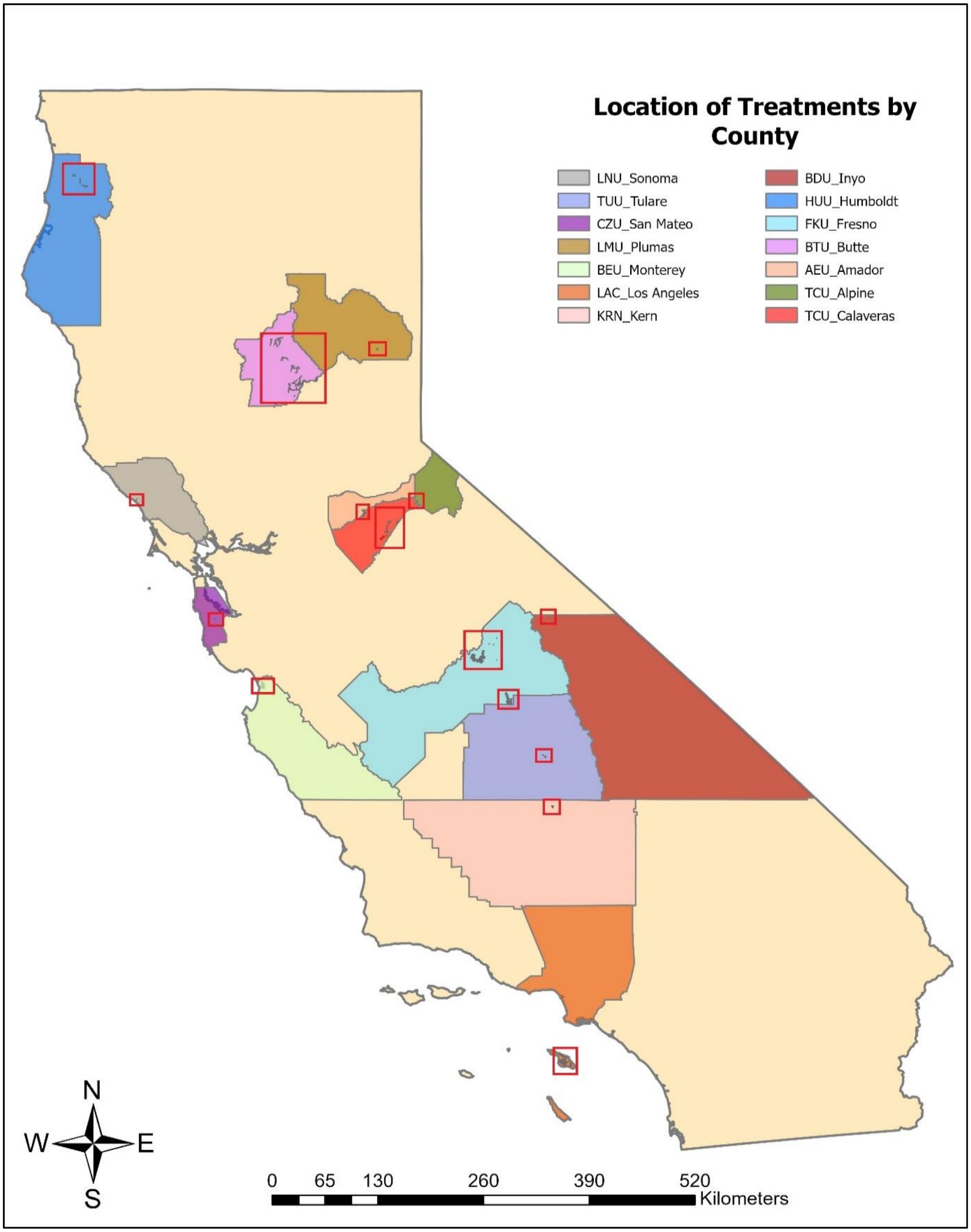


Figure 1. Location of the 24 treatment study sites within California outlined in red and grouped by proximity within their corresponding counties.

3.3 Assessment of Projects

Grant applicants filling out the CARB CCI Forest Health calculator needed to include location, forest type, land ownership type, and forest practice site productivity class. For this research, we have been instructed to use several defaults for the Forest Health Calculator, including a default Class II or III for practice site productivity class (which means studying the net carbon benefits after 70 years), a default of 60 years for the end of projects time period, and an additional 10 years accounting for the effective period for fuels reduction treatment. Looking at carbon emission benefits after 60 years is not typical, as most forestry studies look at long term carbon effects 95-100 years after initial treatment (Hurteau & North, 2010; E. Reinhardt & Holsinger, 2010), however, give the site class parameters prescribed by Cal Fire, we are tasked with observing carbon 70 years after treatment. Given the Scope of Work provided by the grant applicant prescribing a treatment type(s) to the project is at the discretion of the evaluator, but we followed protocol determined by Cal Fire FP program staff to discern treatment type. Treatment polygons were also uploaded to the Cal Fire's Fire Probability for Carbon Accounting (FRAP) online software to assess the mean annual wildfire probability of each project. These account for probabilities from 2021-2050.

3.4 LEMMA Carbon Stocks

In this study, we follow the parameters of the Forest Restoration and Management Quantification Methodology when calculating carbon stocks (*Forest Restoration and Management Quantification Methodology*, 2023). Carbon stock data is acquired by integrating Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) data into provided or georeferenced polygons of the treatment sites. This data was created as a biomass product encompassing carbon stands from all over California and western Oregon (Coffield et al., 2022). FVS uses standardized variant types, and some of the most frequently one used in these simulations included: WS-Western Sierra Nevadas, CA-Inland California and Southern Cascades, and NC-Klamath Mountains. LEMMA data uses nearest neighbor methods to distinguish vegetation structure and species in forest landscapes and match pixels according to these environmental characteristics.

Following LEMMA data extraction to ARC GIS Pro, tables containing carbon stand data and variant type were uploaded into an Access Database for stand and tree data and to upload into the Forest Vegetation Simulator (FVS). Separate simulations were conducted per project which were distinguished by treatment type. However, some projects conducted multiple kinds of treatments, but did not indicate specific areas where each treatment occurred. When this occurs, we were instructed by Cal Fire stakeholders to include multiple treatments across the entire treatment area within the FVS simulations. FVS was used to calculate the carbon stands at baseline- no fire (BSNF), baseline-with fire (BSWF), treatment – no fire (TRNF), and treatment - with fire (TRWF). We utilized the Fire and Fuels Extension within FVS to calculate carbon pools from forest stand developments based on the uploaded LEMMA carbon stand data (E. Reinhardt & Holsinger, 2010). Within this field, the Carb Calc and Fire Calc extensions were also used and serve to run calculations on surface and canopy fuel loads within the distinct treatment and impact areas. When a treatment lies within multiple variant zones, we must manually change the data to reflect the variant with the majority of stands to function within FVS. We marked two main carbon pools for analysis which are reported by FFE-FVS: Aboveground live tree carbon (live tree stems, branches, and foliage) and belowground live (coarse roots of live trees) (Hoover & Rebain, 2011; Vaillant et al., 2013). Carbon in dead tree stands were excluded from FVS calculations because of how fleeting their carbon pools are; therefore, these values would not be significant in long-term carbon recovery analysis (M. D. Hurteau & North, 2010). A noted limitation in this analysis is that only carbon pools from trees can be analyzed in FVS, so these calculations fail to include the presence of Californian shrubbery and grasses known to populate our chaparrals (Allen et al., 2023).

3.5 Simulation Emission Estimates

For each project we conducted simulated wildfires halfway through the time of treatment effectiveness. So, because treatments within site class II or III are typically effective within a span of 10 years, we simulated fires 5 years after the project starting year. If a project started in 2022, we simulated a fire in 2027. The first scenario was when treatment was applied, and the second scenario was when the area was left without treatment to predict how the emissions would be impacted in either scenario. Default weather specifications for the simulated fire were dictated by the QM and included 15 mph wind speed, 90° temperature, very dry moisture levels and time of the year the simulated wildfire occurred (after green up) (The California Air Resources Board, 2021). “Green up” refers to the period of increased vegetation growth, or, in the case of California forest ecosystems, spring. Following the completion of each “run” in the FVS software, the carbon total from each stand will be calculated by adding above ground live and belowground live columns from each tree stand and multiplying each sum by its corresponding C acre (acreage that carbon stand covers). Following the four scenarios, the stands individual C totals are all summed up from each category to equate a value of total C emitted for each four scenarios. These values in (MT $CO2_e$) are then each input into the CARB CCI Forest Health Calculator tool.

After the scenarios are completed for the treatment areas, impact areas double the width of the treated plot must be drawn in ARCGIS and go through the protocol with extracting LEMMA data as explained previously to estimate the MT $CO2_e$ in baseline and treatment scenarios (*Forest Restoration and Management Quantification Methodology*, 2023). After FVS assessment of impact area with and without fire disturbance, polygons from the treatment boundary are uploaded into IFTDSS to model the impact area burn severity with and without treatment. This is accomplished by creating a landscape and running a 97^{th} percentile extreme fire behavior report, which uses landscape information from FlamMap and weather conditions determined by the closest Remote Automatic Weather Station (RAWS) for the predicted landscape burn probability models. This is followed by generating a report from the model which ran the fire model over the impact area to measure the conditional flame length pixel count (8-12 ft and >12 ft flame length) for both scenarios. To achieve the final high burn severity calculations, we divide the sum of the higher severity pixel count categories by the total number of pixels in the impact area. This is the last value to add to the calculator before we can receive the net GHG benefit calculation (*Forest Restoration and Management Quantification Methodology*, 2023).

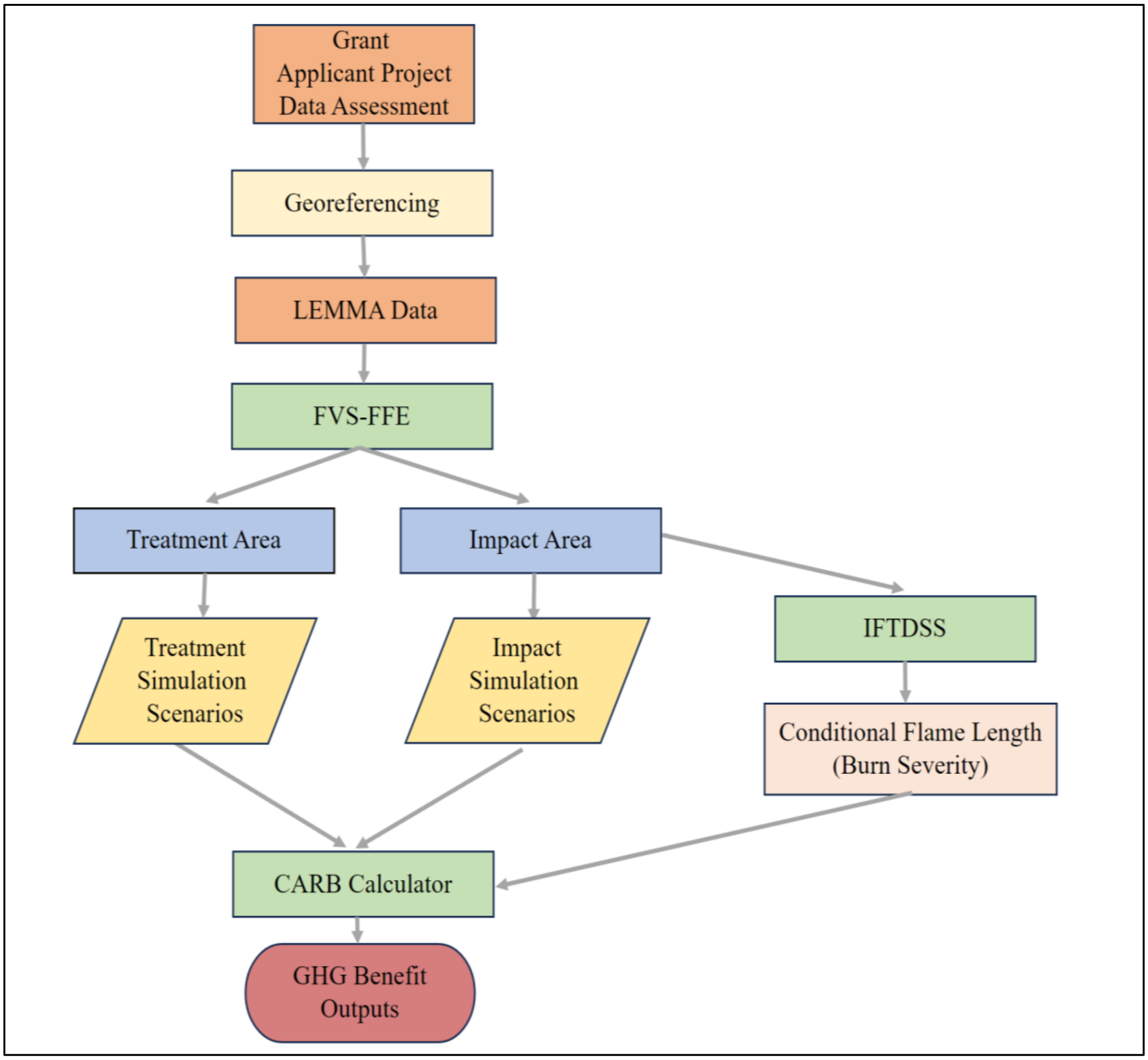


Figure 2. Flow chart highlighting the primary processes and data used for the CARB Calculator to generate GHG benefit from treatment scenarios.

3.6 Calculating GHG Benefit

The QM references three equations used for the evaluation of GHG benefits from fuel treatments. Equation 8 (Fig 1.) is used to calculate carbon storage and emissions from the treated project scenarios. Equation 9 (Fig 2.) is used to calculate carbon storage in the baseline scenarios, where no treatments occur. Finally, Equation 7 (Fig 3.) is used to calculate the final net GHG benefit from the Fuel reduction project and is the difference between the results from Equation 8 and Equation 9. All utilized equations are embedded into the official CARB CCI Forest Health Calculator tool for maximum efficiency (*Forest Restoration and Management Quantification Methodology*, 2023). Once the calculators are filled out to produce the final GHG benefit value for each of the corresponding projects, these results will act as the deliverable sent to Cal Fire for further analysis.

4. RESULTS

4.1 Net GHG Benefits

Statistical analyses for the mean GHG benefit per acre and impact area burn severity were excluded because the projects' simulations had extremely varied inputs, acreage, and occurred within areas with different fire probabilities. Even so, some assumptions were standardized across treatments while others were dependent on detailed applicant parameters, so results will be recognized as comparisons instead of predictive values. Treatments were separated into four categories for comparison: thin from below, mastication, prescribed burn, and multiple treatments. Projects included in the multiple treatments category contain two or more varying treatment combinations, like mastication followed by a broadcast burn, thinning followed by a pile burn, or hand thinning followed by mastication. Because these projects were composed of so many diverse combinations of treatments with varying parameters for each kind, they are simply regarded as multiple treatments in the results. For the final GHG benefits produced from the Forest Health Quantification Methodology Calculator, a negative value indicates that the treatment caused increased carbon loss and yielded no GHG benefits. A positive value indicates that the treatment created GHG benefits.

Of the 24 simulated projects zones, only three projects resulted in GHG emission benefits from the Forest Health Quantification Methodology Calculator and when benefits were present, they averaged 5.38 CO_2e per acre. The projects that recorded a benefit (fell under three separate treatment categories: prescribed burn, mastication, and multiple treatments (Table 1). The 18 other projects resulted in more emissions expended in the treatment scenario, as opposed to the baseline scenario, and therefore yielded negative (no benefits) results. However, averaged results show a negligible difference in CO_2e, indicating the treatments had little effect on the effects of GHG emissions, regardless of treatment type. Due to projects being extremely varied in acreage, benefits were displayed per acre (Table 1).

Grant Tracking No.	Treatment Type	Treatment Acreage	Net GHG Benefit (MT CO2e)	Benefit per acre (MT CO2e)
17-FP-BEU-2069	Thin from Below	77.12	-1,842	-23.88
17-FP-BTU-0067	Rx Burn	127.89	-230	-1.80
17-FP-BTU-0067	Mastication	383.82	-5409	-14.09
17-FP-BTU-1036	Mastication	3219.09	-110153	-34.22
17-FP-CZU-2059	Multiple	18.12	-331	-18.27
17-FP-FKU-0036	Multiple	533.78	-34,868	-65.32
17-FP-FKU-2029	Thin From Below	6015.92	-351,152	-58.37
17-FP-FKU-2074	Multiple	239.98	-24,658	-102.75
17-FP-KRN-2006	Mastication	214.72	-651	-3.03
17-FP-LMU-0039	Mastication	116.61	-729	-6.25
17-FP-LNU-0094	Multiple	31.80	-2650	-83.33
17-FP-TCU-2022	Thin From Below	24.08	-131	-5.44
17-FP-TUU-2003	Multiple	216.92	-4467	-20.59
19-FP-FKU-2044	Thin From Below	613.41	-29364	-47.87
19-FP-FKU-2044	Thin From Below	113.16	-676	-5.97
19-FP-HUU-1106	Rx Burn	406.07	76	0.19
19-FP-HUU-1106	Mastication	283.88	-7686	-27.07
19-FP-LAC-2053	Mastication	49.82	-535	-10.74
19-FP-TCU-2018	Mastication	694.26	-8273	-11.92
19-FP-TCU-2066	Mastication	509.61	-954	-1.87
19-FP-TCU-2066	Multiple	326.46	1489	4.56
19-FP-TUU-2020	Mastication	103.88	1184	11.40
20-FP-AEU-0310	Mastication	596.17	-18462	-30.97
20-FP-BDU-0300	Multiple	2.87	-158	-55.05

Table 1. Summary of GHG benefits by project categorized by grant number, treatment type, accompanying treatment size (in acres) and calculated benefit in MT CO2e.

The ten mastication projects had averaged -12.88 $MTCO_2e$ per acre benefit. Overall average indicates no benefit, as negative values mean that there was more onsite C storage after in the baseline scenario, when compared to the scenario with the fuels reduction activity. The differences in $MTCO_2e$ per project may be attributed to their varying acreage and were considered by showing the results in $MTCO_2e$ per acre. For example, hazardous fuel project 17-FP-BTU-1036 encompassed 3219.09 acres of mastication along 1,300 miles of roadway (Table 1). Project 19-FP-LAC-2053 encompasses 49.82 acres of roadside mastication on Catalina Island. Therefore, showing values as $MTCO_2e$ per acre allowed for a more balanced comparison between projects (Figure 3). All mastication projects showed a C reducation post simulated fires in both tretament and baseline scenarios.

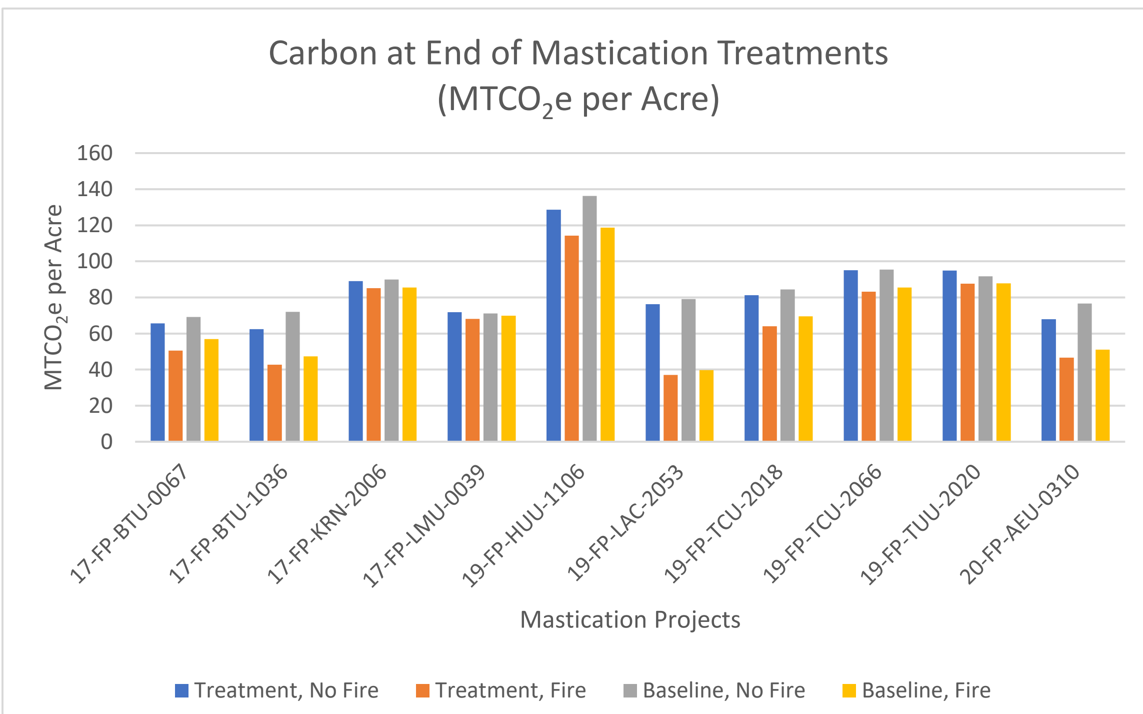


Figure 3. Histogram of the differences between the simulated treatment scenarios and amount of CO2e emitted from each of the ten mastication projects.

Five thin from below projects also resulted in a mean benefit per acre of -28.31 CO_2e. Like the mastication projects, these yielded overall no benefit and indicate that thinning treatments show increased C storage in the baseline scenario rather than the treatment scenario after 70 years. Simulations with fire saw a C loss when compared to simulations without fire.

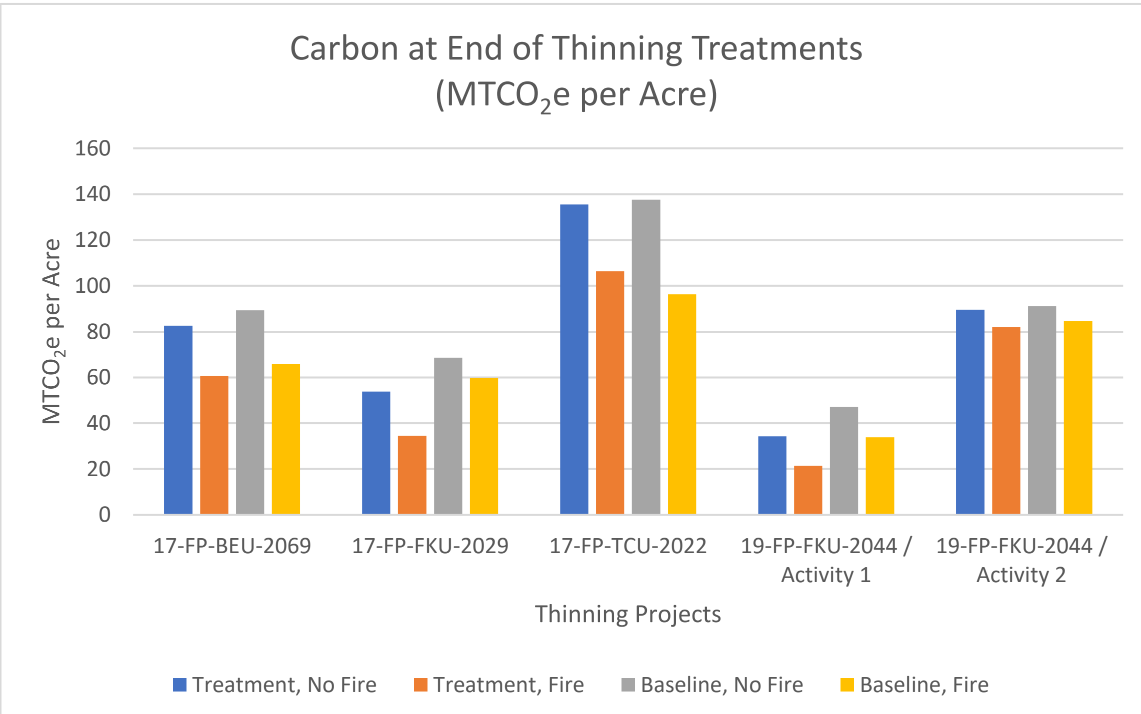


Figure 4. Histogram of the differences between the simulated treatment scenarios and amount of CO2e emitted from each of the five thin from below projects.

Two prescribed burn treatments yielded an average benefit of -0.81 CO_2e. Of our various treatment classifications, prescribed burns were the closest to yielding an overall benefit across projects. Project 17-FP-BTU-0067 shows increased C after the treatment site experienced a simulated fire. This is an anomaly, as most projects show C reductions after fire. It also differs from the baseline scenario, which aligns with other projects showing a C loss after fire. This indicates some effect the treatment had on the landscape causing this difference in C gain. However, only two projects were simulated that were exclusively burns, so the sparse data pool limits the study and attempting to make any encompassing conclusions.

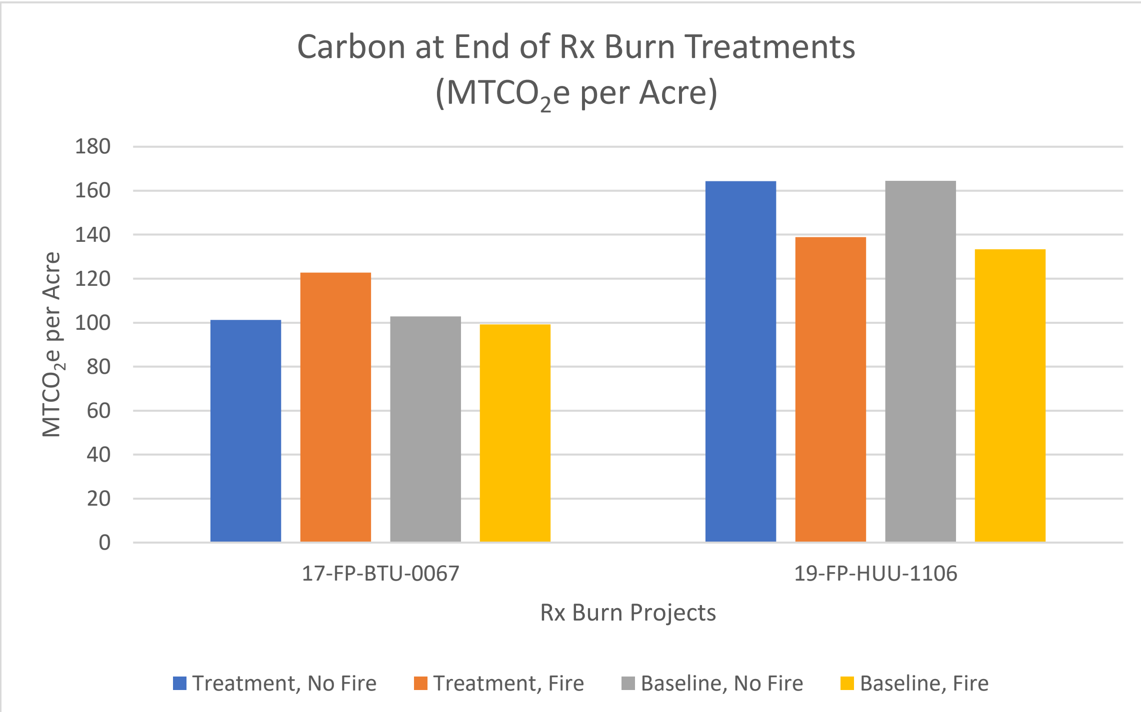


Figure 5. Histogram of the differences between the simulated treatment scenarios and amount of CO2e emitted from each of the two prescribed burn projects.

Projects with multiple treatments showed an average of -48.68 CO_2e per acre benefit from calculator results. Again, this yields no benefits and shows the treatment having no beneficial effect on the resulted emissions within the treatment area. The treatments with the most noticeable results in GHG emission benefits were project sites that experienced multiple treatments, like a combination of a thin from below and a mastication of leftover biomass. Some thinning treatments also classified as Dead and Dying Tree Removal, which altered the DBH parameters within each simulation. These were included in the multiple treatments as well. Project 20-FP-BDU-0300 displayed massive differences in on-site C after simulated fires, when compared to no fire simulations (Figure 6). This may be attributed to the extremely small size of the project, only equaling 2.87 acres, and experiencing an increased fuels reduction (Table 1). Coupled with a low severity FRAP (fire probability) (Appendix B), there is less likelihood of this site experiencing a fire in the first place.

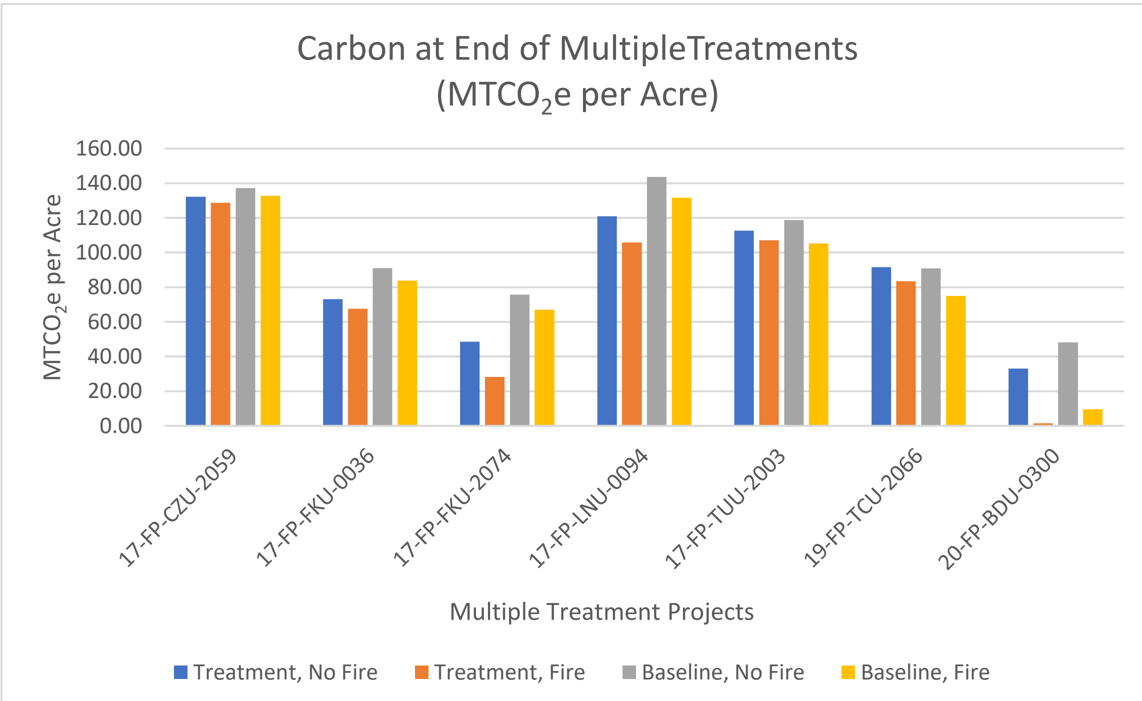


Figure 6. Histogram of the differences between the simulated treatment scenarios and amount of CO2e emitted from each of the 7 projects that experienced multiple combinations of the three primary treatment types.

General patterns across all treatments show that baseline scenarios that included a simulated fire resulted in an average 18.89% C reduction. Treated areas showed an average 20.73% C loss post simulated fire. This indicates that across the board, there was increased C loss when the area was treated, as opposed to experiencing no treatment.

4.2 Impact Area Burn Severity

The impact area encompasses the area surrounding the treatment site and was studied to observe the outside effects the treatment would have on conditional flame length, used as an indicator of burn severity. Results derived from the IFDSS landscape burn probability simulations were highly dependent on the initial FRAP values which show likelihood an area would experience a fire. Therefore, projects located in regions with a high FRAP are more likely to see high severity burn probability benefits from the treatment in the impact area. General patterns from each treatment category suggest there are minimal differences in burn severity values between the baseline and treated scenarios (Table 2). While separated based on treatment, each project was in a different area impacting their fire severity as well. Therefore, max high severity burn probability may be attributed to numerous other factors, not only treatment type. Moreover, the difference between the baseline and treated scenarios shows a more comprehensive comparison.

Treatment Type	**Baseline**		**Treated**	
	Max	**Mean**	**Max**	**Mean**
Mastication	42.60%	26.42%	41.84%	25.84%
Thin from below	32.67%	11.43%	29.43%	10.62%
Prescribed burn	66.00%	34.12%	65.98%	34.17%
Multiple	30.82%	19.93%	29.92%	18.54%

Table 2. Comparison of maximum and mean percentage of the impact area that burned at high severity.

Mastication treatments showed a 0.58% change between the untreated and treated scenario when the fuel treatment projects were simulated (Table 3). Within mastication treatments, project 17-FP-BTU-0067 and project 19-FP-HUU-1106 showed an increase in impact area burn severity in the treatment scenario (Figure 7). This is an anomaly when compared with the other treatments that all indicated that treatments helped decrease burn severity.

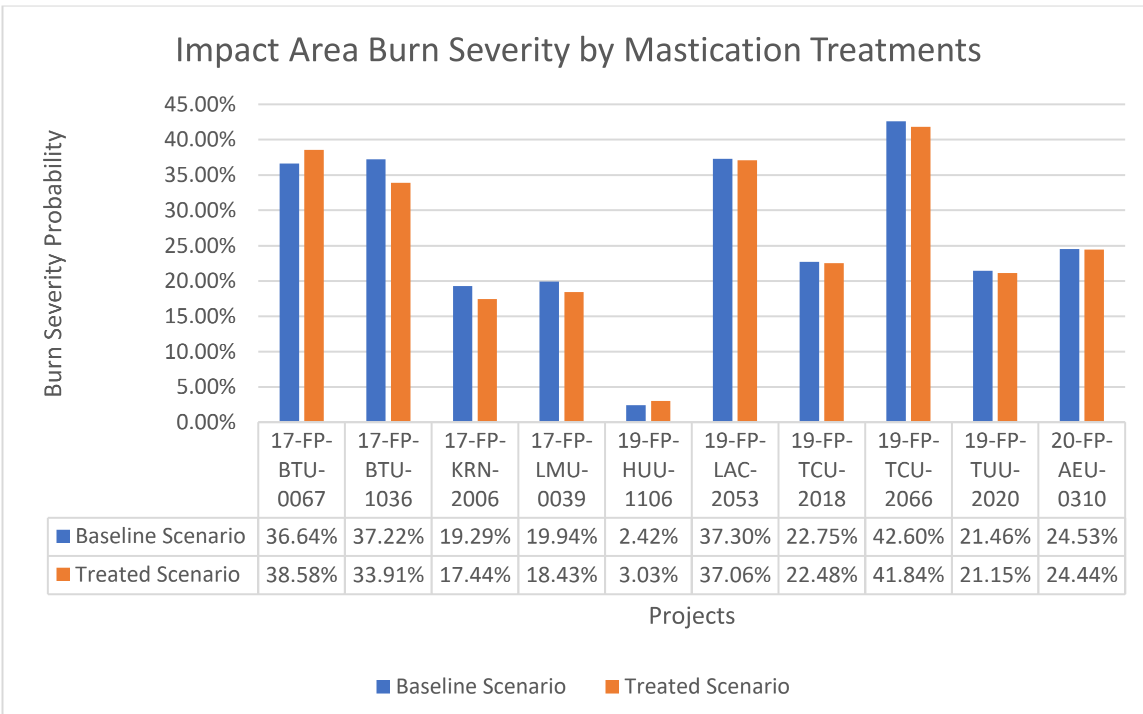


Figure 7. Burn severity probability for each mastication project is determined by conditional flame length metrics.

The thin from below treatment similarly showed an averaged change of 0.81% between the two scenarios (Table 3). While the change is small, it still shows that the thinning treatment reduced overall impact area burn severity. Project 19-FP-FKU-2044, Activity 2 (thin from below), was the only thinning project that showed an increase in burn severity in the treatment scenario (Figure 8). While the 0.89% is a small difference, it shows that treatments may not always yield positive benefits for the site's impact area.

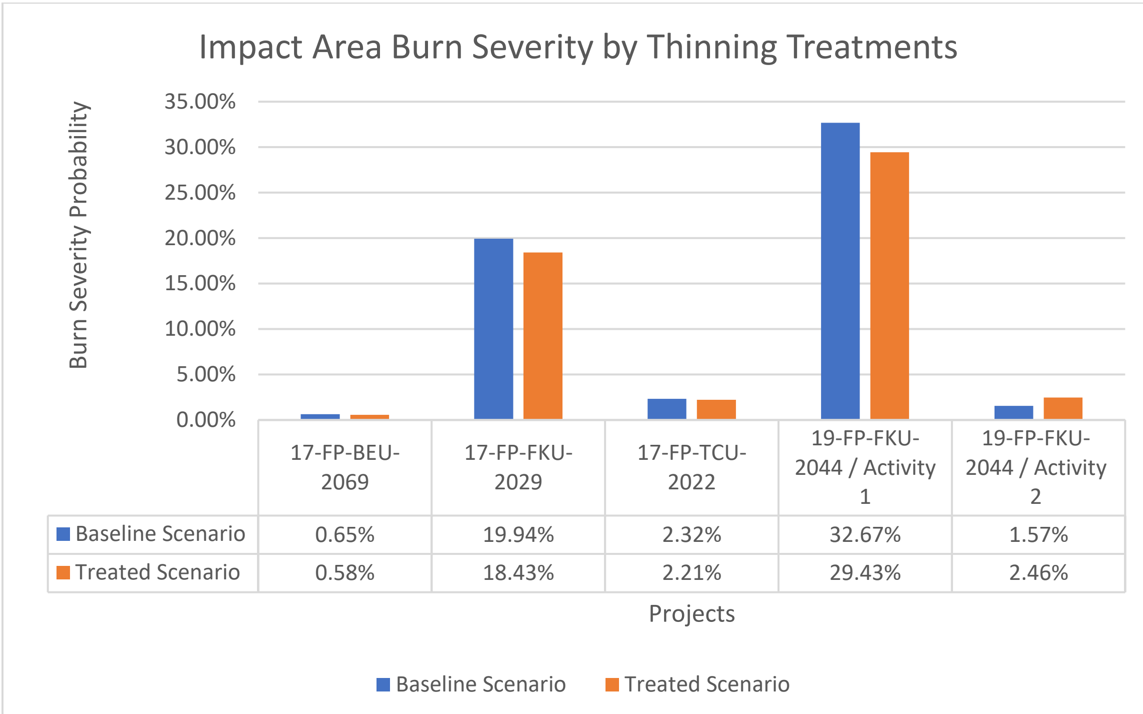
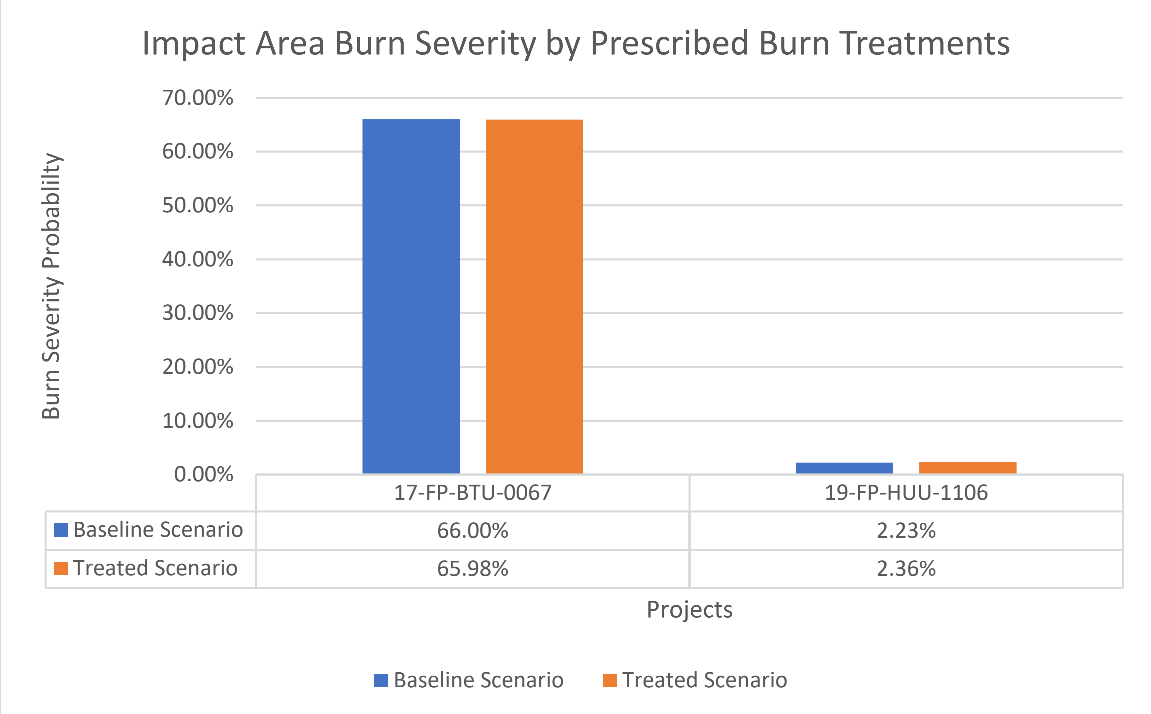


Figure 8. Histogram of the impact area burn severity for the five thinning projects.

The two prescribed burn treatments showed almost null differences in burn severity. While project 17-FP-BTU-0067 yielded a 0.02% decrease in burn severity in the treated scenario, project 119-FP-HUU-1106 showed a 0.13% increase in the impact area's burn severity (Figure 9). Apart from the difference in numbers, IFTDSS showed increased overall burn severity with or without treatment in project 17-FP-BTU-0067 (Figure 9). These large probabilities can be attributed to the landscape's vulnerability to fire in terms of vegetation, or several other depending factors (like fuel characteristics, wind speed during fire simulation, topography influencing spread). The 66.00% baseline scenario burn severity is an anomaly, and it is unknown why this project displayed such intense burn severity calculations (Figure 9).



	17-FP-BTU-0067	19-FP-HUU-1106
Baseline Scenario	66.00%	2.23%
Treated Scenario	65.98%	2.36%

Figure 9. Histogram of the impact area burn severity for the two prescribed burn projects.

In the multiple treatment classification, four of the seven treatments showed decreased impact area burn severity. The remaining three treatments showed an increase in burn severity. However, the projects that saw an increase in burn severity after treatment only rose by an average of 0.62% while projects that saw a decrease in burn severity after treatment were reduced by an average of 2.88% (Figure 10). The average decrease of 2.88% shows that when benefits to burn severity do occur within projects, they are more substantial than in the cases when burn severity rises (0.62% average increase).

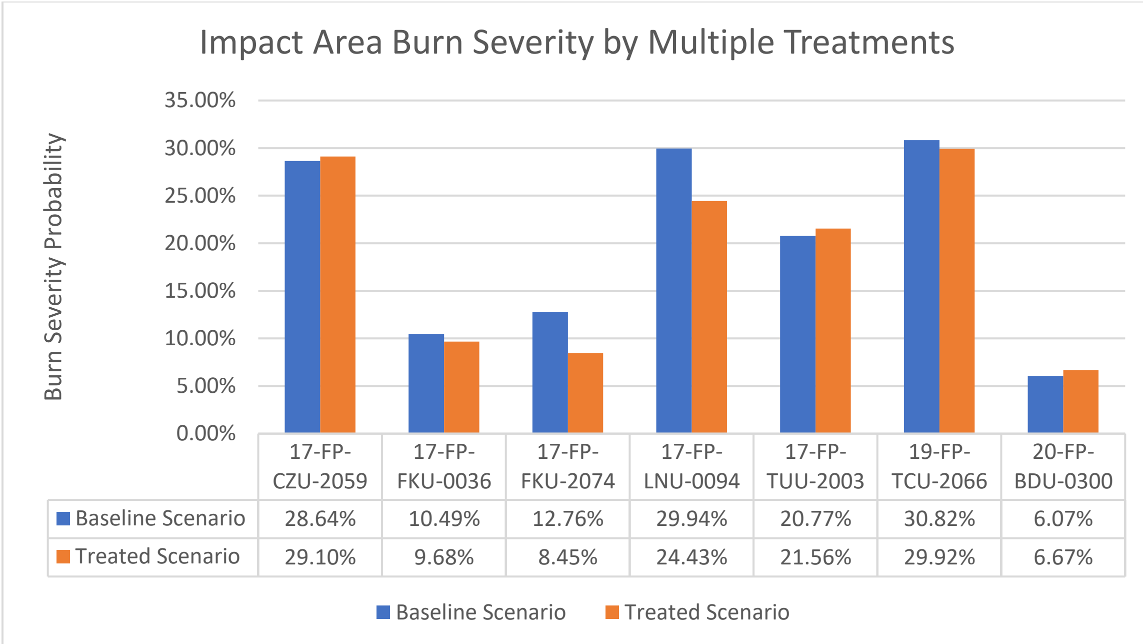


Figure 10. Comparison of burn severity probability between the projects that experienced multiple treatments.

High burn severity probabilities drawn from conditional flame length estimations showed minimal change in the impact areas surrounding the treatment zones. The effect of treatment on burn severity on impact areas around fuel treatments are summarized in Table 2. The percentages are reported from outputs from IFTDSS that calculate the proportion of pixels in the impact zone affiliated with conditional flame lengths at 8 feet or greater, which indicates which areas burned at high severity in an untreated baseline and treated scenario. Projects that experienced multiple treatments and combinations of the three focused treatments resulted in the greatest difference of high burn severity with a 1.39% difference (Table 3).

Treatment	Baseline Scenario	Treated Scenario	Difference (baseline - treated)
Mastication	26.42%	25.84%	0.58%
Thin From Below	11.43%	10.62%	0.81%
Prescribed Burn	34.12%	34.17%	-0.05%
Multiple Treatments	19.93%	18.54%	1.39%

Table 3. Mean high burn severity probabilities for the untreated baseline and treated scenarios. High burn severity is based on the proportion of pixels in IFTDSS likely to burn areas with conditional flame lengths at 8ft or greater.

5. DISCUSSION

A standardized method for the quantification of GHG benefits derived from fuel treatments is not yet established. The methodologies currently being utilized rely upon a multitude of assumptions and combination of many different modeling software and steps, creating an extremely complex process. Fuel treatment effectiveness was assessed from many metrics including fire risk, burn probability and intensity (conditional flame length), and the carbon emission outputs derived from simulations. Because all simulations were based off real fuel treatments performed by Cal Fire applicants, criteria for treatments differed based on varied specifications indicated by applicants. As such, this meant that some grant applicants provided more specific data, while others were extremely vague in their descriptions of treatment type and area. Due to these varying assumptions, the calculated GHG benefit, and conditional burn probability results were compared by treatment type samples for overall treatment effectiveness in these fields and a statistical analysis encompassing predictive values was precluded.

Our results suggest that overall, fuel treatments do not provide any suggestive GHG benefits, and in the few cases there were benefits, they were negligible. This aligns research that report instances of treatments resulting in greater C loss when compared with control scenarios (S. R. Mitchell et al., 2009). However, it is important to note that treatments are variable depending on where they are done. Forests with prolonged fire return intervals would not see the regular benefits of fuel treatments compared to forests with shorter intervals (Mitchell et al., 2009). Treated area that experiences fire showed reduced C emission because available C is reduced (either by actual removal or changing the mode of fuel, which influences fire behavior) (Reinhardt & Holsinger, 2010).

Conditional burn probability results showed consistent if small improvement post treatment across all types of treatments. While areas that experienced more than one treatment showed the largest improvement post treatment, thin from below treatments followed at the second most effective in terms of mean high conditional burn severity probability. The only treatment class that showed an increase in burn probability post treatment was the prescribed burn, however a 0.05% difference is negligible. A minimal change in burn severity may also explain the lack of C emission benefits. Since there was almost no change in the amount of severely burned land in either scenario, it wouldn't have any influence on the C on-site as well.

A broader study including more prescribed burn treatments would better represent the population moving forward. Additionally, inclusion of site-specific weather and fuel moisture data would help improve the accuracy of each simulation, however given the amount of grant awardees, locating, and applying this data may not be feasible. As it stands, most California fuel treatments within the studied programs fall under thinning or mastication.

Reductions in the burn probability suggest that the treatments had a small benefit. Treatments are shown to lose effectiveness at reducing burn severity between 10 and 15 years due to vegetation regrowth (Agee & Skinner, 2005) while other benefits stand to lose potency over a span of 20-40 years (Ager et al., 2020). For example, potential flame length is reduced by a quarter within the first two decades after treatment, however there was surprisingly minimal change in burn area post treatment given the amount of fuels removed from site in the simulation (Ager et al., 2020). Possible reasoning behind these results include differences in fuel characteristics, how fast it takes for vegetation regrowth, and the proximity of urban communities (ignition risk). Frequent treatment of high-risk areas is vital to consistently mitigating burn severity. Prescribed burns, may require numerous treatments to reach the fuel treatment goal, however, there is limited research behind the desired frequency and total number of applications needed for significant fuel reduction benefits due to differing forest types, topography and other dependent factors (Van Mantgem et al., 2016).

Significant treatment benefits are mainly realized in the event of the area experiencing a fire event within the typical effectiveness term between 10 and 40 years, so when the area has a low fire probability, benefits will be lesser than an area which experiences more frequent and intense fires. However, as U.S. wildfire disasters continue to cause devastation, communities with less fire probability still perform fuel treatments as a preventative strategy and to serve an operational benefit in case of emergency.

5.1 Limitations

This study had several limitations which compromise the overall accuracy of quantifying GHG benefits for fuel treatment, however these questions and issues may be addressed in future research and as forest simulations models continue to improve and collaborate. The methodology initially proposed by Cal Fire provided guidance on what calculations were needed to reach a final net benefit value, however, the steps to get those values remain under development for accuracy and efficiency. This method currently accounts for biomass utilization, it does not account for the emissions expended while using the heavy machinery needed for treatments (masticators, chainsaws, etc.).

The FVS-FFE simulation model utilizes stand data to simulate tree growth after treatments and cannot yet reliably process grasses or shrubland (*The Fire and Fuels Extension to the Forest Vegetation Simulator: Updated Model Documentation*, n.d.). Exclusion of grasses and shrubs from the GHG benefits remains an important limitation on carbon quantification and reflecting accurate outputs based on the landscapes being treated. California's shrub dominated chaparral is a widespread ecosystem frequently at risk for wildfires near communities (Grupenhoff & Molinari, 2021), so being unable to account for the carbon of these fuel types majorly ignores much of the benefit that may be had in fuel treatments that target these regions. Additionally, treatments that reduce woody and herbaceous vegetation cover with herbicide or live animals, like goats, are not accurately represented by FVS fuels management selections because these treatments primarily target grasses and shrubs, and not the trees FVS accounts for. Therefore, these treatments are somewhat lost on the current methodology until shrubs can be accounted for or until goats can masticate entire trees at 8 inches DBH or below. Even so, simulations were still completed on required projects assuming that the treatments were still viable at the stand level.

In FVS, not only are the fuels being underestimated, but the growth models (normally applied to the FVS management activities) were found to be overestimating carbon stocks within muti-decade projections. This becomes a problem for programs facilitated by CARB protocol that generally require calculations on treatments' impacts over ten decades (Herbert et al., 2023). Therefore, a 70-year timescale studied in this research may produce errors and inaccurate assessments. Future studies may include a time series analyses across all simulated years between the project start and end (70 years after), therefore accounting for C on-site every ten years. Until these limitations are explored, these simulation outputs and calculations underestimate the carbon accounting within the treatment area.

6. CONCLUSION

Surmounting challenges around wildfire prevention and forest health brings out a substantial need for accurate fuel modelling and the consequent methodology for tracking benefits from California's ambitious management activities. Human ignitions are the dominant cause of wildfire in California, attributing to extreme property damage and mortality statewide (Chen & Jin, 2022; Keeley et al., 2018). Since funding for fuel treatment programs derives from California Climate Investments to be siphoned towards CARB and all the fire prevention programing facilitated by Cal Fire, providing documentation on the GHG benefits is obligatory and provides the state with a measure of fuel treatment effectiveness.

While this study does not indicate any GHG benefits yielded from treatments, they remain an integral management practice for WUI communities, and offer many other benefits like increased accessibility for firefighters and fire suppression emergencies (Moghaddas et al., 2007). Limited fuel loads from treated areas also foster safer working conditions for emergency personnel, reducing the amount of smoke and overall visibility when fighting wildfires (Rogers et al., 2008).

Research behind finding a standardized method in quantifying GHG benefits is still in its infancy and relies upon addressing several limitations within Forest Landscape Models. Simulation modeling on carbon in treatment and impact areas relies on a multitude of assumptions and uncertainties that cannot yet be fully developed. Despite the findings showing no significant GHG benefits from the treatments after 70 years, reductions in burn severity post treatment were consistent, if minimal. The study continues to simulate projects to add to the growing collection of projects and provide more information to this dataset for future research in treatment GHG mitigation effectiveness.

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APPENDICES

A. GHG Benefit Equations from Forest Health Quantification Methodology

Equation 7: GHG Benefit from Fuels Reduction Activities

$$GHG_{FR} = GHG_{FRP} - GHG_{FRB}$$

Where,			Units
GHG_{FR}	=	GHG benefit of fuels reduction activities	MT CO_2e
GHG_{FRP}	=	On-site carbon storage and project emissions in fuels reduction project scenario (from Equation 8)	MT CO_2e
GHG_{FRB}	=	On-site carbon storage in fuels reduction baseline scenario (from Equation 9)	MT CO_2e

Equation 8: On-Site Carbon Storage and Project Emissions in Fuels Reduction Project Scenario

$$GHG_{FRP} = [CTNF_{FRP} + CINF_{FR} - (1 - (1 - APFO_{FR})^{EP}) \times (CTNF_{FRP} + CINF_{FR} - (CTNF_{FRP} - (CTNF_{FRP} - CTWF_{FRP}) \times (CBPT_P/CBPT_B)) - (CINF_{FR} - (CINF_{FR} - CIWF_{FRB}) \times (CBPI_P/CBPI_B) \times (1 - (IFL_B - IFL_P)))))] \times 3.67 - BR_{FRP} \times 0.06$$

Where,			Units
GHG_{FRP}	=	On-site carbon storage and project emissions in fuels reduction project scenario	MT CO_2e
$CTNF_{FRP}$	=	Carbon within the treatment boundary at the end of the project with fuels reduction treatment but without fire disturbance (from FVS)	MT C
$CINF_{FR}$	=	Carbon within the impact boundary at the end of the project without fire disturbance (from FVS) (optional)	MT C
$APFO_{FR}$	=	Annual probability of fire occurrence within the treatment and impact boundaries (mean probability from FRAP Fire Probability and Carbon Accounting map tool)	%
EP	=	Effective period for fuels reduction treatment (maximum 25 years)	Years
$CTWF_{FRP}$	=	Carbon within the treatment boundary at the end of the project with fuels reduction treatment and with fire disturbance (from FVS)	MT C
$CIWF_{FRB}$	=	Carbon within the impact boundary at the end of the project without fuels reduction treatment but with fire disturbance (from FVS and IFTDSS) (optional)	MT C
IFL_B	=	Proportion of impact boundary likely to burn at high severity without fuels reduction treatment (optional)	%
IFL_P	=	Proportion of impact boundary likely to burn at high severity with fuels reduction treatment (optional)	%
$CBPT_B$	=	Conditional burn probability without fuels reduction treatment for the portion of the treatment area likely to burn at high severity in the baseline scenario (without fuels reduction treatment) (optional)	%
$CBPT_P$	=	Conditional burn probability in the project scenario (with fuels reduction treatment) for the portion of the treatment area likely to burn at high severity in the baseline scenario (without fuels reduction treatment) (Optional)	%
$CBPI_B$	=	Conditional burn probability without fuels reduction treatment for the portion of the impact area likely to burn at high severity in the baseline scenario (without fuels reduction treatment) (optional)	%
$CBPI_P$	=	Conditional burn probability with fuels reduction treatment for the portion of the impact area likely to burn at high severity in the baseline scenario (without fuels reduction treatment) (optional)	%
3.67	=	Conversion factor from C to CO_2e	CO_2e/C
BR_{FRP}	=	Biomass removed via mechanical treatments	Bone dry tons
0.06	=	Mobile combustion emission factor for biomass removal in fuels reduction project scenario	MT CO_2e/ bone dry ton

Equation 9: On-Site Carbon Storage in Fuels Reduction Baseline Scenario

$$GHG_{FRB} = [CTNF_{FRB} + CINF_{FR} - (1 - (1 - APFO_{FR})^{EP}) \times (CTNF_{FRB} + CINF_{FR} - CTWF_{FRB} - CIWF_{FRB})] \times 3.67$$

Where,			Units
GHG_{FRB}	=	On-site carbon storage in fuels reduction baseline scenario	MT CO_2e
$CTNF_{FRB}$	=	Carbon within the treatment boundary at the end of the project without fuels reduction treatment and without fire disturbance (from FVS)	MT C
$CINF_{FR}$	=	Carbon within the impact boundary at the end of the project without fire disturbance (from FVS) (optional)	MT C
$CTWF_{FRB}$	=	Carbon within the treatment boundary at the end of the project without fuels reduction treatment but with fire disturbance (from FVS and FFE-FVS)	MT C
$CIWF_{FRB}$	=	Carbon within the impact boundary at the end of the project without fuels reduction treatment but with fire disturbance (from FVS and IFTDSS) (optional)	MT C
$APFO_{FR}$	=	Annual probability of fire occurrence within the treatment and impact boundaries (mean probability from FRAP Fire Probability for Carbon Accounting map tool)	%
EP	=	Effective period for fuels reduction treatment (maximum 25 years)	Years
3.67	=	Conversion factor from C to CO_2e	CO_2e/C

B. Comprehensive Cal Fire Deliverable

Grant Tracking No.	TRT Acreage	Impact Acreage	Annual Fire %	TRNF (MT C)	TRWF (MT C)	BSNF (MT C)	BSWF (MT C)	Impact NF (MT C)	Impact WF (MT C)	%High Sev, BS	% High Sev, TR	Net GHG Benefit	Dominant Variant
17-FP-BEU-2069	77.12	150.90	1.30%	6374.30	4678.50	6890.09	5082.82	12475.36	9526.84	0.65%	0.58%	-1,842	NC
17-FP-BTU-0067	127.89	1025.67	0.42%	12957.72	15702.67	13152.97	12681.06	112965.00	100765	66.00%	65.98%	-230	WS
17-FP-BTU-0067	383.82	2635.53	0.61%	25195.65	19372.19	26564.11	21854.21	211085.12	176918.1	36.64%	38.58%	-5409	WS
17-FP-BTU-1036	3219.09	6522.72	0.61%	200738.80	137491.00	232054.90	152365.00	486277.62	320439.8	37.22%	33.91%	-110153	CA
17-FP-CZU-2059	18.12	82.50	0.63%	2396.26	2331.13	2487.14	2406.37	10859.57	10016.91	28.64%	29.10%	-331	NC
17-FP-FKU-0036	533.78	1001.00	0.50%	39015.05	36037.50	48558.06	44771.50	93072.47	86732.46	10.49%	9.68%	-34,868	WS
17-FP-FKU-2029	6015.92	10370.72	0.68%	323773.90	207655.80	412732.45	360273.90	730586.64	619811.2	19.94%	18.43%	-351,152	WS
17-FP-FKU-2074	239.98	685.30	0.71%	11635.68	6797.03	18181.68	16102.02	52592.54	46921.54196	12.76%	8.45%	-24,658	WS
17-FP-KRN-2006	214.72	1360.21	0.82%	19117.44	18274.08	19307.07	18363.82	137246.27	134274.8	19.29%	17.44%	-651	WS
17-FP-LMU-0039	116.61	274.45	0.49%	8368.61	7936.20	8282.40	8148.27	19353.09	18487.58	19.94%	18.43%	-729	WS
17-FP-LNU-0094	31.80	143.12	0.52%	3845.16	3361.40	4568.31	4185.86	19302.47	17097.86	29.94%	24.43%	-2650	NC
17-FP-TCU-2022	24.08	132.79	0.47%	3262.90	2558.67	3312.34	2319.47	21113.66	12921.25	2.32%	2.21%	-131	WS
17-FP-TUU-2003	216.92	808.04	0.73%	24428.53	23224.45	25762.59	22819.73	106466.62	95996.11	20.77%	21.56%	-4467	WS
19-FP-FKU-2044	613.41	1269.29	0.98%	21035.71	13179.51	28945.83	20742.26	5213.34	619811.20	32.67%	29.43%	-29364	WS
19-FP-FKU-2044	113.16	1042.65	0.55%	10136.30	9287.53	10304.17	9585.68	94931.35	86091.9	1.57%	2.46%	-676	WS
19-FP-HUU-1106	406.07	7390.01	0.55%	66724.84	56408.62	66819.45	54161.30	1050456.57	901883.45	2.23%	2.36%	76	NC
19-FP-HUU-1106	283.88	1640.86	0.55%	36537.12	32451.05	38663.85	33689.95	227398.58	181047.27	2.42%	3.03%	-7686	NC
19-FP-LAC-2053	49.82	54.75	0.65%	3795.26	1847.77	3942.52	1977.14	3573.31	1782.23	37.30%	37.06%	-535	WS
19-FP-TCU-2018	694.26	6718.17	0.58%	56385.00	44433.00	58558.00	48288.00	480578.00	389550	22.75%	22.48%	-8273	WS
19-FP-TCU-2066	509.61	6566.59	0.58%	48419.00	42422.00	48646.00	43571.00	648686.07	603394.2	42.60%	41.84%	-954	WS

19-FP-TCU-2066	326.46	3020.12	0.58%	29898.00	27228.00	29643.00	24449.00	293301.05	276628.91	30.82%	29.92%	1489	WS
19-FP-TUU-2020	103.88	1060.61	0.61%	9866.00	9098.00	9525.00	9128.00	103297.14	88369.15	21.46%	21.15%	1184	WS
20-FP-AEU-0310	596.17	3913.31	0.50%	40467.00	27829.00	45623.00	30475.00	289213.64	223048.66	24.53%	24.44%	-18462	WS
20-FP-BDU-0300	2.87	3.58	0.23%	94.67	4.01	138.10	27.46	162.12	103.32	6.07%	6.67%	-158	WS

Table 4. Comprehensive table showing all information required by Cal Fire in final deliverable. This includes outputs from FVS, ArcGIS Pro, and FRAP web software and the resulting GHG benefit calculation.