APPENDIX I – NATURAL AND WORKING LANDS TECHNICAL SUPPORT DOCUMENT

This Page Intentionally Left Blank

Contents

Overview

Natural and Working Lands (NWL) make up a large carbon pool within California, and can both emit and sequester carbon. This document provides the technical detail on the methods and data that were used to estimate future carbon stocks, stock changes, emissions, and associated costs and benefits used generate the NWL target set out in the 2022 Scoping Plan Update.

The results of this analysis estimate that NWL in California will be a net source of emissions from 2025-2045. The 2022 Scoping Plan Update includes the most complex modeling ever performed towards deriving carbon targets that simulates the intersection of climate change, wildfire, management, costs, and economic and air quality impacts across NWLs in California. However, as with any projection modeling no matter how complex, limitations exist with this analysis and improvements can be made. Climate actions exist that surely have benefits to California lands' ability to sequester and store carbon that could not be included in this analysis because of lack of data, science, time, and/or resources. However, emissions sources in California's NWL also surely exist that were not included in this analysis. As new science, data, and resources become available, improvements to CARB's NWL projection modeling framework will be made to deepen our understanding of the complex carbon dynamics throughout California.

Additionally, unquantifiable uncertainties certainly exist in ecological modeling in respect to unknown unknowns. That is to say, future events will certainly occur that cannot currently be foreseen that may have a large impact on California's NWL and their ability to sequester and store carbon. However, unforeseen events in landscape ecology rarely have climate benefits.

Target Development Approach

Background

Executive Order N-82-20 directed CARB to update the target for the landscapes in support of carbon neutrality as part of the 2022 Scoping Plan, and take into consideration the priorities established in the NWL Climate Smart Strategy. In 2021, the Governor signed SB 27 (Skinner) [1] into law, which directed CARB to establish carbon dioxide removal targets for 2030 and beyond and take into consideration the priorities of the NWL Climate Smart Strategy. The Governor's Executive Order, and SB 27, add to the previous direction from the legislature and past administrations emphasizing the importance of quantifying land-based carbon both statewide [2, 3] and in programs and policies [4], setting targets for natural and working lands to support the State's climate objectives, and advancing actions [5] on lands to support the health and resiliency of these lands.

Landscapes

The focus of the initial modeling is limited to seven land-types as defined by the Intergovernmental Panel on Climate Change (IPCC) [6] and work will continue to incorporate more sectors into the modeling over time. The initial landscapes included in the modeling for the 2022 Scoping Plan Update are:

- Forests
- Shrublands and chaparral
- Grasslands
- Croplands
- Wetlands
- Developed Lands
- Sparsely Vegetated Lands

To quantify how NWL can contribute to California's carbon neutrality objectives, modeling is necessary to quantify both the emissions and the sequestration rates of lands under climate change, and under novel management strategies. Further, California is a diverse landscape with complex topography, climate gradients, communities, and other environmental and society conditions. This diverse landscape requires that modeling is done to ensure the these differences are reflected in ecosystem response to management under novel climate conditions.

An eighth landscape, blue carbon (carbon captured and held in coastal vegetation, such as seagrasses), is also important to consider as we look at long-term climate goals. However, this landscape is not currently covered by IPCC inventory guidelines or included in California's NWL inventory. California's Ocean Protection Council and San Francisco Estuary Institute are partnering to create a new coastal wetlands, beaches, and watersheds inventory which will provide additional information. CARB staff will utilize information from this effort and assess other available data to evaluate how this landscape may be integrated into our efforts in the future as more data becomes available [7].

Target Setting Approach

A target setting approach was developed that outlines the steps towards identifying a carbon target (Figure 1). This approach begins with identifying the scenario objectives (Figure 2). The objective setting step is especially important for land types that are being assessed with dynamic modeling tools because these ecosystems are highly complex and often respond to management and changing climate conditions in novel ways. Once the objectives are set, management strategies are assigned to land types to meet the climate goals defined in each objective scenario. The effects of these management strategies are modeled to quantify ecological and greenhouse gas (GHG) outcomes.

The results of these modeling efforts are used to inform an economic and health analysis explained in this document. The economic and health analysis, along with the ecological and GHG model results, are then used to help stakeholders, partners, members of the public, and CARB's board determine what the NWL carbon target should be. Policy mechanisms are not identified in this target setting approach.

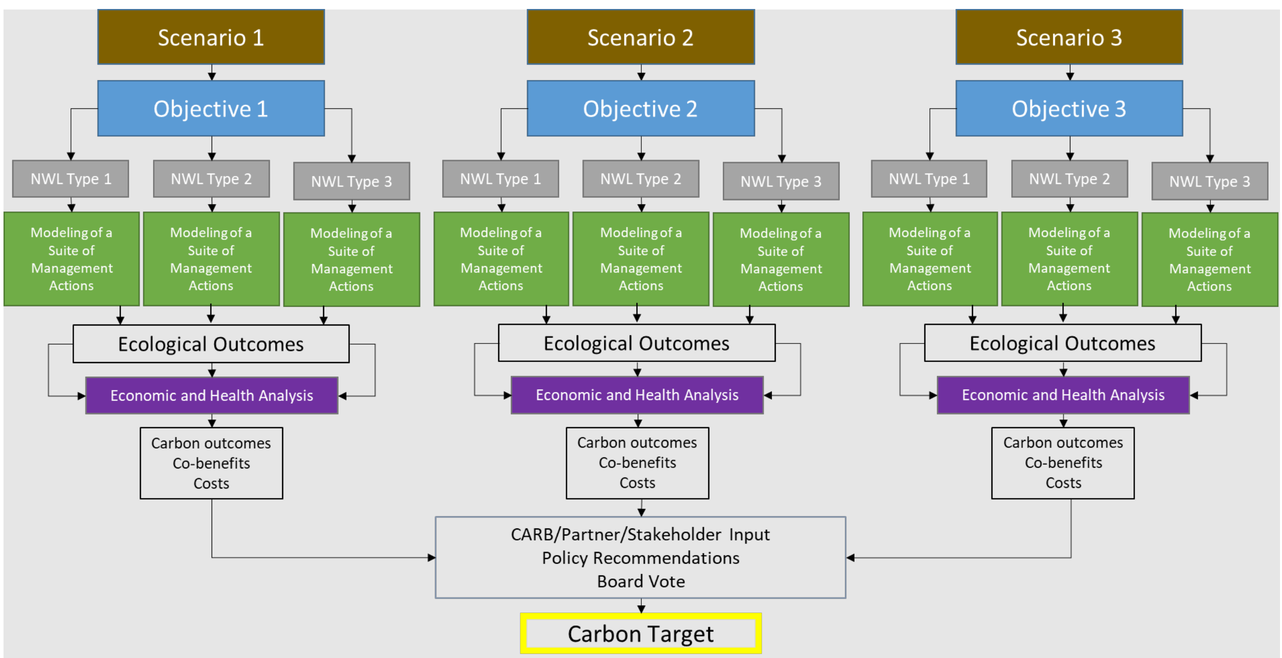

Figure 1: CARB's NWL target setting approach

Policy Objective	Management Strategy	Action	Mechanism Pathway
A jurisdictional goal on future outcomes from the land. This should be the ends that are desired, not how these ends will be met.	An overall approach to on-the-ground land management, including where, when, and what type of actions occur that will meet the objective.	On-the-ground activity that alters the landscape. A management strategy is made of up individual actions.	A portfolio of levers that California can use to elicit desired changes in management strategies (legislation, incentives, regulation, etc).
• Decrease wildfire emissions • Increase carbon stocks • Increase water availability	Within a watershed • Thin 100 acres/3 years • Prescribe burn 400 acres/1 year • Clear cut 80 acres/2 years	• Thinning • Clear cuts • Prescribed burning • Cover cropping • Planting • Etc.	• Ecosystem services markets • Conservation easements • Biomass products and fuels incentives • Subsidies • Etc.
NWL Alternative Scenario: A set of policy objectives, management strategies, and a mechanism pathway			

Figure 2: Definitions used in NWL target setting

In addition to modeling, CARB performed two meta-analyses, or literature syntheses, to document, inventory, understand, and quantify the previous science on future projected carbon stocks in California NWL and how individual actions theoretically can impact both carbon emissions and sequestration rates on a per unit area basis (Figure 3). The literature synthesis was used to compare against modeling outputs, and to inform actions that should be considered within the modeling, or exogenously. The results of these meta-analyses can be found in the Appendix I.1 – NWL Synthesis section at the end of this document.

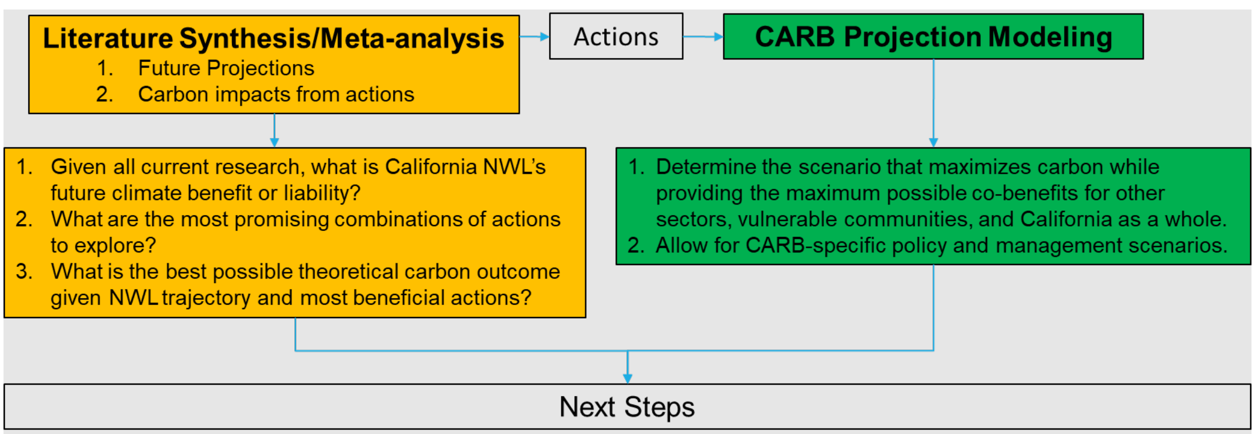

Figure 3: Literature Synthesis and modeling process

Modeling Framework

Climate change is expected to disrupt many ecosystems throughout California [8]. Additionally, land use and management is always changing across all landscapes as climate, society, and the economy change. Further, California is a large state that consists of various ecoregions, and is expected to experience climate change in different ways depending on the region. For these reasons, modeling is an essential tool that can help elucidate the future of carbon and GHG emissions into the future. Modeling management strategies at various levels of climate actions was performed to assess the potential ecological, economic, and air quality outcomes of ecosystems under novel environmental and climate conditions.

To accomplish the task of modeling the effects of various land management strategies on the California landscape into the future, management scenarios were modeled on each land cover types independently (Figure 4). Though every effort should be made to model ecosystems together when they have direct impacts on one another. For this reason, forests, shrublands, and grasslands were modeled together because these systems are intricately intertwined as fire and water travel amongst them.

The primary objective of modeling is to quantify how changes in management strategies, or suite of strategies, effect the carbon stock of the system. Where possible, more ecological outcomes were quantified to provide a more holistic understanding of the suite of benefits provided by the implementation of any one management strategy.

Many ecosystem types exist throughout California (Figure 4). After inventorying all of the various, unique ecosystems that could be modeled, it was then determined how these lands would be modeled, and how many resources could be devoted to developing new models, or utilizing existing models. Priority was given by carbon stock size in land types (Figure 5). Time and staffing are both limitations to how many ecosystems can be modeled, and how complex the modeling can be for a given ecosystem.

This analysis was able to quantify the associated costs and benefits associated with impacts from reduced wildfire emissions as a result of climate action in forests, shrublands, and grasslands. An extensive co-benefit analysis for all NWL land types, and actions was not performed in this analysis. Climate action provides a multitude of co-benefits besides carbon sequestration and storage. However, estimating the myriad co-benefits was restricted by time, resources, and scientific constraints.

Further, an economic analysis was done to estimate the implementation costs of actions and entire alternative scenarios. A macro-economic analysis was also performed to estimate the impact this spending on climate action would have on the gross state product, employment, and person income.

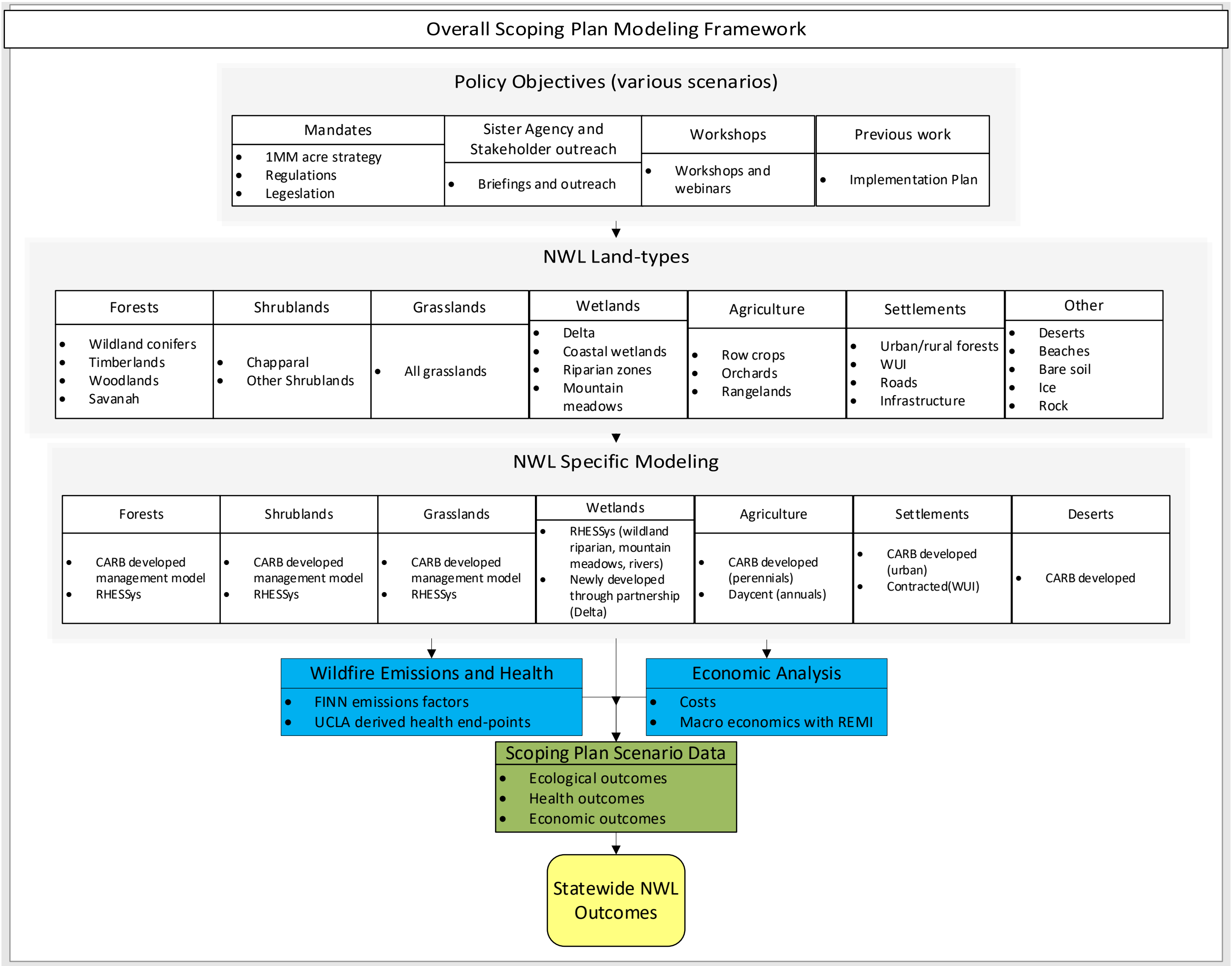

Figure 4: Overall Scoping Plan Modeling Framework

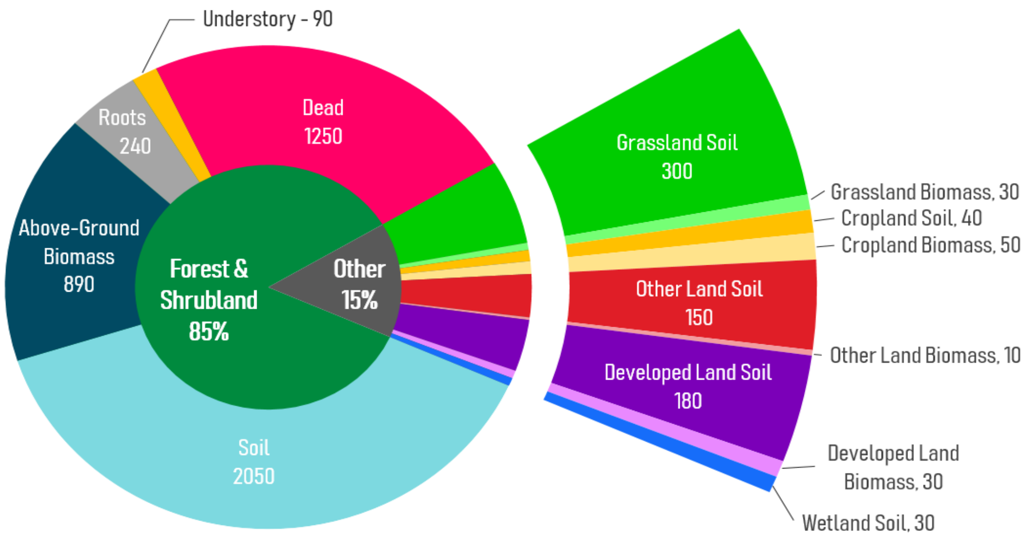

Figure 5: 2014 distribution of biomass and soil carbon stocks on the California landscape in MMT carbon (rounded to the nearest 10 MMT). There is approximately 5,340 MMT of carbon in the carbon pools for the year 2014.

Carbon Pools

The carbon pools that were the focus of the 2022 Scoping Plan Update modeling were those pools that CARB has the scientific tools to model and to monitor. A carbon target must be set using science-based methods, and an ability must exist to track progress towards that target through time as climate action is taken and investments are made. For this reason, not every carbon pool that exists in California, from the top of the tallest tree down to bedrock in the deepest soils and out onto the floor of the ocean was, or could be, included in this assessment.

The modeling and results for this 2022 Scoping Plan Update focused primarily on biomass carbon stocks, as it is this carbon pool that has the most available and reliable empirical data that is taken on regular intervals that can be used for tracking progress and model development. This includes above and below ground, and live and dead carbon pools wherever appropriate and specified. Models exist that can quantify the impact that management has on these pools, and various methods can be used to track this pool on a sufficient time step at a statewide scale, including but not limited to field based plots and remote sensing. Additionally, for forests, the harvested wood products pool was also included.

Soil carbon stocks were included where possible, given modeling and empirical data limitations. In this assessment, soil carbon was included in annual croplands and delta wetlands. However, belowground biomass carbon, litter, and down deadwood carbon was included in every NWL category where possible. Belowground biomass carbon differs from soil carbon in that it includes live and dead roots that have not yet been decomposed to form organic soils. Litter, the carbon sitting on the soil in leaves and small wood pieces, is also considered a separate pool and is tracked in the forests, shrublands, and grasslands land types.

The top 30 cm of the soil is the focus of all NWL soil estimates. This is done for several reasons. First, soil inventories, consisting of empirical data, typically only quantify the first 30cm to 1m. CARB does not collect soils data, but instead relies upon the data collected by other agencies that have jurisdiction to collect such data and extrapolate it to a statewide scale. Second, soil carbon below 30cm rarely changes at a rate fast enough for inventories to detect a change [9]. Finally, best practices from the IPCC on soil carbon direct that the 30cm be the focus of inventories and assessments of climate benefits [10].

It is known, however, that changes in soil organic carbon below 30cm can affect the overall net GHG dynamics of climate action leading to greater source or sink estimates [11]. For such information to be included in any target setting process, statewide soils inventories would need to begin to collect samples at ever deeper depths. IPCC guidance also dictate that carbon stocks in soils should take into account the top 30cm and not include inorganic carbon [10]. Further, quantifying the impact that California's climate action is having on soil carbon is already a difficult task at a 30cm depth, and becomes nearly impossible at depths deeper than 1m as data becomes limited. This is again because tracking progress in these pools requires empirical data, or some proxy, to measure the carbon in these soils[1] at regular intervals sufficient for statewide analysis. Again, CARB is reliant of other organizations' empirical data and scientific expertise to develop modeling and monitoring programs.

Inorganic carbon is carbon that is typically in a mineral form, and not derived biogenically. In California, much of this inorganic carbon is in calcium carbonate and can be found all throughout the state, but is most prevalent in California's desert ecosystems. Inorganic carbon was also not included in the 2022 Scoping Plan Update modeling or target setting due to a lack of empirical data sufficient to track progress, and the lack of available tools to simulate these pools into the future on a statewide scale taking into account management action. No spatially and temporally explicit dataset exists that quantifies inorganic carbon statewide, which is a requisite to at least develop a baseline. Further, it is unclear exactly how changes in management would affect these pools, which is needed for the purposes of modeling. For statewide carbon target setting, models must be scalable and be able to quantify how management can affect carbon, and these models do not yet exist that include inorganic carbon.

Modeling criteria

The amount of models that exist to project future carbon varies depending on land type. Forests, for example, have many models that can be used to assess carbon on various scales. Coastal wetlands, however, do not currently have any models that can simulate future projected carbon stock change on the statewide scale under climate change and given different management strategies and disturbances. Criteria was developed to help guide the

[1] Taking soil samples on a statewide scale sufficient for a regular inventory is a very resource intensive task

decision on which models should be used for each land cover type. In some cases, where no models existed, new models were developed.

Modeling basics

Ecological models exist largely in two forms: statistical (also called empirical) models, and process-based (also called mechanistic) models.

Statistical models are driven by the empirical (data) relationships between observations. In these models, projections are purely based on patterns that are evident from previous observations. For example, if in the historical data trees have always increased growth rates with increasing temperatures, then in the future as temperature increases so too will tree growth rates. These models may include basic feedbacks between climate and vegetation, but these feedbacks are, again, purely data driven and are more easily implemented and can run quickly.

Process-based models simulate the way in which an ecological system reacts to external forces, like climate and human intervention. In these models, physiological and ecological processes simulated based on the underlying chemistry, physics, and biology of the system. The dynamics that result from these models are not limited by historical data, like empirical models. In this way, conditions that have never been seen in the historical record, like climate change, can more accurately be modeled. For example, if temperatures rise, then this will change the photosynthetic capacity and water use efficiency of a tree so growth rates will depend on the amount of water available and the physiology of the tree. This will lead to threshold events where tree growth rates rise with increasing temperature until some point where growth rates start to become negatively impacted by ever increasing temperatures. These models are designed to capture the interaction between all physiological, ecological, and environmental processes and cycles. Process-based models require specialized knowledge to setup and implement, and are difficult to operate. Because California is heading into an uncertain future, where even recent events lack precedence in the historical record, process-based models were preferred whenever possible.

Process-based models used in California and selection criteria

Many process-based models exist that are designed to simulate various types of NWLs. Several of these models have been used or are currently being developed for use in California. These models include: Regional Hydro-Ecological Simulation System (RHESSys), Landis-ii, the Functionally-Assembled Terrestrial Ecosystem Simulator (FATES), DayCent, BiomeBGC, and many others.

A criteria was developed to help guide model selection. These criteria are:

- **The model should be able to simulate various ecosystems if possible.** To fully capture interactions between climate, vegetation, and management and the cumulative effect these factors on the ecosystem services important to the State of California (water, fire risk, wildlife habitat, etc.), it is beneficial to use one model to simulate all NWL cover types (forests, rangelands, agriculture, etc.).

- **The model should have dynamic fire vegetation dynamics.** The State of California has very ambitious fuels reduction goals and the model must capture the effect this will have on both fire and vegetation. Additionally, the model must be able to predict the impact fire will have on the growth and composition of plant communities.
- **The model should have hydrology.** The majority of California's ecosystems are water limited. This means that any change to water availability will have large impacts on California's NWL future. The model must be able to estimate how water travels through space, otherwise we cannot capture the impact that actions will have on water supply and downstream/slope vegetation.
- **The model should have dynamic mortality.** California experiences massive vegetation mortality events, in both our forests and rangelands, as a result of physiological stress caused by drought and pathogens. The process through which vegetation dies is highly complex and if this process is not adequately captured, then recommendations from the model will be spurious.
- **The model should be scalable.** Some models are designed to simulate every tree within a landscape. These models cannot be scaled to statewide simulations because of data and computing resource limitations.
- **The model should have an existing user-base.** People should be currently using this model. This ensures that the model should include the latest science, that there is a sufficient amount of scientists that can assist with modeling, and that students are graduating with knowledge of this model for future development.
- **The model should be open source if possible,** to allow CARB control of source code for future model development and implementation work.
- **The model should be mature.** Maturity in a model ensures that many of the interval errors, and inconsistencies within the model have been corrected. Additionally, maturity ensures that this model has been vetted by the scientific community and proven valuable for making scientific inferences.

These criteria were then used to help assess the known models for the various NWL land types (Table 1). The criteria, the ability to practically apply a model given the 2022 Scoping Plan Update time frame, the specific questions of the SP, and resource availability were then the determining factors to which models were selected. In some cases, no model known to CARB was available that would address all of the 2022 Scoping Plan Update needs, and in these cases, new models were developed, but this was avoided whenever possible (Table 2).

Table 1: Example of how the modeling criteria was used to assess several potential models for forest, shrubland, and grassland modeling.

Model	Various Ecosystems	Dynamic fire	Hydrology	Dynamic mortality	Scalable	User-base	Open Source	Maturity
RHESSys	Yes	Yes	Yes	Yes	Yes	Medium	Yes	High
Landis-ii	Yes	Yes	No	No	Yes	High	Yes	Medium
FATES	Yes	Yes	No	Yes	Yes	Very low	Yes	Very low
LUCAS	Yes	No	No	No	Yes	Low	No	Medium
CALAND	Yes	No	No	No	Yes	Low	Yes	Low

Model selection for forests, shrublands, and grasslands

It was determined that shrublands and grasslands should be modeled within the same system as forests because these systems lie on a gradient and highly influence one another. Further, simulating changes in statewide wildfire and drought was a priority, and fire and water move amongst these systems.

RHESSys was ultimately chosen to assess forests, shrublands, and grasslands (Table 2). This model was developed at UC Santa Barbara and has a long history of modeling the effects of climate change on vegetation and fulfills the technical criteria.

Model selection for wetlands

The Sacramento-San Joaquin Delta is a highly complex ecosystem, consisting mostly of agricultural lands, brackish tidal wetlands, seasonally drained wetlands, and natural fresh-water wetlands. The diversity of land types within this one ecosystem makes modeling the Delta's ecosystem carbon stocks difficult. SUBCALC [12] is a process-based model designed specifically for the Delta. Previously completed SUBCALC simulations, along with flux tower results from literature were used to assess the emissions and sequestration rates for various systems within the Delta.

Wetlands, such as riparian zones and mountain meadows, are implicitly covered by the forest, shrubland, and grassland modeling. However, other wetlands (e.g. coastal wetlands) in California were not included the 2022 Scoping Plan Update modeling, because either the science, data, and/or modeling is not available that is requisite to track carbon stocks and fluxes through time in response to management and climate change, and to model these systems into the future under novel conditions.

Model selection for developed lands

Developed lands were split into urban, and wildland-urban interface lands (WUI). This separation allows for two separate objectives for each of these two different developed lands. In urban lands, it is desirable to increase urban forest carbon, not only for the carbon benefits, but because of all of the co-benefits that these forests produce. Within WUI, however, it is desirable to decrease forest carbon to increase the defensible space around structures to protect these communities from catastrophic wildfire.

A model was newly developed for urban forest carbon. This is because only one model has been currently developed for large-scale assessments and scenario analysis [13]. This model however, was discovered to have a bias towards growth, caused by the compounding nature of its carbon stock change algorithm. Changing this algorithm was not an option as it would require a complete overhaul of the script. It was decided, instead, to develop a California specific model, consistent with the NWL inventory, and which can be improved with time to address California's specific needs.

WUI carbon, is of particular interest in California given the recent rise in catastrophic wildfires. In these lands, California has an existing regulation that mandates all structures to be compliant with defensible space guidelines [14]. To assess how this regulation would impact carbon in these lands, no model existed, and so new modeling was conducted utilizing the latest in remote sensing derived data products, and CARB's NWL inventory methodology.

Model selection for croplands

Various models exist to simulate croplands on different scales. Croplands, unlike natural lands, are extensively managed and management practices are highly dependent on market forces. Croplands were broken up into annual and perennial croplands, as these two types of cropping systems change the ecosystem dynamics into two distinct system types. For annual croplands, two models are currently used by CARB, DNDC, and Daycent. DNDC, or Denitrification-Decomposition [15], is a process-based model that is currently used to assess nitrogen emissions from croplands. Daycent [16], has been used within California to develop the comet-farm and comet-planner tools that are used within CARB's Climate Change Investments program. Daycent is also used within the US EPA's national carbon inventory program. Both models include various dynamics that are important for assessing various aspects of cropping systems. Ultimately, Daycent was chosen to assess annual croplands because it is already designed, parameterized, and setup to assess these lands on large-scales using different management systems under climate change. Daycent is widely used, has available executables that can be utilized within custom programs, and assesses carbon, nitrogen, and water dynamics.

Perennial crops, however, did not have any large-scale models available to CARB that can practically be used to assess carbon stock dynamics given different rates of perennial land expansion, climate change, and management. This lack of current modeling ability for these systems required CARB to design a new model internally. DNDC, is a process-based model that is currently used by CARB for multiple agricultural related purposes as previously explained. This model however, could not be used for this assessment because of processing limitations and resource constraints. With time, process-based models could potentially also be used for future projections in perennial croplands.

Model selection for sparsely vegetated lands

Sparsely vegetated lands, by definition, exist on the extreme edge of where vegetation can exist. Though process-based models can be used to simulate vegetation in specific locations, it is extremely difficult to parameterize these models for entire desert landscapes. Because of this known challenge and resource constraints, an empirical modeling approach focused on land use change was used. To assess carbon in sparsely vegetated lands, a combination of existing carbon stocks from CARB's NWL inventory and land use change modeling from LUCAS was used.

Table 2: Natural and Working Land sub-categories and the models that are used to assess them.

NWL Category	NWL Sub-Category	Model
Forest and Other Natural Lands	Forests	RHESSys
Forest and Other Natural Lands	Shrublands	RHESSys
Forest and Other Natural Lands	Grasslands	RHESSys
Wetlands	Sacramento-San Joaquin Delta	SUBCALC/Literature
Developed Lands	Urban Forests	CARB Urban Forest Carbon Model
Developed Lands	Wildland Urban Interface	California Forest Observatory/CARB NWL Inventory
Croplands	Annual Croplands	Daycent/LUCAS/Literature
Croplands	Perrenial Croplands	CARB Orchard Carbon Model/LUCAS
Sparsely Vegetated Lands	Deserts	CARB NWL Inventory/LUCAS

Alternative Scenario Development

Background

Alternative scenarios are used to assess how different levels of climate action influences the carbon stock outcomes on NWL. As described in the Target Development Approach section, scenarios consist of suites of actions that make up an overall management strategy. These management strategies are developed to fulfill the objectives set for each scenario.

Two types of scenario objectives exist, outcome-oriented objectives and action-oriented objectives. An outcome-oriented objective establishes desired outcomes from a scenario. Once the objective is established, then management strategies are designed to achieve the desired outcome. This strategy does not guarantee the desired outcome stated in the objective, but rather provides guidance for the design of the management strategy within this scenario. After modeling has quantified the impacts of the set management strategy, it may occur that the set management strategy did not result in the desired outcomes. This especially can happen as modeling becomes more complex that can capture novel responses in a system to novel conditions. This type of objective provides flexibility for management strategy design without constraint.

An action-oriented objective, however, states the management strategy within the objective, but the outcome that results from this management is not defined. In this case, the objective might be to treat 1 million acres of forests and other natural lands with fuels reduction treatments. This objective does not stipulate the desired outcome that is needed to fulfill this objective. This type of scenario is easier to design as it does not leave the management strategies open ended. Both of these types of objectives were used within the Scoping Plan.

Scenario Development

CARB staff solicited feedback from topical experts, affected stakeholders, and members of the AB 32 Environmental Justice Advisory Committee (EJ Advisory Committee) for both the NWL modeling. As part of the NWL modeling scenario development process, CARB staff hosted a public workshop in July to present the modeling and target setting approach. CARB staff published the set of draft scenarios for NWLs on December 2, 2021 and also held a workshop on December 2, 2021 to present and discuss the alternative scenarios. CARB staff solicited written feedback on the NWL scenarios and received 91 comments on the scenarios. CARB staff also met with members of the EJ Advisory in December and January to discuss the alternative scenarios. In addition to this public process, CARB staff continued to consult with staff at other state agencies to ensure the scenarios are informed by existing and emerging natural working lands efforts. After the release of the Draft Scoping Plan on May 10, 2022, CARB staff received 980 written comments, 141 oral comments at the June Board Hearing, and 219 Environmental Justice Advisory Committee draft comments followed by 245 final comments. Leading up the June Board Hearing, there were 21 Environmental Justice Advisory Committee meetings, 15 public workshops, and 2 tribal focused workshops.

After the June Board Hearing, there were four public listening sessions, 1 tribal listening session, and 8 tribal consultations. On July 22, 2022, Governor Newsom sent a letter to the chair of the Air Resources Board to adjust the Scoping Plan Scenario. For NWL, this would include increasing ambition so that in conjunction with carbon capture and storage, and direct air capture, the state would remove 20 MMT carbon in 2030 and 100 MMT carbon by 2045. Finally, in August 2022, several bills were passed and some of these bills affect NWL, such as AB 2551 that sets a 10% increase in urban tree canopy cover by 2035 target.

Revisions to the scenario assumptions made by CARB staff were adjusted in response to public and agency feedback. The four alternative scenarios identified in Table 3 were designed to explore the potential impacts of different levels of NWL management actions associated with each scenario. Not listed is the business-as-usual scenario, which is a scenario where no change to management occurs in the face of future climate change.

Table 3: Scenario objectives.

Scenario	Objective
1	Prioritize maximizing short-term carbon stocks, minimize disturbances
2	Prioritize implementation of climate smart land management strategies in current commitments/plans
3	Prioritize restoration and climate resilient carbon stocks
4	Prioritize forest wildfire reduction and other fuel reduction efforts

Within the Business-As-Usual (BAU) scenario the same rate of land management activities that occurred between 2001-2014 was modeled into the future. The management and land use practices that occur within Business-as-Usual scenario are derived from empirical data that can best be used to quantify how each NWL land type was managed during this 2001-2014 period. For forests, shrublands/chaparral, and grasslands, BAU constitutes approximately 250,000 of annual statewide treatments (see section Forest, Shrubland, and Grasslands Modeling - Business-As-Usual Management Quantification). For croplands, BAU represents no healthy soil practices because during this period the healthy soil program did not yet exist. Where land use was considered, BAU rates of land conversion were also taken from empirical data and modeled into the future. For more detailed information on land-type specific BAU scenarios, see the modeling sections for those land-types.

Table 4: NWL type descriptions for each alternative scenario.

NWL Type	1 – Prioritize short-term carbon stocks, minimize disturbances.	2 – Prioritize implementation of strategies in current commitments/plans	3 – Prioritize restoration and climate resilient carbon stocks	4 – Prioritize forest wildfire reduction and other fuel reduction efforts
Forests	No forest management. No land conversion of forests, shrublands/chaparral, or grasslands. Maintain fire suppression at current levels.	Implement 1M acre strategy, 30x30 strategy, NWL Implementation Plan, among other State commitments. ~1 million acres treated Statewide annually in forests, shrublands/chaparral, and grasslands, comprised of regionally specific management strategies that includes prescribed fire, thinning, harvesting, and other management actions. No land conversion of forests, shrublands/chaparral, or grasslands.	Decrease fire severity and create more climate resilient carbon stocks by 2045. 2-2.5 million acres treated Statewide annually in forests, shrublands/chaparral, and grasslands, comprised of regionally specific management strategies that includes prescribed fire, thinning, harvesting, and other management actions. No land conversion of forests, shrublands/chaparral, or grasslands.	Decrease wildfire emissions, wildfire around communities, and fire sizes. 5-5.5 million acres treated Statewide annually in forests, shrublands/chaparral, and grasslands, comprised of regionally specific management strategies that includes prescribed fire, thinning, harvesting, and other management actions. This rate matches the historical rate of disturbance Statewide. No land conversion of forests, shrublands/chaparral, or grasslands.
Shrublands/Chaparral	No shrubland management. No land conversion of forests, shrublands/chaparral, or grasslands. Maintain fire suppression at current levels.	The ~1 million acres treated includes management of shrublands and chaparral to reduce fuels surrounding communities using mechanical treatments appropriate for shrublands and chaparral. Limited prescribed burning in chaparral. No land conversion of forests, shrublands/chaparral, or grasslands.	The 2-2.5 million acres treated includes regionally specific increased management of shrubland and chaparral to reduce fuels surrounding communities using mechanical treatments appropriate for shrublands and chaparral. Limited prescribed burning in chaparral. No land conversion of forests, shrublands/chaparral, or grasslands.	The 5-5.5 million acres treated includes regionally specific increased management of shrubland and chaparral to reduce fuels surrounding structures using mechanical treatments appropriate for shrublands and chaparral. Limited prescribed burning in chaparral. No land conversion of forests, shrublands/chaparral, or grasslands.
Grasslands	No grassland management that would remove above ground carbon. No land conversion of forests, shrublands/chaparral, or grasslands. Maintain fire suppression at current levels.	The ~1 million acres treated includes management of grasslands to reduce fuels surrounding communities using management strategies appropriate for grasslands. No land conversion of forests, shrublands/chaparral, or grasslands.	The 2-2.5 million acres treated includes increased management of grasslands interspersed in forests to reduce fuels surrounding communities using management strategies appropriate for grasslands. No land conversion of forests, shrublands/chaparral, or grasslands.	The 5-5.5 million acres treated includes increased management of grasslands interspersed in forests to reduce fuels surrounding structures using management strategies appropriate for grasslands. No land conversion of forests, shrublands/chaparral, or grasslands.

NWL Type	1 – Prioritize short-term carbon stocks, minimize disturbances.	2 – Prioritize implementation of strategies in current commitments/plans	3 – Prioritize restoration and climate resilient carbon stocks	4 – Prioritize forest wildfire reduction and other fuel reduction efforts
Croplands	Maximize climate smart ag practices for annual and perennial crops at upper bounds of topography, water, and agronomic constraints for carbon – ~ 100,000 acres annually. Only model land conversion away from ag resulting from SGMA, maximize annual crop ag land easements/conservation – ~ 11,000 acres annually. Maximize organic agriculture to feasible extent (30% of all cultivated acres in organic ag by 2045, or ~ 130,000 acres annually).	Implement climate smart practices for annual and perennial crops on ~80,000 acres annually. Land easements/conservation on annual crops at ~8,000 acres annually. Increase organic agriculture to 25% of all cultivated acres by 2045 (~97,000 acres annually).	Implement climate smart practices for annual and perennial crops on ~50,000 acres annually. Land easements/conservation on annual crops at ~6,000 acres annually. Increase organic agriculture to 20% of all cultivated acres by 2045 (~65,000 acres annually).	Implement climate smart practices for annual and perennial crops on ~25,000 acres annually. Land easements/conservation on annual crops at ~3,000 acres annually. Increase organic agriculture to 15% of all cultivated acres by 2045 (~32,000 acres annually).
Developed Lands	Maximize tree cover at upper bounds of biological and physical constraints – investment in tree maintenance and planting increase by 2000% over current levels, and tree watering is 1000% less sensitive to drought. Establish defensible space that accounts for property boundaries.	Investment increase of 200% above current levels and tree watering is 200% less sensitive to drought. Establish defensible space that accounts for property boundaries.	Investment increase of 20% above current levels and tree watering is 30% less sensitive to drought. Establish defensible space that accounts for property boundaries.	Investment increase of 2% above current levels and tree watering is 10% less sensitive to drought. Establish defensible space regardless of property boundaries.
Wetlands	Restore delta wetlands at the upper bounds of biological and feasibility constraints – 120,000 acres.	Restore 18,000 acres of delta wetlands, in line with existing State commitments and plans.	Restore 60,000 acres of delta wetlands.	Restore 18,000 acres of delta wetlands, in line with existing State commitments and plans. Same as alt 2
Sparsely Vegetated Lands	No land conversion.	Land conversion at 25% of BAU land conversion rate.	Land conversion at 50% of BAU land conversion rate.	Land conversion at 75% of BAU land conversion rate.

Scoping Plan Scenario

The Scoping Plan Scenario is a mix of the alternative scenarios. For all NWL sectors, except annual agriculture and developed lands, the Scoping Plan Scenario is aligned with alternative scenario 3. For annual agriculture, the Scoping Plan Scenario is aligned with alternative scenario 2, except for the organic agriculture transition and easements, which are aligned with scenario 3 (Table 5). Developed lands in the Scoping Plan Scenario is aligned with alternative scenario 2. The final 2022 Scoping Plan scenario includes all of these changes and the existing level of action for other NWL sectors (Table 6).

Table 5: Action level in acres or funding that changed between draft and final Scoping Plan scenarios.

Action	Previously Proposed Scenario (50K acres)	Updated Scoping Plan Scenario (80K acres)
Cover cropping (legumes)	6411	9617
Cover cropping (non-legumes)	6411	9617
No Till	3589	5383
Reduced Till	9220	13830
Compost Amendment	26761	40142
Establishing Riparian Forest Buffers	38	56
Alley Cropping	11	17
Establishing Windbreaks/Shelterbelts	12	17
Establishing Tree and Shrubs in Croplands	8	12
Establishing Hedgerows	44	65
Urban Forestry Investment Increase (% of Reference Funding)	20	200

Table 6: Level of action in final 2022 Scoping Plan scenario.

Action	Level of Action
Forest, shrubland, and grassland fuel reduction and restoration (acres/year)	2,300,000
Regenerative agriculture and cropland conservation above BAU (acres/year)	150,000
Urban Forest investment increase above current investment (annual % increase)	200%
Defensible space establishment in wildland urban interface (properties/year)	50,000
Delta wetland restoration (total acres by 2045)	60,000
Desert Conservation above current conservation (acres/year)	15,000

Forests, Shrublands, Chaparral, and Grasslands

Forests, shrublands, and grasslands are modeled together, and because of this, their management strategies are inseparable. The total acreages that are applied statewide follow defined rules for application based on the land type (Table 7). Only certain types of management can occur on forests, shrublands, or grasslands. For example, forests can experience any of our seven management actions, while grasslands can only experience biological, chemical, or herbicide treatments, and prescribed burning. As acreages change statewide, only the land type appropriate management actions occur on any of these three land types. An additional assumption is that riparian zones do not receive any management to maximize restoration for all scenarios. Streams within the modeled watershed are identified through topography, and a user-defined buffer around each creek is applied that defines the riparian zone. The buffer used for all scenarios is 90 meters, which is the smallest unit of measure in the 2022 Scoping Plan Update modeling (see the Forest, Shrubland, and Grasslands Modeling section for more detail).

Table 7: Management actions that can occur on forests, shrublands, or grasslands. This is a user-defined assumption within the management model. This assumption is consistent statewide, and across scenarios. bioChemHer is biological, chemical, or herbicide treatments.

NWL Type	Treatments that can occur in this NWL type
Forests	bioChemHer, clear cut, harvesting, mastication, other mechanical, prescribed burning, thinning
Shrublands	bioChemHer, mastication, other mechanical, prescribed burning
Grasslands	bioChemHer, prescribed burning

Further, only certain management actions are desirable in particular regions throughout the state, in this analysis called ecounits (see the Ecological Unit Development section for more details). The primary objective of all alternative scenarios is to maintain carbon stocks while maintaining or enhancing ecosystem and public health. For this reason, treatments to reduce fuels and stand density are the only treatment types that increase with scenarios. Clear cuts do not increase with any scenario. The treatments that are applied to fulfill scenario objectives are not the same for every ecounit (Table 8). Regional treatment types and acreages were derived through a combination of BAU management, historical fire return intervals, stakeholder and partner outreach, and scientific inference.

Within an ecounit, modeling was conducted at the watershed level. BAU management acres on the watershed scale (as defined in the Business-As-Usual Management Quantification section) are the basis off which alternative management is adjusted. The ratio of fuel and stand density reduction treatment types that occur in the BAU for every ecounit/ownership combination is kept constant with alternative scenarios. Additionally, watersheds that did not experience any management, regardless of ownership, within from 2001-2014, was identified as a no-management ownership. These no-management watersheds never receive any treatments in any of our scenarios, including the BAU scenario. It was not determined why treatments did not occur in these watersheds, but it was assumed that future treatment could also not occur in these watersheds.

Table 8: Management actions that are adjusted for scenarios 2, 3, and 4. In scenario 1, all actions are set to zero, and do not occur.

Ecounit	Treatments that are adjust for scenarios
C. Coastal Evergreen Forest	bioChemHer, mastication, mechanical, prescribed burning, thinning
C. Coastal Wood/Shrublands/Grasslands	bioChemHer, mastication, prescribed burning, thinning
Dry Sierra	bioChemHer, harvesting, mastication, mechanical, prescribed burning, thinning
Great-basin rangelands	bioChemHer, mastication, mechanical, prescribed burning
Humid Sierra	bioChemHer, mastication, mechanical, prescribed burning, thinning
Klamath	bioChemHer, harvesting, mastication, mechanical, prescribed burning, thinning
N.Coastal Wood/Shrublands	bioChemHer, mastication, prescribed burning, thinning
N.Sierra/S.Cascades	bioChemHer, harvesting, mastication, mechanical, prescribed burning, thinning
N/Central Coastal Forest	bioChemHer, mastication, mechanical, prescribed burning, thinning
S. Dry Chaparral	mechanical
S. Humid Chaparral	mechanical
Sierra Foothills	bioChemHer, mastication, mechanical, prescribed burning, thinning

Defining scenarios

Scenario 1

The objective of scenario 1 is to prioritize maximizing short-term carbon stocks. Short-term is explicitly stated to signify that maximizing carbon stocks by the 2022 Scoping Plan Update target year of 2045 is the priority. To preserve the maximum amount of carbon on the landscape by the 2045 carbon neutrality target year the management strategy was to avoid cutting or intentionally burning any lands. This is because, even though fires do release carbon on larger areas, forest management can release more carbon per unit area than fires. For this reason, the management strategy for scenario 1 was to remove all management on all forests, shrublands, and grasslands to conserve carbon stocks by 2045. As with any outcome-oriented objective, management strategies do not guarantee the desired outcome, and it turns out that when this management strategy is input into a highly dynamic model, such as RHESSys, on landscape scales, the outcomes were not fulfilled. This, indeed, demonstrates the need for complex ecological modeling when making long-term, large-scale planning decisions, as novel conditions can produce unexpected outcomes. It should be noted that this occurs because fire behavior, intensity, size, and the carbon that is lost due to fire in this modeling is not pre-specified, but is dynamic within the model and is not bound by previously produced data, such as LANDFIRE-based emissions estimates.

Scenario 2

The objective of scenario 2 is to implement current commitments and plans. For forests, shrublands, and grasslands, the plan that is used as the basis for this scenario is the 1 million acre strategy as outlined by the shared stewardship agreement between the State of California and the United States Forest Service [17]. This agreement specifies that the increase in management should comprise of sustainable vegetation treatments, including thinning in excessively dense stands, timber harvesting, mechanical fuel reduction, prescribed fire, grazing, and reforestation. These treatments should reduce wildfire impacts and restore healthy, resilient forests and rangelands. The lack of specificity of where certain types of treatments should occur and at which intensities, allows for expert opinion to define these details for modeling of this scenario. To increase acres, the BAU management quantification that defined the current land management disaggregated by ecounit and ownership is used as a basis (see the Business-As-Usual Management Quantification section). Utilizing these the BAU acres of management, and the rules that define the management actions for land types and ecounits (Table 7, Table 8), annual treatment acres are increased to 1 million (Table 9). In addition to taking the BAU management into consideration when designing management strategies, even more scientific inference is used to adjust ecounits and ownerships differently (see Scenario 4 for more details). This is also true for scenario 3.

Scoping Plan Scenario (Scenario 3)

Scenario 3 is an outcome-oriented objective and so allows for interpretation of the management strategy that can best be used to fulfill the objective. This scenario was designed with scenario 2 and scenario 4 in mind. As will be described, scenario 4 is designed to reduce fire emissions above all over considerations. Scenario 2 fulfills current commitments, but it may be that 1 million acres of treatment may not be sufficient to fully restore forest and rangeland health statewide. For this reason, scenario 3 was designed to execute a level of management between scenario 2 and 4. Just like scenario 2, management is increased relative to BAU management (Table 9). This scenario results in approximately 2.3 million acres of treatments annually. In all of the scenarios, the absolute amount of acres varies, and the acres in the scenario description is the average annual acres after management modeling is complete.

Scenario 4

Scenario 4 is an outcome-oriented objective and required the most scientific inference of the scenarios to design its management strategy. To design this management strategy, it was assumed that the State has no tolerance for unmitigated wildfire. If the state has no tolerance for unmitigated wildfire, then management must fulfill the role of wildfire in generating the annual amount of disturbance to keep fuels low, and maintain ecosystem structure and function. This leads to the question, how much management is needed to completely replace disturbance generated by wildfires?

To answer this question, a statewide estimate of fire return intervals are needed that would occur given no fire exclusion. Essentially, an estimate is needed of the annual acres of unmitigated wildfire given no prevention or suppression. LANDFIRE is a data product produced by the Nature Conservancy in partnership with the U.S. Forest Service [18]. This dataset contains a spatially explicit dataset of historical fire return intervals that relate to approximately the 1800-1900s. This time-period pre-dates the era of fire suppression in the western United States, though it does already include the era of fire exclusion from cultural burning. As this is the only scientifically published spatially explicit data set of historical wildfire intervals, this data was used to identify an amount of fire that would be needed given no fire suppression. This map was used within the ecoregions and ownerships throughout California to generate an estimate of the amount of acreage that would be needed to complete supplant the acres disturbed by wildfire (Table 9). Management beyond this amount would be considered disturbance above the sustainable level. Utilizing this maximum amount of treatment acres, the treatment types that were identified for each ecounit/ownership combination as fuels reduction treatments (Table 8) were increased to meet the acres needed to meet the historical fire return interval. The acres for each treatment type were increased proportionally to the BAU acres while adhering to the management modeling rules.

In the end, the acres of each treatment type that results for scenario 2, Scoping Plan Scenario, and 4 are derived through a multi-step process:

1) Determine how many acres of disturbance would result if no fire suppression or exclusion existed for every ecounit/ownership combination. This resulted in about 5M acres/year.
2) Develop rules about what types of management actions will occur in ecounits and on which land types.
3) Scale these acreages from the BAU acreages to fit within a statewide 1M, 2.5M, and 5M acre strategy.
4) Create a new management model that will utilize the rules identified to derive management maps.
5) Parameterize new management model to result statewide management strategies that fulfill the target acreages for each scenario.

Table 9: Average annual treatment acres by scenario. See the 2022 Scoping Plan-NWL-Data spreadsheet for detailed information on the explicit combinations of ecounit/ownership/treatment type.

Ecounit/Ownership/Treatment Type	BAU	Scenario 1	Scenario 2	Scoping Plan Scenario	Scenario 4
Central Coastal Evergreen Forest	20560	0	140929	412895	972711
Central Coastal Wood, Shrub, and Grasslands	22200	0	174037	268883	481070
Dry Sierra	159918	0	807202	1861061	3558209
Great Basin Rangelands	4075	0	39553	64550	157157
Humid Sierra	151190	0	287335	500320	1333503
Klamath	130077	0	758632	2313314	5259691
North-Central Coastal Forest	93121	0	191189	292097	483834
Northern Coastal Wood and Shrublands	12865	0	53225	136420	359085
Northern Sierra Southern Cascades	82757	0	228642	371722	756551
Sierra Foothills	34916	0	180368	538091	1574298
Southern Dry Chaparral	11713	0	34459	71530	165775
Southern Humid Chaparral	20951	0	104694	199678	454221
County	2	0	498	2401	5933
Federal	136685	0	521773	1523622	3626181
Forest Industry	51678	0	79083	140988	291293
Private Land	43329	0	196053	393949	909613
Reservation or Rancheria	14840	0	146208	157976	179322
Special District	643	0	18026	27174	30475
State	938	0	38448	97411	142553
bioChemHer	891	0	13664	39253	119002
clearcut	25308	0	21362	24652	19802
harvesting	61345	0	117107	283724	606892
mastication	14167	0	90286	197041	379493
otherMechanical	38577	0	264975	756240	1736904
rxBurning	37235	0	300794	507457	1093877
thinning	70592	0	191901	535155	1229399
Statewide Total	248114	0	1000089	2343521	5185368

Croplands

The actions identified as climate actions for croplands were the existing health soils practices, easements to conserve croplands, and transitioning to organic agriculture. However, the ability to model agricultural climate actions is currently limited, and not all healthy soils practices (HSP) could be assessed on all croplands (Table 10). The practices modeled are defined non-spatially for each scenario. Business-as-usual is assumed to have no climate action as our baseline time period is before the widespread implementation of California Climate Investments.

Defining Scenarios

Scenario 1

To maximize carbon stocks by 2045, the maximum amount of HSP, easements, and acres that transition to organic are applied. The maximum amount of acres of HSP were determined by the California Department of Food and Agriculture and constitute a 10x increase in HSP compared to 2021 acres (Table 10). No conversion is allowed away from croplands, however, conversion from annual to perennial is still allowed, and easements do not affect this conversion as the land is still used as cropland. Thirty percent of annual croplands become organic by 2045.

In terms of easements, the maximum amount of easements used in scenario 1 were derived using the results of the 4th Annual California Climate Assessment land use change modeling. This modeling results in an average conversion of annual croplands away from agriculture at 11,120 acres/year. The average annual easements currently awarded for irrigated lands are 2,735 acres. Rangelands receive the vast majority of easements from the Department of Conservation at 11,748 acres annually. Rangelands, however, are considered in our forest, shrublands, and grasslands modeling, and does not include land use change, therefore, rangelands are 100% conserved in all of our scenarios. The easements used if scenario 1 for annual croplands constitutes a 4x increase in the current level of easements.

Scenarios 2, 3, and 4

These scenarios use scenario 1 as a base and then reduce the amount of action proportionally for each scenario, with 75%, 50%, and 25% of scenario 1 action for scenarios 2, 3, and 4 respectively (Table 10).

Scoping Plan Scenario

The Scoping Plan scenario for perennial croplands is the same as scenario 3. The Scoping Plan scenario for annual croplands is the same as scenario 2, except for the transition to organic and conservation levels which are the same as scenario 3.

Table 10: Annual acres of cropland climate action for each scenario, and a description of the action[2].

Climate action	Description	Alt 1	Alt 2	Alt 3	Alt 4	Scoping Plan
Cover cropping (legumes)	Use of a leguminous seasonal vegetative cover	12,822	9,617	6,411	3,206	9,617
Cover cropping (non-legumes)	Use of a non-leguminous seasonal vegetative cover	12,822	9,617	6,411	3,206	9,617
No Till	Growing annual crops without disturbing the soil through tillage	7,177	5,383	3,589	1,794	5,383
Reduced Till	Growing annual crops with reduced use of tillage	18,440	13,830	9,220	4,610	13,830
Compost Amendment	Application of compost to annual croplands	53,522	40,142	26,761	13,381	40,142
Transition to organic farming	Transition from conventional farming techniques to organic farming techniques on annual croplands	129,516	97,137	64,758	32,379	64,758
Conservation of Annual Cropland	Avoided conversion of annual croplands to other land use	11,120	8,340	5,560	2,780	5,560
Establishing Riparian Forest Buffers	Replacing croplands adjacent to watercourses with woody plants or trees	75	56	38	19	56
Alley Cropping	Planting of rows of trees/shrubs within annual croplands	22	17	11	6	17
Establishing Windbreaks/Shelterbelts	Planting rows of trees/shrubs within or surrounding annual croplands to reduce wind erosion	23	17	12	6	17
Establishing Tree and Shrubs in Croplands	Planting trees and shrubs within annual croplands	16	12	8	4	12
Establishing Hedgerows	Planting dense vegetation surrounding annual croplands	87	65	44	22	65
Establishing Hedgerows in Perennial Croplands	Planting dense vegetation surrounding perennial croplands	191	143	96	48	143
Establishing Windbreak/Shelterbelts in Perennial Croplands	Planting rows of trees/shrubs within or surrounding perennial croplands to reduce wind erosion	72	54	36	18	54

Developed Lands

For urban forests within developed lands, two climate actions are available within the 2022 Scoping Plan Update modeling framework: investment, and water use response to drought. These variables are changed proportionally to fulfill the stated objective of

[2] The Scoping Plan column is included here and not in other land types, because for croplands the Scoping Plan scenario is a combination of alternatives 2 and 3. In other land types, the Scoping Plan Scenario is equivalent to either scenario 2 or 3.

the scenario. For wildland urban interface developed lands, as current regulations state that 100% of structures must have defensible space with no exceptions, this was assumed for all scenarios, with varying levels of defensible space.

Defining Scenarios

Scenario 1

The newly developed urban forest carbon model was parameterized to ensure that the theoretical maximum amount of carbon was achieved by 2045 (see the Urban Forest Modeling section for more details). To accomplish this a 20x investment must be made over BAU spending, and all residents of California must improve their water use through droughts by 20x. This means that essentially, watering of trees in urban areas should never decrease, or even increase, given ever increasing drought.

WUI forests would have 100% compliance with existing defensible space regulations, which would constitute some level of action on 52% of all property parcels in California WUI areas.

Scenarios 2, Scoping Plan, and 4

Urban forest scenarios are order of magnitude reductions of action compared to scenario 1. This order of magnitude reduction is used to produce a reasonable spread of future projections. Scenario 1 is such an extreme increase in forest carbon, driven by a 20x investment, that a linear reduction from this investment did not produce a sufficient spread to assess how different levels of investment can affect NWL's overall potential future outcomes. For this reason scenarios 2, Scoping Plan, and 4 used an investment and water use efficiency increase from BAU of 2x, 1.2x, and 1.02x respectively. The reason this order of magnitude change rate was used between scenarios is because of the large cost associated with scenario 1 (see the Economic Analysis section for more details).

WUI defensible space is the same for scenarios 1, 2, and 3. The objective for scenario 4, however, is fire reduction above all else, so this scenario includes more defensible space than the other scenarios. Current regulation only requires property owners to have defensible space around structures up to their property boundary. However, if a structure is adjacent to its property boundary, and their neighbor's property has existing forest, this structure, essentially, does not have defensible space sufficient to fully protect it from wildfire. For this reason, scenario four disregards property boundaries, and requires all structures to have full defensible space.

Delta Wetlands

The delta is a diverse ecosystem that has a large of amount of drained wetlands used for agriculture that are currently experiencing a rapid rate of subsidence. Subsidence is the gradual sinking of land. This subsidence constitutes a risk to the state's economic system, water supply, public health and safety, and wildlife. This is because subsidence in drained wetlands, not only emit a large amount of GHGs, but also undermine the Delta's levy system and costs millions of dollars a year to pump water to maintain these lands, and to repair and bolster the levy system. For these reasons, each scenario includes various levels of wetland restoration.

Defining Scenarios

Scenario 1

In this scenario, 120,000 acres of wetland are restored which constitutes about 30% of the entire delta. This level of restoration would constitute an unprecedented amount of wetland restoration and would dramatically improve the regions ecological function and reduce the climate change risk on infrastructure and public health.

Scenarios 2 and 4

These scenarios represent a fulfillment of current commitments as defined by the Department of Water Resources EcoRestore program. The EcoRestore program has already restored several thousand acres, and these scenarios fulfill the initial EcoRestore commitment of 30,000 acres of restoration. See the Delta Wetlands Modeling section for more details on specific restoration acres.

Scoping Plan Scenario (Scenario 3)

This scenario doubles the initial EcoRestore commitment, and is half of scenario 1's aggressive restoration rate.

Table 11: Acres that converted to specific wetlands types.

Wetland type converted to permanent wetland	Alt 1	Alt 2	Scoping Plan	Alt 4
Brackish managed seasonal wetlands	38479	2698	16862	2698
Drained wetlands used for agriculture	85378	8901	46995	8901
Seasonal wetlands	1007	1007	1007	1007
Total restoration	124865	12607	64865	12607

Sparsely Vegetated Lands

Deserts and other sparsely vegetated systems are under threat from climate change and contain a large amount of endemic flora and fauna. For this reason, conservation was the focus of scenario development. For this exercise, conservation means reducing the amount of land use change in deserts away from unmanaged sparsely vegetated systems.

Defining Scenarios

Scenario 1

This scenario does not allow for any conversion away from sparsely vegetated lands to any other land type. This constitutes conserving 100% of all sparsely vegetated lands. Though for modeling purposes this constitutes avoiding 2,607 acres of conversion each year, this scenario really means 100% land conservation because this scenario does not allow any conversion anywhere within sparsely vegetated lands.

Scenarios 2, Scoping Plan (3), and 4

These scenarios linearly decrease the 100% conservation in scenario 1, to avoid 75%, 50%, and 25% of land use change away from sparsely vegetated lands for scenarios 2, 3, and 4 respectively.

Forest, Shrubland, and Grasslands Modeling

Background

Forests, shrublands, and grasslands make up approximately 91% of all California Natural and Working Lands (NWL) carbon stocks. Forests, shrublands, and grasslands are intermingled and influence the carbon, fire, and water dynamics between one another. Water and fire flow in and out of forests, shrublands, and grasslands across the state. Fire regimes and the water cycle across a landscape also influences the carbon within a system, and the ability for plants to photosynthesis to sequester carbon.

The carbon and water cycles, as well as fire regimes, within forests, shrublands, and grasslands are strongly influenced by climate and land management. Further, the interaction of management and climate change can have impacts on ecosystems that have not occurred in the scientific record. Because of all of the ecological interactions between climate, management, carbon, water, and fire, a complex modeling effort was undertaking to quantify potential futures of these lands.

Modeling Overview

The Regional Hydro-Ecologic Simulation System (RHESSys) model was used to assess the future of California's forests, shrublands, and grasslands. Through using this complex biogeochemical model, the impacts of future management strategies and climate change on ecological function and structure, including wildfire dynamics, can be assessed. This modeling includes all forests, shrublands, and grasslands throughout California (Figure 6). Recognizing that no ecosystem operates in isolation, these systems are modeled together to elucidate how management in these various system influence one another.

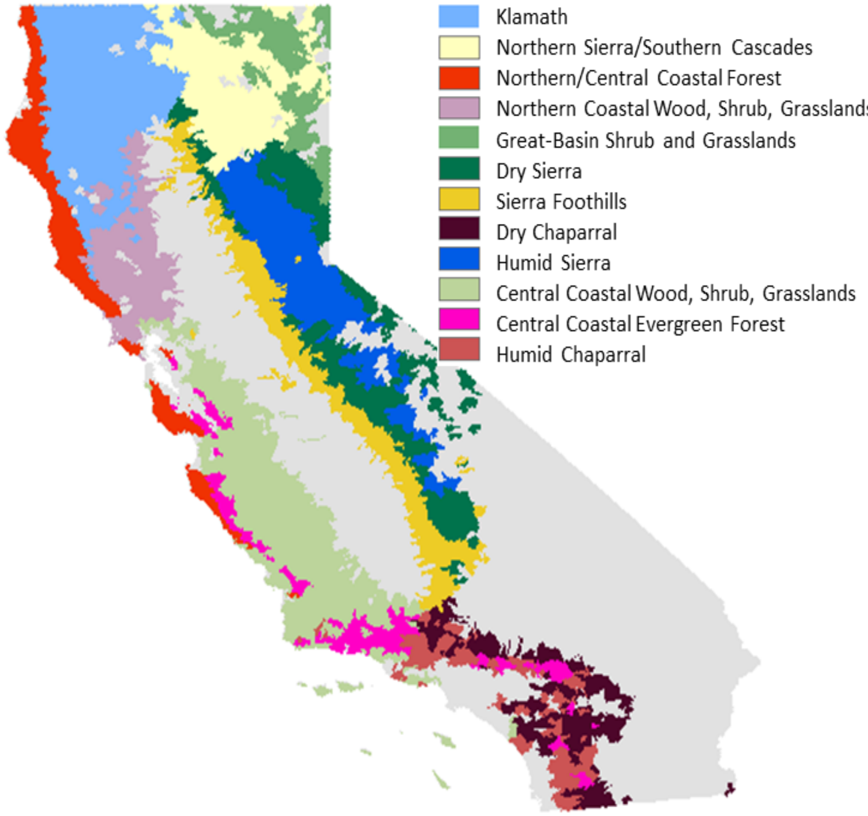

Figure 6: Ecounits of California. These ecounits cover all watersheds that are dominated by forests, shrublands, or grasslands.

The complex nature of this modeling requires several steps and data sets. A modeling framework was developed to answer the specific questions of the Scoping Plan. Namely, this modeling will assess the cumulative impact that management and climate change has on carbon, water, and fire across the entire State of California's forests, shrublands, and grasslands. Many spatially and temporally explicit data sets drive this modeling framework every step of the way. These datasets include climate, site condition, ecosystem function, land use, and various other types of data. This work also requires the development of new models and algorithms to develop the processing pipeline to get to the ultimate goal of answering the Scoping Plan question on climate change and management.

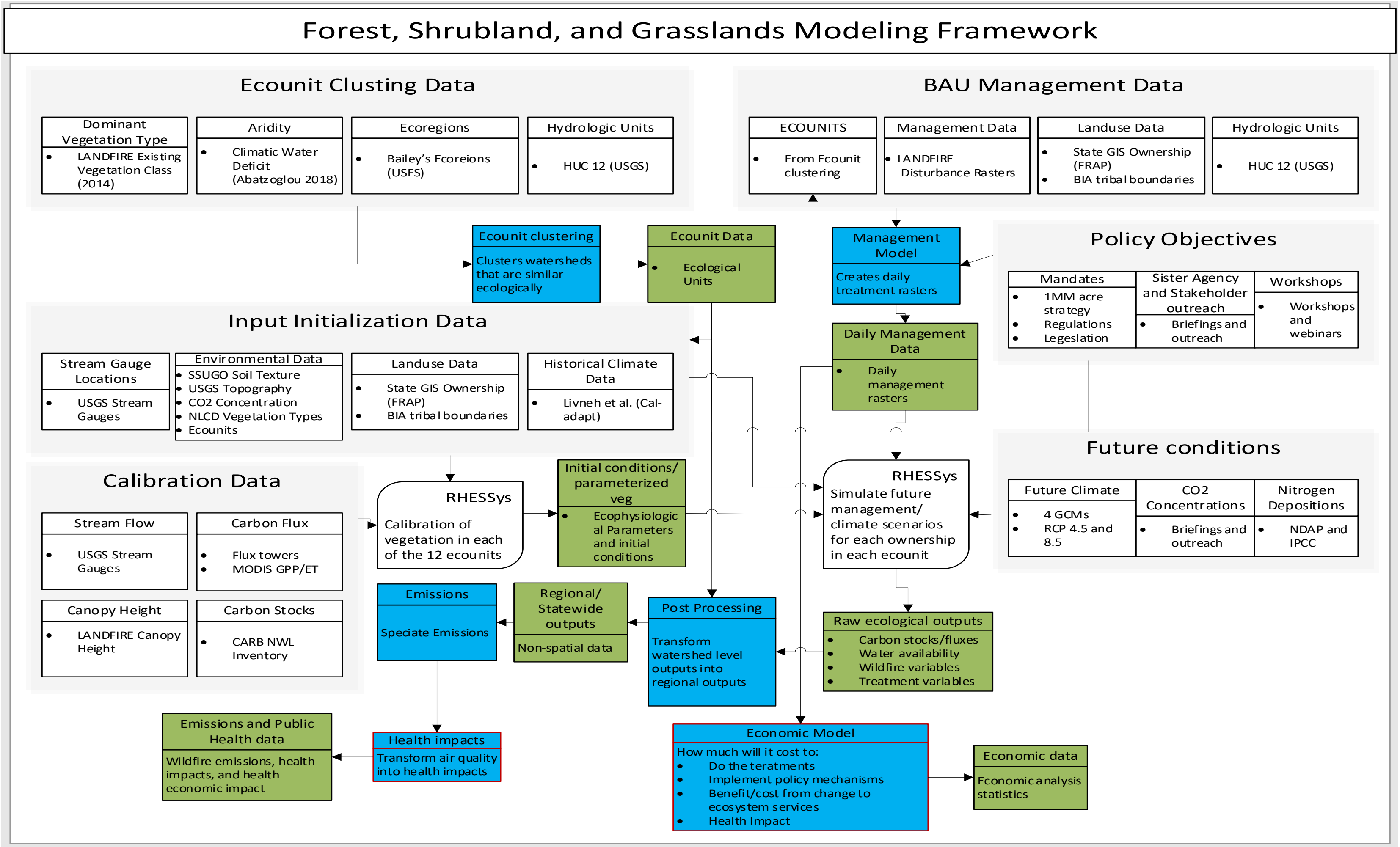

Figure 7: Modeling framework for forests, shrublands, and grasslands for 2022 Scoping Plan update. Blue boxes indicate newly developed algorithms or models developed specifically for this framework. Green boxes indicate newly generated data. White boxes indicate previously developed data as inputs. RHESSys has boxes with rounded edges. Arches in the lines indicate that the lines to not connect.

Ecological Unit Development

Background

The Regional Hydro-Ecologic Simulation System (RHESSys) is a process-based coupled biogeochemical, hydrology, and fire model. The complexity of the model, along with computational limitations, restrict the absolute size of a landscape on which one simulation can be run. Typically, RHESSys is run on individual watersheds. This scale provides the necessary dynamics between vegetation, water, and fire that can provide meaningful scientific results, while still being computationally and practically feasible. To run a simulation in a watershed, a modeler must parameterize the vegetation physiology, and the water and fire dynamics in that particular location. Parameterization is the process of using empirical data to ensure that your modeling is producing realistic results and that the processes are functioning correctly. This parameterization process is the most time consuming component of the modeling process. By clustering watersheds into similar ecological units (ecounits) parameterization can be performed on representative watersheds, which can then be used to represent an ecological unit. Additionally, not every watershed has a stream gauge appropriate for modeling, limiting the number of watersheds that could be modeled because stream gauges are necessary to parameterize water dynamics. Further, in an effort to estimate statewide results, CARB can derive general conclusions for the ecountis based on the simulations from their representative watersheds. As CARB's modeling progresses, CARB staff can use the parameterization from the representative watersheds for each watershed within the same ecounit. Therefore, to utilize limited empirical data, reduce computation resources and modeling complexity, and maintain regional environmental variation across the state, CARB clustered watersheds into ecounits.

Clustering Data

RHESSys is best suited for individual simulations on the tens to low hundreds of square miles scale. Hydrologic Units – 12 (huc12) have an average size of 40 square miles (10 to 40 K acres). For this reason, CARB is using the huc12 scale as the basis for individual watershed simulations. Clustering was done to group environmentally similar huc12 watersheds. In this way, the representative watershed that is eventually modeled, should represent environmentally similar watersheds elsewhere. Clustering is based on numerous metric and watersheds to not have to be spatially contiguous to be associated with a particular ecounit.

Hydrologic Units

Hydrologic units divide the U.S. into various levels of hydrodynamic regions [19]. HUCs are a part of the Watershed Boundary Dataset. The Watershed Boundary Dataset (WBD) is a comprehensive aggregated collection of hydrologic unit (HUC) data consistent with the national criteria for delineation and resolution. It defines the areal extent of surface water drainage to a point except in coastal or lake front areas where there could be multiple outlets as stated by the Federal Standards and Procedures for the National Watershed Boundary Dataset. Watershed boundaries are determined solely upon science-based hydrologic principles, not favoring any administrative boundaries or special projects, nor particular program or agency. The intent of defining HUCs for the WBD is to establish a baseline drainage boundary framework, accounting for all land and surface areas. For this analysis, every huc12 in California was classified by three biogeographic properties: dominate existing vegetation order, aridity, and ecoregion.

Dominate Existing Vegetation

The dominate existing vegetation in a watershed is defined by LANDFIRE's existing vegetation class (Figure 8, Table 12). LANDFIRE (LF) layers are created using predictive landscape models based on extensive field-referenced data, satellite imagery and biophysical gradient layers using classification and regression trees [20, 21].These classes are designed to encompass a group of plant species. These classes in combination of the respective ecoregions in which it appears provides insights into the actual species that may exist on the landscape. Though these classes are less specific than individual species maps, they are more accurate because they are less specific.

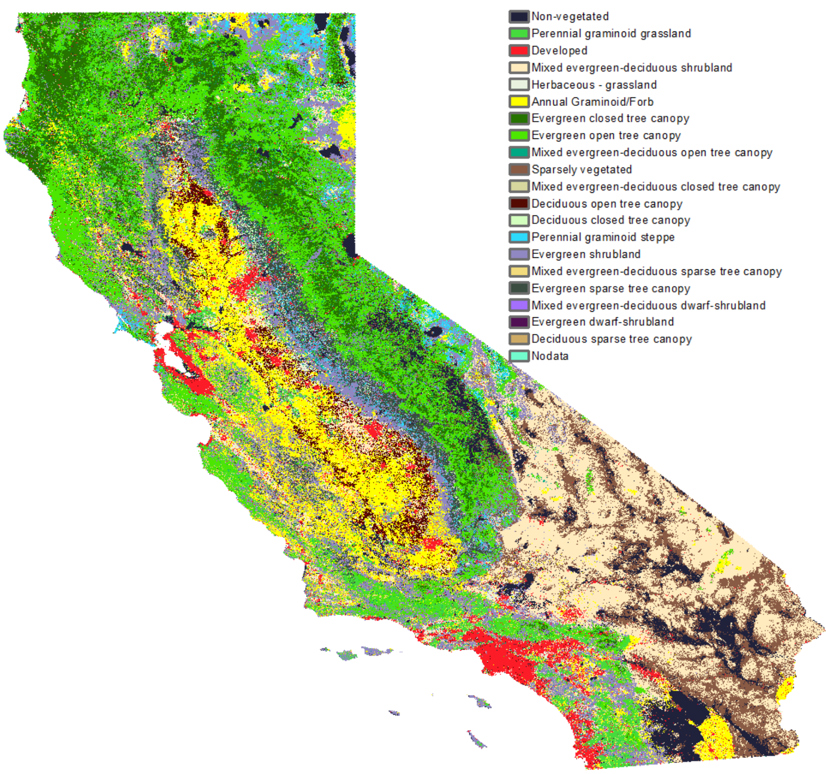

Figure 8: LANDFIRE existing vegetation class for 2014

Table 12: LANDFIRE existing vegetation classes

Code	Existing Vegetation Class
1	Non-vegetated
2	Perennial graminoid grassland
3	Developed
4	Mixed evergreen-deciduous shrubland
5	Herbaceous - grassland
6	Annual Graminoid/Forb
7	Evergreen closed tree canopy
8	Evergreen open tree canopy
9	Mixed evergreen-deciduous open tree canopy
10	Sparsely vegetated
11	Mixed evergreen-deciduous closed tree canopy
12	Deciduous open tree canopy
13	Deciduous closed tree canopy
14	Perennial graminoid steppe
15	Evergreen shrubland
16	Mixed evergreen-deciduous sparse tree canopy
17	Evergreen sparse tree canopy
18	Mixed evergreen-deciduous dwarf-shrubland
19	Evergreen dwarf-shrubland
20	Deciduous sparse tree canopy
21	Nodata

Aridity

Aridity in this analysis is defined by the average climatic water deficit from 1989 to 2019 [22]. Climatic water deficit used in this analysis is quantified by the University of Idaho for their TerraClimate dataset. This dataset is derived by combining WorldClim, CRU Ts4.0 and the Japanese 55-year Reanalysis (JRA55) data. Climatic water deficit is the evaporative demand that the atmosphere is forcing (potential evapotranspiration) minus the actual evapotranspiration from the land.

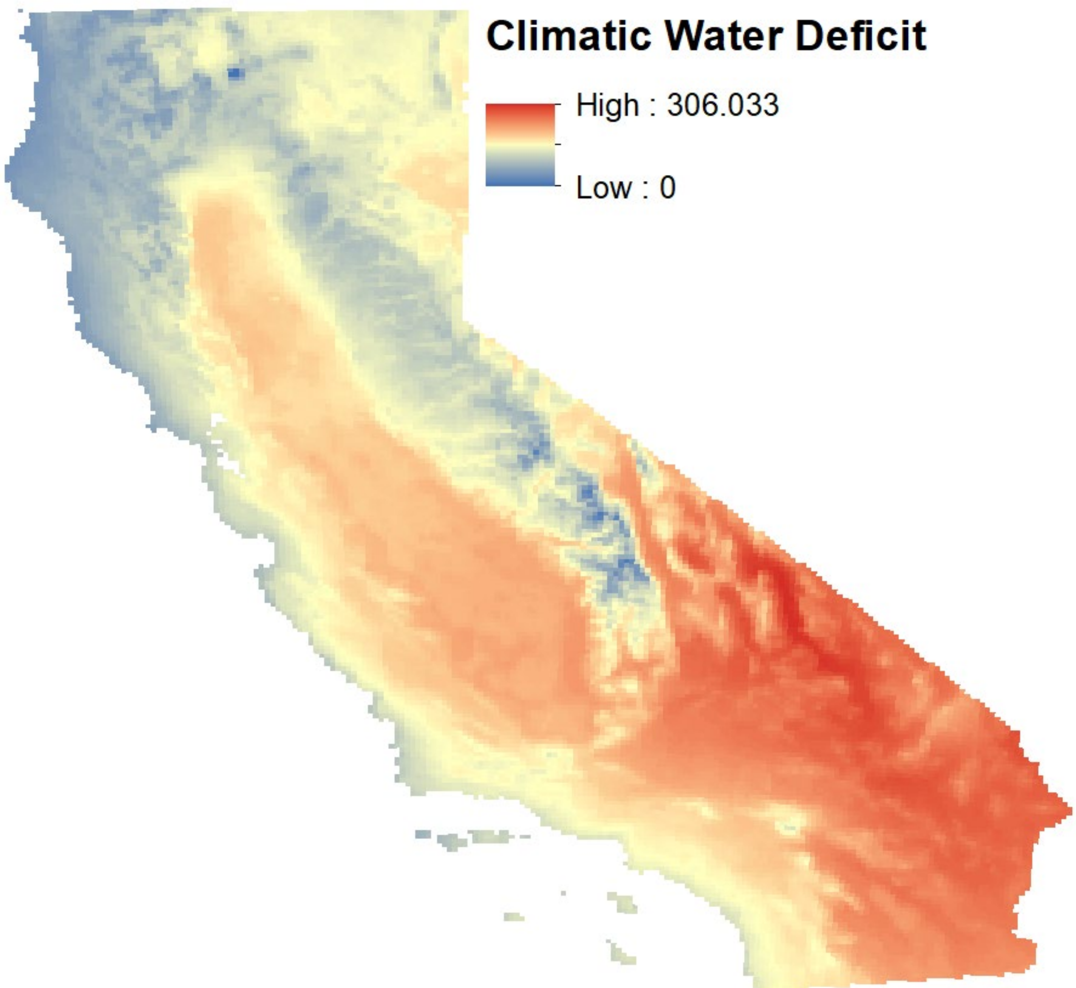

Figure 9: Aridity as measured by climatic water deficit in millimeters

Ecoregions

Ecoregions were developed on the premise that ecological regions can be identified through the analysis of patterns of biotic and abiotic phenomena, including geology, physiography, vegetation, climate, soils, land use, wildlife, and hydrology. The relative importance of each characteristic varies from one ecological region to another. These ecoregions were developed by the U.S. Forest Service [23]. The delineation used in this analysis were ecological sections, of which 18 exist in California.

Figure 10: Ecoregions of California as defined by the USFS

Clustering

The dominant existing vegetation type, average aridity, and dominate ecoregion was then calculated for each huc12. These three variables for each huc12 was then used to classify each huc12 watershed into an ecounit. Even though ecoregions alone is an environmental clustering exercise, it does not delineate our land types of interest enough to represent the heterogeneity of these systems specifically in California.

This classification scheme resulted in 228 unique ecounit classifications across California. These classifications were then either removed, because they are not dominantly forests, shrublands, or grasslands (developed, non-vegetated, sparsely vegetated, and annual croplands) or grouped together to derive larger ecological units (Figure 6). These ecological units represent landscapes that have similar vegetation, growing conditions, site qualities, climate, soil conditions, and disturbance regimes. This level of grouping also results in at least one stream gauge suitable for modeling within each ecounit. These stream gauges are required to accurately parameterize the vegetation and water dynamics within RHESSys.

Resulting Ecological Units

Forests and other natural lands (FONL) in California comprise approximately 93 percent of all California NWL carbon (Figure 6). This means that the resulting ecounit map misses about 7% of California's ecosystem carbon stored outside of FONL. This includes biomass and soil carbon.

Description of Ecological Units

Twelve ecological units were derived in this analysis to cluster watersheds with similar vegetation, climate, and biogeographical conditions. These units can generally be described in Table 13 and the vegetation make up of an average watershed per ecounit can be seen in Figure 11.

Table 13: Narrative descriptions of Ecounits

Name	Description
Klamath	Primarily evergreen forestland of variable density, including evergreen shrublands. Vegetation can range from redwoods in the west to knobcone pine in the east. Rugged terrain and generally humid conditions for California. This area experiences a high amount of commercial timber operations and fires.
Northern Sierra/Southern Cascades	High elevation evergreen forests with scattered shrublands. Drier than the Klamath with a strong west-east humidity gradient (wetter in the west).
Northern/Central Coastal Forest	Redwoods and dense douglas fir stands with areas of evergreen shrub lands closer to the beach. The most humid unit in the state.
Northern coastal wood and shrub lands	Open wood and shrub lands with some open evergreen stands. Humidity decreases further from the coast. Rolling hills.
Great-basin rangelands	Dry shrub and grasslands. The great basin has saline water caused by the endoreic hydrology of the area bringing about open to sparse vegetation.
Dry Sierra mountains	Sierra mountains primarily on the southern and eastern edges of the Sierra Nevada mountain range. These areas typically have yellow pine stands that lead into oak woodlands on the lower elevations to subalpine pines on toward the higher elevations.
Sierra foothills	Mixed woodlands and open evergreen stands of oaks and grey pines. Shrublands are also found in this area.
Southern dry chaparral	Shrub to grasslands. Trees are not common in this area. Rolling hills of sand and limestone.
Humid Sierra mountains	Typically higher elevation mountains. These areas are more humid primarily because of the snow pack throughout most of the winter and spring. These evergreen forests are comprised of douglas firs, and yellow and high elevation pines, such as sub alpine, whitebark, and lodgepole.
Central coastal wood, shrub, and grasslands	Drier than the northern coastal wood and shrub lands. These areas lean towards dry open savannah or grasslands.
Central coast evergreen forest	Mixed evergreen forests of variable density but tending to open stands.
Southern humid chaparral	Mixed chaparral and oak woodlands

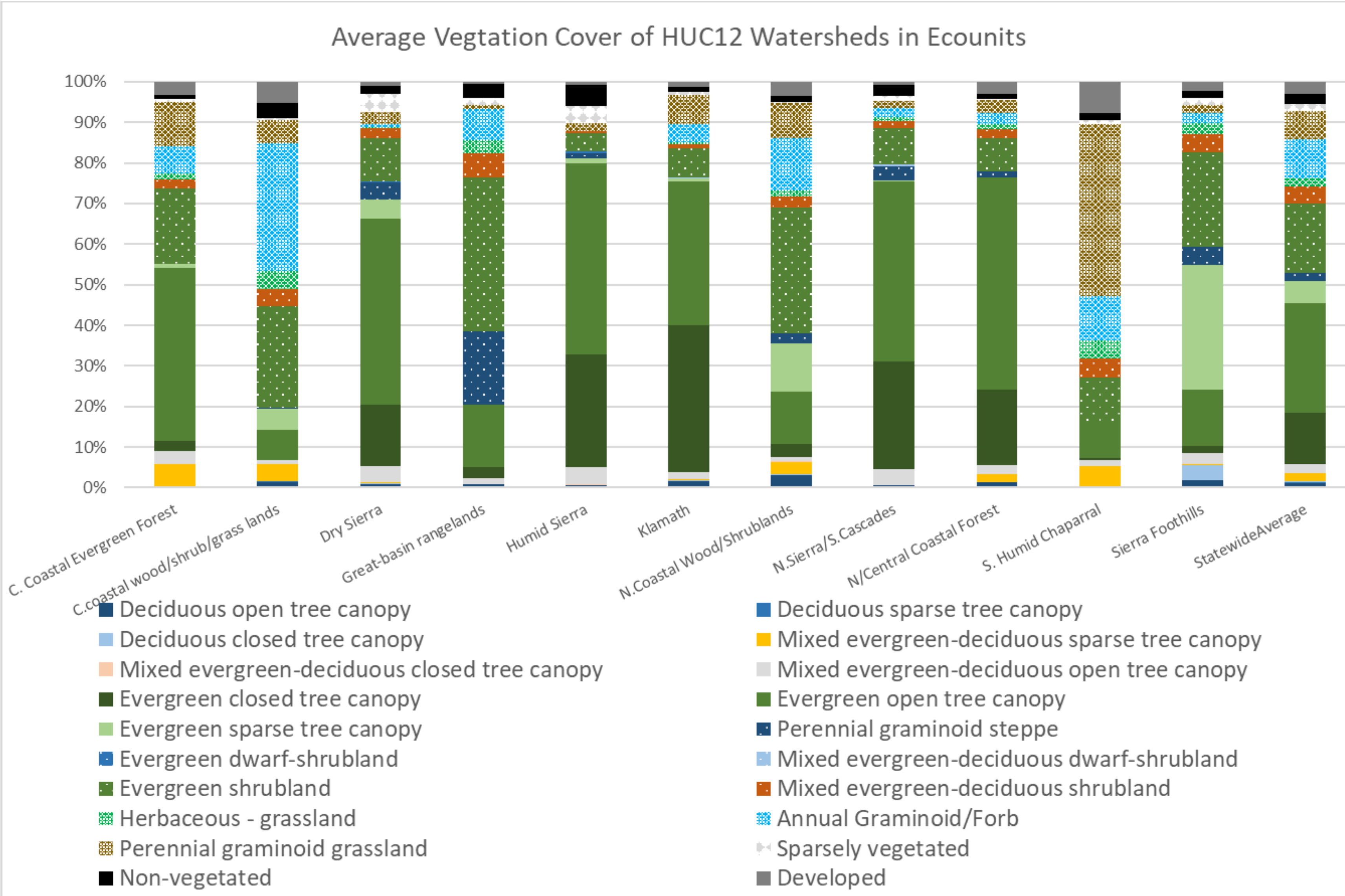

Figure 11: The vegetative make up of an average watershed within an ecounit

Business-As-Usual Management Quantification

Background

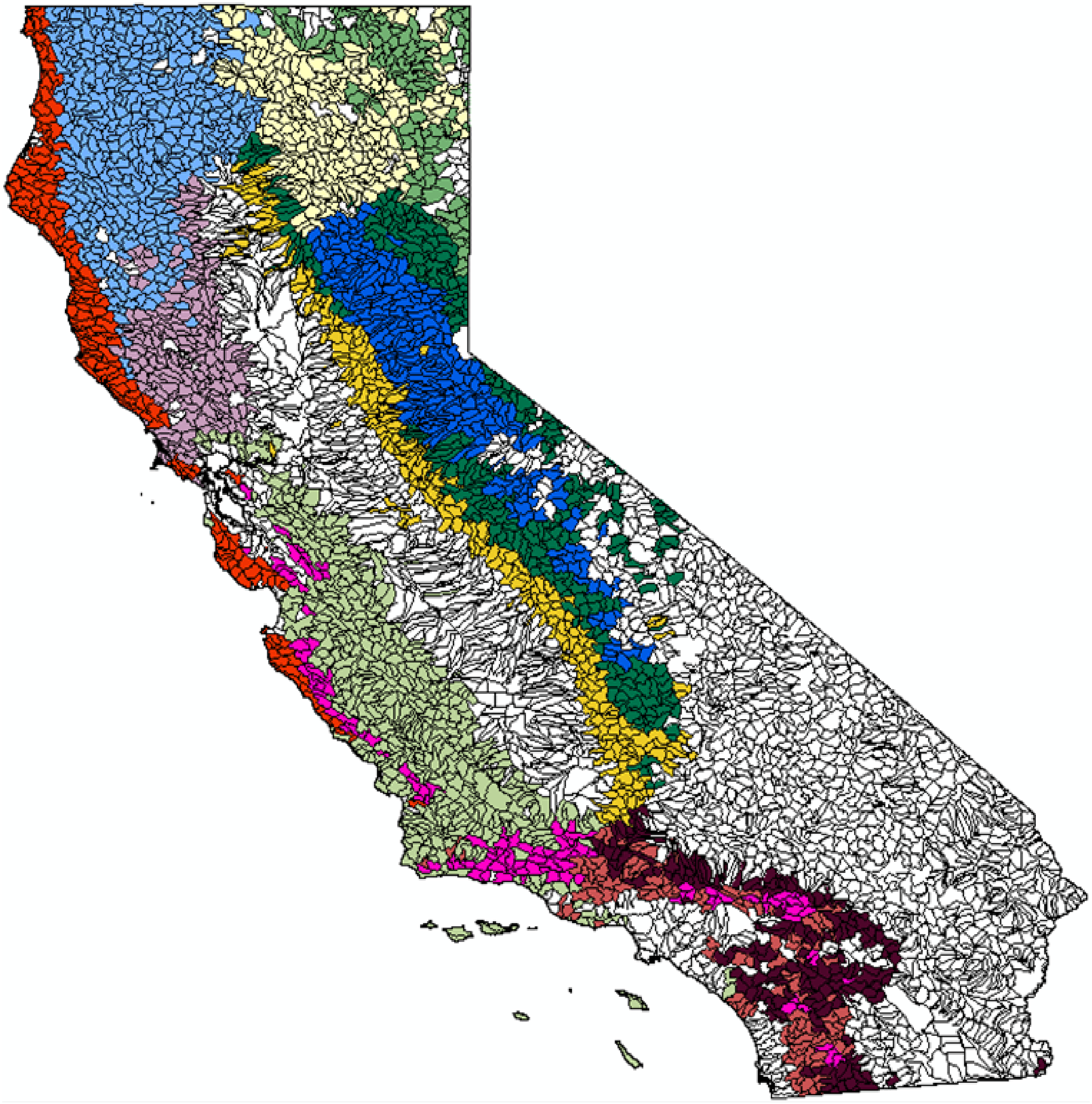

Figure 12: Ecounits of California. Each color represents an eco-unit of California's forest and shrublands. The white area is non-forest, shrubland, or grassland. The small black lines demarcate the watersheds of California under a hydrological unit-12 level.

One future scenario of how human intervention influences ecological outcomes under climate change is particularly illuminating is the Business-As-Usual (BAU) scenario. The BAU scenario assumes that NWL are managed in the same way as they were managed during the baseline period from 2001 to 2014. In this way, this scenario quantifies the result of inaction. The BAU scenario is by far the most difficult scenario to define, because this entails quantifying what has actually been happening on the landscape through time. Quantifying current management across an entire state in a way by which it can be used for modeling is a complex task that requires tailored analysis. To be used in this modeling exercise, BAU management in all forests, shrublands, and grasslands was quantified on the huc12 watershed scale for every ecounit and ownership combination from 2001 to 2014.

The following section outlines how BAU management was quantified. The descriptions of the BAU management are divided by eco-units (Figure 12). The BAU descriptions defined here are designed to be used for watershed scale modeling. This watershed scale modeling will then be scaled to statewide estimate as outlined in the Scaling to Regional and Statewide Level section of this document.

This exercise also goes further in describing the initial conditions of the average watersheds within ecounits and ownerships. This data does not necessarily affect the BAU management quantification, but it does provide context within which management is occurring, and demonstrates the current results of the actual BAU management.

Data

Watersheds

Watersheds are delineated by hydrologic units. Hydrologic units (HUC) divide the U.S. into various levels of hydrodynamic regions [19]. HUCs are a part of the Watershed Boundary Dataset. The Watershed Boundary Dataset (WBD) is a comprehensive aggregated collection of hydrologic unit data consistent with the national criteria for delineation and resolution. It defines the areal extent of surface water drainage to a point except in coastal or lake front areas where there could be multiple outlets as stated by the Federal Standards and Procedures for the National Watershed Boundary Dataset. Watershed boundaries are determined solely upon science-based hydrologic principles, not favoring any administrative boundaries or special projects, nor particular program or agency. The intent of defining HUCs for the WBD is to establish a baseline drainage boundary framework, accounting for all land and surface areas.

Ecounits

For this analysis, every huc12 in California was classified by three biogeographic properties: dominant existing vegetation order, aridity, and ecoregion. There are 12 eco-units for forest, shrublands, and grasslands (Figure 6). The dominant existing vegetation type, average aridity, and dominant ecoregion was then calculated for each huc12. These three variables for each huc12 were then used to classify each huc12 watershed into ecounits. These ecological units represent landscapes that have similar vegetation, growing conditions, site qualities, climates, soil conditions, and disturbance regimes. This level of grouping also results in at least one stream gauge suitable for modeling within each ecounit. These stream gauges are required to accurately parameterize the vegetation and water dynamics within RHESSys.

Carbon

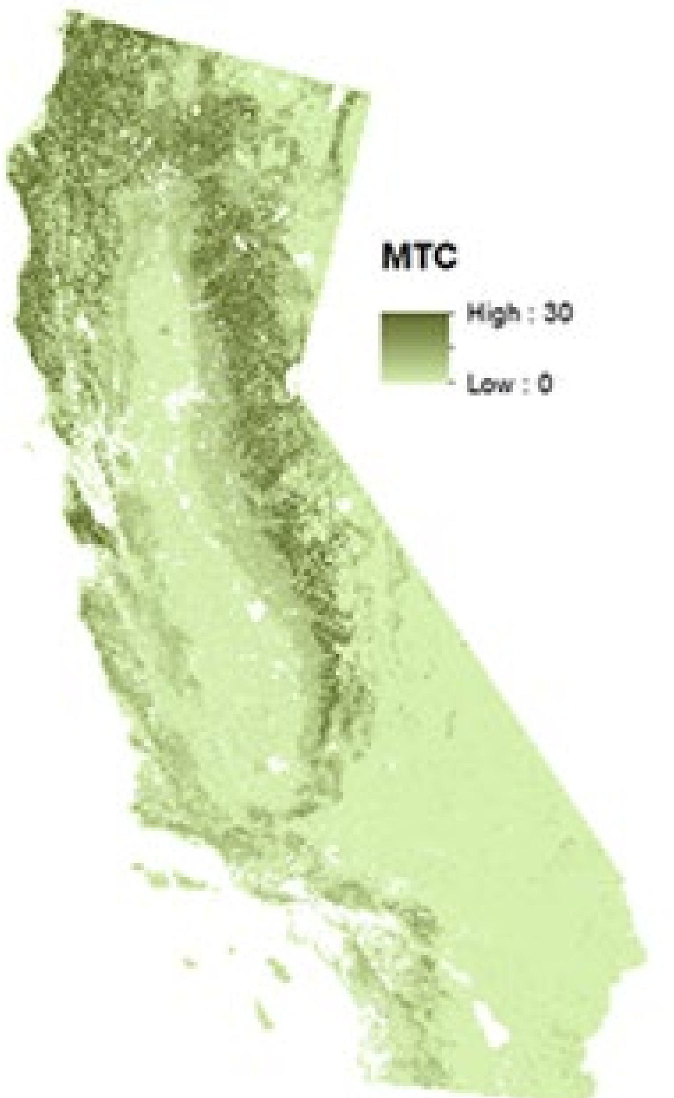

Figure 13: Total biomass carbon (MTC) in 2014 [24].

CARB's NWL inventory [24] was used to quantify the biomass carbon within a watershed (Figure 13). The California Air Resources Board's (CARB) Natural and Working Lands (NWL) Inventory is a quantitative estimate of the existing state of ecosystem carbon stored in the State's land base. It provides estimates of carbon stocks, and stock-change and attributes stock changes to disturbances. This inventory produces geospatial data on a 30x30m resolution statewide. The 2014 data was used for this analysis because it was the latest available dataset that fits within the baseline time-period. The data used in this analysis only utilized CARB's biomass carbon stock estimates. See CARB's NWL inventory technical support document for more details on how this data is derived.

Ownership

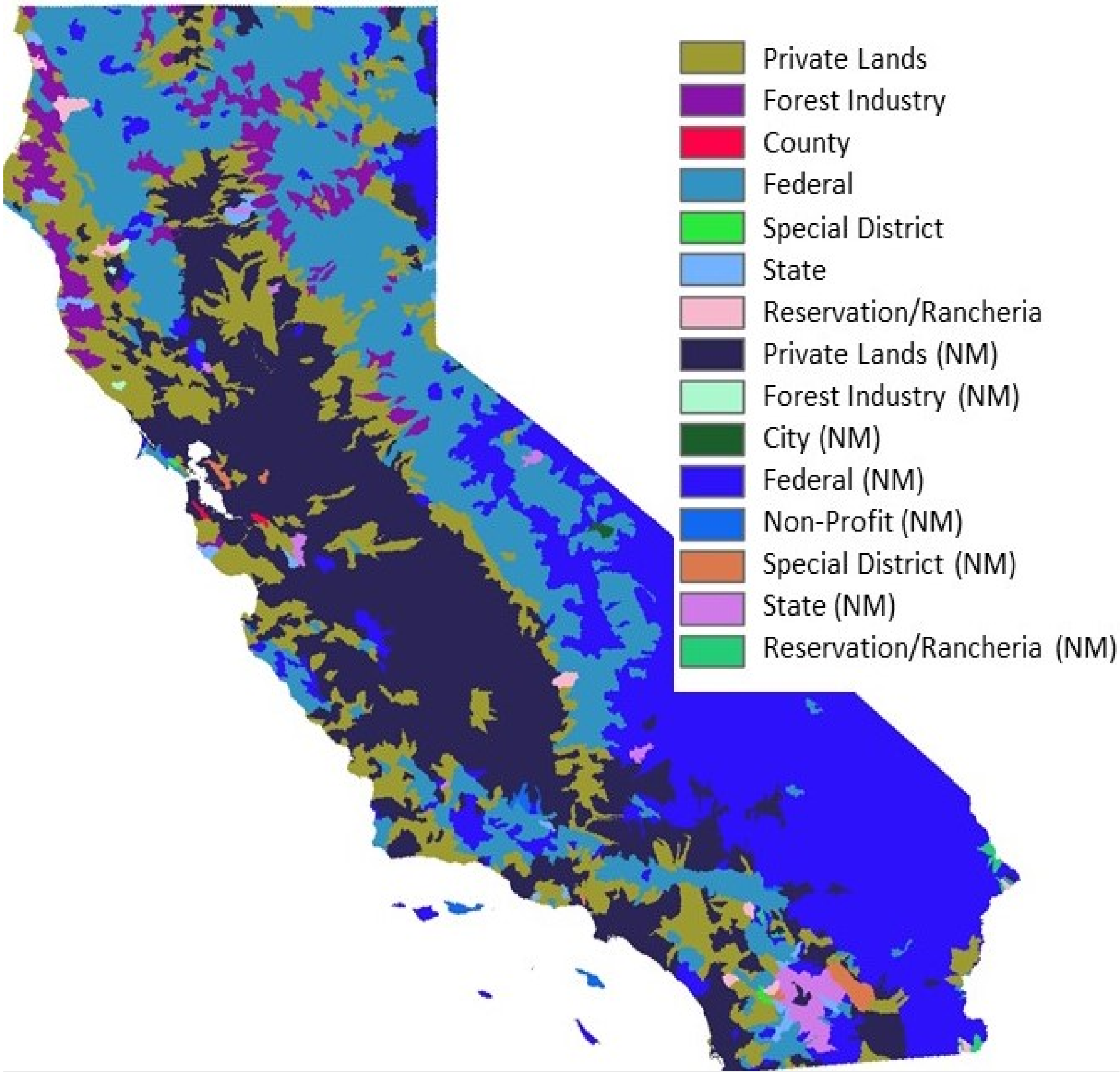

Figure 14: Dominant watershed ownerships. Ownerships with a (NM) mean that those watersheds showed no management within CARB's baseline time period (2001-2014).

This BAU assessment uses a federal ownership extent that matches the Federal Responsibility Areas (FRA) footprint from CAL FIRE's State Responsibility Areas for Fire Protection (SRA) data (Figure 14). Since 2011 when SRA Fees were first implemented, CAL FIRE has devoted significant resources to improving the quality of SRA data. This includes comparing SRA data to data from other federal, state, and local agencies, an annual comparison to county assessor roll files, and a formal SRA review process that includes input from CAL FIRE Units. As a result, the FRA footprints from SRA data provide a solid basis as the footprint for federal lands in California (except in the southeastern desert area).

The methodology CAL FIRE SRA used for federal lands involved: 1) snapping federal data sources to county parcel data; 2) clipping to the FRA footprint from CALFIRE's ownership data; 3) overlaying the federal data sources and using a hierarchy when sources overlap to resolve coding issues (BIA, UFW, NPS, USF, BLM, DOD, ACE, BOR); 4) utilizing an automated process to merge "unknown" FRA slivers with appropriate adjacent ownerships; and 5) a manual review of FRA areas not assigned a federal agency by this process. Non-Federal ownership information was obtained from the California Protected Areas Database (CPAD), was clipped to the non-FRA area, and an automated process was used to fill in some sliver-gaps that occurred between the federal and non-federal data.

In the Southeastern Desert Area, CAL FIRE does not devote the same level of resources for maintaining SRA data, since there is no fire protection responsibility. This includes almost all of Imperial County and the desert portions of Riverside and San Bernardino Counties. In these areas, we used federal protection areas from the current version of the Direct Protection Areas (DPA) dataset. Because there were draw-issues with the previous version of ownership, this version does not fill in the areas that are not assigned to one of the owner groups, and therefore does not cover all lands in the state. Also unlike previous versions of the dataset, this version only defines ownership down to the agency level - it does not contain more specific property information (for example, which National Forest). Ownership level is the hierarchy used for this analysis. Additionally, watersheds within an ownership that did not have any management in the LANDFIRE disturbance data are identified in this ownership map by a "no management" identifier (NM). This is done so that the statistics in this document quantify management details in those watersheds that actually received any management in CARB's baseline time period. Further, this map was updated using the more recent Bureau of Land Management map of Reservation and Rancheria boundaries. CARB held two public workshops for tribes to ensure that this map would sufficiently delineate these boundaries. Finally, forest industry lands were also specifically delineated using CAL FIRE's map of this ownership.

This assessment labels an entire watershed with only the dominant owner. This is because the modeling for the 2022 Scoping Plan Update is done on the watershed scale, and general watershed management strategies for ownerships must be quantified. It is not currently possible to model every watershed in the State, so creating sufficiently generic management strategies was necessary to encapsulate the diversity of strategies that exist throughout the State.

Elevation

The USGS National Elevation Dataset (NED) was developed by merging the highest resolution, best quality Digital Elevation Model (DEM) data available across the United States into a seamless raster format. Thirty-meter resolution DEM data exist for the conterminous United States.

Historical Climate

The historical climate data (minimum and maximum temperatures and precipitation) presented in this analysis are 30-year averages for the time period 1961-1990, which is the base period used within the 4th California climate assessment. This historical information comes from a data set of precipitation and temperature observations, gridded to a 1/16° (~6 km) resolution, for the period 1950–2013. Data was downloaded using the Cal-adapt tool.

Aridity in this analysis is defined by the average climatic water deficit from 1989 to 2019 (Figure 9) [22].Climatic water deficit used in this analysis is quantified by the University of Idaho for their TerraClimate dataset. This dataset is derived by combining WorldClim, CRU Ts4.0 and the Japanese 55-year Reanalysis (JRA55) data. Climatic water deficit is the evaporative demand that the atmosphere is forcing (potential evapotranspiration) minus the actual evapotranspiration from the land.

Future Projected Climate

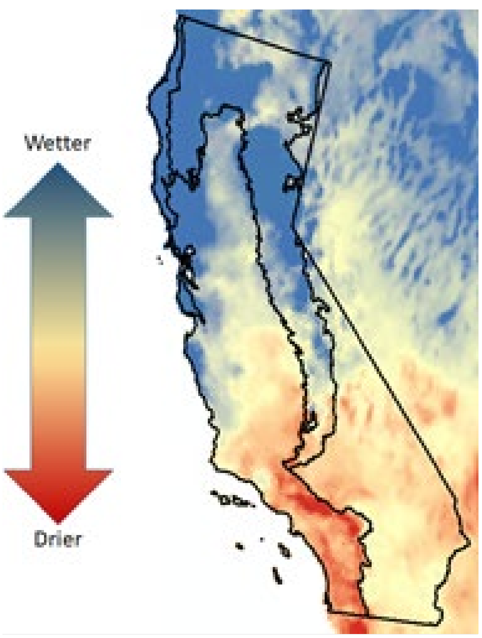

Figure 15: Future projected change in precipitation between historical (1976-2005) and future precipitation (2035-2065).

The future climate data presented in this analysis is the difference in 30-year averages between 30-year averages of 2035-2065 and the modeled 1976-2005 historical climatology from an ensemble of 10 Global Climate Models (Figure 15). This data was created using the LOCA climate downscaling technique for the 4th California climate assessment. Data was downloaded using the Cal-adapt tool.

Vegetation Cover

Vegetation cover used within this analysis is defined by LANDFIRE's existing vegetation class (Figure 8). LANDFIRE layers are created using predictive landscape models based on extensive field-referenced data, satellite imagery and biophysical gradient layers using classification and regression trees [20, 21]. This data is a geospatial map on a 30x30m resolution representing 2014. These classes are designed to encompass a group of plant species. These classes in combination of the respective ecoregions in which it appears provides insights into the actual species that may exist on the landscape. Though these classes are less specific than individual species maps, they are more accurate because they are less specific.

Disturbances and Treatments

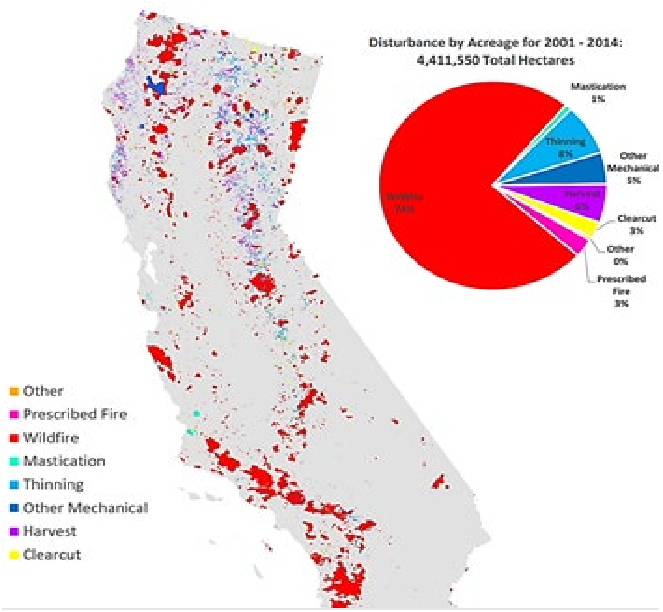

Figure 16: Disturbances that occurred on the California landscape during the 2001–2014 period.

Annual disturbances and treatments from 2001 upto 2014 from LANDFIRE are used for this analysis (Figure 16). LANDFIRE Annual Disturbance products depict where change occurred on the landscape, both spatially and temporally on a 30x30m resolution. Disturbance products are developed by combining fire program data (e.g., Monitoring Trends in Burn Severity (MTBS)), cooperator-provided field data via the LF Events Geodatabase, and change detection methods using Landsat imagery. This data set is the basis for the BAU management quantification and so this analysis is limited to the management actions defined by LANDFIRE. However, for modeling these management actions are parameterized to fit within this modeling framework (see the Management and Treatment Modeling section for more details).

Methods

Introduction

The business-as-usual (BAU) scenario for forests, shrublands, and grasslands is the continued management of these lands as defined by the quantifiable management from 2001upto 2014. The reason this time period is being used is because it represents a time period before CARB's climate investments were fully implemented on the landscape, and because it is during this period that statewide, continuous, and quantitative data is available on management activities.

CARB's modeling of forests, shrublands, and grasslands will be based on watershed scale simulations (~20k acres). Watershed management is different than stand management. The size of a watershed means that forest harvesting, for example, is not defined by rotation lengths, but instead by the frequency and average size of treatments within a watershed.

All statistics within this analysis are performed on the watershed scale and summarized for the eco-unit identified. Within eco-units statistics are derived for the dominant ownerships present within the unit. Even though only one dominant owner is assigned to a watershed, every watershed contains multiple owners. However, when watersheds are aggregated for an entire ecounit, the affect that the influence of the dominant ownership has on management and the landscape become apparent and outweighs the impact from non-dominate owners.

This methods section describes the derived watershed characteristics and management statistics that defines the BAU management. The data used for this analysis can be obtained from the Natural and Working Lands Modeling Data Spreadsheet.

Watershed Characteristics

Watershed characteristics demonstrate the various ways in which landscapes vary between ownerships within an eco-unit. These characteristics can help explain other differences, such has mean elevation, as others can demonstrate the impact of historical management and site characteristics, such as carbon or vegetation cover mix. The future projected change in climate can also explain how different owners will be impacted in different ways by climate change.

Characteristics are averaged or summed for all watersheds by dominant ownership within the eco-unit indicated. The ratio of the different types of vegetation cover is calculated as a fraction of watershed area from LANDFIRE data. Statewide statistics exclude non-forest/shrublands/grasslands.

Watershed Management

Frequency

The frequency of the treatments and disturbances is calculated by counting the years that experienced any amount of treatment or disturbance within a watershed. This is done for each individual treatment and disturbance separately. If, for example, a watershed received any level of thinning for just one year during this time period, it's frequency for thinning would be 1/13.

Size

The size of the disturbance represents the median of the total number of cells treated or disturbed annually within a watershed. Treatments do not have to be contiguous, instead this is the sum of all cells of a treatment type that occur in the same year, regardless of if they are next to one another.

Both the frequency and size statistics are then used within the management model to generate statewide BAU management strategies on an annual basis into the future. The watershed characteristics more not used for management modeling, but demonstrate how this management should affect the watersheds under historical climate conditions.

Management and Treatment Modeling

Background

Management strategies are suites of on-the-ground actions, or treatments, that are used across the landscape to manipulate an ecosystem. Within RHESSys, treatments are done in a spatially and temporally explicit manor. Treatments in this methodology are executed on a 90x90m patch of land on a specified day on a specified year within representative watersheds. This section will explain the technical approach used to determine where and when treatments occur, and how treatments affect ecosystem structure.

RHESSys Management Modeling Method

For the Scoping Plan, RHESSys modeling will be completed on representative watersheds that will be used to scale results up to the statewide level. To accomplish this, the representative watersheds will run as if they were managed under different ownerships. The management that an ownership performs within a watershed on average is defined through CARB's business-as-usual (BAU) management for forests, shrublands, and grasslands quantification method (see the Business-As-Usual Management Quantification section). CARB is modeling seven types of general management actions:

1. Biological, Chemical, and Herbaceous Treatments
2. Clearcut

3. Harvest
4. Mastication
5. Mechanical Treatments
6. Prescribed Burning
7. Thinning

These treatment categories were generated and defined by the LANDFIRE dataset developed in collaboration between the United States Forest Service and The Nature Conservancy. Each treatment category consists of various specific silvicultural and other management actions. They are categorized into these groups to be able to collate information on management from many different sources, which all have slightly different terminology and definitions. Through grouping actions into these treatment categories, it is possible to compare similar actions across jurisdictions. How treatments are applied, in terms of size, frequency and several other variables as described below, can be adjusted to fulfill different management scenarios. Adjustments to the actions are made relative to the BAU for alternative scenarios. For example, we can double the frequency and/or size of average prescribed burning for a particular ownership in a particular region compared to the BAU.

Management Model

To determine where and when various types of actions occur given an ownership and ecounit a model was developed by CARB staff. The management model derives daily maps of a desired watershed, indicating where different types of management actions occur on every day of the year, in the entire simulation period. The management model can simulate daily management maps for any year. For the 2022 Scoping Plan update, daily management will be derived for forests, shrublands, and grasslands from 2001-2100. This will be done for every watershed modeled as if it was owned by all of the various dominant ownerships that exist in the ecounit in which the watershed exists. Additionally, the management model can adjust management to fit the various scenarios that were devised for the 2022 Scoping Plan update.

Inputs

The management model requires several types of input data sets.

1. Statistics associated with the BAU management for a watershed in a specific ecounit under a specific ownership.
2. Spatially explicit geospatial datasets of environmental conditions within the watershed.
3. A scenario file that defines various aspects of how treatments will be applied to the landscape.

Statistics

The watershed level statistics that the model needs to run per treatment type/ecounit/ownership are:

1. Annual frequency

2. Average size when a treatment occurs

Spatial Data

The spatial data that the management model needs for every watershed are:

1. Slope
2. Location of Streams - this is derived through the RHESSys data processing phase to initialize the model

Scenario File

The scenario file defines how management will occur. Every scenario requires one scenario file per watershed and for each ownership type. The data within a scenario file are:

1. StartYear – the year the simulation begins
2. EndYear – the year the simulation ends
3. Number of Monte Carlo Iterations – the number of monte carlo simulations
4. Size of riparian zone buffer – the number of cell around streams that define a riparian zone
5. Slope threshold beyond which treatments cannot occur – beyond this slope, management is no longer possible
6. Clustering strength - When a treatment occurs, how clustered or dispersed treatments will be
7. Treatment frequency change from BAU – how more or less frequently will each type of treatment occur.
8. Treatment size change from BAU – When a treatment occurs, how many cells will experience this treatment (both inside and outside riparian zones)
9. Retreat time lag - After a treatment occurs, how many years does it take for the probability of a retreatment to fully recover
10. Start day in spring when treatments could occur
11. End day in spring when treatments could occur
12. Start day in fall when treatments could occur
13. End day in fall when treatments could occur
14. Do this type of treatment in forests (yes/no)
15. Do this type of treatment in shrubs(yes/no)
16. Do this type of treatment in grasses(yes/no)

Outputs

The primary output from the management model are maps of where and when every treatment will occur within the watershed. These maps are produced for every day that ever received any treatment. Sets of daily treatment maps are created for each representative watershed, ownership, monte carlo iteration, and alternative scenario combination. These maps are then processed into RHESSys modeling inputs and drive the management in the forest, shrubland, and grassland modeling. Additionally, statistics and summary maps are produced as an output.

Algorithm

The algorithm developed to derive management maps utilizes the treatment size and frequency statistics derived for the BAU, and then converts these statistics to probabilities that determine if a treatment will occur in a year, and how many cells will be treated that year. Additionally, the algorithm restricts treatments to cells with slopes less than some user-defined threshold, by whether the cell is within a riparian buffer zone, or depending on the land cover type of the cell. The algorithm also tracks the number of years after a treatment occurred in a cell. The probability that a second treatment can occur in that same year is zero. Then, depending on the user defined recovery time, the probability that a treatment can occur again in that cell increases through time.

The following is the pseudo code that describes the management model algorithm.

```
For every watershed
    For every scenario
        Load input statistics, maps, scenario file
        For every monte carlo iteration
            For every ownership that exists in this ecounit
                Initialize summary output data
                For every year
                   Initialize annual outputs
                      For every treatment type
                          Convert statistics to probabilities
                          If probability that this treatment type will occur > random num
                            For every cell
                              If the cell's slope is below the defined threshold for treatments
                                 1)  Calculate riparian/non-riparian probability this cell will get treated
                                 2)  Test whether this treatment will occur in this landcover type
                                 3)  Get owner specific probability multiplier
                                 4)  Get retreatment probability (testing whether this cell was treated recently)
                                 Probability this cell is treated = 1*2*3*4
                                 If probCellTreated >= random number
                                     Calculate and test clustering probability this treatment type
                                     While clustering options still exist (restricted by slope, cover type, riparian zone, edge)
                                         Place treatment
                                 If not clustering
                                         Test if treatment can happen here
                                         Place treatment and move on to next cell
```

Modeling Treatment Definitions

To simulate the impacts of the various treatments in RHESSys, parameters are set to determine how vegetation and carbon are altered for each treatment category. In RHESSys, within a system, when a treatment occurs carbon is transferred from pool to pool or removed from the system. For example, carbon can be in the heartwood, sapwood, leaves, root, coarse woody debris, etc. When a treatment occurs, the carbon in these pools can either be transformed, meaning that the carbon is impacted in some way by the treatment, or not. The carbon that is transformed can either leave the system, either by harvesting or burning, or remain in the system and be transferred, in most cases, to the coarse woody debris or litter pool. Below is a description of what it means to be transformed for each treatment category and a description of the carbon pools.

RHESSys does not track individual tree or traditional forest inventory related variables. For example, RHESSys does not track diameters, basal area, stand density, etc. Instead, RHESSys tracks carbon pools in the overstory and understory of a system. Therefore when defining the effect that a treatment category has, treatment impacts are defined in terms of carbon pools, not forest inventory variables. In this way, RHESSys is more flexible in that it can simulate management on more ecosystem types than just forests, including shrublands and grasslands.

Forests vs Shrublands vs Grasslands

Users define which treatments occur on the various land-types. For the 2022 Scoping Plan Update analysis, treatments that occur on forests, shrublands, and grasslands, and across ecounits and ownerships are defined in the Alternative Scenario Development section (Table 7, Table 8, and Table 9).

Variable descriptions

The way in which a treatment's impacts are defined below are by identifying the amount of carbon in a specific carbon pool that is transformed, and of that transformed carbon, how much remains in the system (transferred) and how much is removed from the system. Carbon that remains in the system is typically transferred to the coarse woody debris carbon pool, which is essentially the down dead wood. RHESSys does not specify how carbon leaves the system, only that it is no longer accounted for within the model. The carbon could have left via burning or from harvesting. Once the carbon leaves the system, it is no longer a part of RHESSys modeling. The amount of carbon that doesn't get transformed as a result of treatment, stays in its current carbon pool unchanged.

The subsequent days after a treatment occurs will result in altered fuel loads, growth rates, and carbon fluxes as determined by the model. Treatment influences on fire behavior, growth rates, water availability, or future carbon fluxes are not predefined, but result in response to changes in the redistribution of carbon and nitrogen in the system. That is because RHESSys is a biogeochemical dynamic model that simulates those ecological processes given the structure of the watershed, the site condition, and daily meteorology.

Below are definitions of the terms that are used to define how a treatment impacts an ecosystem in RHESSys.

Overstory

The overstory of a forest, typically with a canopy above 12 feet off the ground. This layer of the canopy typically will contain the dominant species of the system. If the watershed being modeled is in a conifer forest, then the majority of conifers can be thought of as in this layer. If the watershed being modeled is in a shrubland system, then the overstory could primarily contain shrubs. In grassland cells, only a herbaceous overstory is simulated with no woody carbon pools.

Understory

The secondary, shorter vegetative structures. In a forested system, this would include shrubs, and very small diameter trees not in the overstory. For the sake of modeling, shrublands and grasslands will not have an understory.

Transformed percent

The percent of vegetative carbon that is killed or impacted during a treatment event. For example, a value of 0.5 means that 50% of the pool will be impacted and either removed or transferred following a treatment.

Removed percent

The percent of the transformed carbon that is removed from the patch of ground, either through export for harvesting or consumed through fire. Using the previous example, a value of 0.5 transformed and 0.5 percent removed, would indicate that 50% of the 50% transformed carbon will be removed, or 0.5 * 0.5 = 0.25 of the original carbon pool would be removed from the system. Removed_percent and remain_percent sum to one.

Remain percent (Transferred)

The percent of the transformed carbon that remains in a cell and is transferred to coarse woody debris or litter carbon pools.

Definition of carbon pool variables

The definitions of general carbon pools that can be manipulated within RHESSys are shown in Table 14. In some cases, these carbon pools are actually broken into several carbon pools within the model, but they are grouped together as we do not manipulate these sub-pools differently during treatments.

Table 14: The RHESSys terms for carbon pools that are directly affected by forest management in RHESSys, and their descriptions.

Carbon Pool	Description
cpool	Non-structural carbohydrates. A temporary pool for carbon generated by photosynthesis before it is allocated to physical structures within vegetation. After treatment, carbon that remains is transferred to litter_litr1c.
leafc	Leaf carbon in foliage and grasses. After treatment, carbon that remains is transferred to litter_litr1c, litter_litr2c, litter_litr3c, and litter_litr4c based on allocation parameters.
dead_leafc	Standing dead leaf carbon in grasses and tree foliage. After treatment, carbon that remains is transferred to litter_litr1c, litter_litr2c, litter_litr3c, and litter_litr4c based on allocation parameters. This is separated out because prescribed burning manipulates overstory live and dead leaves differently.
stemc	Live stem carbon. All woody biomass carbon above the ground to the top of the tree or shrub. Sapwood, heartwood, and branches. After treatment, carbon that remains is transferred to cwdc.
crootc	Coarse root carbon. These are all perennial roots. Carbon in the cambium portion of coarse tree or shrub roots. After treatment, carbon that remains is transferred to cwdc_bg (coarse woody debris belowground).
frootc	Fine root carbon. These are small, typically, annual roots. After treatment, carbon that remains is transferred to litter_litr1c_bg, litter_litr2c_bg, litter_litr3c_bg, and litter_litr4c_bg based on allocation parameters (bg = belowground).
cwdc	Coarse woody debris carbon. This is similar to the above ground dead woody pool, whether standing or down. This pool, with decay or through treatments, breaks down to the litter_litr1c pool. In terms of fuels, cwdc from the overstory represents 100 hr and larger fuels, cwdc originating from the understory are smaller than 100 hr fuels.
litter_litr1c	Litter labile carbon. This is similar to the upper most duff layer. Fastest decaying litter carbon store. Breaks down to litter_litr2c.
litter_litr2c	Litter unshielded cellulose carbon. This is the next duff layer down. Second fastest decaying litter carbon store. Breaks down to litter_litr3c.
litter_litr3c	Litter shielded cellulose carbon. This is the next duff layer down. Third fastest decaying litter carbon store. Breaks down to litter_litr4c.
litter_litr4c	Litter lignin carbon. This is the final duff layer before the soil starts. Slowest decaying litter carbon store. Breaks down to soil_soil1c.
soil_soil1c	Fast microbial recycling pool carbon. Fastest decaying soil carbon store. Breaks down to soil_soil2c, the final soil layer.

Treatment Parameterization

This section describes the treatments to be modeled in RHESSys and includes the parameters associated with each treatment. Treatments affect various carbon pools within the over and understory and grasses of a forest, shrubland or grassland in different ways. Table 15 is a detailed parameter list.

Biological, Chemical, and Herbaceous Treatments

This treatment is a catch-all term for the application of a chemical substance to inhibit biological growth of a target organism. The values selected represent an herbicide application, either for site preparation, release, or invasive control, as this is the most commonly used chemical type in forest lands. Herbicides are used in California wildlands to ensure success of reforestation efforts, to fight invasive species, and to enhance wildlife habitat amongst other uses. This exercise does not specify the pest management method that is used, only the resulting restructuring of the carbon pools. In the real world, every effort should be made to utilize organic and other non-harmful methods of pest management. Overstory carbon transformed is 0% since herbicide application is generally targeted to competing understory vegetation. Percent removed is set to 0% for both over and understory as no material is removed. To replicate an herbicide treatment on and the potential regrowth of understory vegetation, or grasslands, 90% of all leaves are transformed (100% remain onsite). 40% understory mortality is forced in the model to represent immediate mortality of treated vegetation, and the remaining 60% of the understory carbon pool is left to the dynamics of the model to determine whether it lives or dies. In other words, most (90%) of the understory foliage is killed, however, only 40% of the understory is forced to die. The remaining plants with dead foliage can either recover or die depending on climate conditions, water availability, and all of the other dynamics within RHESSys.

Biological, Chemical, and Herbaceous treatments in summary:

- 0% transformation of overstory
- 90% transformation of understory foliage, 100% remaining
- 40% transformation of understory, 100% remain

Clearcut

This treatment replicates a clearcut harvest on industrial forest land. 80% of the overstory and understory are transformed through this intensive treatment, with the remaining 20% representing retention islands, streamside buffers, and other areas that are generally retained during a clearcut. To represent the utilization of merchantable trees, 90% of overstory stemwood is removed. To capture the practices of leaving the some material in the woods and pile burning the tops and branches, 50% of the non-stemwood aboveground components are removed. Understory is assumed to not be the primary objective of the harvest, though it gets pushed over/trampled during operations wherever the overstory is harvested, and so 80% of the understory is transformed. 80% of transformed understory carbon is assumed to remain while 20% is assumed to be removed through the harvesting process or through pile burns.

Clearcut in summary:

- 80% transformation of overstory, 90% stemwood removal, 50% non-stemwood removal
- 80% transformation of understory, 20% removed and 80% remaining

Harvesting

This treatment represents an intermediate to moderate intensity thinning and commercial harvest, less intensive than a clearcut and more intensive than a thinning. In LANDFIRE, this category captures all harvests where there was not enough information to categorize them into either clearcut or thinning. 40% of the overstory is transformed; this value represents an average value across a variety of harvests that are neither clearcut nor thinning. It can be thought of as an "ecological harvest" where the objective is to reduce fire risk and increase heterogeneity, e.g. some type of variable retention or selective harvest. The same percentage removal of stemwood as the clearcut is used to reflect the similar high utilization of merchantable material. 40% understory is transformed, representing a lighter impact on the understory. The same proportions of the transformed carbon as clearcuts are removed or remain. Additionally, as fuels reduction is a secondary objective of this type of treatments, 52% of the coarse wood debris is removed from either pile burns or harvesting for some kind of utilization. This represents removal of coarse woody debris that existed before the harvest took place.

Harvesting in summary:

- 40% transformation of overstory, 90% stemwood removal, 50% non-stemwood removal
- 40% transformation of understory, 20% removed and 80% remaining
- 52% transformation of coarse woody debris is removed

Thinning

This treatment represents a low intensity thin and/or harvest that focuses on reducing tree density and competition, with a minor fuels reduction component. 10% of the overstory and 75% of understory is transformed to represent the focus on retaining largest trees. Similar to clearcuts and harvesting, 90% of overstory stemwood and 50% of other aboveground stores are removed. To represent pile burning of fuels, 75% of understory and coarse woody debris is transformed, with 70% removal and 30% remaining. 52% transformation of coarse woody debris is removed.
Thinning in summary:

- 10% transformation of overstory, 90% stemwood removed and 50% non-stemwood

- 75% transformation of understory, 70% removal and 30% remaining
- 52% transformation of coarse woody debris is removed

Mastication

This treatment represents the rearrangement of fuels through the mastication of vegetation, principally in the understory. 10% of overstory and 90% of understory are transformed, to capture the incidental, or occasion intentional, removal of larger trees and incomplete mastication/regrowth of shrubs in the understory, respectively. The 10% overstory transformation represent an average across treatments, and is likely to underestimate overstory impact in masticating young forests and overestimate in older forests. This is also true for the 90% understory transformation, which likely underestimates impacts in shrublands and overestimates impacts in forests. 0% of transformed carbon is removed, as it is transferred to litter and coarse woody debris (CWD) pools.

Mastication in summary:

- 10% transformation of overstory, 0% removal
- 90% transformation of understory, 0% removal

Other Mechanical

This treatment represents a variety of site preparation and fuels reduction activities that are focused on reducing fuels without the harvest of merchantable trees. 90% of the understory is transformed with 80% removed through pile burning or utilization. This matches mastication in terms of percent transformed, but some of the cut material is removed from the system. 10% of the overstory is transformed to capture some cutting of overstory trees through fuels reduction treatments. 50% of overstory derived (larger diameter) coarse woody debris is removed, and 10% of understory derived (smaller diameter) coarse woody debris is removed. This is to simulate the fact that mechanical treatments tend to gather larger diameter dead wood, with more of the overstory coarse woody debris being removed than the understory coarse woody debris. Litter is not changed because it is assumed that pile burns are done instead of broadcast burning.

Other Mechanical in summary:

- 10% transformation of overstory, 80% removal and 20% remaining
- 90% transformation of understory, 80% removal and 20% remaining
- 50% transformation of large diameter coarse woody debris, 100% removal
- 10% transformation of small diameter coarse woody debris, 100% removal

Prescribed Burning

This treatment represents a low intensity broadcast prescribed burn. 5% of the overstory live biomass is transformed to represent incidental mortality from the burn.

However, 80% of that transformed overstory carbon remains in the system to represent a relatively small amount of combustion that occurs in overstory trees from prescribed broadcast burns. Impacts are focused on the understory, with 62% transformed used to represent an average across burn conditions that may consume more or less biomass. 66% of the understory stemwood is removed through combustion. This is to match an approximate 40% average combustion of understory vegetation as is the average from the First Order Fire Effects Model (FOFEM), which CARB uses to estimate fire emissions. Roots are not combusted. Existing litter and CWD are removed at varying rates, with removals based on the CONSUME model estimates in the fire effects module of RHESSys [25]. Much of the litter pools are transformed and removed completely. 50% of the small diameter CWD from the understory is removed to capture combustion under a variety of burn conditions, while only 34% of larger coarse woody debris is removed.

Prescribed Burning in summary:

- 5% transformation of overstory stemwood, 20% removal, 80% remaining
- 10% transformation of overstory live foliage, 20% removal, 80% remaining
- 10% transformation of overstory dead foliage, 90% removal, 10% remaining
- 62% transformation of understory, 66% stemwood removal and 99% foliage removal
- 34% transformation of large diameter coarse woody debris, 100% removal
- 50% transformation of small diameter coarse woody debris, 100% removal
- 100% transformation of first 2 layers of litter, 100% removal
- 85% transformation of third layer of litter, 100% removal
- 71% transformation of fourth layer of litter and soil carbon, 100% removal

Table 15: Treatments and their associated parameters. The treatment_name is the shorthand name of the treatment. Story refers to whether it is the overstory (1) or the understory (2). Variable is the name of the carbon pool that will be affected by the parameters. Transformed_percent is the amount of carbon in the specified carbon pool that is affected by the specified treatment. Removed_percent is the percent of the transformed carbon that will be removed from the system. Remain_percent is the percent of the transformed carbon that will remain in the system and, in most cases be transferred to the coarse woody debris pool, which is analogous to a dead wood pool.

Treatment_name	Story	Variable	Transformed_percent	Removed_percent	Remain_percent
bioChemHer	1	cs.cpool	0	0	1
bioChemHer	1	cs.leafc	0	0	1
bioChemHer	1	cs.dead_leafc	0	0	1
bioChemHer	1	cs.live_stemc	0	0	1
bioChemHer	1	cs.dead_stemc	0	0	1
bioChemHer	1	cs.live_crootc	0	0	1
bioChemHer	1	cs.dead_crootc	0	0	1
bioChemHer	1	cs.frootc	0	0	1
bioChemHer	2	cs.cpool	0.4	0	1

bioChemHer	2	cs.leafc	0.9	0	1
bioChemHer	2	cs.dead_leafc	0.4	0	1
bioChemHer	2	cs.live_stemc	0.4	0	1
bioChemHer	2	cs.dead_stemc	0.4	0	1
bioChemHer	2	cs.live_crootc	0.4	0	1
bioChemHer	2	cs.dead_crootc	0.4	0	1
bioChemHer	2	cs.frootc	0.4	0	1
clearcut	1	cs.cpool	0.8	0.5	0.5
clearcut	1	cs.leafc	0.8	0.5	0.5
clearcut	1	cs.dead_leafc	0.8	0.5	0.5
clearcut	1	cs.live_stemc	0.8	0.9	0.1
clearcut	1	cs.dead_stemc	0.8	0.9	0.1
clearcut	1	cs.live_crootc	0.8	0	1
clearcut	1	cs.dead_crootc	0.8	0	1
clearcut	1	cs.frootc	0.8	0	1
clearcut	2	cs.cpool	0.8	0.2	0.8
clearcut	2	cs.leafc	0.8	0.2	0.8
clearcut	2	cs.dead_leafc	0.8	0.2	0.8
clearcut	2	cs.live_stemc	0.8	0.2	0.8
clearcut	2	cs.dead_stemc	0.8	0.2	0.8
clearcut	2	cs.live_crootc	0.8	0	1
clearcut	2	cs.dead_crootc	0.8	0	1
clearcut	2	cs.frootc	0.8	0	1
harvesting	1	cs.cpool	0.4	0.5	0.5
harvesting	1	cs.leafc	0.4	0.5	0.5
harvesting	1	cs.dead_leafc	0.4	0.5	0.5
harvesting	1	cs.live_stemc	0.4	0.9	0.1
harvesting	1	cs.dead_stemc	0.4	0.9	0.1
harvesting	1	cs.live_crootc	0.4	0	1
harvesting	1	cs.dead_crootc	0.4	0	1
harvesting	1	cs.frootc	0.4	0	1
harvesting	2	cs.cpool	0.4	0.2	0.8
harvesting	2	cs.leafc	0.4	0.2	0.8
harvesting	2	cs.dead_leafc	0.4	0.2	0.8
harvesting	2	cs.live_stemc	0.4	0.2	0.8
harvesting	2	cs.dead_stemc	0.4	0.2	0.8
harvesting	2	cs.live_crootc	0.4	0	1
harvesting	2	cs.dead_crootc	0.4	0	1
harvesting	2	cs.frootc	0.4	0	1
harvesting	1	cs.cwdc	0.52	1	0
harvesting	2	cs.cwdc	0.52	1	0
mastication	1	cs.cpool	0.1	0	1
mastication	1	cs.leafc	0.1	0	1
mastication	1	cs.dead_leafc	0.1	0	1
mastication	1	cs.live_stemc	0.1	0	1
mastication	1	cs.dead_stemc	0.1	0	1
mastication	1	cs.live_crootc	0.1	0	1
mastication	1	cs.dead_crootc	0.1	0	1
mastication	1	cs.frootc	0.1	0	1
mastication	2	cs.cpool	0.9	0	1
mastication	2	cs.leafc	0.9	0	1

mastication	2	cs.dead_leafc	0.9	0	1
mastication	2	cs.live_stemc	0.9	0	1
mastication	2	cs.dead_stemc	0.9	0	1
mastication	2	cs.live_crootc	0.9	0	1
mastication	2	cs.dead_crootc	0.9	0	1
mastication	2	cs.frootc	0.9	0	1
otherMechanical	1	cs.cpool	0.1	0.8	0.2
otherMechanical	1	cs.leafc	0.1	0.8	0.2
otherMechanical	1	cs.dead_leafc	0.1	0.8	0.2
otherMechanical	1	cs.live_stemc	0.1	0.8	0.2
otherMechanical	1	cs.dead_stemc	0.1	0.8	0.2
otherMechanical	1	cs.live_crootc	0.1	0	1
otherMechanical	1	cs.dead_crootc	0.1	0	1
otherMechanical	1	cs.frootc	0.1	0	1
otherMechanical	2	cs.cpool	0.9	0.8	0.2
otherMechanical	2	cs.leafc	0.9	0.8	0.2
otherMechanical	2	cs.dead_leafc	0.9	0.8	0.2
otherMechanical	2	cs.live_stemc	0.9	0.8	0.2
otherMechanical	2	cs.dead_stemc	0.9	0.8	0.2
otherMechanical	2	cs.live_crootc	0.9	0	1
otherMechanical	2	cs.dead_crootc	0.9	0	1
otherMechanical	2	cs.frootc	0.9	0	1
otherMechanical	0	litter_cs.litr1c	0	1	0
otherMechanical	0	litter_cs.litr2c	0	1	0
otherMechanical	0	litter_cs.litr3c	0	1	0
otherMechanical	0	litter_cs.litr4c	0	1	0
otherMechanical	0	soil_cs.soil1c	0	1	0
otherMechanical	1	cs.cwdc	0.5	1	0
otherMechanical	2	cs.cwdc	0.1	1	0
rxBurning	1	cs.cpool	0.1	0.2	0.8
rxBurning	1	cs.leafc	0.1	0.2	0.8
rxBurning	1	cs.dead_leafc	0.1	0.9	0.1
rxBurning	1	cs.live_stemc	0.05	0.2	0.8
rxBurning	1	cs.dead_stemc	0.05	0.2	0.8
rxBurning	1	cs.live_crootc	0.05	0	1
rxBurning	1	cs.dead_crootc	0.05	0	1
rxBurning	1	cs.frootc	0.05	0	1
rxBurning	2	cs.cpool	0.615	0.99	0.01
rxBurning	2	cs.leafc	0.615	0.99	0.01
rxBurning	2	cs.dead_leafc	0.615	0.99	0.01
rxBurning	2	cs.live_stemc	0.615	0.6585	0.3415
rxBurning	2	cs.dead_stemc	0.615	0.6585	0.3415
rxBurning	2	cs.live_crootc	0.615	0	1
rxBurning	2	cs.dead_crootc	0.615	0	1
rxBurning	2	cs.frootc	0.615	0	1
rxBurning	0	litter_cs.litr1c	1	1	0
rxBurning	0	litter_cs.litr2c	1	1	0
rxBurning	0	litter_cs.litr3c	0.85	1	0
rxBurning	0	litter_cs.litr4c	0.71	1	0
rxBurning	0	soil_cs.soil1c	0.71	1	0
rxBurning	1	cs.cwdc	0.339	1	0

rxBurning	2	cs.cwdc	0.5	1	0
thinning	1	cs.cpool	0.1	0.2	0.8
thinning	1	cs.leafc	0.1	0.2	0.8
thinning	1	cs.dead_leafc	0.1	0.9	0.1
thinning	1	cs.live_stemc	0.1	0.1	0.9
thinning	1	cs.dead_stemc	0.1	0.1	0.9
thinning	1	cs.live_crootc	0.05	0	1
thinning	1	cs.dead_crootc	0.05	0	1
thinning	1	cs.frootc	0.05	0	1
thinning	2	cs.cpool	0.75	0.7	0.3
thinning	2	cs.leafc	0.75	0.7	0.3
thinning	2	cs.dead_leafc	0.75	0.7	0.3
thinning	2	cs.live_stemc	0.75	0.7	0.3
thinning	2	cs.dead_stemc	0.75	0.7	0.3
thinning	2	cs.live_crootc	0.75	0	1
thinning	2	cs.dead_crootc	0.75	0	1
thinning	2	cs.frootc	0.75	0	1
thinning	1	cs.cwdc	0.52	1	0
thinning	2	cs.cwdc	0.52	1	0

RHESSys Watershed Modeling Methods

Overview

The RHESSys-WMFire version of RHESSys is an integrated carbon, water, and nutrient cycling model coupled to a stochastic fire-spread model (WMFire), and is used for this modeling exercise. RHESSys is organized hierarchically, with vertical vegetation layers simulated at the patch-level, the finest resolution in the model, zones that define radiation and meteorology at the next level, then hillslope and watershed levels which control the lateral redistribution of water [26] (Figure 17). A patch is a cell, or a pixel within the map of the watershed being modeled.

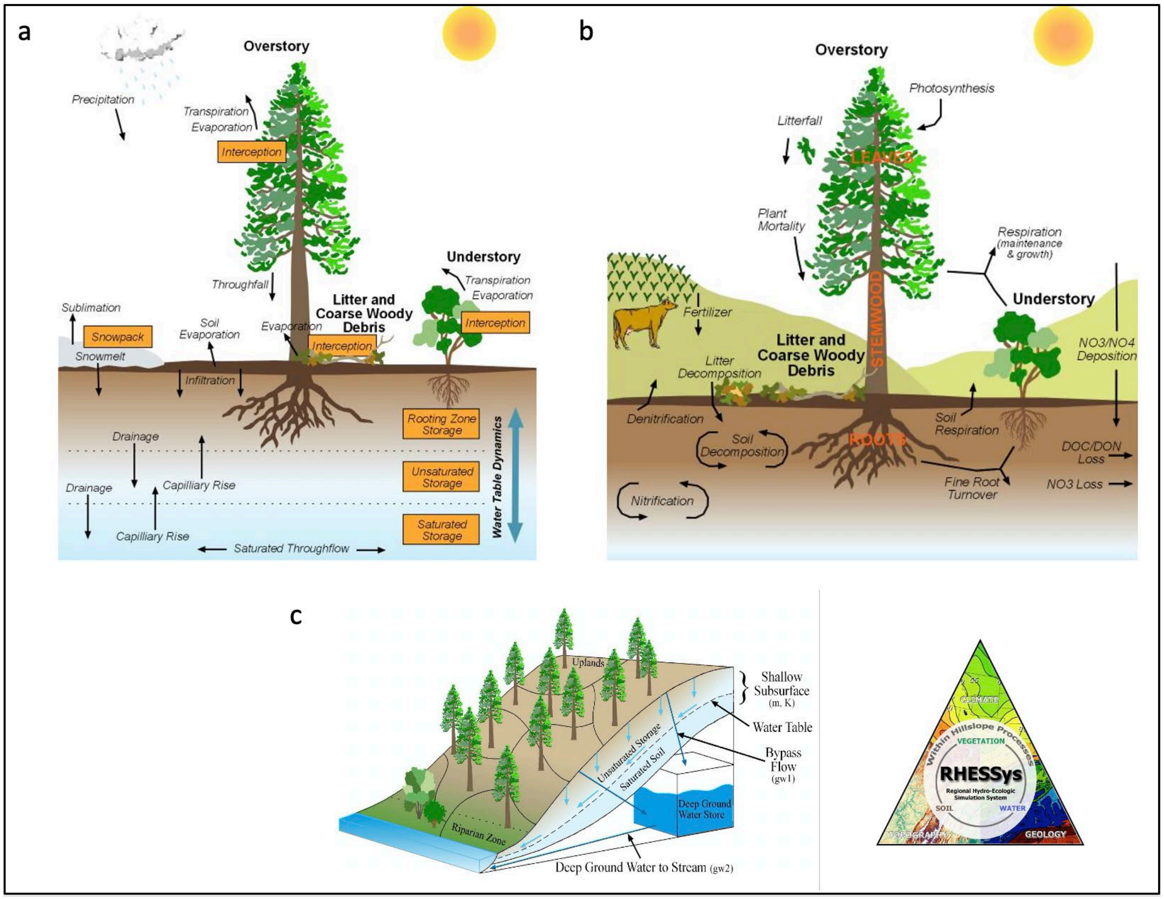

Figure 17: Conceptual model of core processes represented in RHESSys, including a) water cycling processes and b) carbon cycling processes. c) Representation of patch-to-patch water redistribution along a hillslope, as well as drainage to deep groundwater.

The carbon cycling model in RHESSys is a 'big-leaf' model at the patch level and includes processes for photosynthesis, respiration, and the allocation of net photosynthesis to fine root, coarse root, live and dead stem, and leaf carbon stores. Vegetation height is a function of stem carbon stores and rooting depth is a function of root carbon stores. Gross Primary Productivity (GPP) is calculated based on the Farquhar equation [27], and Net Primary Productivity (NPP) is calculated as the difference between GPP and net vegetation respiration. Vegetation respiration processes are based on Ryan [28] and Tjoelker et al. [29] and are a function of temperature and nitrogen content of carbon stores.

The water cycling model in RHESSys includes processes for interception, evaporation, transpiration, and streamflow generation. Incoming radiation is computed as a function of location, terrain, and atmospheric variables. Radiation absorption and transmission is attenuated through each canopy layer to the surface. Surface processes are modeled for vegetation, snowpack, litter, and soil layers. The snow model is a quasi-energy budget model that accounts for canopy cover effects on snow accumulation, melt and sublimation. Precipitation is partitioned to snow and rain using air temperature thresholds. Canopy interception is calculated as a function of vegetation size and type. Penman-Monteith is used to model evaporation, transpiration, and sublimation. Subsurface water fluxes include infiltration and drainage through rooting and unsaturated zones. Lateral drainage of surface flow and shallow saturated subsurface flow to the stream follows surface topography. Groundwater is routed to the stream using a parsimonious linear reservoir model.

As mentioned, RHESSys is hierarchical with processes operating at different scales. The largest scale, the watershed, is the fundamental unit for analyzing streamflow, as streamflow integrates flow from the entire watershed. Thus, all study sites were set up at the watershed scale. For many other processes, including vegetation, the fundamental unit for modeling is the patch, or smallest scale in RHESSys, as vegetation in each patch grows independently of other patches. Patch resolution was set at 90 m. This patch size is small enough to adequately encompass hillslope hydrologic redistribution processes among multiple patches, but large enough to be computationally feasible. Hillslope areas were defined by topography with a target of 10 to 50 patches per hillslope, depending on the watershed. Vegetation within a patch consist of unique canopies that can shade one another depending on vegetation height and cover fraction. For this study, all tree patches contained two canopies, consisting of a conifer overstory and a woody understory, the latter of which is conceptualized as a mixture of young trees and shrubs. Both shrublands and grasses have a non-functional understory.

RHESSys-WMFire is an open-source model and freely available for download at https://github.com/RHESSys/RHESSys. The model version used in this study is version 7.4.

RHESSys Extensions and Simulation Procedure

WMFire was developed to dynamically simulate fire within RHESSys based on simulated conditions within the model [30]. WMFire contains processes for ignition, fire spread, and fire effects. Fire spread in WMFire is organized on a pixelated grid that mirrors the patch structure within the watershed. Each month, random ignitions occur throughout the watershed based on a preset number of average ignitions for the region. Ignition success is based on fuel loads (i.e. litter) in the model and fuel moisture deficit. Fire spread to neighboring patches is stochastic and based on fuel loads, fuel moisture deficit, topography, and wind direction. WMFire computes a probability of spread from one patch to another and this probability of spread within the model acts as a surrogate for fire intensity.

Following fire spread, RHESSys calculates fire-effects based on the probability of spread and ladder fuels via a fire-effects model [31]. For vegetation in the understory, which was defined as less than 4 m tall, the amount of vegetation killed is a function of the fire intensity. The vegetation killed by fire is further partitioned between vegetation that is consumed and vegetation that falls to the surface as litter and coarse-woody debris, based on levels of mortality. Fire propagation to overstory vegetation is based on the amount of litter and understory vegetation that is consumed, with higher understory consumption producing greater overstory mortality. Similar to the understory vegetation, overstory vegetation is partitioned between vegetation that is consumed and vegetation that falls to the surface as litter and coarse-woody debris based on levels of mortality.

For this project, a new module was developed within WMFire to account for fire suppression. Fire suppression reduces the probability of fire spread from one pixel to another, similar to active suppression efforts by fire personal. Fire suppression has a delayed start following ignition, reflecting the time needed to mobilize fire suppression resources. The magnitude of the fire suppression effort is adjustable depending on expected fire suppression resources and the effectiveness of fire suppression is reduced during windy conditions.

RHESSys allows vegetation to be manipulated on designated dates to replicate the effects of forest management. In this project, all management operations were assumed to occur twice a year, on May 15th and November 15th. This assumption was made because of practical processing limitations. By limiting treatments to a spring and fall treatment, this reduced the processing time to manageable lengths. The seven potential treatments included:

1. Biological, Chemical, and Herbaceous Treatments
2. Clearcut
3. Harvest
4. Mastication
5. Mechanical Treatments
6. Prescribed Burning
7. Thinning

Treatments were conducted at a patch scale with the number of treated patches on a given date depending on the ownership type and the management scenario. Vegetation stores are altered on a percent basis and carbon can be shifted from one store to another (e.g., leaf carbon transfers to litter carbon following forest thinning). Vegetation carbon can also be completely removed from a patch, as in the case of forest clearcutting. See the Management and Treatment Modeling section for more detailed information on treatment parameters.

RHESSys contains processes to replicate drought mortality, when vegetation has reduced capacity to photosynthesize due to limited water availability and is susceptible to carbon starvation. In the model, drought mortality is based on levels of on non-structural carbohydrates within the vegetation, which is a reservoir of carbon within vegetation that has not yet been allocated to physical structure (e.g. leaves, stems). Drought mortality is triggered when non-structural carbohydrates within the model fall below a pre-defined level. Full details on design of the drought mortality module in RHESSys can be found in Tague et al. [32].

Input and Evaluation Data

Climate

Daily precipitation, maximum temperature, and minimum temperature data are required to run RHESSys, although the model will accept additional inputs if available. Observed precipitation and temperature data for calibration were obtained through Cal-Adapt [33]. The gridded meteorological dataset had a resolution of ~6-km per pixel and included adjustments for orographic effects. The dataset extended from 1950 to 2013 and was inputted directly into RHESSys from the gridded format.

We used the Localized Constructed Analogs (LOCA) downscaled climate dataset generated by Pierce et al. [34] for projected climate change effects in the selected watersheds. This dataset had a resolution of 1/16th degree (~6 km) and provided daily projections for the four 'essential' general circulation models (GCMs) for California identified by Pierce et al. [35] as part of California's Fourth Climate Change Assessment. The four GCMs include the CanESM2, CNRM-CM5, HadGEM2-ES, and MIROC5 GCMs. The period for future projections with the LOCA product extends 2006 to 2099. Two RCP scenarios were examined, the RCP4.5 moderate scenario and the RCP8.5 business-as-usual scenario.

Soil

Soil information was obtained from the USDA-NCSS detailed soil survey data (SSURGO) (https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx).

Vegetation

Vegetation for each watershed was obtained from the National Land Cover Database (NLCD). All vegetation classes were simplified and reclassified to three representative vegetation types: forest, shrubs, and grass. Future modeling will provide more differentiation across representative vegetation types within each ecounit.

Streamflow

Daily streamflow data was used to calibrate the hydrologic component of RHESSys. These data will be obtained from United States Geological Survey using the USGS R package, dataRetrieval.

Nitrogen Deposition

Nitrogen deposition, which is typically nitrogen that is deposited as a result of man-made pollution, has a large influence on the available nitrogen throughout California wildlands. The effect of this nitrogen deposition is especially prevalent in nitrogen limited soils. To capture the impact that changes in nitrogen deposition will have, through improved air quality as a result of California's climate action, spatially and temporally explicit N deposition data was utilized within this modeling framework.

The base nitrogen deposition data (N-dep) came from the National Atmospheric Deposition Program (NDAP) [36, 37]. This data is a set of maps that are derived from a national network of measured values that are extrapolated utilizing spatially and temporally explicit precipitation data from 2000-present. The year 2020 was the most recent year of N-dep and was then used as the base year off which annual deposition was adjusted. These N-dep maps were then used to derive ecounit specific average rates of nitrogen deposition per unit area.

Table 16: Average annual nitrogen deposition per hectare in each ecounit in 2019.

Ecounit	2019 kg-N/ha/yr
Klamath	2.290091
Northern Sierra/Southern Cascades	1.387885
Northern/Central Coastal Forest	2.765131
Northern Coastal Wood and Shrub Lands	2.491476
Great-Basin Rangelands	0.852249
Dry Sierra Mountains	2.77662
Sierra Foothills	2.778729
Southern Dry Chaparral	2.176206
Humid Sierra Mountains	4.971162
Central Coastal Wood, Shrub, and Grass Lands	1.87296
Central Coast Evergreen Forest	2.621937
Southern Humid Chaparral	2.894895

To develop future projected nitrogen deposition, this ecounit specific base data was then adjusted proportionally to modeled N emissions for RCP4.5 in the annual report 5 from the Intergovernmental Panel on Climate Change (IPCC) [38]. RCP4.5 was chosen because in all alternative scenarios within the Scoping Plan, pollution is projected to decrease. Even though globally CO_2 concentrations are projected to increase at an RCP8.5 rate or higher, locally, California's N deposition, caused by pollution, will decrease. RCP4.5 shows a short-term increase followed by a leveling off and general decrease in N emissions. Relative rates of change from our base year was then developed based off the IPCC emissions. This annual relative change was then applied to the ecounit specific N-dep estimates to develop annual deposition estimates for each ecounit. These annual depositions were then distributed equally 365 ways to derive daily deposition estimates. These daily deposition estimates from 2006-2045 were then used as inputs to the RHESSys model.

Table 17: Estimated annual fractional change in nitrogen deposition from 2020.

Year	Relative fractional change in annual N-Dep
2000	0.885057
2001	0.894023
2002	0.902989
2003	0.911954
2004	0.92092
2005	0.929885
2006	0.938851

2007	0.947816
2008	0.956782
2009	0.965747
2010	0.974713
2011	0.977241
2012	0.97977
2013	0.982299
2014	0.984828
2015	0.987356
2016	0.989885
2017	0.992414
2018	0.994943
2019	0.997471
2020	1
2021	1.003908
2022	1.007816
2023	1.011724
2024	1.015632
2025	1.01954
2026	1.023448
2027	1.027356
2028	1.031264
2029	1.035172
2030	1.03908
2031	1.041609
2032	1.044138
2033	1.046667
2034	1.049195
2035	1.051724
2036	1.054253
2037	1.056782
2038	1.05931
2039	1.061839
2040	1.064368
2041	1.064598
2042	1.064828
2043	1.065057
2044	1.065287
2045	1.065517
2046	1.065747
2047	1.065977
2048	1.066207
2049	1.066437
2050	1.066667
2051	1.065747
2052	1.064828
2053	1.063908
2054	1.062989
2055	1.062069
2056	1.061149
2057	1.06023

2058	1.05931
2059	1.058391
2060	1.057471
2061	1.055632
2062	1.053793
2063	1.051954
2064	1.050115
2065	1.048276
2066	1.046437
2067	1.044598
2068	1.042759
2069	1.04092
2070	1.03908
2071	1.037011
2072	1.034943
2073	1.032874
2074	1.030805
2075	1.028736
2076	1.026667
2077	1.024598
2078	1.022529
2079	1.02046
2080	1.018391
2081	1.017471
2082	1.016552
2083	1.015632
2084	1.014713
2085	1.013793
2086	1.012874
2087	1.011954
2088	1.011034
2089	1.010115
2090	1.009195
2091	1.008506
2092	1.007816
2093	1.007126
2094	1.006437
2095	1.005747
2096	1.005057
2097	1.004368
2098	1.003678
2099	1.002989
2100	1.002299

CO2 Concentrations

Carbon dioxide (CO2) concentrations influence the efficiency by which plants can grow and use water. CO2 concentrations are rapidly changing and may change in several different ways going into the future. To include the impact of changing CO2 concentrations on California's vegetation, daily CO2 concentrations were developed.

Decadal current and future CO2 concentrations from the IPCC annual report 5 were used as the basis for calculating daily CO2 concentrations for RHESSys [38]. The 2022 Scoping Plan Update modeling exercise utilized RCP4.5 and RCP8.5 concentrations. Single estimates of concentrations were utilized for the entire state. Decadal concentrations were linearly extrapolated temporally to generate annual and then daily CO2 concentrations that were inputs into RHESSys.

Table 18: Annual CO2 concentrations (ppm) for representative concentration pathways 4.5, and 8.5.

Year	RCP4.5	RCP8.5
2000	368.9	368.9
2001	370.88	370.88
2002	372.86	372.86
2003	374.84	374.84
2004	376.82	376.82
2005	378.8	378.8
2006	380.86	380.9
2007	382.92	383
2008	384.98	385.1
2009	387.04	387.2
2010	389.1	389.3
2011	391.3	391.95
2012	393.5	394.6
2013	395.7	397.25
2014	397.9	399.9
2015	400.1	402.55
2016	402.3	405.2
2017	404.5	407.85
2018	406.7	410.5
2019	408.9	413.15
2020	411.1	415.8
2021	413.49	419.1
2022	415.88	422.4
2023	418.27	425.7
2024	420.66	429
2025	423.05	432.3
2026	425.44	435.6
2027	427.83	438.9
2028	430.22	442.2
2029	432.61	445.5
2030	435	448.8
2031	437.58	452.86
2032	440.16	456.92
2033	442.74	460.98
2034	445.32	465.04
2035	447.9	469.1
2036	450.48	473.16
2037	453.06	477.22
2038	455.64	481.28
2039	458.22	485.34

2040	460.8	489.4
2041	463.37	494.51
2042	465.94	499.62
2043	468.51	504.73
2044	471.08	509.84
2045	473.65	514.95
2046	476.22	520.06
2047	478.79	525.17
2048	481.36	530.28
2049	483.93	535.39
2050	486.5	540.5
2051	488.74	546.8
2052	490.98	553.1
2053	493.22	559.4
2054	495.46	565.7
2055	497.7	572
2056	499.94	578.3
2057	502.18	584.6
2058	504.42	590.9
2059	506.66	597.2
2060	508.9	603.5
2061	510.44	610.86
2062	511.98	618.22
2063	513.52	625.58
2064	515.06	632.94
2065	516.6	640.3
2066	518.14	647.66
2067	519.68	655.02
2068	521.22	662.38
2069	522.76	669.74
2070	524.3	677.1
2071	524.98	685.21
2072	525.66	693.32
2073	526.34	701.43
2074	527.02	709.54
2075	527.7	717.65
2076	528.38	725.76
2077	529.06	733.87
2078	529.74	741.98
2079	530.42	750.09
2080	531.1	758.2
2081	531.36	766.86
2082	531.62	775.52
2083	531.88	784.18
2084	532.14	792.84
2085	532.4	801.5
2086	532.66	810.16
2087	532.92	818.82
2088	533.18	827.48
2089	533.44	836.14
2090	533.7	844.8

2091	534.17	853.91
2092	534.64	863.02
2093	535.11	872.13
2094	535.58	881.24
2095	536.05	890.35
2096	536.52	899.46
2097	536.99	908.57
2098	537.46	917.68
2099	537.93	926.79
2100	538.4	935.9

Gross Primary Productivity (Eddy Covariance Tower)

Observed daily Gross Primary Productivity (GPP) for water years 2018 through 2020, with water year defined as October of the prior year to September of the current year, were obtained from an eddy covariance tower located within Sagehen, which is the representative watershed for the Humid Sierra Mountains. The footprint for the eddy covariance tower is located within a Woody Savanna & Evergreen Needleleaf Forest. This data is used within the parameterization process.

Gross Primary Productivity - MODIS

Estimates of vegetation productivity for patches and watersheds without a flux tower were obtained from satellite data. Specifically, annual GPP was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD17 product for the period between 2001 and 2020 [39]. For patch-scale comparisons, the nearest MODIS tile with contiguous vegetation of the corresponding vegetation type (e.g. tree, shrub, grass) was selected. For watershed-scale comparisons of GPP, all MODIS tiles within the respective watershed were spatially averaged. This data is used within the parameterization process.

Tree Height dataset

Spatially distributed heights for the overstory tree canopies, which are used as growth targets during patch-scale vegetation spin-up, were obtained from the global dataset generated by Simard et al. [40].

Fire

Historical fire return intervals for most landscapes in California are non-existent due to forest management over the past 100+ years that has altered fire regimes and fuel accumulation. Consequently, direct calibration of the fire model to observed data was not possible. Instead, the fire component of RHESSys-WMFire was tuned by 1) consulting the relevant literature for estimates of the natural fire return interval under historical fire regimes in California, and 2) comparing spatially distributed fire return interval patterns in RHESSys-WMFire to the fire return interval product generated by LANDFIRE (https://www.landfire.gov/fri.php). While the LANDFIRE product is derived from a model and does not provide direct evidence of historical fire return intervals, LANDFIRE estimates were used to explore consistencies and discrepancies between the LANDFIRE and RHESSys-WMFire. Additionally, fire return interval departure data from LANDFIRE is used to help parameterize the fire suppression model.

Representative Watersheds

A single watershed was selected to represent each ecological unit throughout California (Figure 18). The ecological units were generated based on dominant vegetation, aridity, and baseline ecoregions. Within each ecological unit, 'reference' gauged watersheds were identified based on the US Geological Survey's Gages II database (https://water.usgs.gov/GIS/metadata/usgswrd/XML/gagesII_Sept2011.xml). Reference watersheds are considered to be relatively unmanaged and to not be significantly modified in terms of hydrologic storage (e.g. dams) and water extractions. The potential watershed list was further culled to watersheds with areas between 15 and 200 km^2. At this size, the watersheds were large enough to provide sufficient spatial heterogeneity but small enough to be computationally feasible for modeling multiple scenarios. This scale equates to the approximate size of HUC12 watersheds.

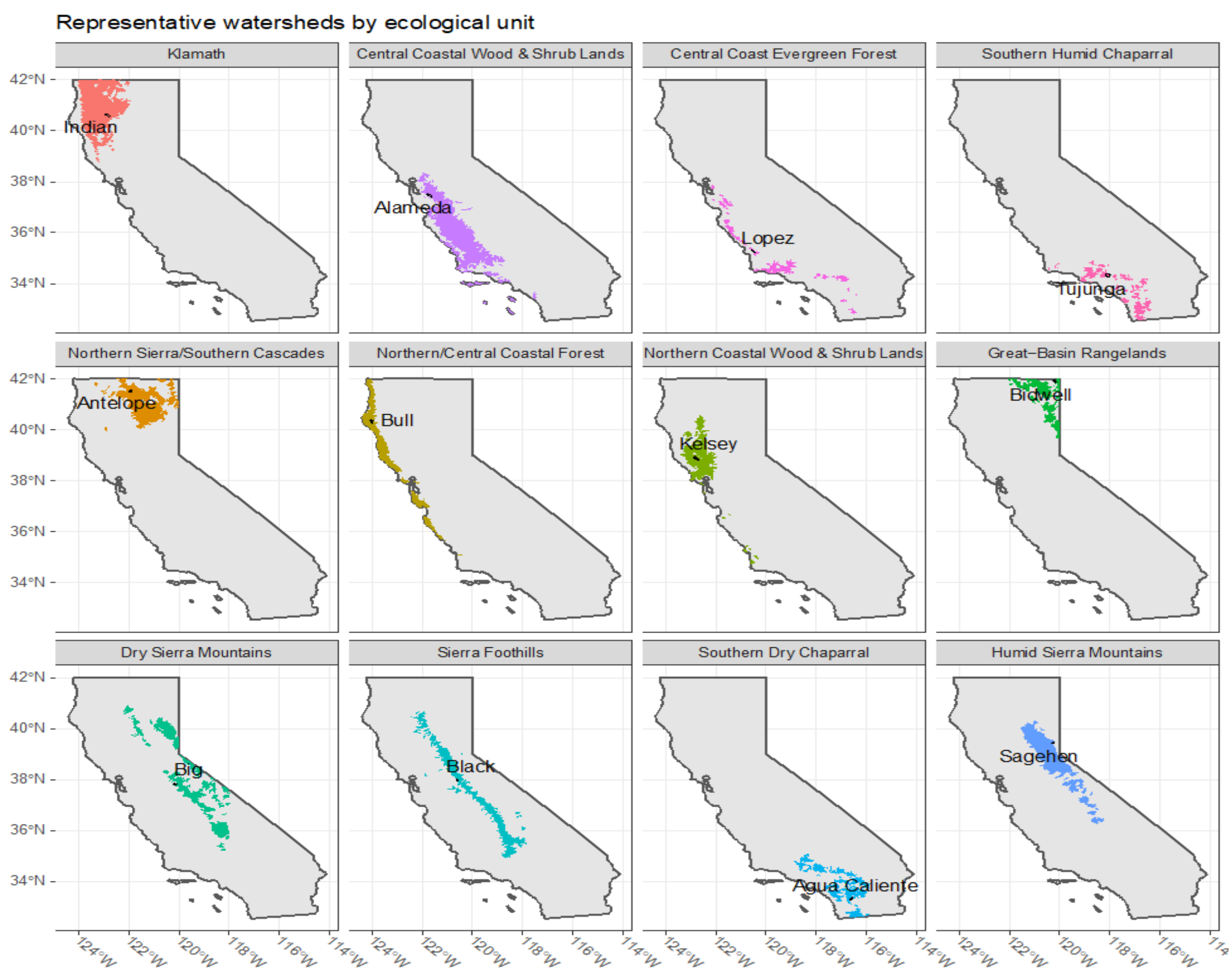

Figure 18: A map showing the representative watersheds located within each ecounit.

A threshold was set that all the potential watersheds must have a minimum observed streamflow record of 15 years. To account for interannual variability (i.e. wet and dry years), streamflow calibration in RHESSys needs five or more years of data. A 15-year record provides sufficient data for an extended calibration as well as an option for validation. To maximize the number of potential watersheds in each ecological unit, gauges that are not presently functioning were included as options, as long as the gauges have functioned during the 1950 to 2013 period, which corresponds with the Livneh meteorological data product. The number of potential representative watersheds in each ecounit ranged from a single watershed in the Great-Basin Rangelands ecounit to 17 watersheds in both the Central Coast Evergreen Forest and Humid Sierra Mountains ecounits.

The area for the twelve representative watersheds ranged from 27.7 km^2 in Sagehen to 168.0 km^2 in Tujunga (Table 19). As expected, the watersheds had a wide range of meteorological and physical characteristics, depending on their respective ecounit. For example, mean annual precipitation ranged from 443 mm/year in Agua Caliente in the Southern Dry Chaparral ecounit to 2375 mm/year in Bull located in the Northern/Central Coastal Forest (Table 20).

Table 19: Physical and vegetation characteristics of representative watersheds.

Representative Watershed	USGS Gauge ID	Area (km2)	Minimum Elevation (m)	Maximum Elevation (m)	Trees (%)	Shrubs (%)	Grass (%)
Agua Caliente	11031500	49.5	892	1979	28.1	69.5	2.4
Alameda	11172945	86.4	281	1164	39.4	40.4	20.2
Antelope	11489500	40.0	1588	2305	84.7	12.1	3.1
Bidwell	10360900	66.7	1467	2527	76.4	23.5	0.1
Big	11284400	41.7	784	1208	69.9	24.7	5.3
Black	11299600	37.6	230	706	38.2	44.6	17.2
Bull	11476600	71.4	85	1010	89.8	3.9	6.4
Indian	11525670	87.1	510	2120	71.5	25.6	2.8
Kelsey	11449500	95.9	455	1437	38.4	41.0	20.7
Lopez	11141280	53.8	179	871	73.1	24.0	2.9
Sagehen	10343500	27.7	1933	2656	90.6	9.0	0.4
Tujunga	11094000	168.0	818	2144	4.5	91.5	4.0

Table 20: Meteorological and streamflow characteristics of representative watersheds.

Representative Watershed	Ecounit	Mean Annual Precipitation (mm)	Mean Annual Minimum Temperature (C)	Mean Annual Maximum Temperature (C)	Mean Annual Streamflow (mm)
Agua Caliente	Southern Dry Chaparral	443	4.6	21.7	47
Alameda	Central Coastal Wood and Shrub Lands	527	8.3	18.9	201
Antelope	Northern Sierra/Southern Cascades	1103	-3.9	12.6	752
Bidwell	Great-Basin Rangelands	753	-1.5	13.7	333
Big	Dry Sierra Mountains	935	4.9	20.9	185
Black	Sierra Foothills	647	8.0	23.3	197
Bull	Northern/Central Coastal Forest	2375	4.7	14.8	1341
Indian	Klamath	1134	1.8	18.1	302
Kelsey	Northern Coastal Wood and Shrub Lands	1234	3.5	19.8	653
Lopez	Central Coast Evergreen Forest	598	6.1	19.0	146
Sagehen	Humid Sierra Mountains	929	-4.8	13.6	374
Tujunga	Southern Humid Chaparral	687	6.8	19.7	63

Parameterization

Parameterization is the process of selecting model parameters that best represent the system being examined. For this project, a three-step approach was used to parameterize RHESSys, corresponding to the parameterization of vegetation, hydrology, and fire. Further, the general parameterization approach described in Refsgaard [41] for distributed modeling was followed. The Refsgaard approach emphasizes that parameterization should seek to have as few parameters as possible requiring formal calibration. Instead, most parameters should be determined and fixed based on literature sources and/or expert knowledge. Model parameterization occurred at two different scales depending on the process and the available data, with vegetation parameterization occurring at both the patch and watershed scale, while hydrology and fire were parameterized at the watershed scale.

Within each watershed, a single representative patch was selected for each vegetation type to guide parameterization. For most watersheds, the representative patch was selected based on having the median elevation among all watershed patches of a given vegetation type. This approach ensured that the patch was representative across the elevational gradient in the watershed. For watersheds that included an eddy-covariance tower that measures canopy carbon and hydrologic fluxes at a single site (e.g. Sagehen), the RHESSys patch that overlapped the eddy-covariance tower was selected.

Many of the vegetation parameters were identified and fixed within the model using a combination of established RHESSys default parameter values and parameters based on literature values. An iterative approach that included simulation, evaluation, and parameter adjustment was used to evaluate the sensitivity of parameters. In some cases, due to parameter interactions and/or equifinality, only the range of parameters values was identifiable. In these cases, formal parameterization was used to identify the best parameter sets. The parameterization procedure for RHESSys-WMFire occurs in three steps; processing of the vegetation component of the model, followed by the hydrologic component, and the fire component (Figure 19). For each watershed, 2000 parameter sets were selected using a latin hypercube sampling of the parameters specified in Table 21. Initial parameter ranges were selected to represent a plausible distribution of vegetation, hydrologic, and fire parameter values. The multi-step parameterization approach emphasized the elimination of non-behavioral parameter sets at each step, with only the behavioral parameter sets being passed to the subsequent stage of parameterization. Thus, the top parameter set that is ultimately passed on to model simulation will, by definition, have been behavioral at all steps in the parameterization process.

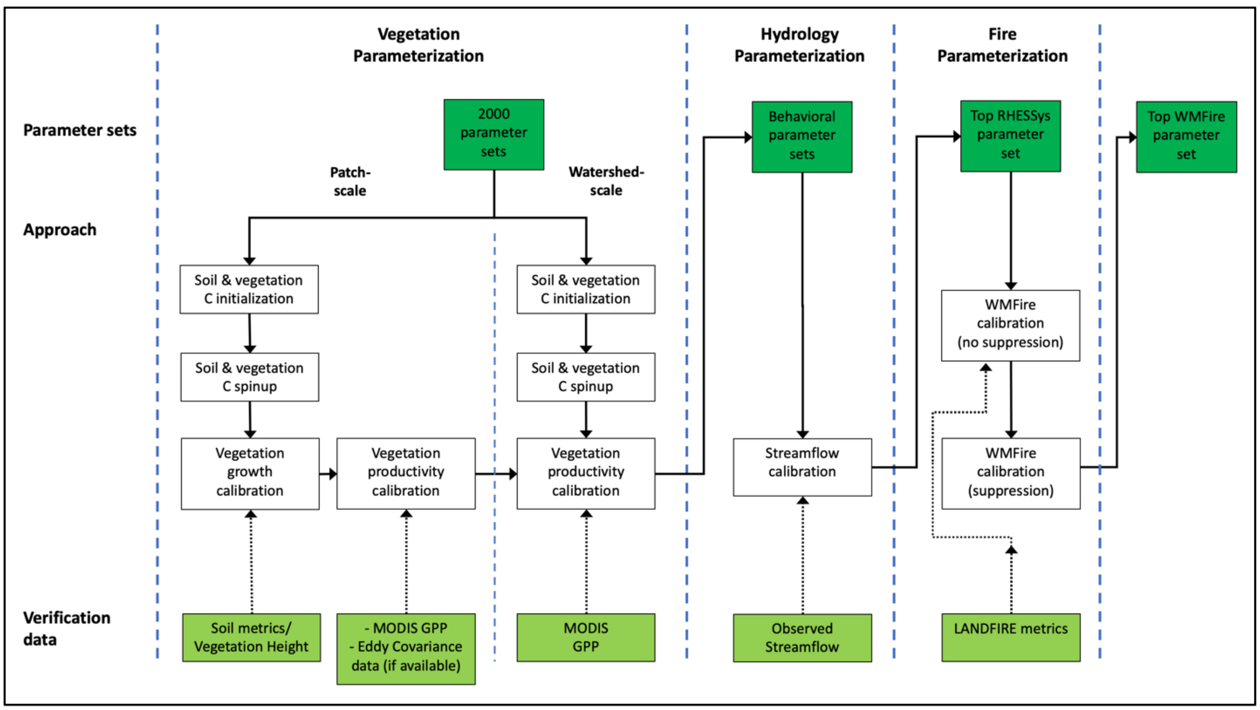

Figure 19: Flowchart of model parameterization for vegetation, hydrology, and fire components of RHESSys-WMFire.

Table 21: Vegetation, hydrologic, and fire parameters used to calibrate RHESSys-WMFire..

Parameter Type	Parameter Description	Units
Vegetation	Allocation	
Vegetation	New fine root to new leaf C allocation	-
Vegetation	New coarse root to new stem C allocation	-
Vegetation	New stem to new leaf C allocation	-
Vegetation	New livewood to total wood C allocation	-
Vegetation	Annual turnover of leaf C to litter	yr^{-1}
Vegetation	Annual turnover of livewood C to deadwood	yr^{-1}
Vegetation	Annual turnover of stem C to CWD	yr^{-1}
Vegetation	Height to stem carbon relation coefficient	m Kg C^{-1}
Vegetation	Photosynthesis	
Vegetation	Specific leaf area	m^2 Kg C^{-1}
Vegetation	Maximum stomatal conductance	m s^{-1}
Vegetation	Respiration increase per 10C increase in temperature (Q10)	-
Vegetation	Fraction of nitrogen in rubisco	kg / kg
Vegetation	C:N ratios	
Vegetation	Leaf C:N	kg C kg N^{-1}
Vegetation	Fine Root C:N	kg C kg N^{-1}
Vegetation	Litter C:N	kg C kg N^{-1}
Hydrologic	Decay of hydraulic conductivity with depth	m^{-1}
Hydrologic	Saturated hydraulic conductivity	m d^{-1}
Hydrologic	Soil air entry pressure	m
Hydrologic	Pore size index	-
Hydrologic	Groundwater bypass flow	%
Hydrologic	Groundwater drainage rate	%
Hydrologic	Soil depth	m
Fire	Fire monthly ignitions parameter	-
Fire	Fire effects overstory scale parameter	Kg/m^2
Fire	Fuel load probability of spread slope parameter	-
Fire	Fuel moisture probability of spread slope parameter	-
Fire	Suppression magnitude parameter	-
Fire	Suppression effectiveness parameter	-
Fire	Suppression windmax parameter	-

Vegetation

The parameters calibrated for vegetation growth and productivity are listed in Table 21. These include four parameters related to photosynthesis, eight parameters related to carbon allocation following photosynthesis, and three C:N-ratio parameters related to model respiration.

Vegetation parameterization at the patch scale began with the initialization of soil and vegetation carbon stores (Figure 19). For soil carbon, initial values were set at the low end of the expected carbon value range to lessen the length of soil spin-up times. Initial vegetation carbon stores were set at zero to replicate vegetation growth following a stand replacing disturbance.

A patch-scale spinup was conducted for 100 years without fire, a length that was determined to be a suitable period for generating mature vegetation stands across the watersheds. The height for each conifer patch was compared to the height from the Simard tree height dataset for the respective patch, with the parameter set being considered behavioral if the modeled height was between 50% and 120% of the Simard height. For conifer understory and shrubs, behavioral vegetation heights were determined to be between 1.25 m and 3.5 m, while behavioral grasses had behavioral heights between 0.25 m and 1.25 m. For soil carbon, parameter sets were considered behavioral if soil carbon was either steady (i.e. soil carbon did not decrease more than 10%) or increased during the 100-year spinup. All parameter sets that met the individual behavioral criteria for vegetation growth and soil metrics for all three vegetation types were considered behavioral overall.

The model was calibrated against vegetation productivity metrics derived from MODIS for all representative patches that did not contain an eddy covariance tower. RHESSys was run for the period between 2000 and 2013; the period where MODIS overlaps with the Livneh meteorological dataset. Annual GPP from the model was compared to annual GPP from MODIS using root mean square error (RMSE). As the absolute values for MODIS GPP can be biased, only the relative patterns of annual GPP were compared to one another. Parameter sets corresponding with the top 80% of RMSE values were retained. For tree patch in Sagehen that contained an eddy covariance tower, vegetation productivity was calibrated by simulating RHESSys for water years 2018 to 2020, which corresponded to data availability from the tower. Daily GPP was compared to the tower GPP using RMSE and the parameter sets with the top 80% of RMSE values were retained.

Once the behavioral parameter sets were established at the patch scale, watershed-scale scale parameterization was conducted in a similar manner. Soil and vegetation carbon at the watershed scale were initialized using the same approach as at the patch scale. A 100-year spinup without fire was then conducted to establish vegetation throughout the watershed. Vegetation productivity was calibrated at the watershed scale, with annual GPP averaged across all patches within the watershed being compared to MODIS GPP averaged across all pixels encompassing the watershed. Once again, parameter sets representing the top 80% of RMSE values were considered behavioral and passed to the hydrologic component of the parameterization process.

Streamflow

Modeling hydrology at a watershed scale generally requires calibration of subsurface parameters. However, direct measurement of subsurface parameters is limited by the heterogeneity and difficulty of directly measuring subsurface characteristics. For example, hydrologic conductance at the watershed scale may be an order of magnitude higher than at the point (i.e. soil matrix) scale due to the presence of macropores (e.g. tree roots, soil clumping).

The hydrology component of the model was calibrated by evaluating daily modeled streamflow with observed streamflow. For each behavioral parameter set passed from the vegetation parameterization, RHESSys was run for eleven water years without fire, with the first three water years used as a spin-up to initialize hydrologic subsurface stores. Modeled streamflow was evaluated quantitatively using the Kling-Gupta Efficiency (KGE) objective function [42] at a daily time-step. KGE is a goodness-of-fit measure that compares the correlation, variability, and bias between the observed and the modeled streamflow. Values of 1 indicate perfect agreement, with smaller values indicating greater differences between observed and modeled streamflow.

The hydrologic parameters to be calibrated included two parameters that control the hydrologic conductance in the model (decay of hydraulic conductivity with depth and saturated hydraulic conductivity), two parameters that influence water-holding capacity and wilting point of the soils (soil air entry pressure and pore size index), two parameters that control how much infiltrative flow moves to groundwater and the rate that the water is then released back to the stream (groundwater bypass flow and groundwater drainage rate), and a parameter for soil depth (Table 21). The parameter set with the highest KGE value was selected as the top parameter set used for simulations involving RHESSys. This parameter set was subsequently passed to the fire calibration with WMFire. Future work will permit multiple parameter sets to be passed to WMFire, allowing a more robust evaluation of watershed behavior.

Fire

For each watershed, WMFire was parameterized to replicate a natural fire regime, with fire regime defined as the typical characteristics of fire such as size, seasonality, fire return interval, intensity, and severity. However, this task was made challenging since there is little to no modern natural fire regime data in California. In California, policies of fire suppression over the past century by the United States Forest Service and other land management agencies have altered the fire regime in most natural lands. Further, California indigenous communities shaped and managed California landscapes using fire prior to the era of fire suppression. Thus, there is no clear agreement of what constitutes a natural fire regime in California. Due to this limitation, we used natural fire-return interval and seasonality maps generated by LANDFIRE to evaluate WMFire [43]. LANDFIRE, like the MODIS GPP product, is itself a modeled product. However, in the absence of direct natural fire regime data in California, LANDFIRE provided verification that WMFire was capturing the major characteristics of fire in each watershed. The two primary parameters in WMFire that were calibrated were the monthly fire ignitions parameter, which is a primary control on the frequency of fire within a watershed, and the overstory scale parameter, which controls how easy fire spreads from the understory to the forest canopy via ladder fuels (Table 21).

WMFire parameterization of a natural fire regime involved 50-year RHESSys simulations with WMFire turned on but with no fire suppression. Watershed-average fire return intervals were compared to LANDFIRE, while fire severity was evaluated against expected behavior (i.e. fire severity in the forest overstory ranged from minimal to severe depending on fire characteristics such as fuel loads, moisture deficits, temperatures, and wind speeds). The WMFire fire spread parameter set that best matched the expected fire behavior was then fixed for parameterization of fire suppression.

WMFire parameterization for fire suppression was conducted in a similar manner to a natural fire regime, but for suppression parameters (Table 21). The effect of fire suppression on fire behavior was to lessen fire spread and fire severity for a given set of fuel or meteorological conditions. Using the LANDFIRE historic fire returned intervals, that were also used for scenario development, and current fire return intervals, a suppression rate was determined. The suppression rate was the current fire return interval divided by the historical fire return interval. This essentially creates a fraction of the current fire that burns relative to the historic burn rates.

The difference in fire behavior between a natural fire regime and a fire suppressed fire regime is shown in Figure 20 for the Indian watershed. In this example, fire was a regular occurrence in the watershed without suppression and the occurrence of fire events burning over half the watershed was common. Due to the frequency of fire without suppression, the associated severity of these fires was low (not shown). When suppression was added to the model, the number of patches burned each year showed a large decrease, reflecting the reduction in probability of spread. However, fire suppression frequently generated an increase in fuel loads over time due to a reduction in the amount of vegetation carbon consumed within the watershed. This is observed in the large event in 2058 under the suppression scenario, when meteorological and fuel conditions combined to overcome suppression effects.

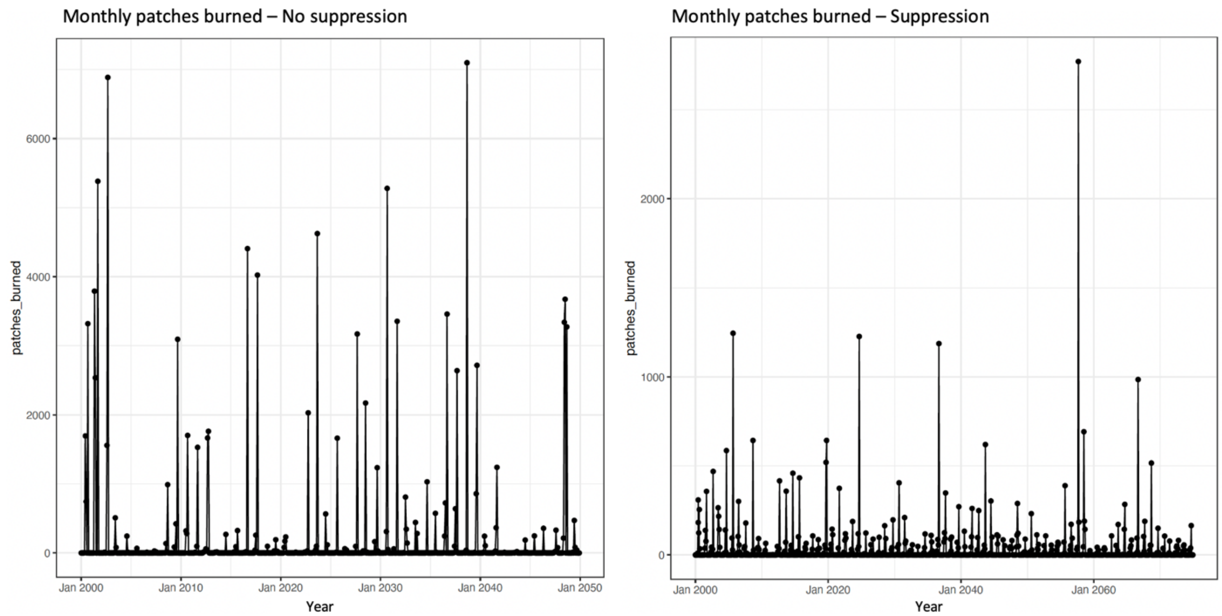

Figure 20: Monthly patches burned for the Indian watershed under No suppression (left panel) and Suppression (right panel) scenarios. Total number of patches in Indian watershed is 10747. Note that the y-axis scales are different for each panel.

Simulations

Once the top parameter set was selected, each representative watershed was reinitialized using the new parameter set. However, due to the size of some of the watersheds, it was computationally prohibitive to directly spinup soil carbon pools until they were stable. Instead, soil spinup was first conducted in each of the three representative patches within the watershed (e.g. tree, shrub, grass) for 3000 years, with the meteorological data looped to provide continuous inputs. These stabilized soil carbon values were then used to initialize soil carbon for all patches of the respective vegetation type in the watershed. To generate variability in the soil carbon stores across the watershed, the full watershed was subsequently simulated under precolonial conditions with a natural fire regime (i.e. fire was primarily limited by fuel and weather) for a period ranging from 75 years in Tujunga, the largest watershed, to 500 years in Sagehen, the smallest watershed. By the end of the precolonial period, the simulated conditions within each watershed represented conditions prior to Western management of the natural lands in California.

A colonial period was simulated following the precolonial period to represent the effects of fire suppression by the federal and state government, as well as a business-as-usual (BAU) management scenario for different ownership types. The BAU management scenario included land management treatments that are consistent in time and space to historical land management within the respective ecounit. The colonial period was simulated for 156 years (1850 to 2006) for each watershed except Bull, Indian, and Tujunga, which had 106 year colonial simulations (1900 to 2006).

The simulations between 2007 and 2024 represent the period when fire suppression and BAU management continue within each watershed, but meteorological inputs shift from the historical dataset to the four GCM scenarios and two RCP scenarios used in this project. The simulations for this period reflect the impact of climate change during the early part of the 21st century on fire, vegetation, and streamflow.

Simulations between 2025 and 2045 represent the period when climate change continues to affect the representative watersheds but also when the potential alternative management scenarios were assessed. The management scenarios were expanded to include a Conservation scenario, a Business-as-Usual scenario, a Current Commitments scenario, a Climate Resilience scenario, a Wildfire Mitigation scenario.

For each phase of the simulations, the number of runs increased as the combinations of inputs increased (Table 22). For example, in the last phase, all combinations of watersheds, ownerships, management scenarios, GCMs, and RCPs were simulated.

Table 22: Number of RHESSys-WMFire runs associated with each phase of the future simulations.

Period	Number of runs
Precolonial	36
Colonial	177
Climate change/ BAU	1593
Climate change/ New Management	6669

Output Data

The simulations conducted with RHESSys-WMFire generated several terabytes of outputs. Specifically, outputs from each run included carbon stores related to vegetation, soil, litter, and coarse woody debris; as well as fluxes related to changes in vegetation carbon due to management, fire, and mortality; and hydrologic variables (Table 23). These variables represent a small subset of the variables that can be outputted from RHESSys-WMFire but were selected due to the breath of information contained between the variables and the need to minimize the number of outputs due to the number of runs conducted.

Table 23: Output variables obtained from RHESSys-WMFire simulations and associated temporal and hierarchical scale.

Output variable	Temporal scale	Hierarchical scale
Streamflow	Daily	Watershed
Vegetation C	Annual	Stratum
Leaf C	Annual	Stratum
Stem C	Annual	Stratum
Root C	Annual	Stratum
Litter C	Annual	Patch
Soil C	Annual	Patch
Coarse Woody Debris (above ground)	Annual	Stratum
Coarse Woody Debris (below ground)	Annual	Stratum
C Mortality	Annual	Stratum
Transpiration	Annual	Stratum
Evaporation	Annual	Patch
C Removed from Treatments	Twice Yearly	Stratum
C Remaining from Treatments	Twice Yearly	Stratum
C Mortality by Fire	Monthly	Stratum
C Consumed by Fire	Monthly	Stratum

Figure 21 shows an example of the fire results that were generated by the model for the Alameda watershed, which is has a mix of trees, shrubs, and grasses, for the MIROC5 GCM and 8.5 RCP scenario. Cumulative area burned showed variation with across management scenarios as well as among ownership types. Greater area burned was associated with less intensive management. Variability of cumulative area burned across ownerships was greater for the less intensive management scenarios, whereas variability was smaller for the more intensive management scenarios. Figure 22 shows cumulative mortality due to fire in the Alameda watershed for the MIROC5 GCM scenario and 8.5 RCP scenario. Higher fire mortality was observed for less intensive management scenarios, reflecting the greater area burned under those scenarios.

In both of these figures, the results are representative of one GCM, one RCP scenario, and one watershed. 95 similar plots would be needed to fully characterize the response of area burned across all scenarios/watersheds examined in this project. This demonstrates the large amount of results generated by this project, as well as the detail it provides when assessing responses across different watersheds and climate scenarios in California.

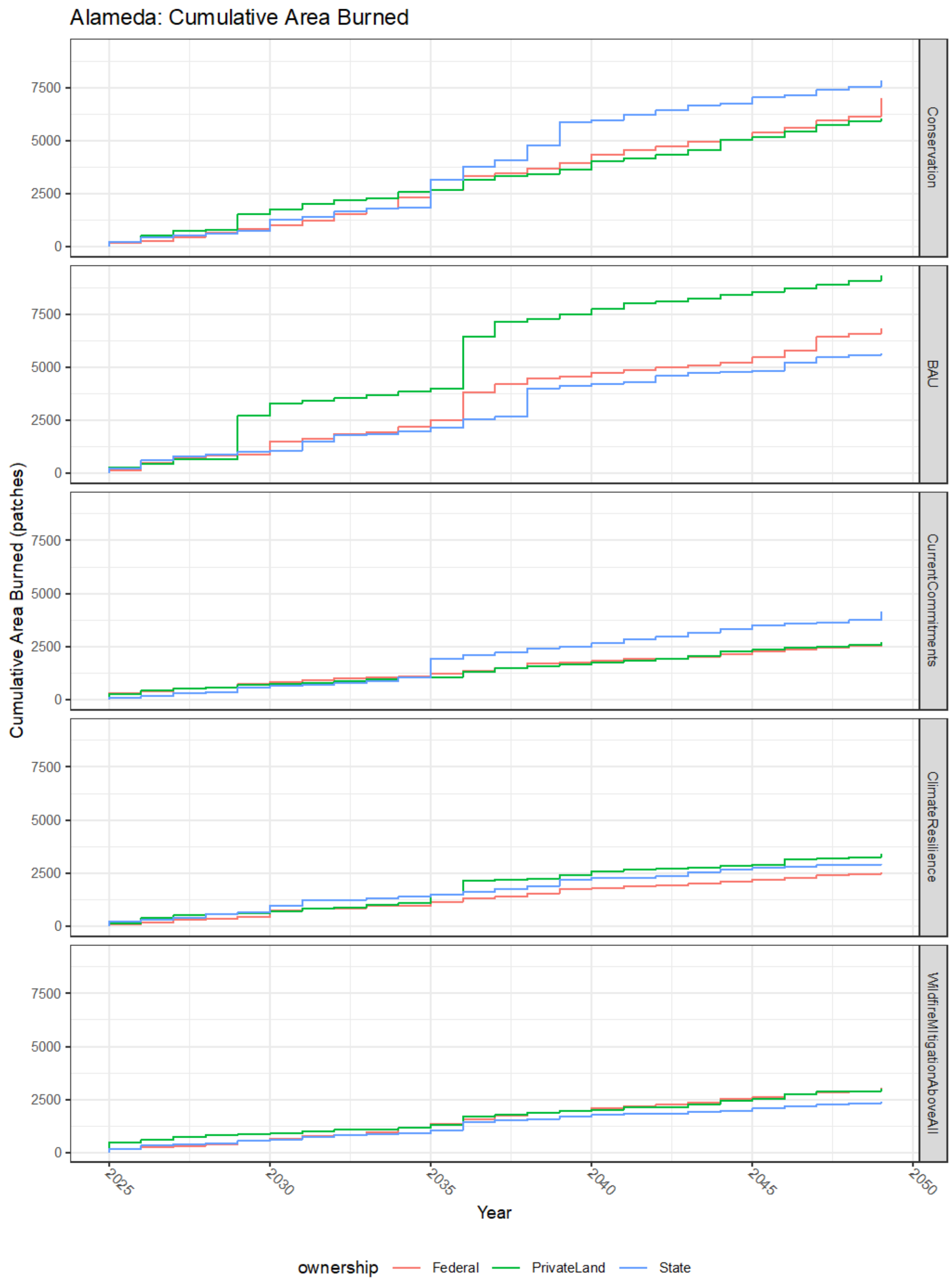

Figure 21: Cumulative area burned in the Alameda watershed under different management scenarios and ownerships for the MIROC5 GCM scenario and 8.5 RCP scenario.

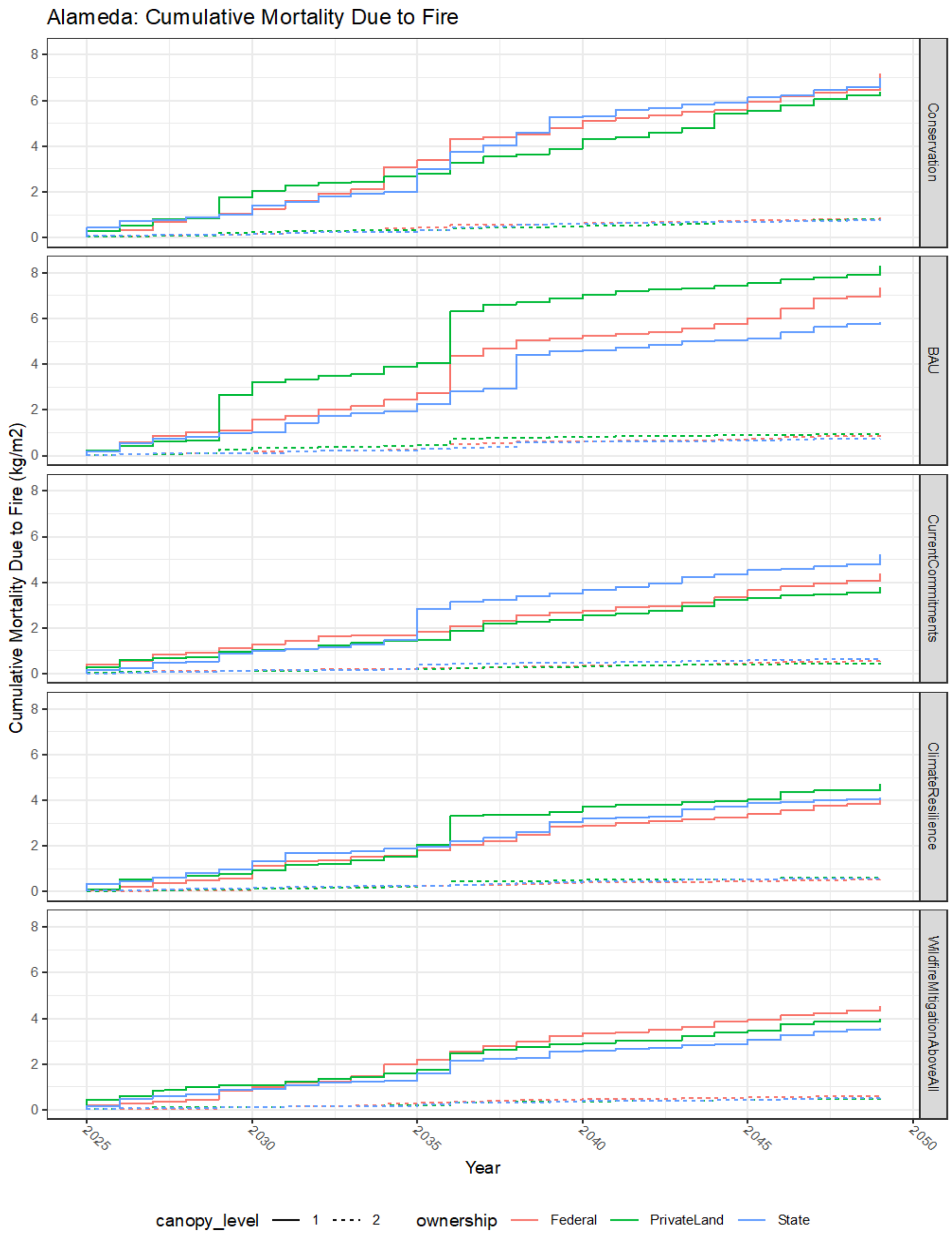

Figure 22: Cumulative mortality due to fire in the Alameda watershed under different management scenarios and ownerships for the MIROC5 GCM scenario and 8.5 RCP scenario. Canopy level 1 indicates forest canopy, shrubs, and grasses. Canopy level 2 indicates forest understory.

Figure 23 demonstrates the variability of litter carbon across different GCM and RCP scenarios for the BAU management scenario in the Kelsey watershed. Litter carbon is an important control on fire spread and fire effects. Litter carbon accumulation is dependent on vegetation productivity and subsequent processes such as leaf drop, while litter carbon decay is dependent on temperature, litter moisture, and disturbances such as fire. The net effect of these controls manifests as the variability in litter carbon in Figure 23. A more detailed examination of the controls on litter carbon through time will be necessary to better understand fire behavior in the RHESSys-WMFire.

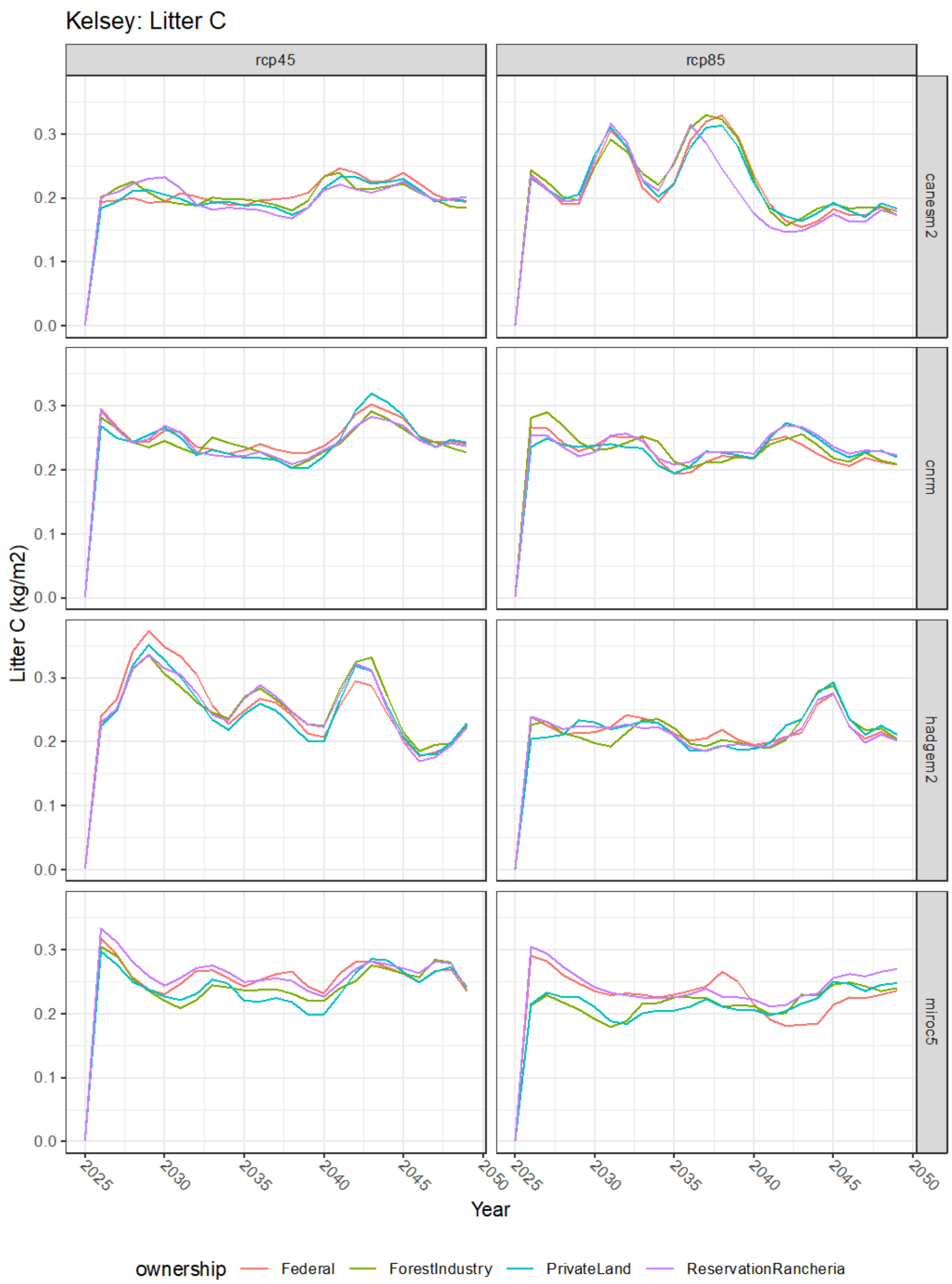

Figure 23: Time-series of litter carbon for the BAU management scenario for different GCM, RCP, and ownership combinations in the Kelsey watershed.

Figure 24 shows the response of streamflow to different GCM and RCP scenarios for the BAU management scenario in the Sagehen watershed. The figure demonstrates that the primary control on streamflow response is precipitation, as the greatest cumulative streamflow is observed for the GCMs with the highest predicted precipitation (e.g. Canesm2).

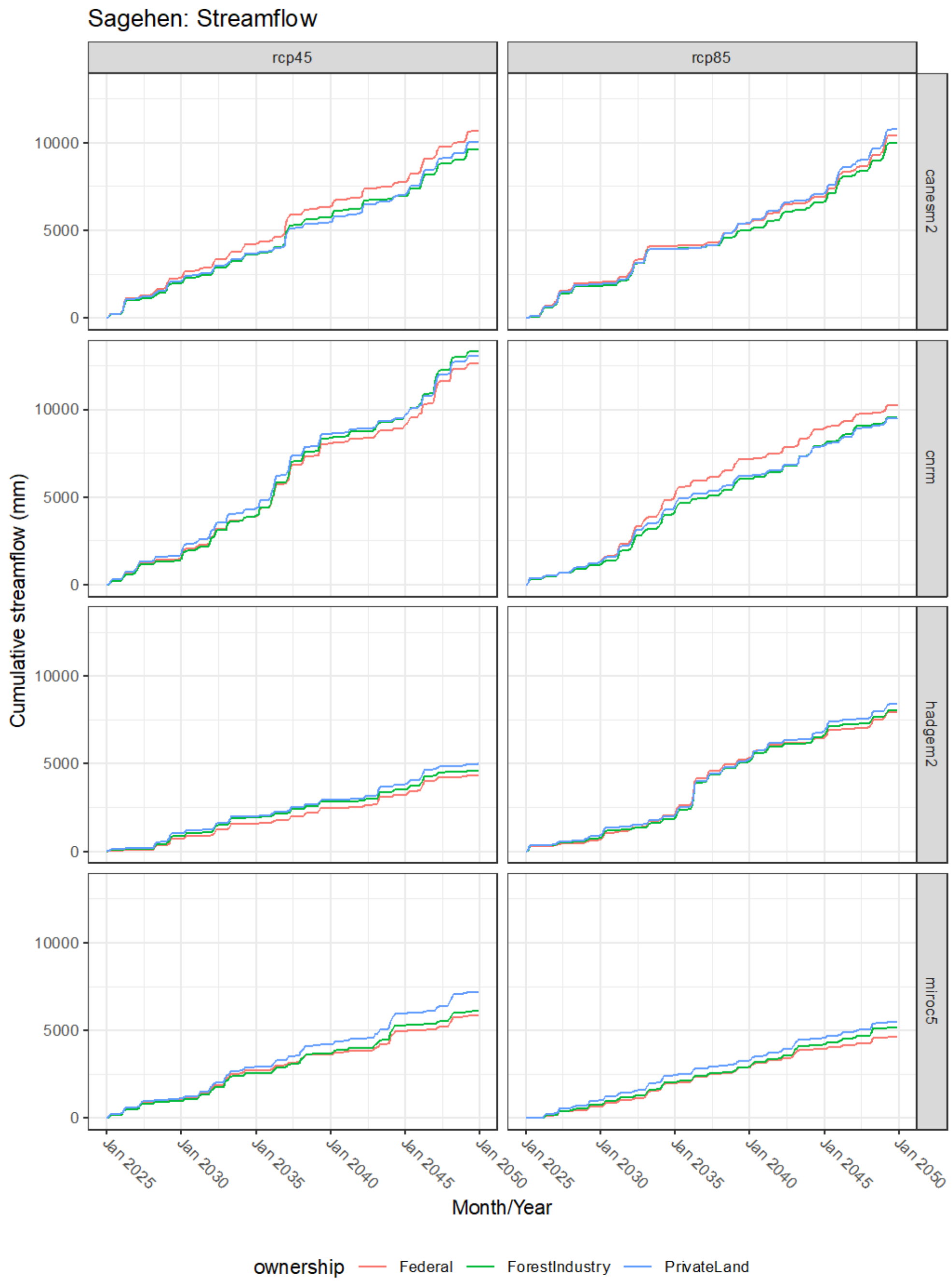

Figure 24: Cumulative streamflow for the BAU management scenario for different GCM, RCP, and ownership combinations in the Sagehen watershed.

Scaling Data

Scaling to Regional and Statewide Level

Raw RHESSys outputs generate thousands of maps that represent a single variable, each for a single time-step, for a single run, of one single watershed. This data has to then be processed to derive statewide time series estimates for all identified variables. This upscaling and processing, utilizes machine learning and large spatially explicit data to extrapolate the watershed level outputs generated by RHESSys to capture the heterogeneity of the ecounit that the watershed represents.

Each watershed is modeled as if it were owned by different ownership types (Figure 26). The management associated with each ownership is defined by the BAU assessment. Additionally, each of ownerships are also modeled under various GCM/RCP combinations and three management/fire monte carlo simulations. All of these iterations must be processed individually.

Various statewide spatial datasets are used to extrapolate the watershed level raw outputs to a statewide estimate. Though this process could generate spatially explicit data sets, this method was developed to generate ecounit to statewide estimates and so data below the ecounit level was not derived. Additionally, the computational resources, time, and storage necessary to derive spatially explicit data infeasible. For example, one statewide map is approximately 3.5GB. It takes approximately 15 minutes to generate one map. Four GCMs, two RCPs, 3 monte carlo runs, and 5 scenarios are run for every ownership in 12 ecounits. This equates to 120 runs that must be upscaled statewide (4x2x3x5). These 120 statewide, just one variable for one month, takes 420GB of storage, and 30 hours of processing time. If 10 variables were desired, to generate the full set of spatially explicit data would take these values times 4,680 (12 months x 39 years x 10 variables). This equates to almost 2 Petabytes of storage, and 16 years of processing time. This is clearly infeasible and so in the end non-spatial ecounit and statewide level estimates were generated in lieu of spatially explicit data.

The data used to derive multipliers for individual patch level data from RHESSys consisted of six statewide datasets: ecounit, vegetation type, ownership, elevation, slope, aspect, and site condition (Figure 26). The ecounit data is described in the Ecological Unit Development section and the ownership data is described in the Business-As-Usual Management Quantification section. The elevation, slope, aspect, and vegetation data are the same used for RHESSys modeling previously described.

The site condition data is a new data set that was derived for this exercise. The data used to derive site condition was the same historical climate data previously described, elevation previously described, and CARB’s NWL carbon stock data. The method used generate this data utilizes a combination of clustering, KNN, and empirical models and has previously been used to generate similar data for the entire continent of Europe [44].

Utilizing these seven datasets, a KNN (n=1) method was used to determine how many patches outside of the modeled watershed each patch within the modeled watershed should represent. In this way, not every patch within the modeled watershed is weighted equally for upscaling. Instead every patch is weighted by how representative it is within the entire ecounit that it represents. Given that ecounits were developed to cluster very similar watersheds, and that the representative watersheds were selected to be the most representative watershed possible, the patches within the modeled watersheds should contain values that represent the diversity of the ecounit to the most extent possible.

This process was done for every simulation iteration for every watershed to generate temporally explicit ecounit and statewide estimates. These estimates represent the outcomes from using the various GCMs and RCPs that were input into RHESSys. In the past, modelers have been criticized for producing too optimistic projections because of climate data averaging, which would incorporate best-case climate change scenarios [45]. To avoid this bias towards unrealistically optimistic ecological outcomes, the 2022 Scoping Plan Update results only utilize the RCP8.5 pathway, and does not include the CNRM-CM5 model, which produces a cool and wet future [46]. In this way, the 2022 Scoping Plan Update estimates represent the previously quantified BAU trajectory of global CO2 emissions. Utilizing this assumption still results in optimistic future carbon stock change when compared to the NWL inventory and previous independent modeling exercises (see the BAU Synthesis section at the end of this document for more details). Ideally, the modeled results from 2006 to 2014 would match the NWL inventory. However, the modeling results are visually biased towards more stable carbon stocks than are observed when compared to the NWL inventory (Figure 25). Utilizing an overly optimistic assumption of future climate change would further compound this bias.

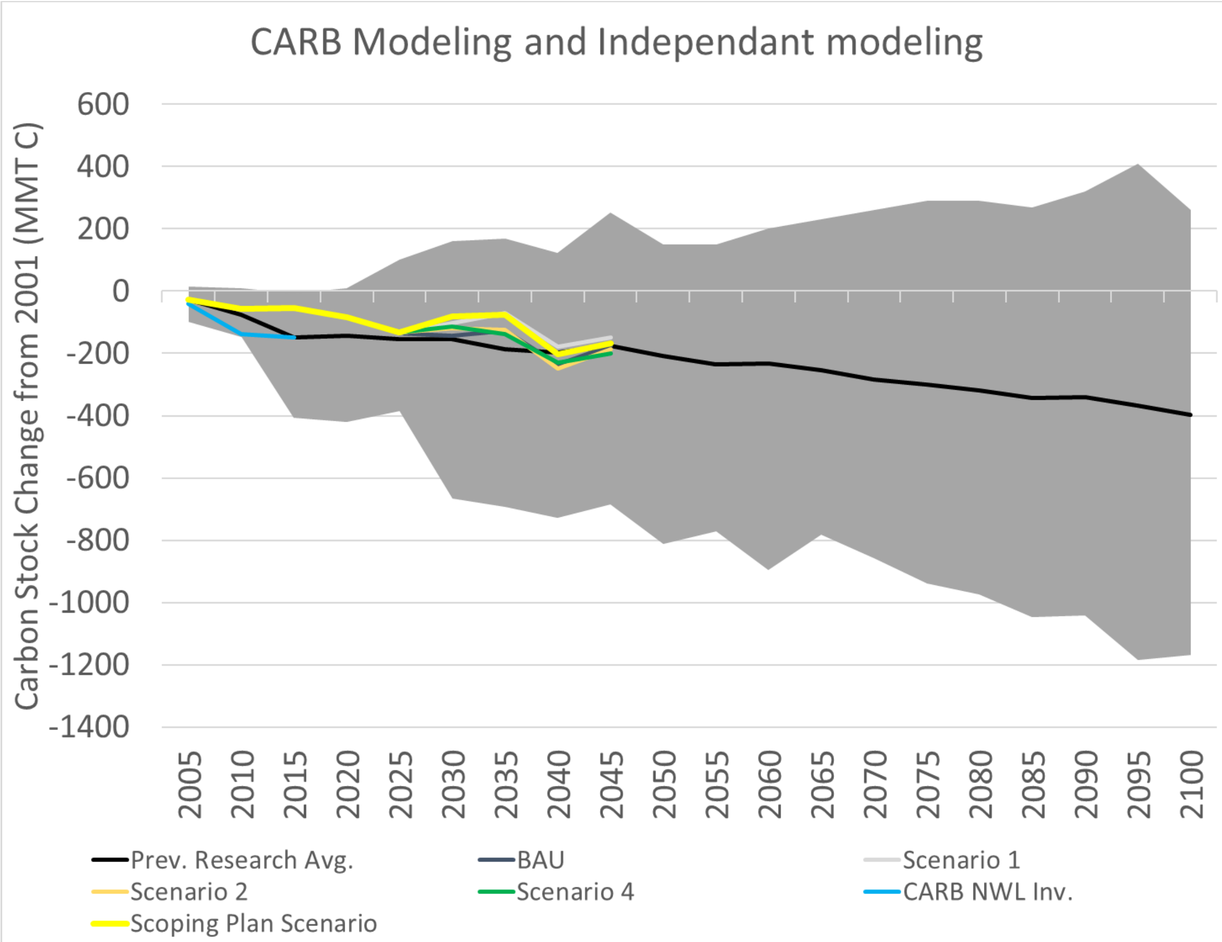

Figure 25: The results from the 2022 Scoping Plan Update modeling exercise for all NWL compared to independent previous research and the CARB NWL inventory. The Scoping Plan modeling results show less carbon stock loss than the NWL inventory or the weighted average of previous research demonstrating an optimistic projection. The grey shadow shows the range of results from previous research. See the Appendix I.1 – NWL Synthesis section for more details on the previous research used here.

Additionally, as modeling results were generated, it became clear that the modeling to represent the Dry Sierra was not valid. For this reason, this watershed wasn't used. Instead, the statewide estimates were adjusted so that all of the other ecounit results compensate for this missing ecounit. That is to say, a multiplier was derived that compensates for the missing ecounit that is applied to the rest of the aggregated statewide estimates. This can be done because this method was designed specifically for statewide outputs, and the ecounit breakdown, though guided by science, could have resulted in any number of ecounits. The removal of one ecounit does not affect the statewide estimates, but it does limit the ability to break those estimates down to an ecounit level.

The statewide estimates at this point still consist independent ecounit modeling efforts parameterized to flux towers and MODIS data. These estimates must be made consistent across the state to ensure validity. Further, these estimates must be consistent with CARB's NWL inventory so that results can be used to generate relative carbon targets. To ensure consistency across the state and with the NWL inventory, the 2014 spatially explicit biomass carbon stock NWL inventory was used. After processing statewide time-series modeled data, multipliers were generated that ensure that across ecounits, and ownerships, the modeled carbon stocks exactly match the inventory in 2014. These multipliers are then used throughout the entire time series. This ensures that the carbon stocks are consistent across ecounits, ownerships, and through time, and can be directly compared to the NWL inventory.

Harvested wood products (HWP) result from harvesting stem wood from forested ecosystems. Only stem wood from the forest ecosystems are counted in the HWP. The statewide stem wood carbon removed from the ecosystem as a result of harvesting is tracked every year as defined in the Management and Treatment Modeling section of this document. Of the total stem wood removed, 48% of that carbon is transformed into HWP. This ratio is a generalization of the ratios that are found in the U.S. Forest Services HWP tool, utilized within CALFIRE's estimates of HWP in California [47]. Once alternative scenarios begin in 2025, this annual HWP carbon is aggregated through time. This cumulative HWP carbon pool is added to the overall carbon stocks for the scenarios in the forest carbon stock outputs. This is because carbon that is put into HWP is not emitted into the atmosphere, and assuming that all of the carbon that gets harvest is emitted is not valid. This simple aggregating approach, however, assumes that HWP carbon that enters the system stays in the system at least until 2045. Future developments of this assessment should incorporate some decay factor that captures the gradual loss from this pool, but only associated with the inputs from the simulated years. This assessment is not tracking the total HWP pool, only the HWP that were generated from 2025 to 2045.

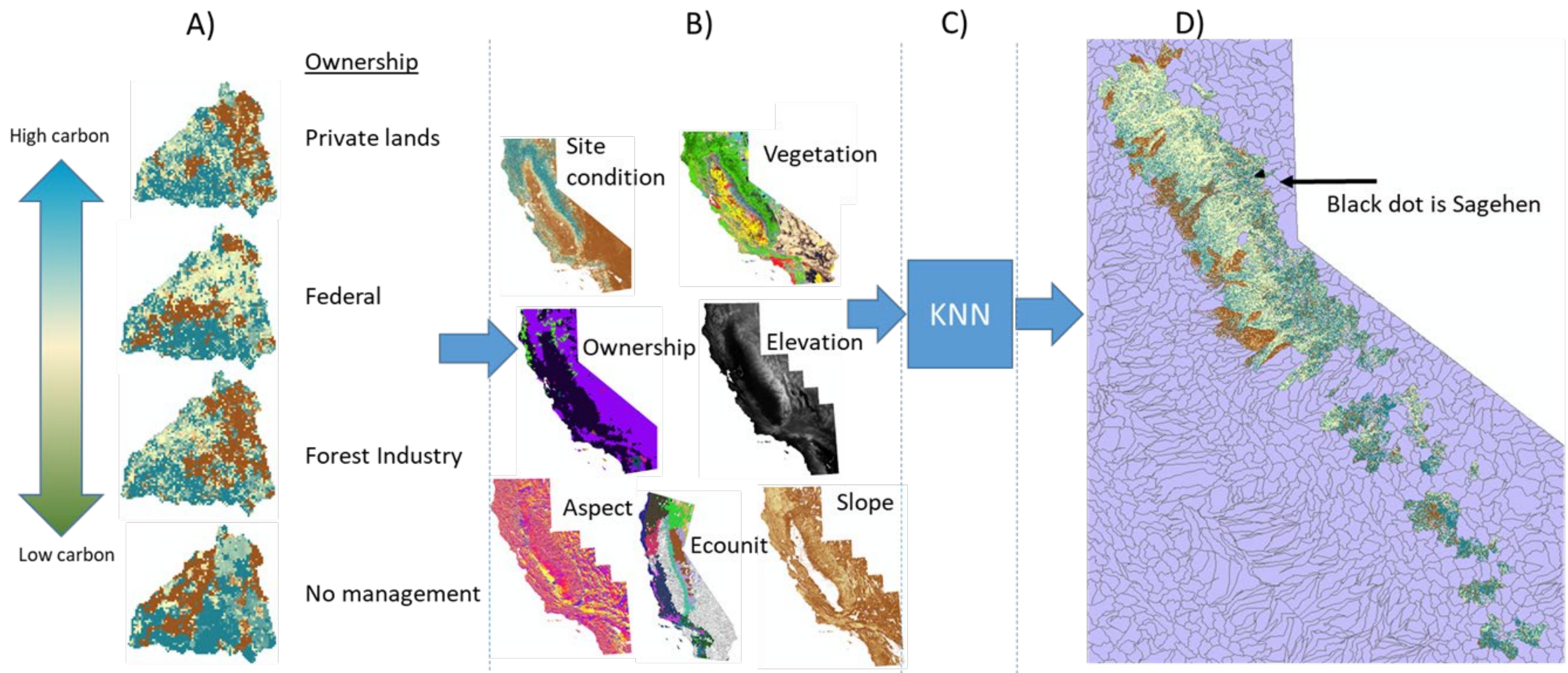

Figure 26: Upscaling process from RHESSys watershed level outputs to statewide outputs. A) Raw outputs from RHESSys, shown is carbon stocks as an example. These outputs come out differently for each ownership type. B) Multiple statewide datasets are used to upscale the raw RHESSys data. C) A KNN (N=1) algorithm is used to generate multipliers for every pixel in A that are used to derive ecounit level estimates D). Sagehen represents the Humid Sierra ecounit

Carbon Stock Results

The most accurate way to assess the impact of the alternative scenarios under climate change, is to consider all three, forests, shrublands, and grasslands together (Figure 27). This is because these systems were modeled together to specifically assess how they may affect one another. However, it is possible to separate the carbon stocks in the individual systems as well (Table 24, Table 25, Table 26, and Table 27).

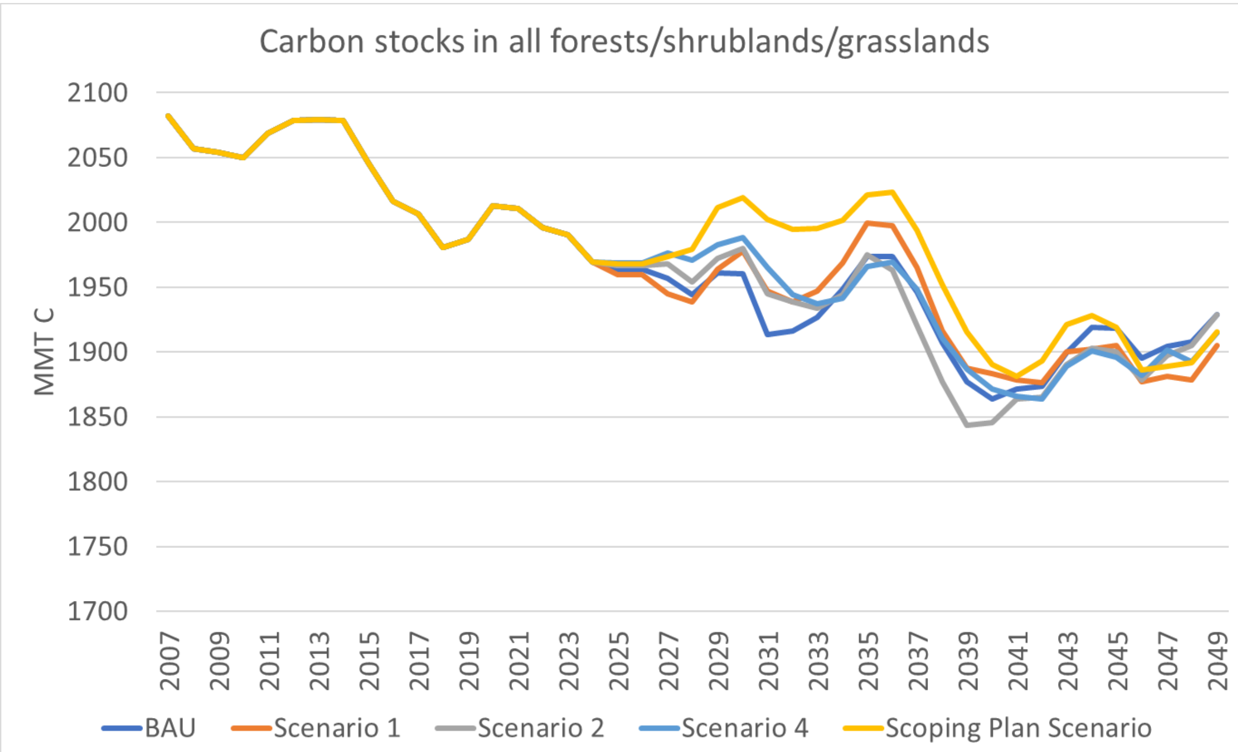

Figure 27: Total modeled biomass and HWP carbon stocks in all California forests, shrublands, and grasslands.

Table 24: Carbon stocks in forest biomass, and harvested wood products (MMT C).

Year	BAU	Scenario 1	Scenario 2	Scoping Plan Scenario	Scenario 4
2001	1296.20	1296.20	1296.20	1296.20	1296.20
2002	1296.20	1296.20	1296.20	1296.20	1296.20
2003	1296.20	1296.20	1296.20	1296.20	1296.20
2004	1296.20	1296.20	1296.20	1296.20	1296.20
2005	1296.20	1296.20	1296.20	1296.20	1296.20
2006	1296.20	1296.20	1296.20	1296.20	1296.20
2007	1296.20	1296.20	1296.20	1296.20	1296.20
2008	1280.08	1280.08	1280.08	1280.08	1280.08
2009	1280.63	1280.63	1280.63	1280.63	1280.63
2010	1279.39	1279.39	1279.39	1279.39	1279.39
2011	1294.24	1294.24	1294.24	1294.24	1294.24
2012	1297.82	1297.82	1297.82	1297.82	1297.82
2013	1295.69	1295.69	1295.69	1295.69	1295.69
2014	1294.59	1294.59	1294.59	1294.59	1294.59
2015	1264.38	1264.38	1264.38	1264.38	1264.38
2016	1245.02	1245.02	1245.02	1245.02	1245.02
2017	1241.83	1241.83	1241.83	1241.83	1241.83
2018	1224.12	1224.12	1224.12	1224.12	1224.12
2019	1223.80	1223.80	1223.80	1223.80	1223.80
2020	1242.31	1242.31	1242.31	1242.31	1242.31
2021	1253.57	1253.57	1253.57	1253.57	1253.57
2022	1255.22	1255.22	1255.22	1255.22	1255.22
2023	1258.38	1258.38	1258.38	1258.38	1258.38
2024	1248.93	1248.93	1248.93	1248.93	1248.93
2025	1244.28	1242.52	1246.50	1247.53	1247.95
2026	1244.28	1242.52	1246.50	1247.53	1247.95
2027	1233.93	1227.54	1241.53	1246.14	1248.40
2028	1221.76	1220.66	1223.89	1243.36	1236.90
2029	1227.58	1236.74	1226.54	1260.47	1234.35
2030	1221.32	1244.51	1225.62	1260.38	1231.06
2031	1182.38	1219.67	1193.77	1243.80	1208.13
2032	1186.59	1215.85	1191.24	1238.03	1189.06
2033	1194.34	1223.08	1183.66	1238.20	1178.86
2034	1208.52	1236.88	1189.12	1241.02	1178.97
2035	1227.00	1256.95	1210.72	1255.79	1195.15
2036	1231.81	1258.07	1206.39	1263.76	1202.67
2037	1218.92	1241.80	1181.25	1250.26	1195.45
2038	1196.02	1210.95	1153.07	1222.60	1172.60
2039	1173.33	1189.09	1130.06	1193.76	1158.17
2040	1162.42	1187.69	1133.55	1171.48	1147.01
2041	1167.63	1184.41	1148.35	1164.85	1144.58
2042	1168.63	1182.45	1150.11	1174.35	1142.51
2043	1186.32	1197.45	1166.84	1192.59	1158.46
2044	1200.25	1196.73	1173.69	1196.80	1165.98
2045	1200.56	1201.78	1172.90	1191.61	1165.16
2046	1185.92	1183.12	1160.77	1169.85	1159.35
2047	1185.11	1181.16	1171.78	1167.76	1170.37
2048	1185.40	1175.23	1176.00	1168.37	1160.97
2049	1203.53	1194.22	1194.42	1187.57	1179.12

Table 25: Cumulative harvested wood products carbon (MMT C).

Year	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2026	0.11529066	0	0.295148	0.758531	1.688375
2027	0.192945962	0	0.5942	1.335921	3.572207
2028	0.288744948	0	0.820116	2.136473	4.838357
2029	0.304618504	0	1.076007	2.841388	6.211747
2030	0.359670995	0	1.347166	3.753549	7.588457
2031	0.37453034	0	1.661084	4.671836	9.095001
2032	0.493507905	0	1.837825	5.684763	10.54585
2033	0.520496526	0	2.348735	6.305477	11.97361
2034	0.593450997	0	2.675455	6.869868	13.47876
2035	0.666088131	0	3.095556	7.682877	14.87803
2036	0.718776019	0	3.269862	8.27581	15.99379
2037	0.973357612	0	3.472569	9.175404	17.16337
2038	1.040834913	0	3.790271	9.709774	18.96739
2039	1.153536734	0	4.116665	10.36183	20.73731
2040	1.164157023	0	4.599739	11.1568	22.87945
2041	1.188740206	0	4.900367	11.726	23.78085
2042	1.40843793	0	5.172207	12.50677	24.97709
2043	1.437101219	0	5.439683	13.03415	26.0393
2044	1.506611966	0	5.844308	13.65012	27.45026
2045	1.560371841	0	6.213588	14.35501	28.70098
2046	1.571818654	0	6.534712	15.19498	29.60747
2047	1.671961189	0	6.82441	15.7014	30.51143
2048	1.773509188	0	6.979648	16.43289	31.37731
2049	1.785028161	0	7.204182	17.11804	32.48011

Table 26: Above and below, live and dead, shrubland biomass carbon stocks (MMT C).

Year	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2001	664.81	664.81	664.81	664.81	664.81
2002	664.81	664.81	664.81	664.81	664.81
2003	664.81	664.81	664.81	664.81	664.81
2004	664.81	664.81	664.81	664.81	664.81
2005	664.81	664.81	664.81	664.81	664.81
2006	664.81	664.81	664.81	664.81	664.81
2007	664.81	664.81	664.81	664.81	664.81
2008	656.24	656.24	656.24	656.24	656.24
2009	654.86	654.86	654.86	654.86	654.86
2010	655.34	655.34	655.34	655.34	655.34
2011	657.03	657.03	657.03	657.03	657.03
2012	658.31	658.31	658.31	658.31	658.31
2013	656.66	656.66	656.66	656.66	656.66
2014	658.00	658.00	658.00	658.00	658.00
2015	655.87	655.87	655.87	655.87	655.87
2016	645.68	645.68	645.68	645.68	645.68
2017	638.81	638.81	638.81	638.81	638.81
2018	630.04	630.04	630.04	630.04	630.04
2019	632.17	632.17	632.17	632.17	632.17

2020	637.55	637.55	637.55	637.55	637.55
2021	629.11	629.11	629.11	629.11	629.11
2022	619.40	619.40	619.40	619.40	619.40
2023	617.26	617.26	617.26	617.26	617.26
2024	610.88	610.88	610.88	610.88	610.88
2025	605.09	604.49	604.65	604.69	604.77
2026	605.09	604.49	604.65	604.69	604.77
2027	604.89	604.41	604.96	605.81	605.94
2028	603.27	605.19	604.92	608.51	607.79
2029	608.77	611.86	613.31	617.48	616.46
2030	612.22	616.75	618.46	621.78	621.02
2031	608.89	613.10	616.11	621.87	620.50
2032	605.78	608.14	612.37	620.84	617.93
2033	604.43	607.76	613.69	619.58	619.63
2034	608.87	612.45	616.28	620.71	622.72
2035	615.31	619.41	623.02	622.94	628.06
2036	610.68	615.10	616.18	617.02	624.49
2037	597.84	601.97	602.32	603.99	614.09
2038	584.91	587.55	589.85	594.49	602.31
2039	578.94	581.34	579.96	588.37	593.38
2040	576.92	579.80	578.72	586.53	590.25
2041	577.33	578.39	581.59	583.96	587.47
2042	576.99	576.82	581.26	585.55	587.05
2043	585.64	584.52	590.25	594.94	596.17
2044	590.54	586.52	594.71	597.51	599.70
2045	589.87	585.85	594.48	595.18	597.56
2046	582.19	578.05	585.84	584.91	590.23
2047	587.01	580.57	589.31	585.46	594.70
2048	587.97	578.92	589.95	583.80	591.98
2049	590.60	585.11	594.97	588.45	595.38

Table 27: Above and below, live and dead, grassland biomass carbon stocks (MMT C).

Year	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2001	120.79	120.79	120.79	120.79	120.79
2002	120.79	120.79	120.79	120.79	120.79
2003	120.79	120.79	120.79	120.79	120.79
2004	120.79	120.79	120.79	120.79	120.79
2005	120.79	120.79	120.79	120.79	120.79
2006	120.79	120.79	120.79	120.79	120.79
2007	120.79	120.79	120.79	120.79	120.79
2008	120.80	120.80	120.80	120.80	120.80
2009	118.42	118.42	118.42	118.42	118.42
2010	115.19	115.19	115.19	115.19	115.19
2011	117.29	117.29	117.29	117.29	117.29
2012	122.55	122.55	122.55	122.55	122.55
2013	126.99	126.99	126.99	126.99	126.99
2014	126.30	126.30	126.30	126.30	126.30
2015	125.15	125.15	125.15	125.15	125.15
2016	125.61	125.61	125.61	125.61	125.61
2017	125.68	125.68	125.68	125.68	125.68
2018	126.28	126.28	126.28	126.28	126.28

2019	131.19	131.19	131.19	131.19	131.19
2020	132.99	132.99	132.99	132.99	132.99
2021	127.91	127.91	127.91	127.91	127.91
2022	121.54	121.54	121.54	121.54	121.54
2023	114.58	114.58	114.58	114.58	114.58
2024	109.82	109.82	109.82	109.82	109.82
2025	114.48	112.54	115.74	115.54	115.89
2026	114.48	112.54	115.74	115.54	115.89
2027	118.14	112.95	121.85	121.87	122.33
2028	119.26	112.64	125.45	127.16	126.12
2029	124.64	115.24	132.09	133.71	131.82
2030	126.72	116.49	136.00	137.00	136.19
2031	121.96	114.48	135.32	136.43	136.57
2032	123.66	114.61	135.03	135.98	137.31
2033	127.73	116.09	136.72	137.65	138.54
2034	130.74	119.52	139.00	139.96	139.81
2035	131.19	123.28	141.53	142.39	142.71
2036	130.93	124.13	140.65	142.86	142.43
2037	129.59	121.65	136.99	139.62	138.82
2038	125.96	117.84	134.14	134.86	135.43
2039	124.84	117.40	133.57	133.24	134.98
2040	124.12	116.20	133.28	132.37	134.22
2041	126.76	115.81	134.03	132.65	134.00
2042	127.86	116.94	133.92	133.43	134.10
2043	127.61	117.83	133.42	133.78	134.24
2044	128.04	119.25	134.32	134.02	135.07
2045	127.73	117.44	132.98	132.04	133.08
2046	127.47	115.66	131.51	131.30	132.42
2047	131.93	119.74	136.06	135.55	136.57
2048	134.58	124.59	139.20	139.29	139.75
2049	135.03	125.45	139.78	139.18	140.25

Wildfire Emissions, Health, and Health Economic Impact

Overview

Wildfires in California have been increasing in size, severity, and destructive capacity over the last 2 decades. As a consequence, the emissions from smoke emitted from these fires have also been increasing. The emissions from this smoke has the potential to cause serious and widespread harm to public health and these public health impacts can cost society billions of dollars per year [48]. Preliminary research conducted by The University of California in Los Angeles, funded by The California Air Resources Board (CARB), estimates that from 2008 to 2018, wildfire emissions alone were responsible for nearly 50,000 deaths, and cost society almost $400 billion.

As climate change exacerbates wildfire conditions, it is imperative that governments, and private entities alike, utilize the tools at their disposal to mitigate the negative impacts of wildfires, while improving ecosystem and public health. The tools available to society to lessen wildfire emissions that lead to poor public health are the use of fuels reductions treatments. State and Federal governments currently have a goal of treating one million acres per year of California with fuel reduction treatments to restore forests and bolster climate resilience.

To quantify the impact that management can have on wildfire emissions on a statewide scale, four different alternative management strategies were modeled for the 2022 Scoping Plan Update. These strategies range from treating 0 to 5 million acres per year. This effort found that increasing forest management beyond current levels has beneficial impacts to public health by reducing wildfire emissions.

Objective

The objective of this assessment was to speciate the emissions that resulted from CARB's 2022 Scoping Plan Update modeling in forests, shrublands, chaparral, and grasslands into annual PM2.5 emissions. These emissions were used to calculate future public health impacts and their associated economic impacts.

Methods

Wildfire Emissions Method

As previously explained in the RHESSys Watershed Modeling Methods section, RHESSys modeling produced estimates of the biomass consumed from wildfires in all forests, shrublands, and grasslands each year. These estimates were scaled to annual statewide estimates as also explained in the RHESSys Watershed Modeling Methods section. Utilizing these annual biomass consumption estimates, emissions factors from NCAR (FINN) were applied [49]. These emissions factors are used for large-scale estimates of fire emissions throughout the world, being cited in over 1000 scientific journal articles. The FINN emissions factors were derived from existing literature and are vegetation type specific (Table 28).

Table 28: Land use/land cover classifications as assigned by the MODIS Land Cover Type, assigned generic land cover class, and PM 2.5 emission factors (g kg Biomass Burned−1). BOR = Boreal Forest; TROP = Tropical Forest; TEMP = Temperate Forest WS = Woody Savannah/Shrubland; SG = Savanna/Grassland; CROP = Croplands.

Classification Vegetation Type	PM2.5 Emission Factor
Evergreen Needle leaf Forest BOR	13
Evergreen Broadleaf Forest TROP	9.7
Deciduous Needle leaf Forest BOR	13
Deciduous Broadleaf Forest TEMP	13
Mixed Forests TEMP	13
Closed Shrublands WS	9.3
Open Shrublands WS	9.3
Woody Savannas WS	9.3
Savannas SG	5.4
Grasslands SG	5.4
Permanent Wetlands SG	5.4
Croplands CROP	5.8
Cropland/Natural Vegetation Mosaic SG	5.4
Barren or Sparsely Vegetated SG	5.4

PM2.5 is the emission species from wildfires that has the greatest effect on public health [48], and for that reason, this assessment focused on estimating the PM2.5 emissions from wildfires. Further, because the RHESSys modeling distinguishes the vegetation type on which the fire is burning, vegetation specific emissions factors for PM2.5 from FINN could be used. The emissions factors for mixed forests, shrublands, and grasslands were used (Table 28). The biomass consumed from the RHESSys modeling was multiplied by the appropriate emissions factor and aggregated annually across forests, shrublands, and grasslands to derive a statewide annual estimate of wildfire emissions. These raw modeled emissions were then corrected to ensure that the average modeled annual PM2.5 emissions were the same as the observed PM2.5 emissions over the same time period (2001-2020) from CARB's NWL wildfire emissions inventory [50]. This is done to ensure that the health and economic impacts of future projected emissions are as realistic as possible, by ensuring that the modeled historical emissions are valid.

Health and Economic Impacts

Preliminary research by UCLA estimated the historical impact of Californian wildfires for various health endpoints. Using these health endpoints, the economic impact from the detrimental public health effects from wildfire emissions was also estimated (Table 29). This data was derived using a combination of modeling and literature values. Details on the methods and specific results will be described in forth coming UCLA peer-reviewed publications.

Table 29: Health endpoints calculated within preliminary study by UCLA that is used for this assessment. HA = Hospital Admissions, ERV = Emergency Room Visits, COPD = Chronic Obstructive Pulmonary Disease, Resp = Respiratory, Card = Cardiovascular

Health end point
HA Asthma
HA COPD without Asthma
HA All Resp Outcomes
ERV Asthma
ERV All Resp Outcomes
ERV All Card Outcomes
All-Cause Mortality

CARB keeps a contemporary PM2.5 specific wildfire emissions inventory (Figure 28). Using the estimated health and economic impacts from 2008-2018 and the associated statewide wildfire specific PM2.5 emissions, a ratio relating the impacts to emissions was calculated for each health end-point, called the incidence-per-ton factor [51]. Thus, changes in emissions are approximately proportional to changes in health outcomes. These incidence-per-ton values were then multiplied by the modeled statewide annual tons of wildfire-specific PM2.5 emissions derived from using the RHESSys and FINN model. This results in an annual estimate of the public health and economic impact from wildfire smoke. Note that this approach of using an incidence-per-ton factor to estimate future impacts from changes in emissions is similar to CARB's incidence-per-ton methodology for calculating health benefits of PM2.5

reductions from combustion sources [51]. After the initial incidence-per-ton were calculated the resulting model was bias corrected against the UCLA estimates from 2008-2018.

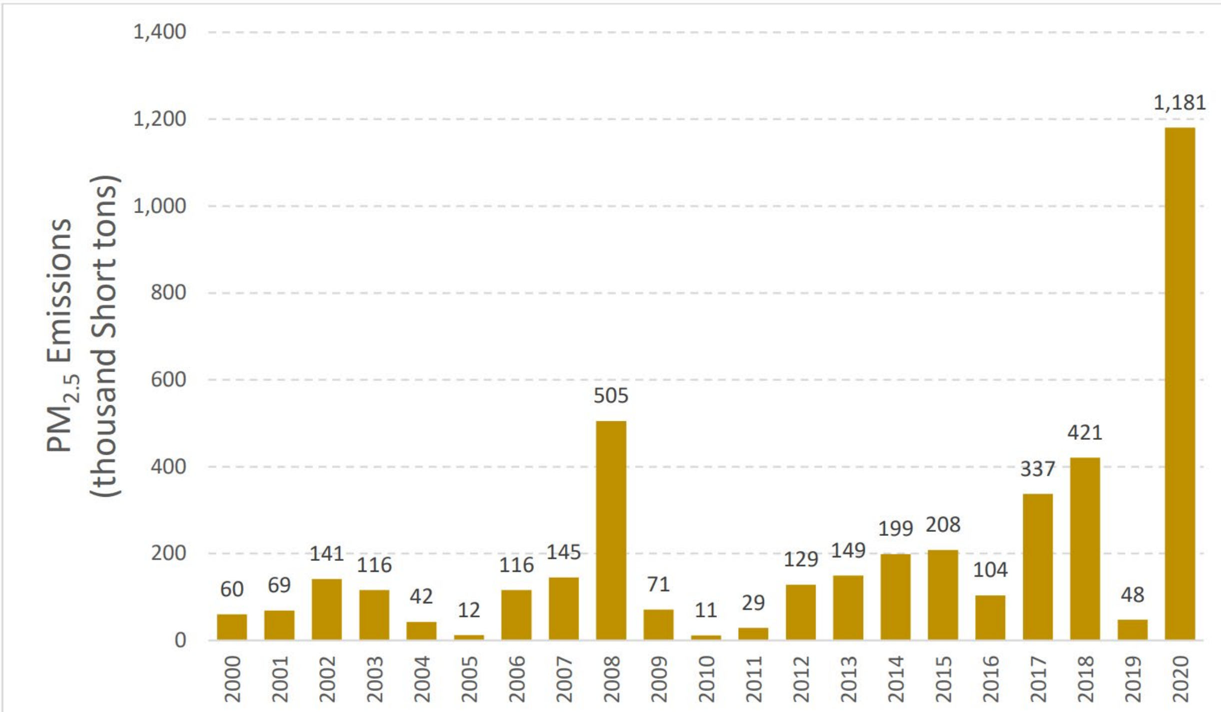

Figure 28: Estimates of California specific wildfire PM2.5 emissions.

Results

Wildfire Emissions

Projected wildfire emissions vary greatly from year to year (Figure 29, Table 30). This variation is primarily caused by natural climate variation, such as El Niño, or La Niña events. These emissions also do not drastically increase in longer time frames as may be expected. This is driven by fuels reductions that occur on an annual basis, whether through aggressive fuels reduction treatments, such as in scenario 3 and 4, or through large wildfires. Further, growth and recovery of the state's forests, shrublands, and grasslands, become diminished as growing conditions worsen with climate change. This combination of large fuels reductions caused by both wildfires, and human intervention, and the lack of recovery after disturbance, leads to future emissions that are equivalent, or lower than those from 2006-2024. Generally, with either large, frequent catastrophic wildfires, or through aggressive human intervention, wildfires eventually become fuel limited. However, letting catastrophic wildfire reduce fuels in an unmitigated way, will lead to ecological degradation, deforestation, and negative public health and safety outcomes. These outcomes can be mitigated through the reduction of fuels in a managed and controlled way through human intervention. The modeling performed for the 2022 Scoping Plan Update estimates that wildfire emissions can be substantially reduced through aggressive climate action to reduce fuels statewide (Figure 30).

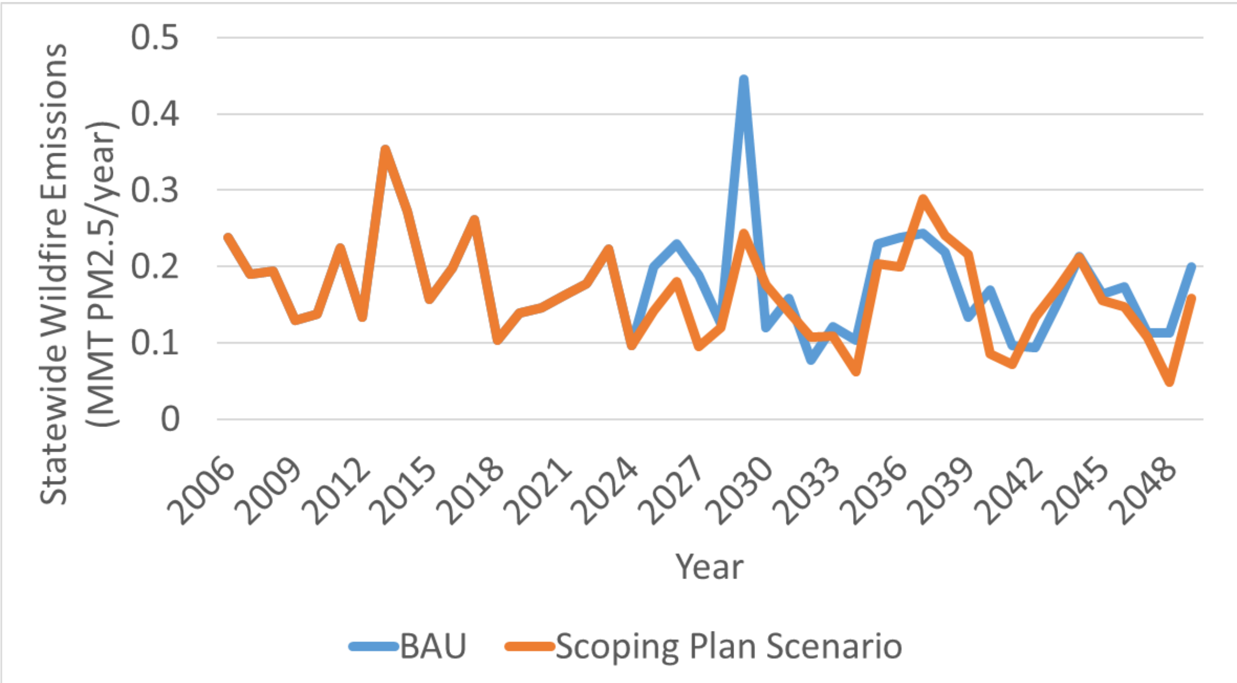

Figure 29: Annual modeled California wildfire specific PM2.5 emissions.

Table 30: Annual modeled California wildfire specific PM2.5 emissions (MMT PM2.5/year) for each future scenario.

	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2006	0.237669	0.237669	0.237669	0.237669	0.237669
2007	0.189807	0.189807	0.189807	0.189807	0.189807
2008	0.193749	0.193749	0.193749	0.193749	0.193749
2009	0.129138	0.129138	0.129138	0.129138	0.129138
2010	0.137193	0.137193	0.137193	0.137193	0.137193
2011	0.224669	0.224669	0.224669	0.224669	0.224669
2012	0.13341	0.13341	0.13341	0.13341	0.13341
2013	0.353776	0.353776	0.353776	0.353776	0.353776
2014	0.271918	0.271918	0.271918	0.271918	0.271918
2015	0.157419	0.157419	0.157419	0.157419	0.157419
2016	0.198037	0.198037	0.198037	0.198037	0.198037
2017	0.260984	0.260984	0.260984	0.260984	0.260984
2018	0.102707	0.102707	0.102707	0.102707	0.102707
2019	0.139467	0.139467	0.139467	0.139467	0.139467
2020	0.145636	0.145636	0.145636	0.145636	0.145636
2021	0.162716	0.162716	0.162716	0.162716	0.162716
2022	0.177275	0.177275	0.177275	0.177275	0.177275
2023	0.223459	0.223459	0.223459	0.223459	0.223459
2024	0.097054	0.097054	0.097054	0.097054	0.097054
2025	0.199707	0.239981	0.146271	0.141557	0.08205
2026	0.229268	0.220106	0.2837	0.179977	0.179789
2027	0.188244	0.158318	0.194944	0.094488	0.197093
2028	0.124658	0.075325	0.086862	0.119247	0.125899
2029	0.445993	0.33451	0.375406	0.242848	0.242304
2030	0.120042	0.206433	0.153343	0.176696	0.220748
2031	0.158241	0.144694	0.213704	0.140458	0.184674
2032	0.077187	0.093594	0.148874	0.106956	0.124662
2033	0.121146	0.08562	0.052092	0.109016	0.073685
2034	0.103112	0.127458	0.127891	0.061386	0.049896
2035	0.230023	0.219477	0.292944	0.204216	0.150416
2036	0.237372	0.27672	0.230663	0.199183	0.194149
2037	0.243413	0.285139	0.284256	0.288409	0.192526
2038	0.219017	0.138556	0.156318	0.240294	0.147675
2039	0.133697	0.203342	0.06574	0.215558	0.141042
2040	0.169012	0.179324	0.153919	0.085993	0.10793
2041	0.096607	0.083747	0.100095	0.072357	0.070962
2042	0.093461	0.213621	0.136016	0.133692	0.090819
2043	0.150733	0.114055	0.138581	0.17017	0.128474
2044	0.213191	0.21914	0.189135	0.212437	0.143217
2045	0.163498	0.157363	0.092078	0.156019	0.045505
2046	0.173727	0.225672	0.147704	0.146871	0.202065
2047	0.113362	0.103542	0.107179	0.107601	0.08859
2048	0.11319	0.081854	0.086675	0.047758	0.04834
2049	0.199156	0.135487	0.113662	0.158531	0.11487

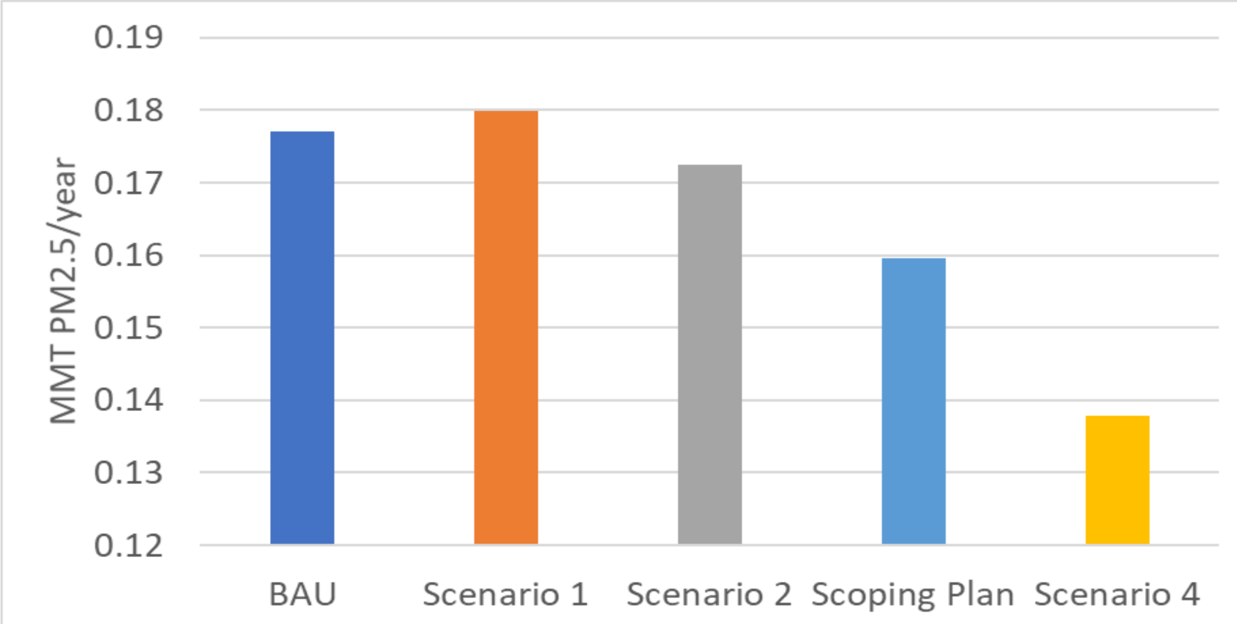

Figure 30: Statewide average annual wildfire specific PM2.5 emissions from 2025-2045.

Health and Economic Impacts

The ramification between allowing catastrophic wildfire to reduce fuels as opposed to utilizing forest management to reduce those fuels, can be exemplified by assessing the public health impacts from the resulting future wildfire emissions across 2022 Scoping Plan Update scenarios. The incidents-per-ton (IPT), and resulting cost-per-ton, from this analysis demonstrate the negative public health and economic impact that result from allowing wildfires to burn unmitigated (Table 31). When using these IPT numbers on emissions from 2008 – 2018, the model performs well (Table 32).This is to be expected however because the limited number of samples required the use of the entire data set for model development, and the accuracy assessment is performed on the same data points. Further, the IPT were bias corrected to ensure that no bias exists in the IPT model. This has most likely led to an over fitting of the model to the training data, but with such few training data points, it was necessary to utilize all available training data for model development.

Table 31: Incidents-per-ton, and cost-per-ton of PM2.5 used for projection modeling of health impacts from wildfire specific annual PM2.5 emissions. HA = Hospital Admissions, ERV = Emergency Room Visits, COPD = Chronic Obstructive Pulmonary Disease, Resp = Respiratory, Card = Cardiovascular.

Health end-point or economic cost	Incidents or cost(dollars)
HA Asthma	0.0012
HA Asthma Cost	20
HA COPD w/o Asthma	0.0011
HA COPD w/o Asthma Cost	25
HA All Resp Outcomes	0.004
HA All Resp Outcomes Cost	102
ERV Asthma	0.009
ERV Asthma Cost	4
ERV All Resp Outcomes	0.024
ERV All Resp Outcomes Cost	20
ERV All Card Outcomes	0.009
ERV All Card Outcomes Cost	9
All Cause Mortality	0.023
All Cause Mortality Cost	176406

Table 32: Performance metrics for All-cause mortality cost estimates for years 2008-2018. MBE = Mean bias error, MAE = Mean absolute error.

MBE	MAE	R2	Bias
0.104615777	0.527565	0.71	0

The IPT values are applied to future projected California wildfire specific PM2.5 emissions from all forests, shrublands, and grasslands. To assess the effectiveness of scenarios on wildfire emissions requires quantifying long-term emissions. For this reason, this assessment utilizes all years after climate action begins in 2025 to 2045, the 2022 Scoping Plan Update target year (Table 33). Across all health end-points increasing forest management results in better public health outcomes, and decreased health cost (Figure 31). It should also be noted that the RHESSys model includes wildfire suppression at current rates. This means that even while utilizing the unprecedented amount of current wildfire suppression, wildfires will still occur, and that the only way to reduce wildfire emissions into the future is not through fire suppression, but through wildfire mitigation from fuels reduction treatments.

Table 33: Projected average annual health end-points and economic costs in dollars from 2025-2045 associated with Californian wildfire emissions by scenario. HA = Hospital Admissions, ERV = Emergency Room Visits, COPD = Chronic Obstructive Pulmonary Disease, Resp = Respiratory, Card = Cardiovascular.

Health end-point	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
HA Asthma	221	224	215	199	172
HA Asthma Cost	3,552,654	3,608,945	3,462,072	3,202,265	2,765,119
HA COPD without Asthma	198	201	193	178	154
HA COPD without Asthma Cost	4,387,346	4,456,862	4,275,482	3,954,633	3,414,780
HA All Resp Outcomes	638	648	622	575	497
HA All Resp Outcomes Cost	18,020,125	18,305,649	17,560,668	16,242,845	14,025,511
ERV Asthma	1,568	1,593	1,528	1,413	1,220
ERV Asthma Cost	759,628	771,664	740,260	684,708	591,237
ERV All Resp Outcomes	4,247	4,314	4,138	3,828	3,305
ERV All Resp Outcomes Cost	3,462,056	3,516,911	3,373,784	3,120,602	2,694,604
ERV All Card Outcomes	1,584	1,609	1,543	1,427	1,233
ERV All Card Outcomes Cost	1,613,623	1,639,190	1,572,481	1,454,475	1,255,923
All-Cause Mortality	3,997	4,060	3,895	3,602	3,111
All-Cause Mortality Cost	31,229,074,247	31,723,890,986	30,432,829,962	28,149,028,841	24,306,364,805
Total Cost	31,260,869,679	31,756,190,208	30,463,814,709	28,177,688,369	24,331,111,980

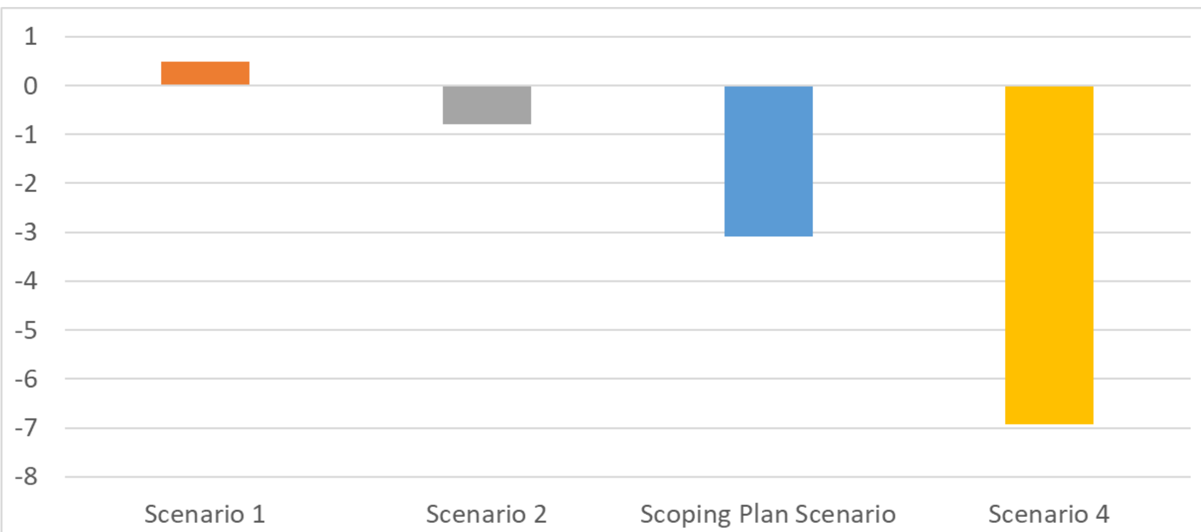

Figure 31: Average annual health related cost difference between BAU and alternative scenarios.

Biomass Residues and Potential Carbon Benefits

Introduction

Increased wildfire risk in California's forests pose substantial health and safety concerns [52]. As of 2020, the State of California and the U.S. Forest Service established a joint agreement to work toward treating one million acres of forested land annually to help mitigate these risks [53]. Some of the forest treatment strategies that will be employed to support ecosystem health and resilience will create new biomass residue in addition to that generated by existing forest practices [54].

Biomass residue from forestry treatments is regarded as a waste product due to its limited economic value. Residues are costly to collect and transport relative to other sources of wood biomass (such as mill residues, biomass from orchard removal, or urban wood waste), and some potential bio-products that could be made from residues lack markets to reduce these costs. Without cost effective biomass removal options, residues are often left on-site in large piles to be burned under appropriate weather conditions that minimize wildfire ignition risk and exposure to smoke. There is interest in supporting markets to help recover this resource for beneficial uses and to further reduce wildfire risks. The State is dedicating substantial resources to explore and identify forestry treatment and residue-utilization strategies that could achieve greenhouse gas (GHG) benefits in addition to other public health and ecosystem benefits [55].

California was one of the first states to promote the utilization of forest-derived biomass for electricity generation and this remains one of the leading uses for forestry residues even as biomass electricity generation capacity has declined statewide by over 150 MW since the early 1990s [56]. These pathways rely on subsidies for biomass energy production to motivate the collection, transport, and processing of non-merchantable biomass residues. While energy use is one option, existing programs like BioMAT [57] experience high costs, as well as opposition from communities concerned about adverse health and environmental impacts from combustion emissions for these projects [58].

There is need to simultaneously address forest health and resilience, wildfire-related risks, GHG emission impacts, and local environmental and air quality concerns. Careful consideration must be made to assess the viability and least-regrets pathways for making use of potential forestry residues generated under the NWL land management alternative scenarios. This section describes work by CARB staff to better understand potential resource availability, and to evaluate the costs and benefits of mobilizing biomass residues from forestry treatments through a social cost lens—that is, considering not only the costs borne by the entity performing the treatments or the user of biomass or biomass-based product, but the costs and benefits to the public.

It's important to understand that this analysis is intended to (1) identify the forest biomass residues generated from implementation of the Scoping Plan that may be available and socially beneficial to mobilize for energy purposes, and (2) provide an indication of where it may be more beneficial, because of cost or air quality reasons, to deploy forestry biomass residues for energy pathways or for alternatives other than energy pathways. How much biomass is utilized, from where it is sourced, and to what end use application it is directed will ultimately depend on a myriad of federal, state, local, and private actors making decisions that take into account more considerations and site-specific variables than what is assessed under this statewide analysis. This analysis is also not intended to be a substitute for local or regional decision-making nor to represent every forest biomass policy, direct cost, or environmental consideration (i.e., technical feasibility, feedstock specifications, accessibility, proximity to infrastructure, or other factors) that affects decisions.

Maps provided in this section help provide context, at a county-level, for areas where prioritizing biomass mobilization appears most likely to yield GHG and criteria emission benefits. Results of this analysis include an estimate of the annual quantity of forest residue that could be socially beneficial to mobilize statewide, and the share of mobilized residue that should be allocated to an energy end use. As discussed in Appendix H, the quantity of forest residue allocated to energy based on this analysis is combined with supplies of other sources of woody biomass residue (agricultural and urban waste), and input to the PATHWAYS model as a resource for use in hydrogen via non-combustion conversion technology (gasification) with CCS.

Note that the analysis is carried out in a step-wise fashion enabling the exploration of intermediate results, such as the fractions of technically mobilizable residue that may be socially beneficial to use for non-energy products, including but not limited to mass timber and other construction applications, cellulosic nanotechnology applications, bio-based plastics, mulch, compost, and biochar, and geologically-sequestered CO_2. The social cost and benefits of non-energy uses for biomass residues were not modeled, but discussion of alternative utilization options is provided in this section.

Estimating Costs and Benefits for Different Biomass Residue Fates

CARB applied a socially beneficial cost modeling framework to explore the extent to which forestry residue mobilization can yield GHG and criteria emission benefits statewide. The modeling approach is described in detail in this section; briefly, the approach considers:

- the savings from avoided health damages (i.e., a social benefit) by utilization of residues rather than managing residue at the forest treatment site;
- the costs of collecting and transporting residues to an industrial facility;
- the cost of converting residues to advanced biofuel; and
- the carbon benefits from fossil fuel displacement.

The California Biomass Residue Emissions Characterization (C-BREC) model [59] characterizes forestry treatment and biomass mobilization scenarios at a 30-meter resolution across California forested lands. Outputs from the C-BREC model provided by researchers at Cal Poly Humboldt were used to inform CARB's analysis of available forestry residues and affiliated criteria emissions for various treatment options.

C-BREC results alongside cost information from NREL's Fast Pyrolysis Biorefinery Model [60] and damage estimates for criteria emissions from the AP2 Model [61] were used to construct a subset of scenarios to explore social benefits and social costs affiliated with forestry treatment and residue mobilization strategies.

The developers of C-BREC provided a dataset that recorded areas where forest treatment activities were conducted in California on almost 400,000 acres of land that were reported from 2016 through 2019. By combining these past forest treatment records with the scenario analysis output from the C-BREC model, an estimate of the technically mobilizable biomass residue and reference case emissions for each of these historically treated parcels was created. The C-BREC authors categorized each historically treated parcel into the most likely silvicultural treatment category for each 30x30 meter pixel across the state. These treatment categories, shown in Table 34, were selected to cover a range of silvicultural activities including commercial timber harvest, thinning, forest health, and fuels reduction.

Table 34. Forest silvicultural treatment categories for past treatments records [59]

Remove 100%	Clear-cut 100% of standing trees
Thin from Below by 20%	Remove 20% of basal area starting with smallest DBH trees
Thin from Below by 40%	Remove 40% of basal area starting with smallest DBH trees
Thin from Below by 60%	Remove 60% of basal area starting with smallest DBH trees
Thin from Below by 80%	Remove 80% of basal area starting with smallest DBH trees
Thin from Above by 20%	Remove 20% of basal area starting with largest DBH trees
Thin from Above by 40%	Remove 40% of basal area starting with largest DBH trees
Thin from Above by 60%	Remove 60% of basal area starting with largest DBH trees
Thin from Above by 80%	Remove 80% of basal area starting with largest DBH trees

To estimate the emissions profiles for uncollected residues, C-BREC reference case residue management scenarios include emissions from 1) decay of biomass left on-site and subject to annualized wildfire probability; 2) residues piled and burned; 3) residues scattered and broadcast burned; or 4) both pile and broadcast burn. More detail on these reference cases, underlying assumptions, and the methodology used to account for wildfire probability can be found in the C-BREC model documentation [59]. The criteria pollutant emissions are calculated in terms of mass per unit biomass, allowing CARB to associate an emissions estimate with the technically mobilizable biomass from the past treatment records.

CARB then combined the estimates of emissions from technically mobilizable biomass from past treatments with the AP2 county-level emission damage estimates. The AP2 marginal damage estimates provide a way to value possible avoided air quality damages for various residue management strategies. AP2 estimates emissions damages from PM2.5 at a county level, while C-BREC models emissions and treatment scenarios at a 30-meter resolution. Substantial aggregation of past treatment areas was therefore required to estimate the counties where mobilization might be prioritized for this analysis.

Mobilization costs include collecting and transporting residues to a processing or conversion facility, and converting those residues into a viable product. Transport and logistic costs for forestry residues were derived from the Department of Energy's Billion Ton Report [62]. Conversion costs and process yields for residue came from the NREL JEDI Fast Pyrolysis Biorefinery Model [60]. Finally, a social cost of carbon of $200 per MTCO$_2$e was applied to the displaced fossil fuel on an energy-equivalent basis, using a yield of approximately 10 MMBtu/ton of feedstock.

Note that while the conversion costs and fossil fuel displacement factors associated with use of residue for biofuel applications was used to represent the mobilization case in this analysis, this is not intended to suggest that all mobilized biomass is likely to be directed toward energy applications. Various non-energy bio-product applications may be more or less profitable than biofuel applications, and may have carbon substitution ratios greater or less than biofuel displacement, therefore the biofuel use case is used to represent one possible use case for mobilized biomass.

Identifying Socially Beneficial Biomass Residue Fates

Figure 32 shows the relative marginal damages for PM2.5 across California based on AP2 results. Marginal damages are typically greater in regions that have larger populations and that have higher background emissions, indicating that burning residues has a higher social cost, or health impact, in these areas. In the socially beneficial analysis framework, these damages are considered avoided costs (i.e., a savings) when residue is mobilized rather than burned onsite following forest treatment.

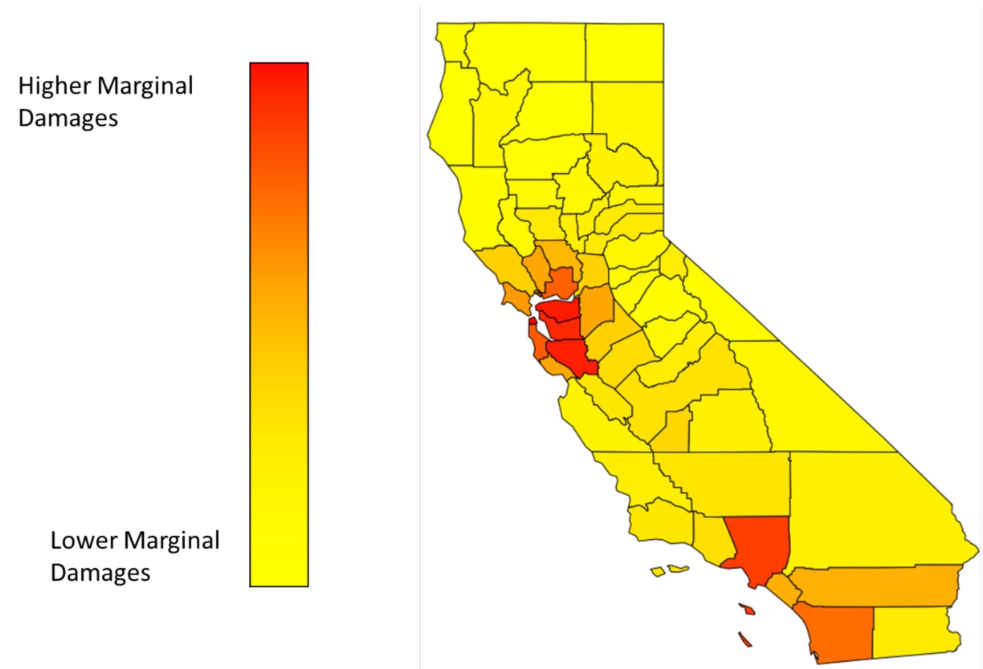

Figure 32. Relative damages affiliated with PM2.5 for counties in California based on AP2 Model Outputs

Next, the benefits (avoided damages due to mobilization) were combined with the costs to mobilize and convert biomass into biofuel. This combined cost and benefit assessment was used to better understand where biomass residue could be mobilized to yield positive social benefits (negative costs) compared to an alternative residue fate where biomass residue is burned on-site creating substantial criteria pollutant emissions (Figure 33).

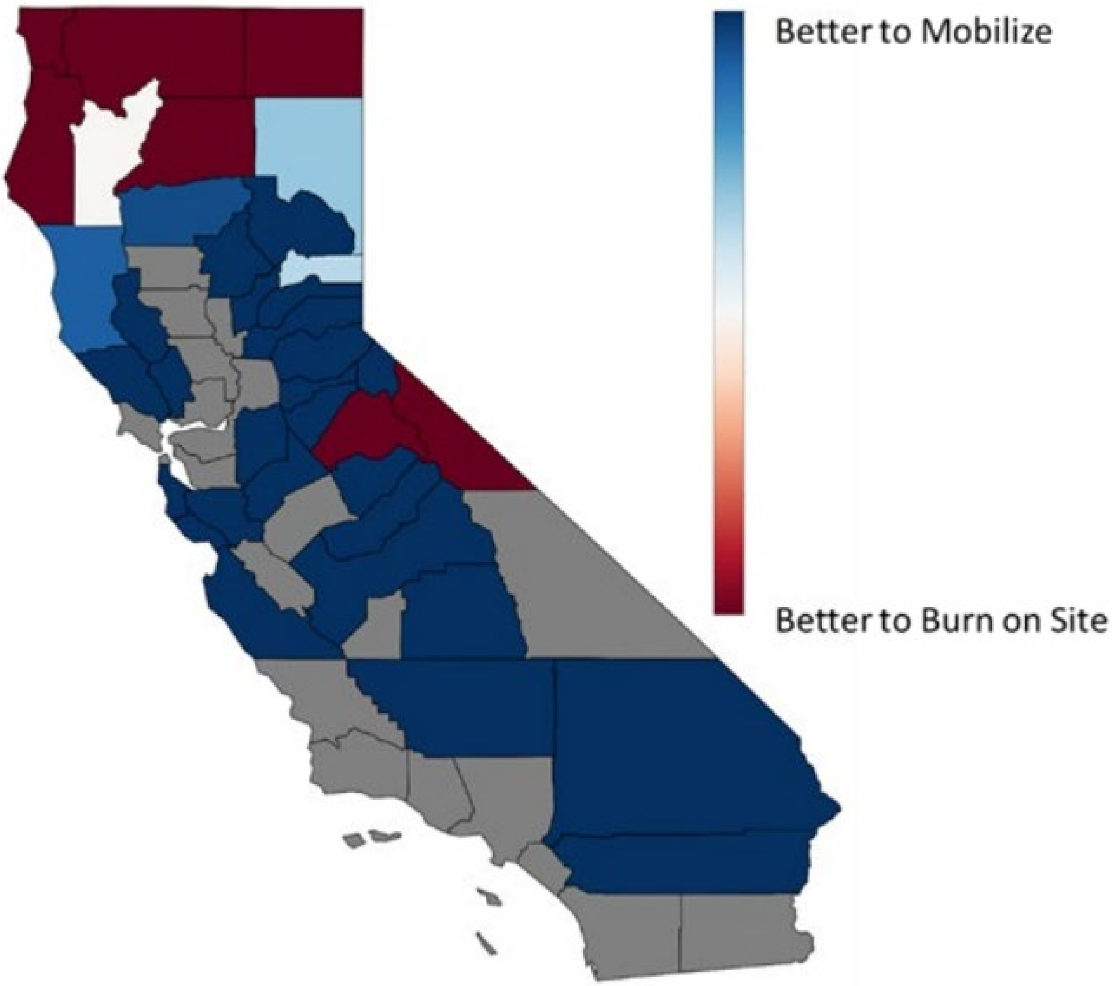

Figure 33. Social benefits from residue mobilization relative to on-site burning. Darker blue counties on the map are areas where mobilization of forestry residue may result in greater social benefits than on-site burning. Dark gray counties are areas where past treatment data did not exist.

As shown in Figure 33, areas in the state with lower estimated criteria emission damages are less likely to yield beneficial social outcomes if biomass residue is moved toward energy markets compared to burning the residue on-site. The red areas on the map in Figure 33 indicate where mobilization and conversion costs are high relative to the avoided criteria emissions damages. For the past treatment areas in California where avoided criteria emissions benefits are less than the costs of biomass mobilization, it may be more beneficial to manage residues on-site in these areas, and to focus resources to mobilize residue or reduce wildfire risks in other parts of the state. As discussed previously, this analysis is not intended to represent nor to substitute for local or regional decision-making, as these factors can vary considerably for a given site within each county. Local decision-making will account for factors including project specific costs, feasibility, feedstock specifications, accessibility, proximity to infrastructure, and other market factors.

The analysis conducted for Figure 33 represents the "Best Case" for mobilization scenarios that assumes that the counterfactual fate for biomass residue is that it would have been burned on-site (a low-cost disposal option). However, there is no evidence to suggest that biomass residue is always "burned on-site." In some areas, residue may be left in place to aerobically decompose over time.

To illustrate the impact of the "no burn" counterfactual, an analysis was performed in which residue mobilization was compared to a leave-in-place counterfactual, representing a "Worst Case" for mobilization scenario. Figure 34 shows the resulting net social costs affiliated with criteria emissions due to mobilizing biomass resources under a "no burn" counterfactual. Damage costs are based on AP2 marginal damage estimates. There are additional costs affiliated with feedstock collection, transport, and processing that are not captured in Figure 34. This analysis serves to highlight counties in California (shown in red) where mobilization is less likely to yield social benefits under a counterfactual where residue burning can be avoided. In other words, in areas where on-site, no-burn strategies for forest treatment operations are feasible, these are likely preferable to mobilization.

On-site techniques can be used (e.g., chipping or lop and scatter) to accelerate decomposition and reduce fire hazard or reduce criteria emissions in the event of a wildfire. However, on-site fuel management that reduces wildfire risks adds cost and may not be feasible for many sites, including the existing "forgotten" burn piles that have been left unburned in forested areas across California. Depending on a slew of factors including climate, fire return intervals, species composition, size class, and moisture content, leaving material on-site may result in reduced criteria and GHG emission impacts compared to mobilization or burning residue.

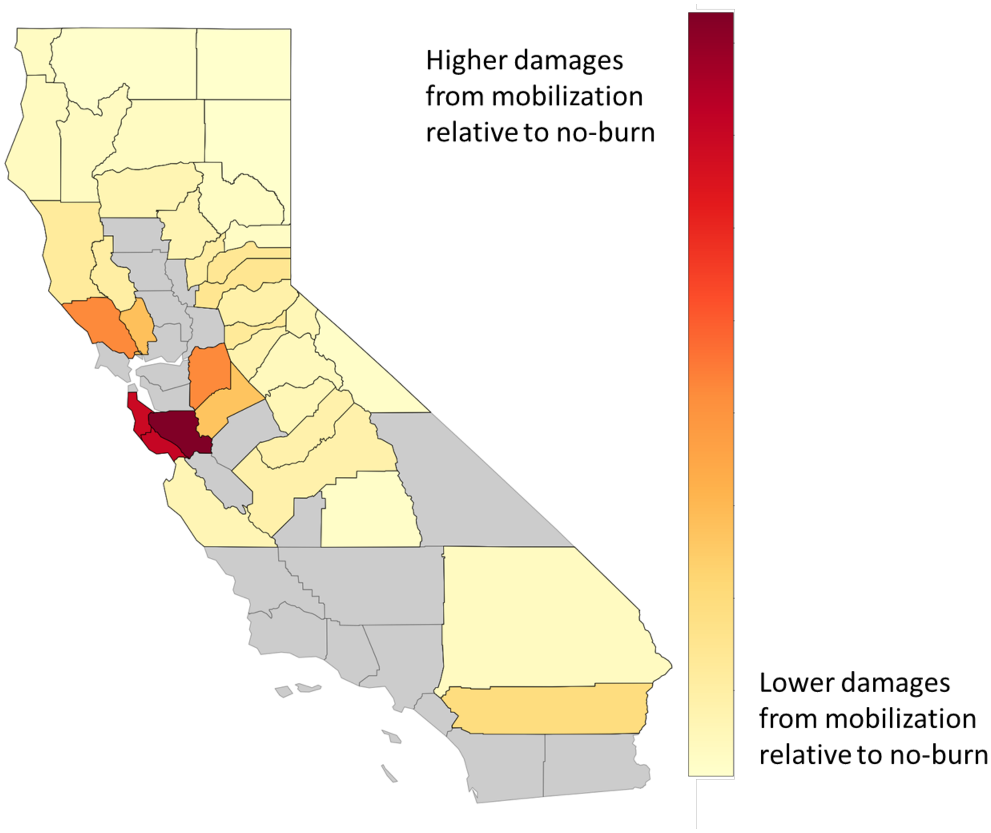

Figure 34. Counties that are darker red indicate areas where mobilizing biomass residue has higher social costs relative to a no-burn alternative for biomass residue. Counties shown in grey are areas where past treatment data did not exist.

Estimating Mobilizable Biomass Residue for the Scoping Plan Scenario

The social benefits analyses in the previous section consider the social cost of criteria emissions and displaced fossil carbon affiliated with mobilizing residues, leaving residues in place, or burning residues on-site. Next, the mobilizable residue output from C-BREC was used to estimate the quantity of residues that would be available under each NWL management alternative scenario developed for the Scoping Plan. Historically treated parcels were mapped onto areas by ecounit/ownership combination (see the section Ecological Unit Development for details), and treated acres were scaled up to estimate the quantity of mobilizable residues that would be generated for each acre that is treated under the NWL management scenarios.[3] Finally, the social benefits analyses were used to determine the areas where mobilization may be socially beneficial and the associated share of residues. The modeling steps described in this section are depicted in Figure 35.

[3] Not all forest management activities result in residue generation. To determine the treatment acres yielding residue, the acres treated in each scenario (see Table 7) using the following activities are summed: Thinning, Harvesting, Clearcuts, and Other mechanical.

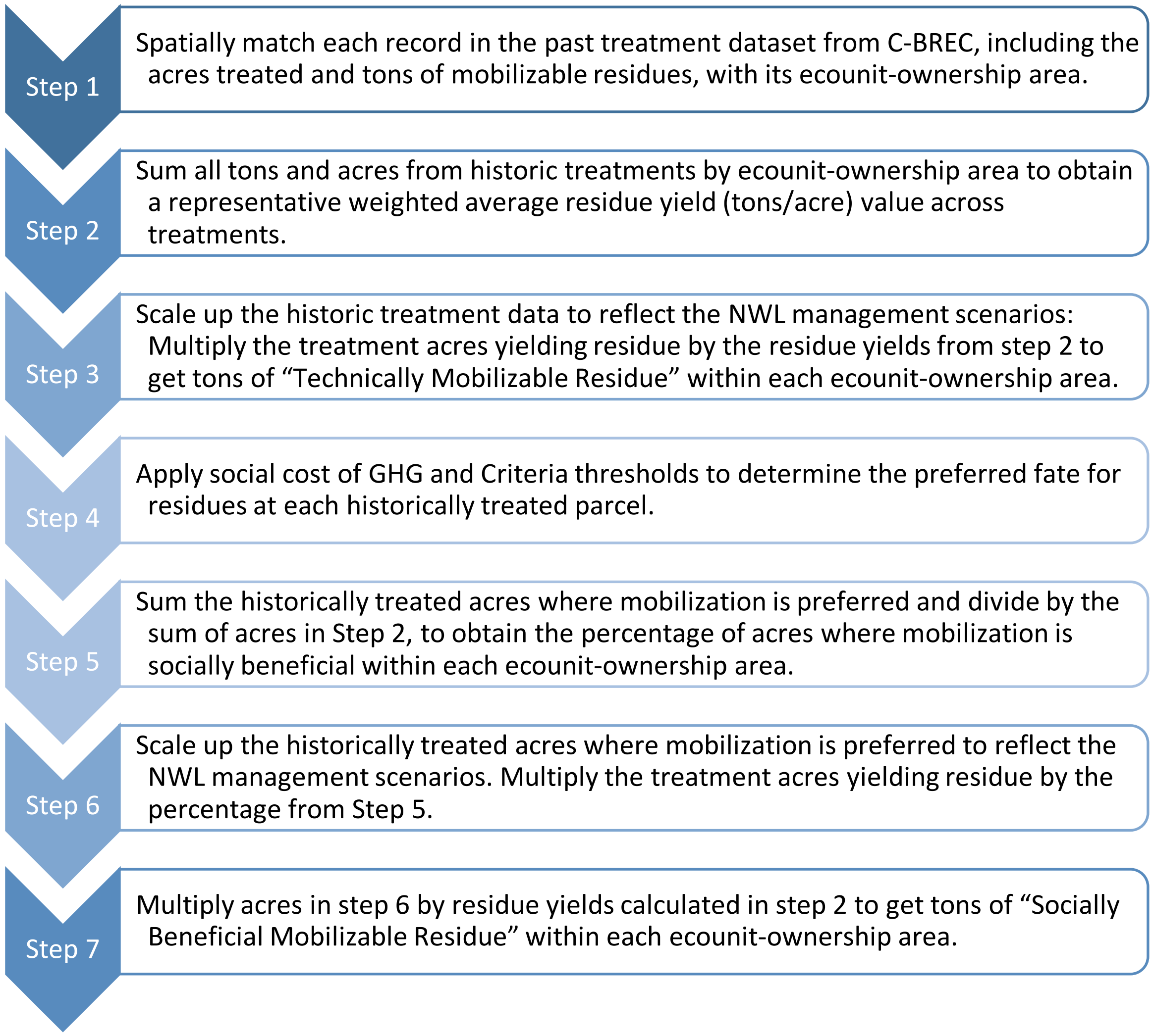

Figure 35. Description of modeling steps to determine the technically mobilizable residues and socially beneficial mobilizable residues per ecounit-ownership area under each NWL management scenario.

The following cutoff criteria were used to determine preferred fates for the mobilizable residue generated on each historically treated parcel. Preferred fates were limited to mobilize or leave in place (default on-site management strategy):

1) Leave in place was preferred for residues when the social cost of mobilizing that resource and directing it toward biofuel applications was more costly than the damages from burning on-site
2) Mobilization was preferred for residues when the social cost of mobilizing a residue for biofuel applications was less than the damages from burning on-site

Table 35 shows the mobilizable biomass yield (tons per acre) for each ecounit/ownership combination in which historic treatments occurred, as estimated by the C-BREC model. Table 35 reflects past treatment data, prior to scale-up and social benefits filter (i.e., the result of modeling Step 3 shown in Figure 35).

Table 35: Estimated mobilizable residue yields for ecounit-ownership areas for which past treatment data is available.

Ecounit-Ownership Area	Acres Treated (2016-2019)	Technically Mobilizable Residues (Tons)	Mobilizable Residue Yield (Tons/Acre)
Central Coast Evergreen Forest - Federal	161	809	5
Central Coast Evergreen Forest - PrivateLand	62	604	10
Central Coastal Wood and Shrub Lands - PrivateLand	219	2,531	12
Central Coastal Wood and Shrub Lands - PrivateLand_NotManaged	176	3,833	22
Dry Sierra Mountains - Federal	56,589	411,635	7
Dry Sierra Mountains - ForestIndustry	4,484	89,767	20
Dry Sierra Mountains - PrivateLand	20,634	239,436	12
Dry Sierra Mountains - PrivateLand_NotManaged	0	0	2
Great-Basin Rangelands - Federal	1,299	2,948	2
Great-Basin Rangelands - PrivateLand	392	2,420	6
Humid Sierra Mountains - Federal	58,276	562,651	10
Humid Sierra Mountains - ForestIndustry	7,440	73,336	10
Humid Sierra Mountains - PrivateLand	6,031	79,228	13
Klamath - Federal	12,588	111,878	9
Klamath - Federal_NotManaged	196	4,101	21
Klamath - ForestIndustry	7,285	110,147	15
Klamath - PrivateLand	5,155	116,993	23
Klamath - ReservationRancheria	509	3,028	6
Northern Coastal Wood and Shrub Lands - Federal	269	1,528	6
Northern Coastal Wood and Shrub Lands - PrivateLand	204	4,054	20
Northern Coastal Wood and Shrub Lands - PrivateLand_NotManaged	28	695	25
Northern Sierra/Southern Cascades - Federal	40,094	173,952	4
Northern Sierra/Southern Cascades - Federal_NotManaged	84	295	3
Northern Sierra/Southern Cascades - ForestIndustry	26,410	223,462	8
Northern Sierra/Southern Cascades - PrivateLand	3,044	11,560	4
Northern/Central Coastal Forest - Federal	87	2,493	29
Northern/Central Coastal Forest - ForestIndustry	30,183	568,230	19
Northern/Central Coastal Forest -	11,246	238,983	21

PrivateLand			
Northern/Central Coastal Forest - PrivateLand_NotManaged	1	24	22
Northern/Central Coastal Forest - ReservationRancheria	1,268	40,714	32
Northern/Central Coastal Forest - State	2,454	42,912	17
Sierra Foothills - Federal	10,162	105,202	10
Sierra Foothills - PrivateLand	16,694	173,445	10
Sierra Foothills - PrivateLand_NotManaged	14,888	67,399	5
Southern Humid Chaparral - Federal	1	11	13
Other ("un-modeled areas") *	377	8,216	22
TOTAL	**338,994**	**3,478,518**	**AVERAGE 10**

* For "un-modeled" areas in the NWL alternative scenarios, either an ecounit or an ownership type was not explicitly present as an ecounit-ownership pair in the past treatment dataset. As such, a land-management strategy (acres treated) could not be referenced for these "un-modeled" areas. Over 99% of acres treated in the past treatment dataset were able to be matched to land management areas in the alternative scenarios as defined in Table 35.

The past treatment data, criteria damage estimates, and techno-economic data used to identify the preferred residue management strategy were combined with the land-management strategies for each NWL alternative scenario to estimate the total technical potential quantity of biomass residue in bone dry tons (BDT), and the share that may be socially beneficial to mobilize for any end use application (not limited to energy uses) rather than manage in place. The technically mobilizable residue potential is regarded as an upper limit of supply that may be expected to be available on average each year and is provided to enable comparison to existing assessments of resource potential, current mobilization rates, and to support future analyses.

Table 36 shows statewide annual results. The results for each ecounit and ownership area under The Scoping Plan Scenario are provided at the end of the chapter in Table 38. These results are provided for methodological transparency and are not intended to represent nor to substitute for local or regional decision-making. Local decision-making will account for factors including project-specific costs, feasibility, feedstock specifications, accessibility, proximity to infrastructure, and other market factors.

Table 36. Statewide annual mobilizable residue estimates for each Natural and Working Lands Scenario

Scenario, Total Area Treated (Million Acres)	Treatment Area Yielding Residue (Million Acres)	Technically Mobilizable Residue Potential (Million BDT)	Socially Beneficial Mobilizable Residue (Million BDT)
BAU Scenario, 0.25	0.2	2.1	1.4
Scenario 1, 0	0	0	0
Scenario 2, 1.00	0.5	5.6	3.1
Scenario 3, 2.34	1.5	14.5	8.3
Scenario 4, 5.19	3.4	33.1	19.5

The estimated residue availability results provided in Table 36 are comparable to the findings of other independent assessments of statewide biomass resources, as illustrated in Table 37. For example, the California Biomass Collaborative (CBMC) estimated that between 7 and 11 million BDT/year non-merchantable biomass from forest thinning and logging slash could be available under current forest management practices in the State and under a hypothetical forest management strategy that maximizes wildfire risk reduction, respectively. Supply curves generated in the CBMC study provide further perspective on the fraction of residue that could be available at different costs in various regions and by land ownership. The findings of an economic analyses of forest residue supply conducted by ICF for the American Gas Foundation [63] is also shown for comparison. Available data for current mobilization is provided for additional perspective on the magnitude of growth reflected in these results; it is estimated that approximately one million tons of forest residue is currently utilized for energy each year and nearly an equal amount of material is generated as a by-product of timber harvest but uncollected.

Table 37. Comparison of California forest biomass resource assessments[4]

Study	Resource Estimate (million BDT/year)	Details
California Biomass Collaborative, 2015 Assessment [64]	8.4	Technical potential for biomass from forestry with consideration of ecological requirements, terrain limitations, and inefficiencies in collection and handling.
California Biomass Collaborative, 2015 Biofuel Potential [65]	6.9	Current Management Scenario: Technical potential for biomass from forest thinning and logging slash under current forest management practices over a period of 40 years.
California Biomass Collaborative 2015 Biofuel Potential [65]	10.9	Optimized Management Scenario: Technical potential for biomass from forest thinning and logging slash under a hypothetical selection of forest treatments areas optimized for fire-hazard risk reduction.
Cabiyo et al., 2021 [66]	7.3	Technical potential for scenarios to explore impact of increased demand for residues for innovative wood products.
Getting to Neutral, 2020 [67]	15.1	Refers to analyses [65] and [66], but appears to assume 15 tons/acre based on personal communication, and forest treatment of 1 million acres/year.
ICF and American Gas Foundation, 2019 [63]	1	Estimated economic use of residues for biomethane production via gasification under a price cap of $100/ton; assumes no increased harvest or management.
SB 498 Biomass Conversion Facility Reporting, 2021 [68]	0.7	Biomass from forest sources reported for power generation in 2021; in addition, 1.3 million BDT mill residues were reported.
UM-BBER for CalFIRE, 2019 [69]	0.9	Uncollected logging residue associated with timber harvest in 2016.

[4] Note that sawmill residues are excluded from CARB's analysis and the comparisons shown in Table 35, as the 2 million tons of mill residues [64] generated each year are commonly considered to be fully utilized and therefore not available for additional applications.

Socially Beneficial Residue Supply for Energy and Other End Uses

To estimate the biomass-energy supply for input to PATHWAYS fuel modeling, a range of potential social costs of carbon were used to identify the fraction of the statewide socially beneficial residue supply that may be suitable for use as energy. Staff assumed that biomass that became socially beneficial to mobilize at carbon prices between \$50/ton and \$200/ton would be usable for advanced (non-combustion) biofuel applications, given the supportive state and federal energy policies for these end uses, while any biomass that was beneficial to mobilize at carbon prices below \$50 per ton would have better uses in non-energy applications, such as durable wood products.

The socially beneficial share of technically mobilizable biomass can be estimated for different carbon prices (Figure 36). Up to 48% of residues are estimated to be mobilizable for non-energy applications at carbon prices up to \$50 per $MTCO_2$. Carbon pricing above \$50 per ton expands mobilizable biomass quantities by an additional 20%. Therefore, of the 8.3 million BDT/year that was determined beneficial to mobilize under Scenario 3, staff estimates that 20% of the residue, or 1.6 million BDT/year should be directed toward energy applications.

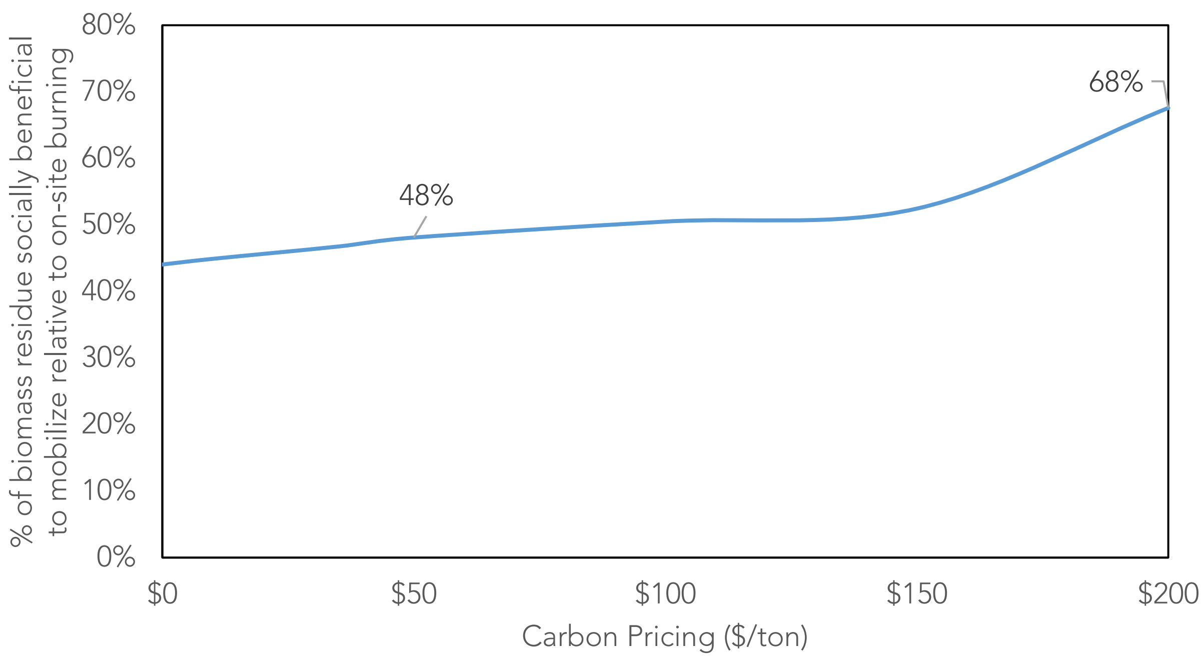

Figure 36. Percent of biomass residue that may be socially beneficial to mobilize at different carbon prices.

In addition to considering the fraction of biomass supply that should be directed to energy applications, the annual carbon sequestration potential associated with the biomass that is socially beneficial to mobilize in Scenario 3 is 15 $MMTCO_2e$ per year (1.8 $MTCO_2e$/BDT). This estimate assumes that each bone-dry ton of biomass contains 0.5 tons of carbon and 100% capture rate—and thus should be considered a theoretical maximum. The result provides some perspective on the gross tons of carbon dioxide from forest residues that could be captured and permanently stored through a combination of hydrogen with CCS or other BECCS applications, biomass carbon removal and storage (BiCRS) applications [55], and/or durable product applications.

For the mobilized biomass residue that is not directed toward energy applications, other alternatives have been identified which may create improved environmental and social benefits. For example, Cabiyo et al. (2021) explored the potential demand and carbon benefits of engineered wood products such as oriented strand board that can be made from residues, concluding that durable products confer carbon benefits comparable to bioenergy applications with carbon capture and sequestration [66].

While quantifying the net carbon benefits and economic feasibility of various end-use alternatives was beyond the scope of this analysis, the State has identified several existing and potential utilization opportunities that align with key goals and core values identified across collaborating agencies, including: mass timber, cement additives, specialty products such as posts and poles, and soil additives such as mulch, compost, and biochar [70]. Further, these end uses should not be considered as solely *competing* alternatives, as no single technology is expected to be the optimal, preferred, or best suited use for every site and residue type. Rather, a suite of utilization options and technologies can likely achieve favorable synergistic cost, material, and logistical efficiencies, particularly when developed as integrated wood products "campuses" such as envisioned at the Sierra Institute's Indian Valley Wood Utilization Campus.

Recognizing the potential carbon benefits of a wide variety of end uses, additional policies are needed to support market growth for innovative bioenergy and non-energy uses for forest residues and other types of biomass waste. As discussed in the recent interagency sustainable woody biomass industry development framework [70], the State has convened a collaborative process to advance new market development strategies to mobilize residues into utilization options that contribute to climate, air quality, and wildfire mitigation goals.

Table 38. Breakdown of the percentage of treatment acres for which mobilization is preferred, and the quantities of residue considered socially beneficial to mobilize by ecounit-ownership area for the Scoping Plan Scenario.

Ecounit Ownership Area	Percent of Treatment Area Preferred Mobilize	Socially Beneficial Mobilizable Residue (BDT)
Central Coast Evergreen Forest – Federal	100.0%	114,909
Central Coast Evergreen Forest – PrivateLand	100.0%	119,780
Central Coastal Wood and Shrub Lands – PrivateLand	100.0%	2,726
Central Coastal Wood and Shrub Lands – PrivateLand NotManaged	100.0%	0
Dry Sierra Mountains – Federal	93.3%	1,767,439
Dry Sierra Mountains – ForestIndustry	91.1%	215,302
Dry Sierra Mountains – PrivateLand	91.1%	466,640
Dry Sierra Mountains – PrivateLand NotManaged	100.0%	0
Great-Basin Rangelands – Federal	9.6%	1,814
Great-Basin Rangelands – PrivateLand	100.0%	72,239
Humid Sierra Mountains – Federal	97.9%	740,281
Humid Sierra Mountains – ForestIndustry	99.9%	118,485
Humid Sierra Mountains – PrivateLand	100.0%	178,073
Klamath – Federal	27.6%	1,371,697
Klamath – Federal NotManaged	0.0%	0
Klamath – ForestIndustry	34.3%	176,204
Klamath – PrivateLand	1.1%	10,743
Klamath – ReservationRancheria	99.5%	79,787
Northern Coastal Wood and Shrub Lands – Federal	0.0%	0
Northern Coastal Wood and Shrub Lands – PrivateLand	100.0%	86,989
Northern Coastal Wood and Shrub Lands – PrivateLand NotManaged	100.0%	0
Northern Sierra/Southern Cascades – Federal	20.9%	57,230
Northern Sierra/Southern Cascades – Federal NotManaged	0.0%	0
Northern Sierra/Southern Cascades – ForestIndustry	29.4%	93,918
Northern Sierra/Southern Cascades – PrivateLand	0.7%	128
Northern/Central Coastal Forest – Federal	0.0%	0
Northern/Central Coastal Forest – ForestIndustry	59.0%	315,645
Northern/Central Coastal Forest – PrivateLand	60.7%	233,818
Northern/Central Coastal Forest – PrivateLand NotManaged	100.0%	0
Northern/Central Coastal Forest – ReservationRancheria	0.0%	0
Northern/Central Coastal Forest – State	40.9%	22,204
Sierra Foothills – Federal	100.0%	534,955
Sierra Foothills – PrivateLand	100.0%	916,028
Sierra Foothills – PrivateLand NotManaged	97.3%	0
Southern Humid Chaparral – Federal	100.0%	640,443
Other ("un-modeled" areas) *	4.9%	1,762
TOTAL		**8,339,240**

* For "un-modeled" areas in the NWL alternative scenarios, either an ecounit or an ownership type was not explicitly present as an ecounit-ownership pair in the past treatment dataset. As such, a land-management strategy (acres treated) could not be referenced for these "un-modeled" areas. Over 99% of the areas in the past treatment dataset were able to be matched to land management areas in the alternative scenarios as defined in Table 35. To account for the remainder, the acres treated in these "un-modeled" areas were scaled up in proportion to the total treatment acres yielding residue under each scenario relative to the past treatment data.

Cropland Modeling

Background

Modeling of croplands for the 2022 Scoping Plan update was done to determine how agricultural lands can contribute to carbon neutrality in California. In California, croplands contain approximately 90 million metric tons of carbon, which accounts for 1.6% of all statewide NWL carbon [71]. These lands are divided into three sub-categories: rangelands, perennial croplands, and annual croplands. Rangelands, which are shrub and grasslands that consist primarily of unirrigated native vegetation that are occasionally grazed by livestock, is currently modeled in the forest, shrubland, and grassland NWL category. Refer to the forest, shrubland, and grassland modeling documentation for information on how rangelands are being modeled for the Scoping Plan update.

Perennial croplands, consisting of orchards and vineyards, and annual croplands, consisting of crops that do not persist from one year to the next, and these two types of croplands are modeled using two different methods. These two agricultural lands have different physiology that requires different modeling techniques. Though these two agricultural land types are modeled separately, their results will be combined for the Scoping Plan analysis.

This document outlines the technical aspects of how croplands are modeled for the 2022 Scoping Plan Update.

Perennial Agriculture

Orchards are modeled using an allometric-based model derived by CARB. An allometric-based model uses empirical data on measurable forest structures, like diameters and heights of trees, to derive models to estimate unmeasurable variables, like total carbon stock. In this modeling framework, the orchard type and age are the independent variables, meaning that once the perennial crop type and age are determined, the model can estimate the above ground live carbon per unit area. The model then uses the statewide age distribution of perennial crop types and total crop type acreage to calculate the statewide carbon per crop type. The orchard types quantified in this modeling are oranges, pistachios, almonds, and walnut.

Input Data

Age Distribution

The amount of carbon in perennial agriculture is based on the California acreage reports [72, 73] for almonds, walnuts, pistachios, and oranges. For each orchard type, these acreage reports provide the number of acres in a given age class. However, these acreages are not always consistent through time, and for this reason the acreages are slightly modified for use in this model. The primary inconsistency is that sometimes the amount of acres in a cohort (group of orchards that are all planted at the same time) are reported to increase through time, which is impossible. For example, completely hypothetically, 1000 acres of almonds are planted in some year, but then the reported acres in this cohort the next year might be 1250, which is 250 acres more than in the year that these orchards were planted. Since acres in a cohort can only decrease through time the maximum number of acres ever reported in a cohort are forced to be the number of acres in year 1, and the following years can only either remain constant or decrease.

Model

The algorithm to calculate projections of future perennial agricultural carbon is based on CARB's method for calculating its perennial carbon inventory. Building upon CARB's inventory method, this new orchard model also estimates the amount of acres that are pushed (or removed) each year, and acres planted for replacement and expansion.

Every year in the historical record, the number of acres planted for a particular orchard type is known given input data. Each year after a cohort of orchards are planted, a certain number of acres gets pushed starting after age 11 for almonds, and 15 for other orchard types. The rate of getting pushed is linear until the orchard cohort reaches its maximum age, after which that orchard cohort no longer exists on the landscape.

Acres planted in future years were calculated by first using the historical mean of acres planted, calculated using years 2001-2019, then adjusting the mean to account for both from annual to perennial cropping systems in California and the effects of drought. To accomplish this, first an additional 13,590 acres of perennial cropland were added to the historical mean for each future projection year, based on land use change modeling from the fourth climate assessment [74]. To account for the climactic influences on perennial cropland acreage, the acreage was then scaled to incorporate the influence of drought by decreasing the total perennial acreage by 300 acres per annum.

$$Acreage_n = Prcp_n \times (HM + (P - (E \times n))$$

Where:

$Acreage_n$ = Perennial acres planted on the California landscape in year n

HM = Historical median of 2001 – 2019 perennial acres

n = years above 2019

P = 13590

E = 300

This model assumes no expansion of perennial agriculture into natural lands. Two climate smart agricultural practices can also be applied, hedge rows, and windbreak/shelterbelt establishment. The carbon impact that these practices have were taken from previous modeling done in the development of COMET-PLANNER and are per unit area multipliers [75]. The sequestration rates for hedgerow planting and windbreak establishment are both 6.7 MT CO2e/ac/yr.

Allometric Equation

The amount of statewide perennial agricultural carbon in a particular year is calculated using allometric equations and the amount of acres within an age distribution. Every year the acres within an age distribution for the 4 orchard types tracked is calculated. Using the number of acres that are a certain age and a particular orchard type, the carbon is calculated. Then the carbon for all ages is summed:

$$C_{total} = Sum(C_{age})$$

Where C is summed over all ages in lbs. and C_{age} is the statewide carbon for orchards of a certain age:

$$C_{age} = C_{acre} * Acres_{age}$$

Where C_{acre} is the carbon per acre given an orchard's age, and $Acres_{age}$ are the acres that are of a certain age in a particular year.

$$C_{acre} = TPA * C_t$$

Where TPA is trees per acres given an orchards age, and C_t is the above and below ground live carbon per tree given the orchard age.

$$TPA = a * ln(age_o) + b$$

Where a and b are allometric parameters, and age_o is the age of an orchard.

$$C_t = d * {age_o}^f$$

Where d and f are allometric parameters and age_o is the age of an orchard (Table 39).

Table 39: Parameters for orchard allometric model.

Orchard Type	**a**	**b**	**d**	**f**	**Maximum Age**
Almonds	-15.45	125.72	12.98	1.39	30
Walnuts	-19.97	103.5	9.32	1.61	50
Pistachios	-24.7	184.98	1.29	1.88	45
Oranges	-34.71	223.83	2.44	1.37	35

The results of the allomtric equations show that there is a tradeoff between trees per acre (Figure 37) and the amount of carbon per tree (Figure 38). That is to say, that as you grow larger trees, there cannot be as many trees on an acre of land. However, when these two dynamics are combined it becomes clearer how carbon content per acre change with age for each orchard type examined (Figure 39).

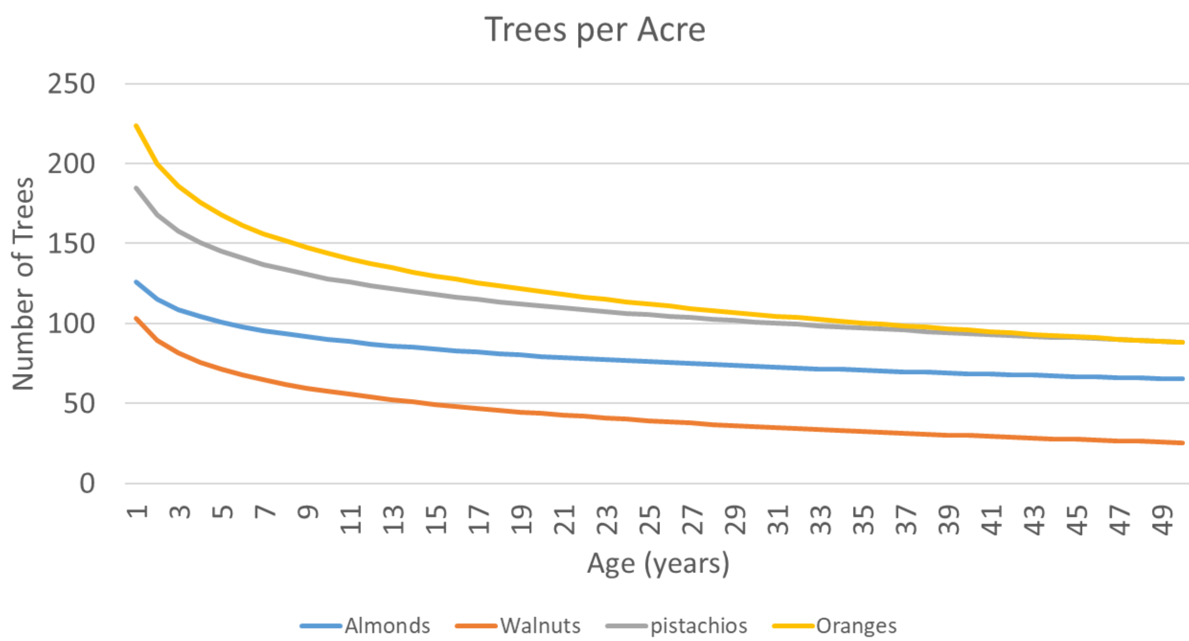

Figure 37: Trees per acre by age for almonds, walnuts, pistachios, and oranges.

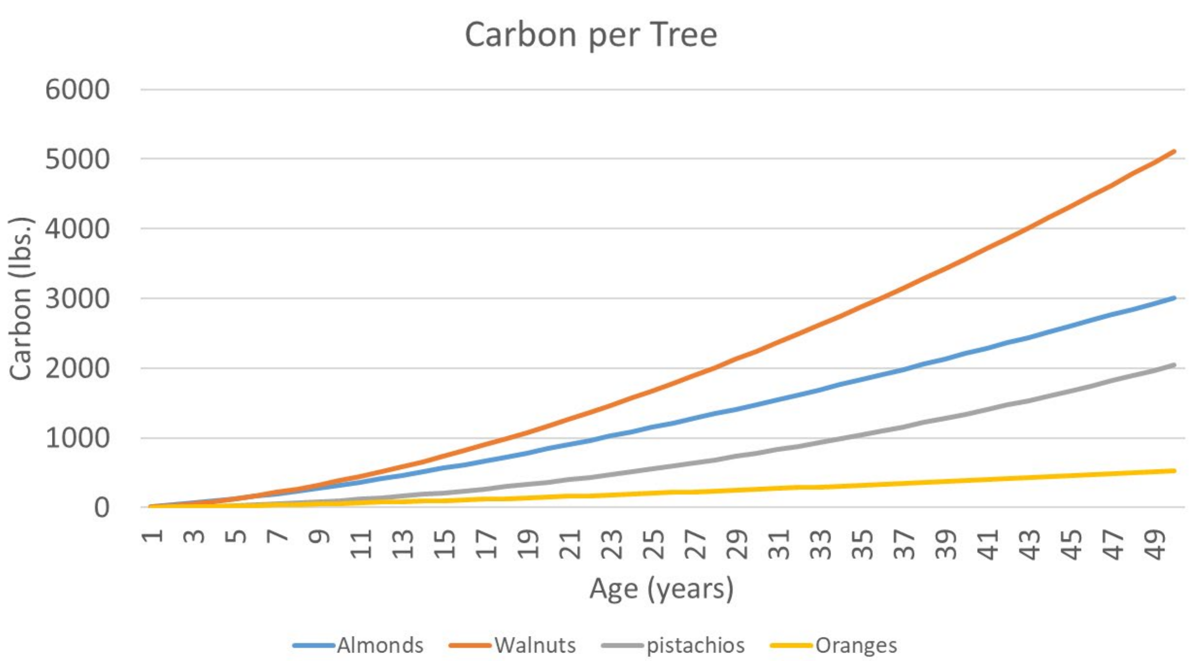

Figure 38: Carbon content per tree by age in almonds, walnuts, pistachios, and oranges.

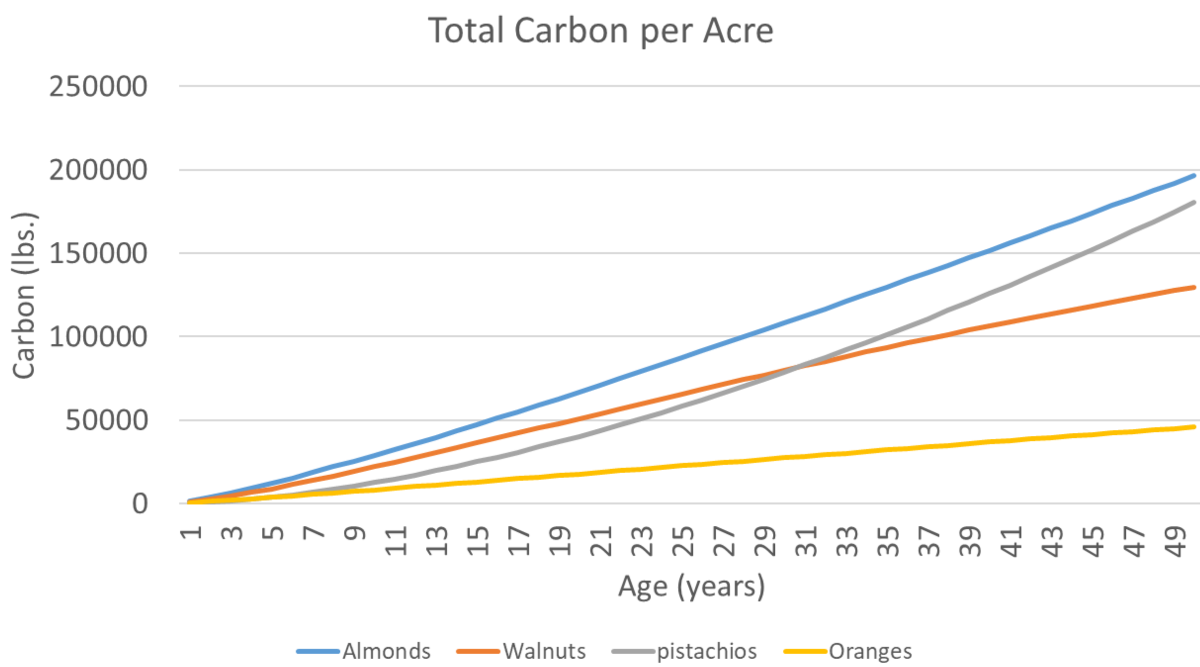

Figure 39: Total above and below ground carbon content in orchard acres by age for almonds, walnuts, pistachios, and oranges.

Output Data

The model produces the annual perennial carbon stocks by orchard type and age distribution. Additionally, the model outputs the amount of carbon and acres that are planted and pushed each year.

Strengths and Limitations

The strength of this model is that it clearly tracks the carbon of orchard cohorts through time, making visualizing carbon growth and loss simple, informative and interesting. Additionally, this model can estimate the carbon or acres that are planted and pushed allowing for estimates of future costs, and biomass available for whole orchard recycling, composting, or bioenergy.

The limitations of this model are that it currently only estimates biomass carbon. Water, soils, and other resource demands may be included in the future. Additionally, no alternative agricultural practices are incorporated in this model, such as alley cropping, or composting.

Annual Croplands

Annual croplands are modeled using the Daycent model [76]. Daycent is a biogeochemical model that ingests climate, site quality, vegetation physiology, and management data to simulate the carbon, water, and nitrogen cycles within a system [77]. Using this information, the model calculates photosynthesis, respiration, carbon allocation, mortality, decomposition, and numerous other biophysical processes. Through the interaction between these processes, the model can estimate how management and climate affects carbon, water, and nutrients.

For the 2022 Scoping Plan Update, Daycent was run on 435 points that were randomly selected across all annual crops in California. Each point was modeled for the business-as-usual (BAU) management and various alternative climate smart practices under numerous future climate change scenarios. Daycent outputs annual values for each of these points, which were then aggregated to the statewide level.

In addition to Daycent modeling, the carbon impact of some climate smart agricultural practices were taken from literature and/or previous modeling efforts, such as the modeling done to derive California's comet-farm and comet-planner tools [75]. These carbon sequestration values are applied annually without taking into account climate change or cumulative impacts, which are captured via Daycent modeling.

Input Data

Historical and future climate data used for Daycent modeling came from California's 4th climate assessment [78]. Climate data used for modeling came from four global climate models (GCM) and 2 representative concentration pathways (RCP). The four GCMs that were used for modeling represent 'hot-dry' (HadGEM2-ES), 'hot-wet' (CNRM-CM5), 'average' (CanESM2), and 'complementary' (MIROC5) conditions, and were chosen through the climate assessment process to represent the range of future projected climate from all GCMs. The RCPs that were analyzed were RCP 4.5 (best case future emissions) and RCP 8.5 (our approximate current trajectory of emissions). This data is daily, on a 4km resolution, statewide, and includes minimum, and maximum temperature, precipitation, and incoming solar radiation.

Site data includes information on the elevation, soil characteristics and hydrologic data [79, 80]. Crop planting/harvest dates and fertilizer rates, as well as crop histories were used to develop cropping system parameters [81, 82, 83].

Climate Smart Agricultural Practices

The impact that climate smart agricultural practices have on the landscape and to emissions was estimated in two different ways: from Daycent modeling, or from literature or previous modeling exercises. The practices that were modeled using Daycent are cover cropping with legumes, cover cropping without legumes, reduced-till, no-till, and composting (Table 40).

Practices that were taken from previous modeling exercises are riparian forest buffer, alley cropping, windbreak/shelterbelt establishment, tree/shrub establishment, and hedge rows. The impact that these practices have were done in the development of COMET-Planner [84].

Easements were also assessed. The BAU for this assessment assumes 11,120 acres of annual cropland loss per year to non-agricultural land uses, which equates to the maximum allowable easements per year. This number comes from the landuse change modeling performed for the 4th California Climate Assessment using the LUCAS model [74]. If an acre of easement is indicated that means that this acre is not removed from the annual cropland carbon pool and can continue sequestering or emitting carbon as if nothing changed on that acre.

Table 40: All climate smart agricultural practices that were assessed for the 2022 Scoping Plan Update, and how they were assessed.

Climate Smart Agricultural Practice	Method for Assessment
Cover cropping with legumes	Daycent
Cover cropping without legumes	Daycent
No Till	Daycent
Reduced Till	Daycent
Composting	Daycent
Easements	Daycent & LUCAS
Transition to organic agriculture	Meta-analysis
Riparian Forest Buffer	COMET-Planner values
Alley Cropping	COMET-Planner values
Windbreak/Shelterbelt Establishment	COMET-Planner values
Tree/Shrub Establishment	COMET-Planner values
Hedge rows	COMET-Planner values

The soil organic carbon impact from transitioning to organic agriculture from conventional is taken from a literature review and meta-analysis [85]. For each acre that transitions to organic, .74 Mg C/acre/year (0.3 Mg C/ha/year) is added to the BAU value for that year. This remains constant for 5 years, after which this benefit declines linearly until there is no sequestration benefit after 25 years. This gradual decline in climate benefit is to simulate the effect of carbon saturation referenced in the literature.

Composting replaces synthetic fertilizer in this modeling. When modeling the impacts of composting a C:N ratio of 12.5 was used. This number is considered a low nitrogen compost number by CDFA [86] and is consistent with other reports [87], while still representing compost as a result of manure and municipal waste composting. At C:N ratios around 16 or higher, this starts to become parent material for composting, and not the finished compost itself [88, 89]. Currently, the over 3/4 of California’s compost comes from manure sources, followed by yard waste [90]. This parent material would lend itself to lower C:N ratios. However, the proportions of parent material are expected to shift away from manure and towards more yard, and food or municipal waste. This is due to expected herd size reductions and expanded municipal waste collection as a result of recent legislation. This would still make manure the largest source of compost, but at a substantially lower majority. Municipal waste, however, also produces compost with relatively low C:N ratios. Therefore, to capture the current to future changes in composting C:N ratios a value of 12.5 was used that should be slightly higher than manure based, but slightly lower than municipal or yard waste composts.

Aggregation

Once Daycent was run on all 435 points across annual croplands in California, the per acre results to aggregated to the statewide level. First, the points were clustered by the county in which they reside, and for each GCM/RCP combination, annual averages were derived. Then to aggregate to the statewide level these county averages were weighted by the amount of annual agriculture within that county. This results in annual statewide averages per acre. This aggregation was done for the BAU management and for each climate smart agricultural practice that were run in Daycent.

The point level modeling of the HSP practices is temporally explicit and is associated with specific years that have specific CO2 concentrations, and climate conditions. These runs are done on the front end and scenarios are built off of the scaled up outputs from this modeling. However, results per acre after scaling are still tied to specific years. For this reason, total acreages for every scenario are applied in year 2025, or year one of the alternative scenarios. Therefore, even though a scenario is a certain acreage per year, all of the acreages over the 20 year application time period (2025-2045) are applied in year 2025. This does not apply for the transition to organic agriculture, which makes up, by far, the most acreage of all annual cropland climate smart practices. This application of acreage in year 1 leads to an over estimation of the climate benefits because it provides 20 years of action for every acre ever applied. This was a bi-product of the practical need for flexible modeling that would allow for adjustments to scenarios through stakeholder and partner collaboration and considerations. In contrast, the forest and other natural lands (FONL) modeling can apply specific acreages in specific years. However, this FONL modeling is inflexible and scenarios cannot easily be iterated with stakeholders. Scenarios are extremely difficult to simulate in the FONL model, but can apply specific acreages to specific years. The annual cropland modeling allows for flexible scenario development, but cannot apply specific acreages to specific years. Because of the exceptional focus from stakeholders, the public, and partners on annual croplands and many comments throughout the entire process on scenario development, this more flexible modeling structure was necessary for this land type. Even though this compromise was made to allow better responsiveness to public and partner comments, this modeling still provides the second most complicated modeling of NWL and incorporates the impacts of management, climate, and ecosystem dynamics into its results.

Output Data

Temporal and Spatial Resolution and Scale

Even though Daycent modeling is simulated on a daily time-step, output data is on a monthly time-step. Aggregated data, however, is on an annual time-step as daily data is not required to answer the questions of the Scoping Plan. Daycent is run on an undefined size, point location. Outputs, however, are on a per acre basis. Once aggregation occurs, however, outputs are statewide totals, where outputs represent all annual croplands as defined by CARB’s NWL inventory.

Carbon, N2O, and Synthetic Fertilizer

The ecosystem carbon outputs from this modeling include the biomass and soil carbon stocks and stock changes. Biomass carbon in annual croplands, however, are typically minimal, unless some HWP practices that incorporates increased biomass or even perennial biomass is incorporated.

N2O emissions from annual croplands is also included. N2O emissions can change with HSP practices. For example, with cover cropping using legumes increases N2O emissions through time. No till can reduce N2O emissions through time. Composting only slightly reduces N2O emissions compared to BAU.

Transitioning from synthetic fertilizer to composting is incorporated in this modeling and is reflected in the Scoping Plan results. In this modeling, it is assumed that when an acre transitions to composting, it no longer receives any synthetic fertilizer. This does not change the N2O emissions very much however, because nitrogen is still being applied to the system and this model cannot distinguish the isotopic differences between nitrogen produced as a result of fossil fuels and nitrogen produced biogenically. CARB knows of no model that distinguishes between different $\delta^{15}N$ values. Further, it is unclear how different $\delta^{15}N$ values affect all the interconnected biogeochemical processes within ecosystems. Therefore, incorporating the transition from synthetic fertilizers to non-compost organic forms of nitrogen amendments cannot be done by any model known to CARB. However, replacing synthetic fertilizers with compost is incorporated in the 2022 Scoping Plan Updated modeling.

Other Variables

Besides soil organic carbon, Daycent output several other variables for the Scoping Plan modeling (Table 41). The impact that climate smart practices have on non-carbon outputs were only assessed for practices modeled with Daycent.

Table 41: Output variables from the Daycent model for annual croplands in the 2022 Scoping Plan Update.

Variable	Definition	Unit
cinput	annual carbon inputs to soil	g C /m2
cproda	annual accumulator of C production = net primary production	g C /m2
somsc	soil organic carbon of top 30 cm	g C /m2
snfxac1	annual accumulator for symbiotic N fixation	g N/m2
prcann	annual precipitation	cm
petann	annual potential evapotranspiration	cm
annet	annual actual evapotranspiration	cm
strmac1	annual deep percolation of water	cm
strmac2	Annual nitrogen leaching (nitrate)	cm
irrtot	Annual total irrigation	cm
fertot11	Annual total nitrogen added from synthetic fertilizer	g N/m2

omadtot	annual accumulator for C added to the system through organic matter addition events	g C /m2
omaetot1	annual accumulator for N added to the system through organic matter addition events	g N/m2
volpac	annual accumulator for N volatilized from plant at harvest, senescence, and/or from grazing removal for grass/crop	g N/m2
runoff	Annual total surface runoff of water	cm
n2oflux	Annual accumulator for nitrous oxide	g N/m2
noflux	Annual accumulator for nitric oxide	g N/m2
n2flux	Annual accumulator for nitrogen gas	g N/m2

Strengths and Limitations

Every modeling exercise has strengths and weaknesses. Biogeochemical models, such as Daycent, have the benefit of being able to model various ecological processes under conditions that have never occurred in the empirical record. That is to say, that biogeochemical models are not limited to using past ecological behavior in the empirical data record to estimate how climate change may influence the response of the system, but instead can simulate how novel climate conditions change the systems response to management and climate together. Additionally, these models can provide estimates for ecological variables that we do not have the empirical data to quantify. For example, soil organic carbon is difficult and costly to measure, and because of this, there is no regular soil sampling inventory across large areas, such as the State of California. Therefore, estimating how climate and management affects statewide soil organic carbon through empirical records alone is not possible. However, by anchoring a biogeochemical model in measurable empirical data, such as above ground carbon, one can use the holistic nature of these models to estimate changes in soil organic carbon in response to management and climate change. One of the greatest benefits of biogeochmical models is estimating of the cumulative effects of actions and climate through time. Changes to ecosystems accumulate through time and affect how the system functions. Likewise, management actions do not just affect the system in the year that the action is applied but affects the system for many years afterwards, and this is captured with these models.

The benefits of biogeochemical models, however, come at a cost. These models are complex, require numerous input datasets, are difficult to parameterize, and require strong ecological modeling skills to operate effectively. These are not models that are designed for public consumption to answer general questions. This means that these models require time to prepare and cannot easily be adjusted after this preparation is complete. As explained earlier, this was overcome by modeling points through time for BAU and each of the HSP practices without specificity as to when action would be taken. This allows for easy and rapid scenario development and modification, as simple acreage multipliers can then be applied to DayCENT outputs. However, this means that all acreages are applied in year 2025.

Using values from literature, as is done for the carbon benefit from the transition to organic agriculture, is also easy to use, and is grounded in various empirical studies. These numbers, however, like the Comet-Planner values alone do not take into account climate or the baseline off of which the carbon benefit is applied. Because of this, these values alone are not sensitive to climate, and do not provide information on absolute emissions or sequestration. The carbon sequestration benefits of transitioning to organic were added on top of the BAU DayCENT simulations to develop a times series. However, whether transitioning to organic will result in greater or fewer climate benefits under climate change is not quantified in this analysis and is assumed to be the same as it has been in the past.

Results

Results are derived as statewide totals (Table 42 - Table 48). Healthy soils practices do not affect the planting or push rate of perennial agriculture, so only one time series is provided as it is the same for every scenario (Table 47, Table 48). The average annual carbon pushed from orchards from 2025 to 2045 is 2.86 MMT C/year.

Table 42: Annual total annual cropland carbon stocks in annual croplands (MMT C).

Year	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2001	39.49	39.49	39.49	39.49361721	39.49
2002	39.62	39.62	39.62	39.62245295	39.62
2003	39.76	39.76	39.76	39.76038384	39.76
2004	39.82	39.82	39.82	39.81946989	39.82
2005	39.83	39.83	39.83	39.83383708	39.83
2006	39.80	39.80	39.80	39.80071852	39.80
2007	39.81	39.81	39.81	39.80684309	39.81
2008	39.82	39.82	39.82	39.82151327	39.82
2009	39.82	39.82	39.82	39.81557058	39.82
2010	39.79	39.79	39.79	39.79429576	39.79
2011	39.82	39.82	39.82	39.81559742	39.82
2012	39.87	39.87	39.87	39.86565468	39.87
2013	39.98	39.98	39.98	39.97534948	39.98
2014	40.00	40.00	40.00	40	40.00
2015	39.89	39.89	39.89	39.88879291	39.89
2016	39.85	39.85	39.85	39.84535519	39.85
2017	39.97	39.97	39.97	39.96594154	39.97
2018	39.94	39.94	39.94	39.93865551	39.94
2019	39.87	39.87	39.87	39.86631765	39.87
2020	39.75	39.75	39.75	39.74786985	39.75
2021	39.65	39.65	39.65	39.64982484	39.65
2022	39.61	39.61	39.61	39.60622507	39.61
2023	39.60	39.60	39.60	39.59527802	39.60
2024	39.59	39.59	39.59	39.5850732	39.59
2025	39.47	39.58	39.55	39.52930795	39.50
2026	39.43	39.66	39.60	39.5547829	39.49
2027	39.40	39.77	39.68	39.60754774	39.50
2028	39.46	39.95	39.83	39.73594309	39.58
2029	39.48	40.11	39.95	39.83455386	39.64

2030	39.45	40.21	40.02	39.88377662	39.64
2031	39.41	40.29	40.07	39.91096269	39.63
2032	39.36	40.36	40.11	39.92523759	39.61
2033	39.47	40.57	40.29	40.08813898	39.74
2034	39.37	40.58	40.28	40.05888294	39.68
2035	39.25	40.56	40.23	39.99017355	39.58
2036	39.34	40.73	40.38	40.12172373	39.69
2037	39.25	40.73	40.36	40.08323314	39.62
2038	39.25	40.82	40.43	40.13377506	39.64
2039	39.28	40.93	40.52	40.20714307	39.69
2040	39.20	40.95	40.51	40.18654149	39.64
2041	39.14	40.96	40.50	40.16158942	39.59
2042	39.05	40.94	40.47	40.11643813	39.53
2043	39.13	41.08	40.59	40.22391466	39.61
2044	39.05	41.07	40.57	40.18904143	39.56
2045	38.93	41.01	40.49	40.09931185	39.45
2046	38.97	41.09	40.56	40.15708091	39.50
2047	38.88	41.06	40.51	40.09980454	39.42
2048	38.85	41.08	40.53	40.10364795	39.41
2049	38.87	41.15	40.58	40.14806816	39.44
2050	38.80	41.14	40.55	40.11266837	39.39
2051	38.71	41.09	40.49	40.0467295	39.30
2052	38.64	41.06	40.45	39.99783623	39.24
2053	38.72	41.19	40.57	40.10521466	39.34
2054	38.62	41.13	40.51	40.03340839	39.25

Table 43: Annual N2O emissions in annual croplands (MMT CO2e). Negative values are emissions.

Year	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2001	-0.51764	-0.51764	-0.51764	-0.51764	-0.51764
2002	-0.5188	-0.5188	-0.5188	-0.5188	-0.5188
2003	-0.5071	-0.5071	-0.5071	-0.5071	-0.5071
2004	-0.47498	-0.47498	-0.47498	-0.47498	-0.47498
2005	-0.4319	-0.4319	-0.4319	-0.4319	-0.4319
2006	-0.42808	-0.42808	-0.42808	-0.42808	-0.42808
2007	-0.43512	-0.43512	-0.43512	-0.43512	-0.43512
2008	-0.48092	-0.48092	-0.48092	-0.48092	-0.48092
2009	-0.422	-0.422	-0.422	-0.422	-0.422
2010	-0.43983	-0.43983	-0.43983	-0.43983	-0.43983
2011	-0.4203	-0.4203	-0.4203	-0.4203	-0.4203
2012	-0.50821	-0.50821	-0.50821	-0.50821	-0.50821
2013	-0.49415	-0.49415	-0.49415	-0.49415	-0.49415
2014	-0.48576	-0.48576	-0.48576	-0.48576	-0.48576
2015	-0.4403	-0.4403	-0.4403	-0.4403	-0.4403
2016	-0.44848	-0.44848	-0.44848	-0.44848	-0.44848
2017	-0.47097	-0.47097	-0.47097	-0.47097	-0.47097
2018	-0.4935	-0.4935	-0.4935	-0.4935	-0.4935
2019	-0.49027	-0.49027	-0.49027	-0.49027	-0.49027
2020	-0.41062	-0.41062	-0.41062	-0.41062	-0.41062

2021	-0.43647	-0.43647	-0.43647	-0.43647	-0.43647
2022	-0.47701	-0.47701	-0.47701	-0.47701	-0.47701
2023	-0.49947	-0.49947	-0.49947	-0.49947	-0.49947
2024	-0.49919	-0.49919	-0.49919	-0.49919	-0.49919
2025	-0.51486	-0.40384	-0.43159	-0.45747	-0.4871
2026	-0.53178	-0.41558	-0.44463	-0.47127	-0.50273
2027	-0.49797	-0.39334	-0.41949	-0.44436	-0.47181
2028	-0.52268	-0.41172	-0.43946	-0.46547	-0.49494
2029	-0.53991	-0.42488	-0.45364	-0.48042	-0.51115
2030	-0.47562	-0.379	-0.40316	-0.42667	-0.45147
2031	-0.47894	-0.3833	-0.40721	-0.43081	-0.45503
2032	-0.48225	-0.38628	-0.41027	-0.43396	-0.45826
2033	-0.49277	-0.39039	-0.41598	-0.4401	-0.46717
2034	-0.50598	-0.40475	-0.43006	-0.45474	-0.48067
2035	-0.49883	-0.40032	-0.42495	-0.44919	-0.4742
2036	-0.49851	-0.39678	-0.42221	-0.44636	-0.47308
2037	-0.47806	-0.38681	-0.40962	-0.4327	-0.45524
2038	-0.48472	-0.39066	-0.41418	-0.4375	-0.4612
2039	-0.52166	-0.4202	-0.44557	-0.47058	-0.4963
2040	-0.47477	-0.38754	-0.40934	-0.43203	-0.45296
2041	-0.43363	-0.35468	-0.37441	-0.39506	-0.41389
2042	-0.47864	-0.39129	-0.41313	-0.43584	-0.45681
2043	-0.47232	-0.38438	-0.40636	-0.42869	-0.45034
2044	-0.48486	-0.39531	-0.4177	-0.44053	-0.46247
2045	-0.49554	-0.40651	-0.42877	**-0.45202**	-0.47328
2046	-0.49226	-0.39783	-0.42144	-0.44445	-0.46865
2047	-0.49097	-0.4041	-0.42582	-0.44869	-0.46926
2048	-0.49465	-0.40664	-0.42864	-0.4516	-0.47264
2049	-0.51323	-0.42106	-0.4441	-0.46784	-0.49019
2050	-0.4719	-0.39196	-0.41194	-0.43368	-0.45192
2051	-0.45271	-0.3758	-0.39503	-0.41581	-0.43348
2052	-0.47185	-0.39377	-0.41329	-0.43486	-0.45233
2053	-0.47738	-0.39441	-0.41515	-0.43689	-0.45664
2054	-0.51026	-0.42312	-0.4449	-0.46806	-0.48848

Table 44: Annual carbon sequestration or emissions in live and dead biomass in annual croplands (MMT C). Negative values are emissions.

Year	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2002	0.471539	0.471539	0.471539	0.471539	0.471539
2003	0.504827	0.504827	0.504827	0.504827	0.504827
2004	0.216255	0.216255	0.216255	0.216255	0.216255
2005	0.052584	0.052584	0.052584	0.052584	0.052584
2006	-0.12121	-0.12121	-0.12121	-0.12121	-0.12121
2007	0.022416	0.022416	0.022416	0.022416	0.022416
2008	0.053693	0.053693	0.053693	0.053693	0.053693

2009	-0.02175	-0.02175	-0.02175	-0.02175	-0.02175
2010	-0.07787	-0.07787	-0.07787	-0.07787	-0.07787
2011	0.077964	0.077964	0.077964	0.077964	0.077964
2012	0.18321	0.18321	0.18321	0.18321	0.18321
2013	0.401483	0.401483	0.401483	0.401483	0.401483
2014	0.090221	0.090221	0.090221	0.090221	0.090221
2015	-0.40702	-0.40702	-0.40702	-0.40702	-0.40702
2016	-0.15898	-0.15898	-0.15898	-0.15898	-0.15898
2017	0.441346	0.441346	0.441346	0.441346	0.441346
2018	-0.09987	-0.09987	-0.09987	-0.09987	-0.09987
2019	-0.26476	-0.26476	-0.26476	-0.26476	-0.26476
2020	-0.43352	-0.43352	-0.43352	-0.43352	-0.43352
2021	-0.35884	-0.35884	-0.35884	-0.35884	-0.35884
2022	-0.15958	-0.15958	-0.15958	-0.15958	-0.15958
2023	-0.04007	-0.04007	-0.04007	-0.04007	-0.04007
2024	-0.03735	-0.03735	-0.03735	-0.03735	-0.03735
2025	-0.42534	-0.01627	-0.11854	-0.2041	-0.32307
2026	-0.14925	0.288152	0.178801	0.093238	-0.0399
2027	-0.08621	0.40037	0.278725	0.193119	0.035433
2028	0.205862	0.672467	0.555815	0.469927	0.322513
2029	0.076543	0.570246	0.44682	0.360915	0.199969
2030	-0.10092	0.384596	0.263216	0.180155	0.020456
2031	-0.15192	0.290365	0.179794	0.099501	-0.04135
2032	-0.19083	0.236622	0.129759	0.052246	-0.08397
2033	0.388795	0.766593	0.672143	0.596219	0.483244
2034	-0.33998	0.066367	-0.03522	-0.10708	-0.2384
2035	-0.44273	-0.09597	-0.18266	-0.25148	-0.35604
2036	0.314498	0.627753	0.549439	0.481474	0.392812
2037	-0.33143	0.007466	-0.07726	-0.14088	-0.24671
2038	0.005365	0.327339	0.246845	0.184983	0.085858
2039	0.09654	0.405217	0.328048	0.268527	0.173709
2040	-0.26283	0.061279	-0.01975	-0.0754	-0.1818
2041	-0.24122	0.029272	-0.03835	-0.09132	-0.1736
2042	-0.31575	-0.04852	-0.11533	-0.16525	-0.24894
2043	0.27019	0.500556	0.442964	0.393364	0.327781
2044	-0.26685	-0.02163	-0.08293	-0.12764	-0.20554
2045	-0.43334	-0.23855	-0.28724	-0.32841	-0.38464
2046	0.120624	0.296409	0.252462	0.211435	0.16457
2047	-0.32834	-0.12186	-0.17348	-0.20963	-0.27672
2048	-0.08812	0.094313	0.048704	0.014067	-0.04251
2049	0.056934	0.241474	0.195339	0.162578	0.103069
2050	-0.24696	-0.04896	-0.09846	-0.12956	-0.19746
2051	-0.33917	-0.16806	-0.21083	-0.24134	-0.29639
2052	-0.26382	-0.10947	-0.14806	-0.17895	-0.22524
2053	0.310949	0.466436	0.427565	0.393005	0.349821
2054	-0.35545	-0.19153	-0.23251	-0.26281	-0.31447

Table 45: Total Annual emissions/sequestration in annual croplands (MMT CO2e). Negative values are emissions.

Year	BAU	Scenario 1	Scenario 2	Scenario 3	Scenario 4
2002	-0.04726	-0.04726	-0.04726	-0.04726	-0.04726
2003	-0.00228	-0.00228	-0.00228	-0.00228	-0.00228
2004	-0.25872	-0.25872	-0.25872	-0.25872	-0.25872
2005	-0.37931	-0.37931	-0.37931	-0.37931	-0.37931
2006	-0.5493	-0.5493	-0.5493	-0.5493	-0.5493
2007	-0.4127	-0.4127	-0.4127	-0.4127	-0.4127
2008	-0.42722	-0.42722	-0.42722	-0.42722	-0.42722
2009	-0.44375	-0.44375	-0.44375	-0.44375	-0.44375
2010	-0.5177	-0.5177	-0.5177	-0.5177	-0.5177
2011	-0.34233	-0.34233	-0.34233	-0.34233	-0.34233
2012	-0.32501	-0.32501	-0.32501	-0.32501	-0.32501
2013	-0.09267	-0.09267	-0.09267	-0.09267	-0.09267
2014	-0.39553	-0.39553	-0.39553	-0.39553	-0.39553
2015	-0.84732	-0.84732	-0.84732	-0.84732	-0.84732
2016	-0.60746	-0.60746	-0.60746	-0.60746	-0.60746
2017	-0.02962	-0.02962	-0.02962	-0.02962	-0.02962
2018	-0.59336	-0.59336	-0.59336	-0.59336	-0.59336
2019	-0.75502	-0.75502	-0.75502	-0.75502	-0.75502
2020	-0.84414	-0.84414	-0.84414	-0.84414	-0.84414
2021	-0.79532	-0.79532	-0.79532	-0.79532	-0.79532
2022	-0.63659	-0.63659	-0.63659	-0.63659	-0.63659
2023	-0.53953	-0.53953	-0.53953	-0.53953	-0.53953
2024	-0.53654	-0.53654	-0.53654	-0.53654	-0.53654
2025	-0.9402	-0.42011	-0.55013	-0.66157	-0.81017
2026	-0.68103	-0.12743	-0.26583	-0.37803	-0.54263
2027	-0.58418	0.007035	-0.14077	-0.25124	-0.43638
2028	-0.31682	0.260751	0.116358	0.004454	-0.17243
2029	-0.46337	0.145365	-0.00682	-0.11951	-0.31118
2030	-0.57655	0.005593	-0.13994	-0.24652	-0.43101
2031	-0.63086	-0.09293	-0.22742	-0.33131	-0.49638
2032	-0.67307	-0.14966	-0.28051	-0.38171	-0.54222
2033	-0.10397	0.376205	0.256161	0.156119	0.016073
2034	-0.84597	-0.33838	-0.46528	-0.56182	-0.71907
2035	-0.94156	-0.49629	-0.60761	-0.70067	-0.83024
2036	-0.18401	0.230974	0.127227	0.035111	-0.08027
2037	-0.80949	-0.37934	-0.48688	-0.57358	-0.70195
2038	-0.47935	-0.06332	-0.16733	-0.25251	-0.37535
2039	-0.42512	-0.01498	-0.11752	-0.20205	-0.32259
2040	-0.73759	-0.32626	-0.42909	-0.50743	-0.63476
2041	-0.67484	-0.3254	-0.41276	-0.48638	-0.58748

2042	-0.79439	-0.43982	-0.52846	-0.60109	-0.70575
2043	-0.20213	0.116177	0.0366	-0.03532	-0.12256
2044	-0.75171	-0.41694	-0.50063	-0.56817	-0.66801
2045	-0.92888	-0.64506	-0.71601	-0.78043	-0.85792
2046	-0.37164	-0.10142	-0.16898	-0.23302	-0.30408
2047	-0.81931	-0.52597	-0.5993	-0.65832	-0.74598
2048	-0.58277	-0.31232	-0.37994	-0.43753	-0.51516
2049	-0.4563	-0.17959	-0.24877	-0.30526	-0.38712
2050	-0.71886	-0.44092	-0.51041	-0.56325	-0.64938
2051	-0.79188	-0.54386	-0.60586	-0.65714	-0.72988
2052	-0.73567	-0.50324	-0.56135	-0.61381	-0.67757
2053	-0.16643	0.07203	0.012415	-0.04389	-0.10681
2054	-0.86571	-0.61464	-0.67741	-0.73087	-0.80294

Table 46: Perennial Cropland total biomass, above and below ground, carbon stocks.

Year	Total Above and Below Biomass Carbon Stocks (MMT C)	Total Above and Below Biomass Carbon Stocks (MMT C)	Total Above and Below Biomass Carbon Stocks (MMT C)	Total Above and Below Biomass Carbon Stocks (MMT C)	Total Above and Below Biomass Carbon Stocks (MMT C)
Year	BAU	Scenario 1	Scenario 2	Scenario 3	Scenario 4
2001	26.92908	26.92908	26.92908	26.92908	26.92908
2002	26.90104	26.90104	26.90104	26.90104	26.90104
2003	26.96894	26.96894	26.96894	26.96894	26.96894
2004	26.94946	26.94946	26.94946	26.94946	26.94946
2005	28.09957	28.09957	28.09957	28.09957	28.09957
2006	28.48393	28.48393	28.48393	28.48393	28.48393
2007	29.69499	29.69499	29.69499	29.69499	29.69499
2008	29.69122	29.69122	29.69122	29.69122	29.69122
2009	30.32085	30.32085	30.32085	30.32085	30.32085
2010	30.62577	30.62577	30.62577	30.62577	30.62577
2011	31.63652	31.63652	31.63652	31.63652	31.63652
2012	32.61671	32.61671	32.61671	32.61671	32.61671
2013	34.02085	34.02085	34.02085	34.02085	34.02085
2014	35.20182	35.20182	35.20182	35.20182	35.20182
2015	36.27862	36.27862	36.27862	36.27862	36.27862
2016	37.16155	37.16155	37.16155	37.16155	37.16155
2017	38.47083	38.47083	38.47083	38.47083	38.47083
2018	39.28239	39.28239	39.28239	39.28239	39.28239
2019	40.45693	40.45693	40.45693	40.45693	40.45693
2020	39.89131	39.89131	39.89131	39.89131	39.89131
2021	39.4294	39.4294	39.4294	39.4294	39.4294
2022	38.95191	38.95191	38.95191	38.95191	38.95191
2023	38.42097	38.42097	38.42097	38.42097	38.42097
2024	37.87295	37.87295	37.87295	37.87295	37.87295
2025	37.39725	37.39773	37.39761	37.39749	37.39737
2026	37.03588	37.03733	37.03696	37.0366	37.03612
2027	36.73494	36.73783	36.73711	36.73639	36.7353
2028	36.50107	36.50589	36.50468	36.50348	36.50155

2029	36.41251	36.41974	36.41793	36.41612	36.41311
2030	36.46456	36.47468	36.47215	36.46962	36.46529
2031	36.62793	36.64142	36.63805	36.63468	36.62878
2032	36.8814	36.89875	36.89441	36.89008	36.88237
2033	37.17354	37.19522	37.1898	37.18438	37.17463
2034	37.42834	37.45484	37.44821	37.44159	37.42954
2035	37.89183	37.92363	37.91568	37.90773	37.89315
2036	38.68118	38.71876	38.70936	38.69997	38.68262
2037	39.71681	39.76066	39.74969	39.73873	39.71838
2038	40.89279	40.94338	40.93073	40.91808	40.89448
2039	42.12765	42.18547	42.17101	42.15656	42.12946
2040	43.38042	43.44595	43.42957	43.41319	43.38235
2041	44.65886	44.73258	44.71415	44.69572	44.66091
2042	46.02422	46.10661	46.08601	46.06542	46.02639
2043	47.4074	47.49894	47.47605	47.45317	47.40969
2044	48.80068	48.90186	48.87656	48.85127	48.80308
2045	50.23711	50.34792	50.32022	50.29252	50.23952
2046	51.74589	51.86634	51.83623	51.80612	51.7483
2047	53.27299	53.40308	53.37056	53.33803	53.2754
2048	54.8357	54.97542	54.94049	54.90556	54.83811
2049	56.26018	56.40955	56.37221	56.33487	56.26259
2050	57.56052	57.71952	57.67977	57.64002	57.56293
2051	58.71033	58.87897	58.83681	58.79465	58.71274
2052	59.72129	59.89956	59.85499	59.81042	59.7237
2053	60.68427	60.87218	60.8252	60.77823	60.68668
2054	61.52343	61.72097	61.67159	61.6222	61.52584

Table 47: Statewide acres of perennial agriculture planted annually.

Year	BAU
2002	90508.85
2003	72140.81
2004	74375.03
2005	121879.3
2006	159514.6
2007	153268.9
2008	120824
2009	111828.7
2010	94425.15
2011	88849.3
2012	90961.13
2013	107002.6
2014	121998.6
2015	124405.6
2016	116535
2017	103097.8
2018	100339.8
2019	98336.76
2020	89907.92
2021	71805.51
2022	88567.87
2023	137002.6

2024	145909.8
2025	176883.3
2026	152044.6
2027	200659.9
2028	193999.3
2029	175353
2030	175103.9
2031	191654.1
2032	204795.7
2033	254121.6
2034	253623.4
2035	171429.7
2036	197473.7
2037	226545.3
2038	219827.3
2039	224341.3
2040	171939.2
2041	122564.8
2042	110461.1
2043	136000.6
2044	122436.3
2045	109011.2

Table 48: Statewide average annual perennial acres pushed

Year	BAU
2002	87270.1
2003	76290.72
2004	67478.69
2005	112649.3
2006	8770.509
2007	103961.3
2008	19860.32
2009	108812.2
2010	24110.9
2011	100371.6
2012	18060.25
2013	84628.21
2014	57820.85
2015	67236.71
2016	35941.64
2017	115118.1
2018	30168.2
2019	121061
2020	42239.31
2021	134455.8
2022	133104.2
2023	132563.8
2024	130945.1
2025	128224.7
2026	125780.2
2027	125077.6

2028	123595.7
2029	121169.4
2030	118236.5
2031	116353.7
2032	113838.7
2033	114562.4
2034	114653.9
2035	113457.5
2036	108905.4
2037	105974.2
2038	104334.5
2039	104882.6
2040	106025
2041	107047.3
2042	108093.3
2043	111615.1
2044	115942.6
2045	120733.0

Urban Forest Modeling

Background

Urban forests, along with acting as a reservoir of carbon across California, provide a multitude of co-benefits to local populations including temperature modulation, air filtration, and mental well-being. Urban forests are one of the only ecosystems in California that are projected to either maintain or enhance their current level carbon stocks in the 2022 Scoping Plan Update modeling. These lands, however, are also vulnerable to changes in irrigation, rising temperatures, and investment. For this reason, the variables used within the alternative scenarios for the 2022 Scoping Plan Update are investment, and water use in response to level of recent drought.

Methods

The overall method for modeling urban forest carbon is to use CARB's NWL inventory for urban forest carbon within census urban areas, along with future projected climate data from various global climate models to derive an aspatial empirical model.

Data

California Air Resources Board's Developed Lands Inventory

In the NWL urban forest carbon inventory canopy cover within census urban areas are tracked through time and carbon is adjusted proportional to canopy cover. The carbon estimate, as per CARB's established method, is derived from the canopy cover change from a baseline in 2010 census urban areas. The statewide urban area carbon content was quantified for 2010, and the annual carbon stock change is derived from a change in canopy cover from that point in time. An update to this methodology provides annual urban forest carbon stock estimates from 2001-2017.

LOCA Downscale Climate Projections

Daily climate projections for California at a resolution of 1/16° (about 6 km, or 3.7 miles) generated to support climate change impact studies for California's Fourth Climate Change Assessment. The data, derived from 32 coarse-resolution (~100 km) global climate models from the CMIP5 archive, were bias corrected and downscaled using the Localized Constructed Analogues [91] statistical method. The data cover 1950-2005 for the historical period and 2006-2100 [46].

Model Development

Future projected above and below ground live urban tree carbon is controlled by two factors, the consistent annual growth controlled by investment, and the fluctuation in growth and loss caused by the California's population's perception of drought and the subsequent water use change caused by that perception. These two variables were assumed to be the primary controls of urban forest carbon collaboration with state and federal urban foresters. Using this information, the inventory time-series was decomposed into two different signals that represent the influence of these two independent variables.

The overall time-series of statewide urban forest carbon from CARB's NWL inventory empirically as a linear increasing trend and a sinusoidal oscillation around this linear trend (Figure 40). The increasing linear trend is assumed to be the result of increased investment into urban forests. Growth in existing canopy, expansion of canopy within existing urban areas, and expansion of urban forests into expanding urban areas are all included in this investment assumption and are not disaggregated. This is because no matter how the canopy expands, it is assumed that the investment in this canopy must increase at the same rate. Refer to the Economic Analysis section for more information on how investment is made in the urban tree canopy. For modeling purposes, to be consistent across all NWL land types, only inventory data from 2001-2014 was used for model development as this is the baseline time period. This also allows for several years after 2014 to be used for assessment of model performance. The linear trend model is:

$$y = 0.9303x + 92.888$$

Where y is the carbon stock in response to investment, and x in the year after the beginning of the simulation period. The a variable (0.9303) gets adjusted for scenario modeling. As this increases, this represent more investment and correspondingly more carbon stocks.

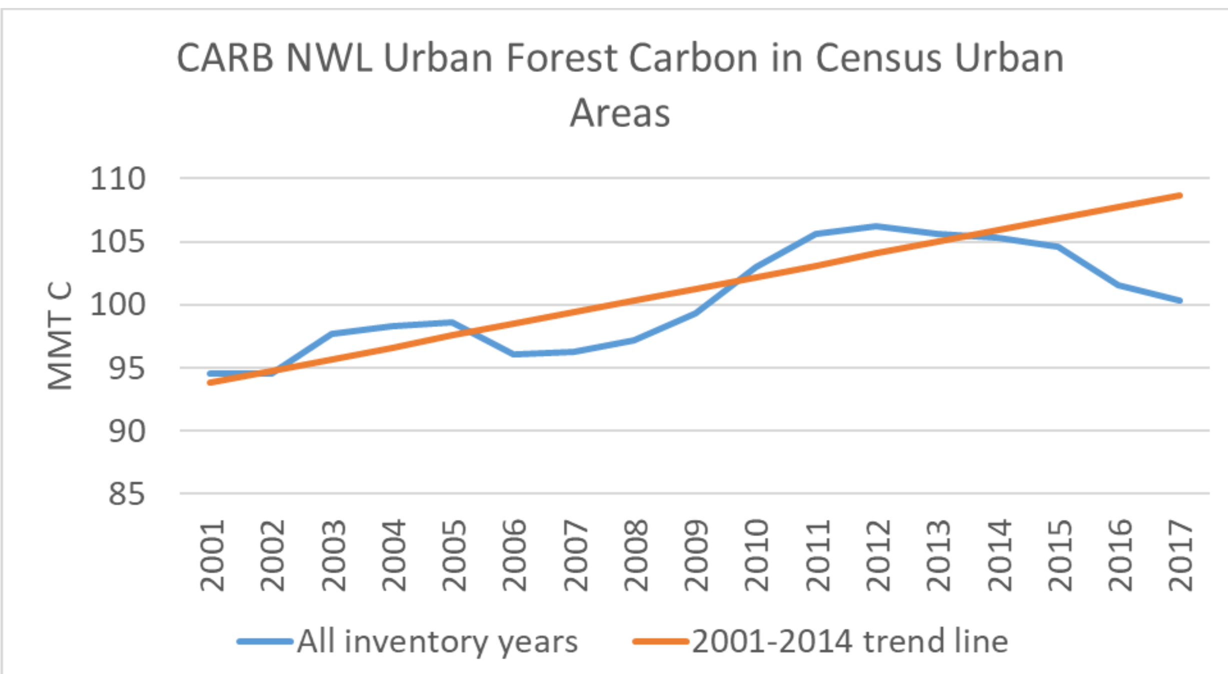

Figure 40: CARB NWL inventory carbon stocks in census urban areas and the linear trend line for 2001-2014.

Using the linear trend line for the years 2001-2014, the inventory data could be detrended and residuals from this trend could be extracted (Figure 41). The residuals are assumed to come from society's response to drought, which results in either more, or less irrigation in urban forests. As society's perception of drought limited water supply, whether this is a real limitation or not, it is assumed that people stop watering lawns, gardens, and trees. This reduction in irrigation, has dramatic impacts on urban forest carbon, as these trees are even more susceptible to drought than even wild forests, due to the urban heat island affect.

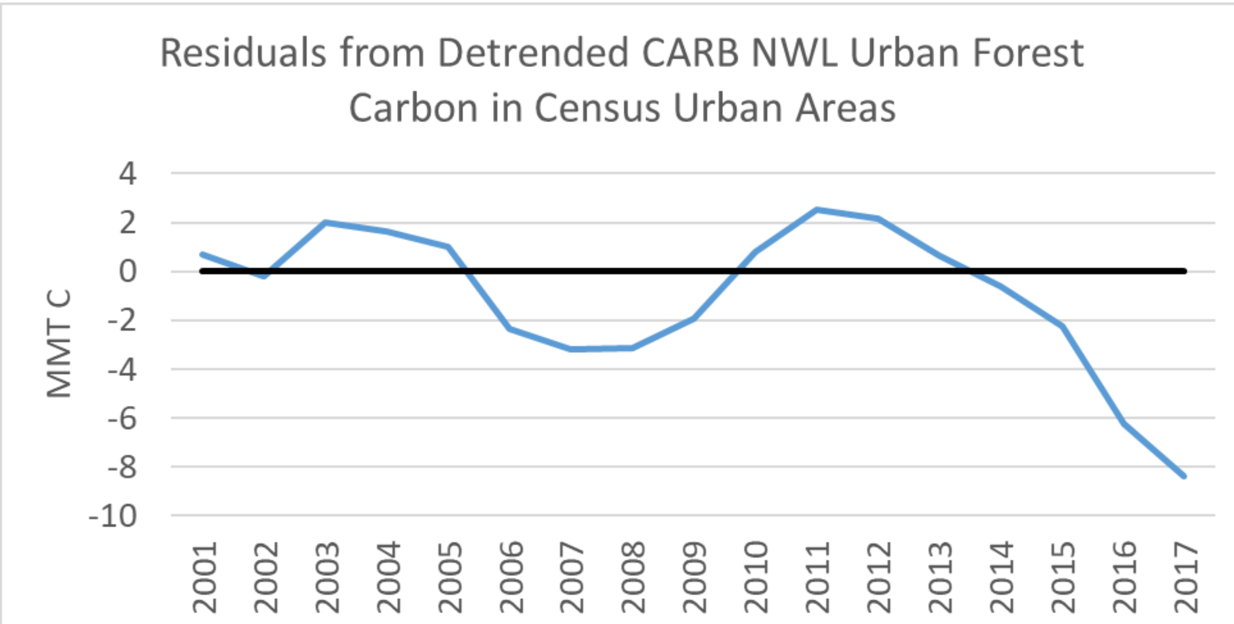

Figure 41: Detrended CARB NWL inventory urban forest carbon stocks from a linear trend line.

The derived residuals, however, represent an absolute change in canopy cover. A time-series model that aims to be responsive to climate, however, must utilize rate of change as the dependent variable in response to the independent variable, in this case drought. The derivatives of the residual time-series was used to derive the rate of loss or growth in response to drought (Figure 42). It is this rate of loss and growth that is used to change the overall urban forest carbon in response to drought.

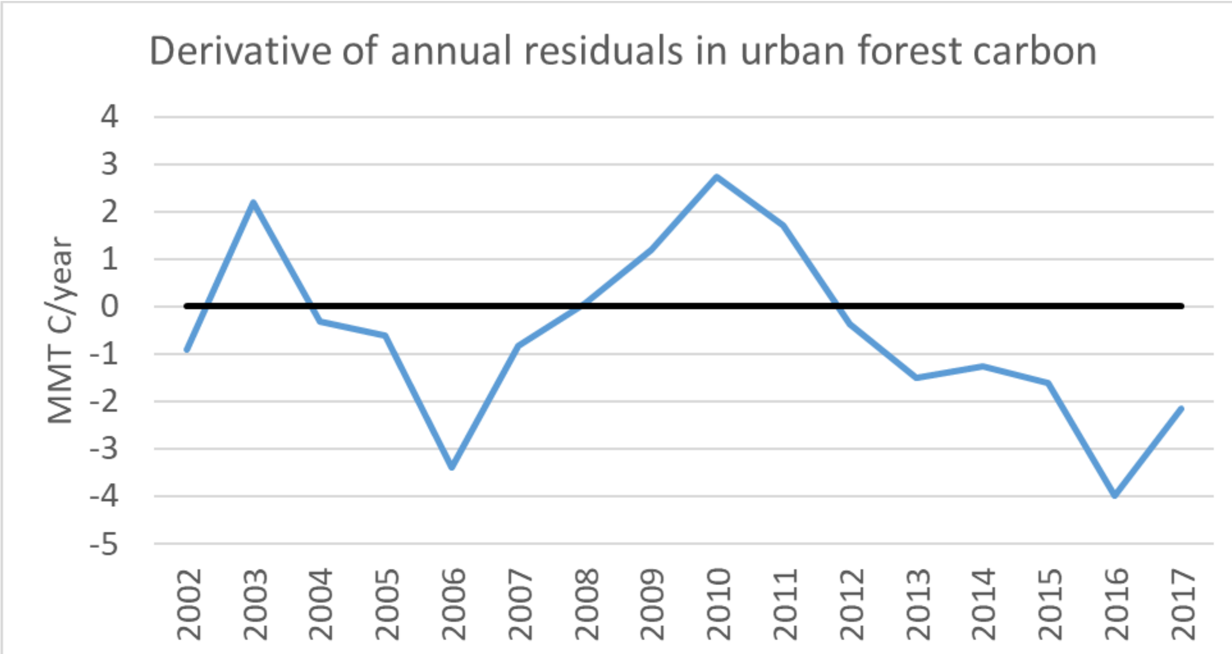

Figure 42: The derivatives of the annual residuals from a linear trend line in annual urban forest carbon stocks.

It is assumed that sufficient water always exists to water all urban forest canopy cover, as long as society reduces water use wisely in other areas. For example, Californian's should stop watering lawns during drought, however, even if lawns are not watered, trees should always be watered. Additionally, trees should be watered deeply and infrequently. Therefore, even if droughts occur, society should maintain regular deep irrigation of their urban tree canopy. If trees are not watered they can die and urban forest carbon is diminished as a response. Further, the State's perception of the severity of drought changes through time. For this reason, a five-year moving average of precipitation levels are used to assess the relative drought level of a given year. That is to say, the drought metric used in this model is the current years precipitation relative to the last five years precipitation. In this way, as California comes in and out of droughts, the population adjusts their irrigation accordingly. Using this relative drought index to the last five years, along with the growth and loss rates derived from the residuals around the linear trend line, a model is derived to incorporate society's irrigation response to drought (Figure 43). The resulting model is:

$$y = 0.1341x - 0.9396$$

Where y is the growth or loss in MMT carbon, and x is the difference in precipitation of a given year relative to the preceding 5 years. The a (0.1341) and b (0.9396) variables are adjusted for scenario modeling. As they both decrease, this represents a society that is less sensitive to drought and so less growth or loss occurs given different levels of drought. If these variables are increased, society increases in sensitivity, and urban forest carbon will change more given different levels of drought.

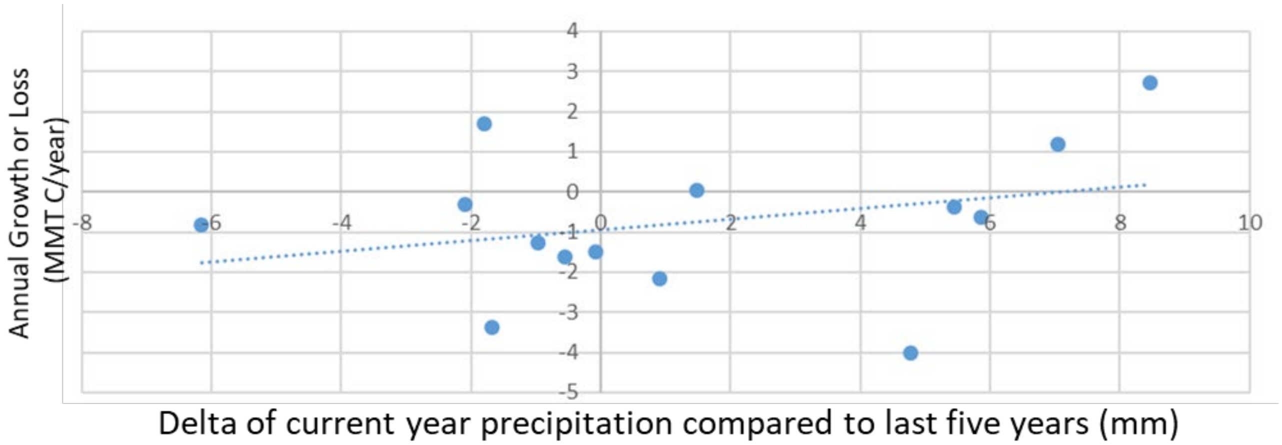

Figure 43: Urban forest carbon growth/loss with change in precipitation relative to the previous 5 years of precipitation.

As urban forest canopy cover begins to expand into site conditions less suitable for growing and maintaining trees, it becomes more costly to maintain these trees. For this reason, a theoretical maximum of urban tree canopy cover was utilized to calculate an asymptotic effect [92]. As the urban forest carbon approaches its theoretical maximum, less growth is possible, until finally, no more carbon can be added to the system. This theoretical maximum assumes that in 2010, only 42% of suitable lands contained forest canopy. Therefore, no matter the investment or water use efficiency level, carbon cannot be above the theoretical maximum. This affect only becomes an issue in scenarios 1 and 2, with extreme levels of annual investment.

Results

The resulting model is used to estimate the impact of different levels of investment, improved water use, and drought has on future urban forest carbon (Figure 44, Table 49). Scenario 1 asymptotes as it approaches the theoretical maximum amount of carbon possible in urban forests. BAU has a moderate increase without any additional investment or improved water use. Scenarios 2, 3, and 4 lie on a regular gradient between BAU and Scenario 1 by 2099.

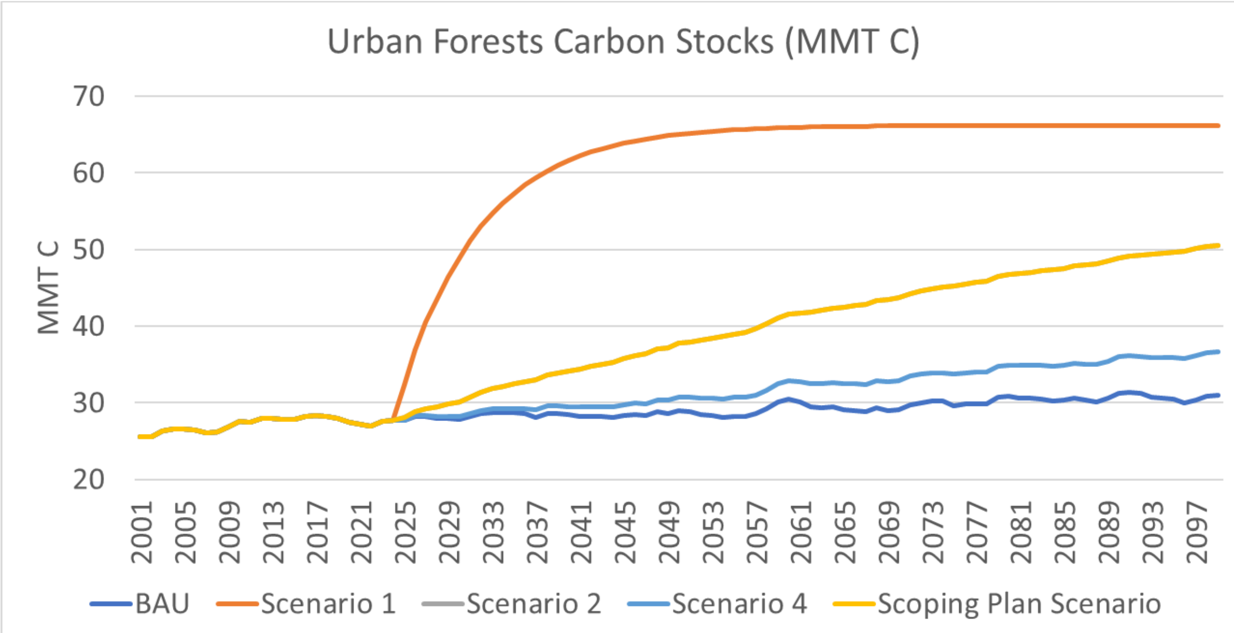

Figure 44: Results of scenario modeling for California urban forests. The inventory data comes from CARB's NWL carbon inventory.

Table 49: Results of scenario modeling for Californian urban forest carbon stock (MMT C).

Year	BAU	Scenario 1	Scenario 2	Scoping Plan	Scenario 4
2001	94.51343	94.51343	94.51343	94.51343	94.51343
2002	94.52885	94.52885	94.52885	94.52885	94.52885
2003	97.65677	97.65677	97.65677	97.65677	97.65677
2004	98.25901	98.25901	98.25901	98.25901	98.25901
2005	98.56563	98.56563	98.56563	98.56563	98.56563
2006	98.13642	98.13642	98.13642	98.13642	98.13642
2007	96.56065	96.56065	96.56065	96.56065	96.56065
2008	97.04966	97.04966	97.04966	97.04966	97.04966
2009	99.3815	99.3815	99.3815	99.3815	99.3815
2010	102.1369	102.1369	102.1369	102.1369	102.1369
2011	101.6882	101.6882	101.6882	101.6882	101.6882
2012	103.4321	103.4321	103.4321	103.4321	103.4321
2013	103.4107	103.4107	103.4107	103.4107	103.4107
2014	103.1675	103.1675	103.1675	103.1675	103.1675
2015	103.0272	103.0272	103.0272	103.0272	103.0272
2016	104.5395	104.5395	104.5395	104.5395	104.5395
2017	104.825	104.825	104.825	104.825	104.825
2018	104.4729	104.4729	104.4729	104.4729	104.4729
2019	103.5887	103.5887	103.5887	103.5887	103.5887
2020	101.911	101.911	101.911	101.911	101.911
2021	100.6428	100.6428	100.6428	100.6428	100.6428
2022	99.99435	99.99435	99.99435	99.99435	99.99435
2023	101.9388	101.9388	101.9388	101.9388	101.9388
2024	102.4418	102.4418	102.4418	102.4418	102.4418
2025	102.4879	120.0153	103.8035	103.8035	102.5924

2026	104.6202	136.7095	106.8762	106.8762	104.7583
2027	104.4392	150.0254	108.1131	108.1131	104.7876
2028	103.6511	161.6663	109.196	109.196	104.5727
2029	103.6445	171.9302	110.4531	110.4531	104.6725
2030	103.0038	180.9006	111.5524	111.5524	104.5182
2031	104.4967	189.2768	113.9616	113.9616	106.0506
2032	105.9196	196.5471	116.285	116.285	107.5144
2033	106.5443	202.6807	117.9622	117.9622	108.2137
2034	106.5321	207.9066	119.137	119.137	108.3087
2035	106.1642	212.4812	120.2227	120.2227	108.2619
2036	105.8406	216.496	121.3089	121.3089	108.233
2037	104.2326	219.9922	122.1093	122.1093	107.695
2038	105.9194	223.3042	124.4788	124.4788	109.3879
2039	105.8581	225.9963	125.5832	125.5832	109.4627
2040	105.2927	228.3509	126.5727	126.5727	109.3394
2041	104.6518	230.4163	127.539	127.539	109.1872
2042	104.6597	232.2366	128.6352	128.6352	109.2955
2043	104.3012	233.8291	129.642	129.642	109.2547
2044	103.8834	235.226	130.6284	130.6284	109.191
2045	104.8748	236.504	132.3609	132.3609	110.2145
2046	105.5148	237.6037	133.8361	133.8361	110.9099
2047	104.7918	238.5363	134.7272	134.7272	110.7273
2048	106.6531	239.4207	136.9728	136.9728	112.5506
2049	105.8165	240.1306	137.8162	137.8162	112.324
2050	107.3385	240.7959	139.7897	139.7897	113.8255
2051	106.7909	241.3386	140.6638	140.6638	113.7106
2052	105.3746	241.8124	141.3723	141.3723	113.2634
2053	104.7457	242.2305	142.2202	142.2202	113.1201
2054	104.07	242.5973	143.0533	143.0533	112.9598
2055	104.6826	242.9286	144.37	144.37	113.613
2056	104.4523	243.2107	145.2632	145.2632	113.6219
2057	105.7864	243.472	146.9798	146.9798	114.9254
2058	108.0955	243.7082	149.2472	149.2472	117.1082
2059	111.7157	243.9231	152.2501	152.2501	120.4734
2060	112.932	244.0918	153.8182	153.8182	121.6648
2061	111.2954	244.2301	154.3902	154.3902	121.1379
2062	109.1743	244.3511	154.8824	154.8824	120.4352
2063	108.8412	244.4587	155.6648	155.6648	120.4028
2064	108.9936	244.5539	156.5782	156.5782	120.6303
2065	107.9603	244.6362	157.2356	157.2356	120.3397
2066	107.4251	244.7088	157.9667	157.9667	120.2341
2067	106.7061	244.7723	158.6639	158.6639	120.062
2068	108.4658	244.8324	160.3833	160.3833	121.6922
2069	107.3955	244.8808	161.0076	161.0076	121.392
2070	107.6613	244.924	161.9235	161.9235	121.7149
2071	110.2734	244.9654	164.0149	164.0149	124.074
2072	111.0017	244.9988	165.133	165.133	124.796
2073	111.7534	245.0279	166.2494	166.2494	125.5375
2074	111.736	245.0525	166.9777	166.9777	125.6184
2075	109.8434	245.0739	167.4331	167.4331	125.0211
2076	110.5572	245.0935	168.4961	168.4961	125.7232
2077	110.5262	245.1101	169.2018	169.2018	125.7991

2078	110.3988	245.1246	169.8879	169.8879	125.8406
2079	113.8662	245.1392	172.2021	172.2021	128.8976
2080	114.1369	245.1503	173.0044	173.0044	129.2157
2081	113.3262	245.1599	173.5645	173.5645	129.0107
2082	113.2694	245.1683	174.2201	174.2201	129.0752
2083	113.1165	245.1757	174.8572	174.8572	129.1055
2084	112.1829	245.1822	175.3879	175.3879	128.8589
2085	112.2954	245.1879	176.0843	176.0843	129.0404
2086	113.4589	245.1931	177.2299	177.2299	130.1099
2087	112.6326	245.1975	177.7558	177.7558	129.9024
2088	111.5012	245.2013	178.2407	178.2407	129.5893
2089	113.2392	245.2049	179.5876	179.5876	131.1282
2090	115.8263	245.2081	181.2691	181.2691	133.3751
2091	116.2965	245.2107	182.0556	182.0556	133.8511
2092	115.484	245.2128	182.5437	182.5437	133.6489
2093	113.6444	245.2147	182.9085	182.9085	133.0918
2094	113.2042	245.2164	183.4347	183.4347	133.022
2095	112.8473	245.2179	183.966	183.966	132.9814
2096	111.0406	245.2192	184.3304	184.3304	132.4449
2097	112.6403	245.2204	185.5002	185.5002	133.8285
2098	114.182	245.2215	186.633	186.633	135.1636
2099	114.6053	245.2224	187.3339	187.3339	135.589

Additionally, several performance metrics were calculated (Table 50). These metric demonstrate that little bias and error exist in this model. However, as with any empirical model, it is expected that empirical models perform well when simulating historical conditions. Under novel conditions, however, empirical models do not perform as well as process-based models. It could be that under climate change, the carbon carrying capacity of California's urban forests decrease. This is almost certain, as the vapor pressure deficit is sure to increase with increasing temperatures, exacerbated by the urban heat island effect. This increase in climatic water deficit cannot be countered by irrigation alone, and so trees in urban areas in California under climate change are sure to suffer, no matter how we water them. However, effects like this cannot be captured by an empirical model like the one described here.

Table 50: Performance metrics of the urban forest carbon model. Predicted vs Observed carbon stock (2001-2017). Values in MMT C.

MBE	MAE	RMSE
-0.06	0.37	.55

Wildland Urban Interface Modeling

Background

The objective of this analysis was to quantify the amount of vegetative carbon removal that would be needed to achieve full compliance with CALFIRE defensible space regulations for all structures in the wildland urban interface (WUI) of California. A high-resolution (3m) vegetation data from the California Forest Observatory (Forest Observatory Website) was used for this analysis, along with publicly available data on structures and parcel data. The CALFIRE defensible space guidelines [93] as well as the original legislation [94], Board of Forestry guidelines, and more recent legislation [95] was the basis to develop the rules for the spatial analysis.

Data Sources

Wildland Urban Interface (vector)

Source: CALFIRE [96]

Parcels

Source: California Parcel Vectors

Structures

Source: Microsoft Building Footprint Dataset [97]

Vegetation Canopy Height, Canopy Cover, LadderFuels, 2020 3m resolution

Source: California Forest Observatory (2020) [98]. A Statewide Tree-Level Forest Monitoring System. Salo Sciences, Inc. San Francisco, CA. Introductory webinar on the system and technology is available [99].

Data preparation

Parcels were cleaned by filtering out:

- Parcels that did not *intersect* the WUI interface or intermix
- Parcels containing no structures
- Parcels with size <400 m^2 (0.01 ac)

Structures were cleaned by filtering out:

- Any structures that don't intersect with the cleaned parcel set from above

Figure 45: Parcel and structure cleaning. Parcels (pink with grey outline) included in the analysis because they intersect WUI zones (blue shading) and contain at least one structure. Red are structures which were excluded because they do not intersect a WUI zone.

Zone construction

Zone 0 = 1.5m buffer (0-5ft)

Zone 1 = 9m buffer (5-30ft)

Zone 2 = 30m buffer (30-100ft)

Zones were created by:

1. Buffering structure dataset by each value above
2. Differencing each merged zone to remove overlapping inner zones
3. Merging within zone type where any overlap with nearby zones

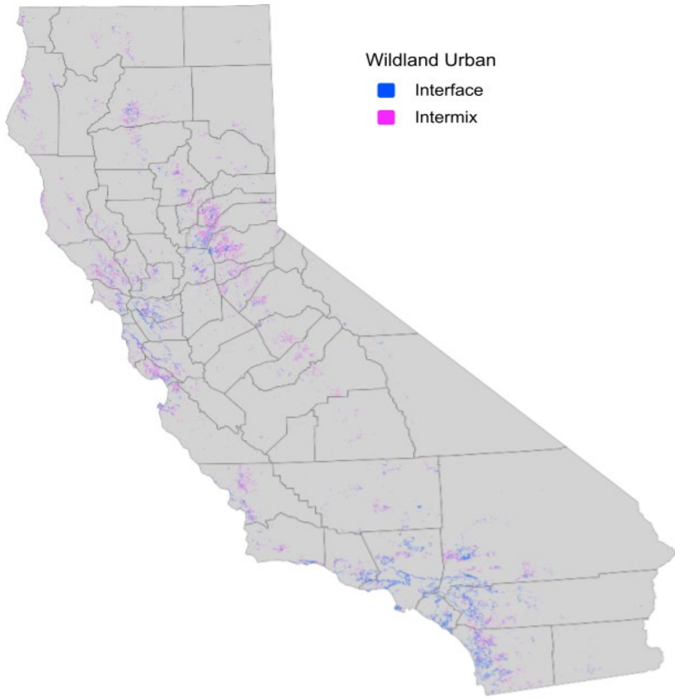

Figure 46: Map of WUI areas in California. While all 58 counties contain some amount of WUI, the concentration is much higher in Southern California, North-Central Sierra, and Bay Area counties.

Property analysis pathway

Per the regulations, this analysis was limited to the area of each zone within the boundaries of its associated parcel.

For this analysis, zones were clipped to the parcel boundary that contains the centroid of the structure.

Methods

Adjacency analysis pathway

On the request of CARB, a second analysis was conducted where the analysis did not limit zones to parcel boundaries and considered potential defensible-space on adjacent parcels. These data are not parcel-specific and are only used for aboveground carbon calculations.

For this analysis zones were not clipped, but were merged with overlapping zones from adjacent parcels to avoid double-counting.

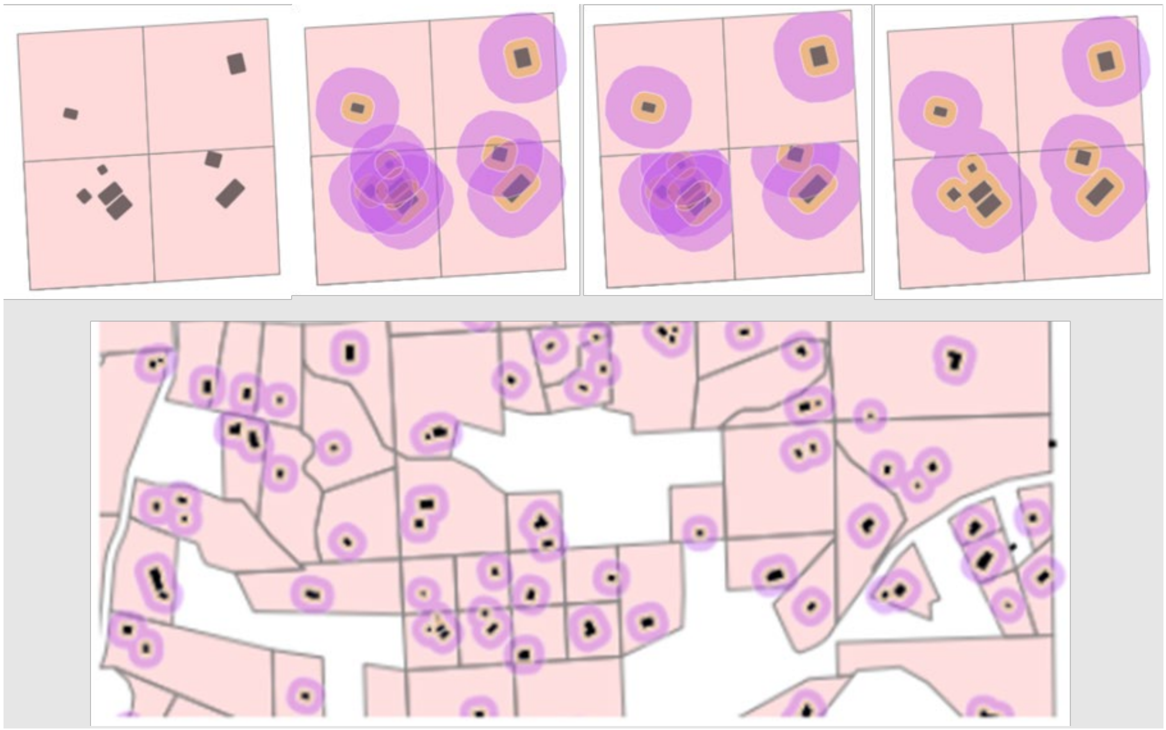

Figure 47: Adjacency analysis example. Top, from left to right: Adjacent parcels (pink) with structures (black); Zones 0/1/2 added; Zones of same type merged within each parcel; Zones of same type merged across parcels. Bottom: view of a neighborhood showing final zone configuration.

Defensible Space Vegetation Analysis

Canopy cover data were partitioned into tree cover and shrub cover using binned canopy height mask: tree cover ≥5m, shrub cover <5m & ≥1m. Shrub cover received an additional mask, allowing only pixels with ≥20% ladder fuels (understory vegetation density) to be considered part of the shrub layer.

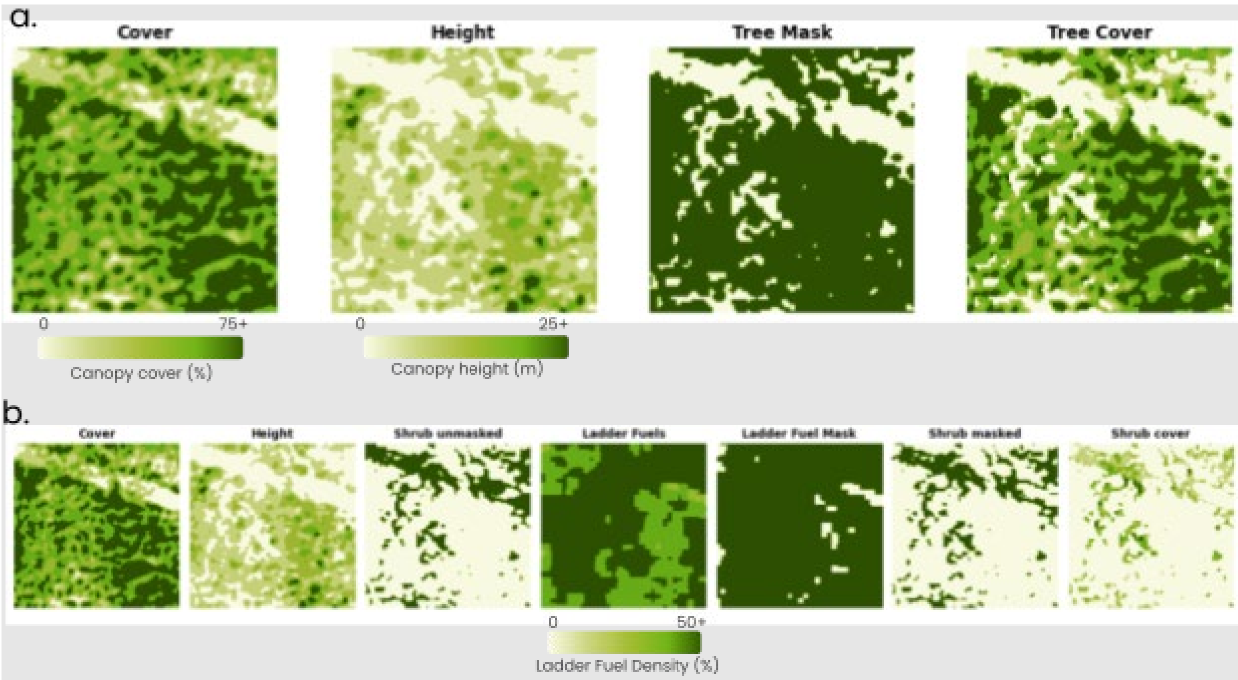

Figure 48: Vegetation layer preparation. Sequence of masking steps to produce tree cover map (a). Sequence of masking steps to produce shrub cover map (b).

The tree and shrub cover layers described above are then processed by a function to determine which pixels need to be altered to reduce cover to a predetermined threshold by zone. For Zone 2, groups of up to four pixels were allowed to remain but must be separated by at least one pixel on all sides (~10 ft). For Zone 1, only single pixels were allowed to remain and must be separated by at least two pixels on all sides (~20 ft). No vegetation is allowed to remain inside Zone 0, which includes vegetation that overhangs a structure.

Approximately 3.5% of parcels analyzed had an average slope of >20%, which requires more stringent spacing of 20 ft between vegetation. For these parcels, the buffer distance between groups of pixels in Zone 2 was increased to 20 ft (or two pixels).

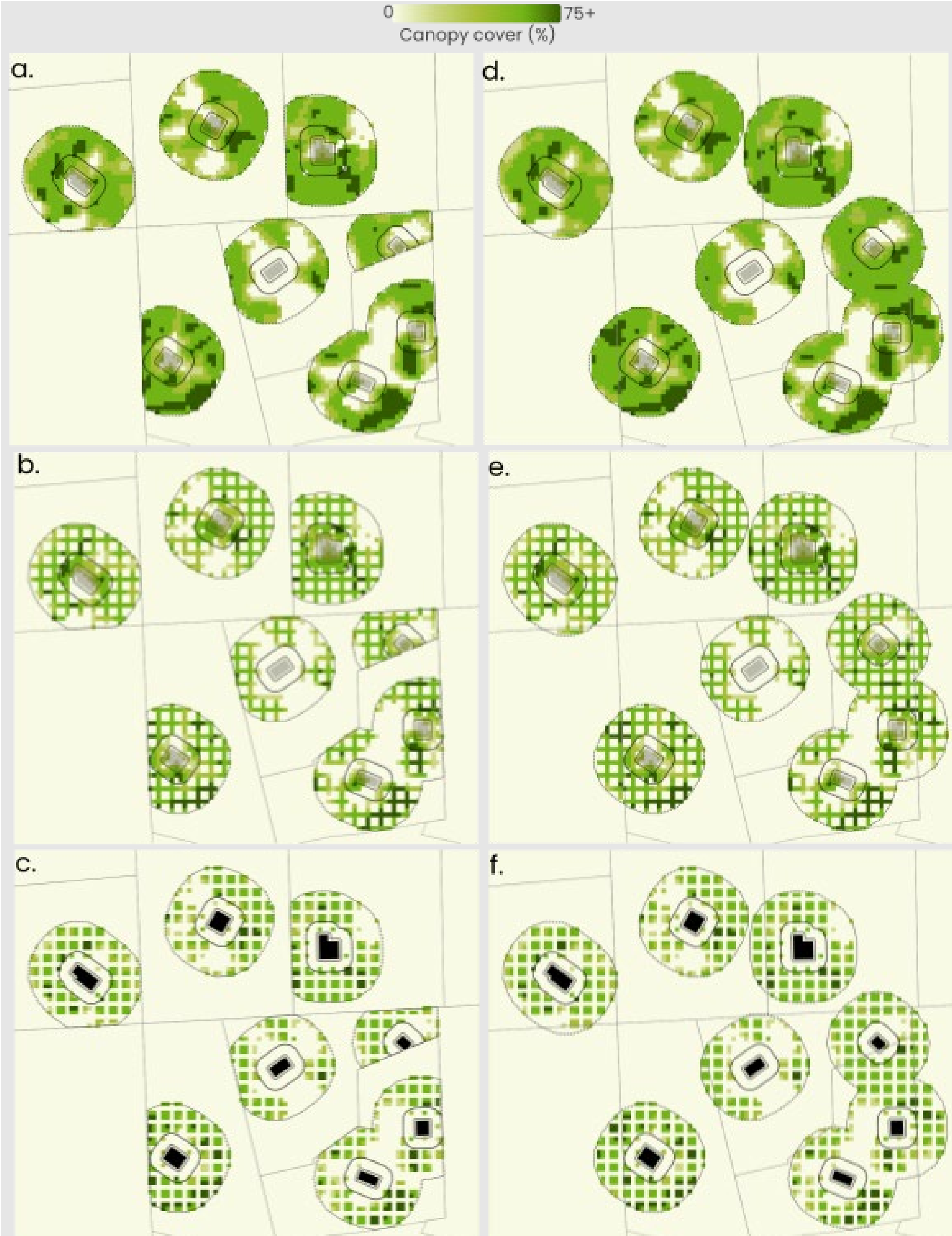

Figure 49: Defensible space cover analysis. Current canopy cover within defensible space zones for the property (a) and adjacency analysis (d). Defensible space canopy cover removals needed to be in compliance (b) shown above the resulting canopy cover after compliance removals in each zone (c) for the property analysis. Same defensible space analysis but using the adjacency analysis pathway (e and f). Canopy cover outside defensible space zones is masked.

Carbon Removal

CARB requested a test run of the steps needed to calculate the amount of aboveground carbon stored in the vegetation that would need to be removed to meet defensible space compliance. We reprojected an example 30m-resolution carbon map to the spatial projection, resolution, and extent of our vegetation cover removal map. We rescaled the pixel values from metric tons of carbon (MtC) per $30m^2$ pixel to MtC per $3m^2$ pixel by dividing each pixel by 100. We then summed the amount of carbon that overlapped each pixel identified as a pixel needing vegetation cover removal to meet compliance.

Incomplete Areas

Due to an issue with the parcel dataset, a small section of northwest San Diego county could not be analyzed for defensible space compliance or included in the carbon calculations. As a result, a total of 38,179 structures across 20,237 parcels that met the requirements for the analysis in this area were not included in the final results.

Figure 50: Area of California that could not be assessed because of data corruption in the parcel data set.

Results

A total of 2,188,530 structures on 1,510,398 parcels in the WUI of California were assessed, covering a total defensible space area of 955,920 acres.

Defensible Space Compliance

General compliance with regulation was also assessed. However, it should be noted that this is compliance via a top down assessment, and can only assess what a satellite can see. For Zone 0 a parcel is considered out-of-compliance if any vegetation removal is needed. For Zones 1 and 2 a parcel is considered out-of-compliance if more than 2.5% of the zone by area needs vegetation removal. See compliance rate curve (Figure 51) for statewide compliance rates given different out-of-compliance assumptions.

Table 51: Compliance rates by zone:

Zone 0	46.7%
Zone 1	51.9%
Zone 2	68.1%

Table 52: Counties with lowest compliance rates.

Zone 0	Nevada (15.0%)	Tuolumne (17.7%)	El Dorado (20.9%)
Zone 1	Orange (38.6%)	Modoc (38.4%)	Alpine (35.1%)
Zone 2	Tulare (47.7%)	Alpine (47.1%)	Modoc (41.3%)

Table 53: Counties with highest compliance rates.

Zone 0	Kings (76.5%)	Merced (70.7%)	Imperial (68.7%)
Zone 1	Amador (70.9%)	Tuolumne (70.7%)	Nevada (70.4%)
Zone 2	Amador (85.1%)	Nevada (84.0%)	Tuolumne (82.7%)

Table 54: Number of structures out-of-compliance by zone.

Zone 0	1,165,750
Zone 1	731,590
Zone 2	462,289

Table 55: Number of parcels out-of-compliance by zone.

Zone 0	887,893
Zone 1	729,472
Zone 2	461,400

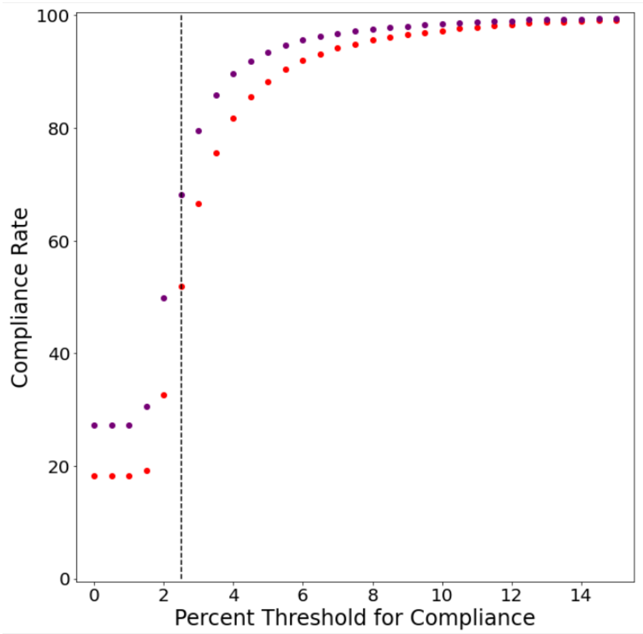

Figure 51: Compliance rate curve. Change in compliance rate as function of percent threshold of each zone by total area that needs vegetation removal for Zone 1 (red) and Zone 2 (purple). Dashed line shows the 2.5% threshold chosen for this analysis. Note: the percent threshold is based on the total area of a zone, not the total potential area for removal as this varies widely as a function of proximity to parcel boundary, existing cover, and size/shape of each structure.

Vegetation Removals

As each 3m pixel covers an area of 9m2, this calculation accounts for the likelihood that only a fractional area of each pixel is covered by vegetation, especially for pixels with <50% cover.

Total area needing vegetation removal (independent of vegetation cover): 195,130 acres

Total area to be cleared (factoring in vegetation cover): 85,604 acres

Counties needing most vegetation removal by area:

Los Angeles (7156 ac), El Dorado (6779 ac), Nevada (5589 ac)

Carbon Removals

Property analysis (defensible space restricted to parcel boundaries)

Carbon stocks in defensible space zones: 15,206,061 MtC

Carbon stocks to be removed: 4,230,284 MtC

Adjacency analysis (defensible space *not* restricted to parcel boundaries)

Carbon stocks in defensible space zones: 18,455,970 MtC

Carbon stocks to be removed: 5,382,642 MtC

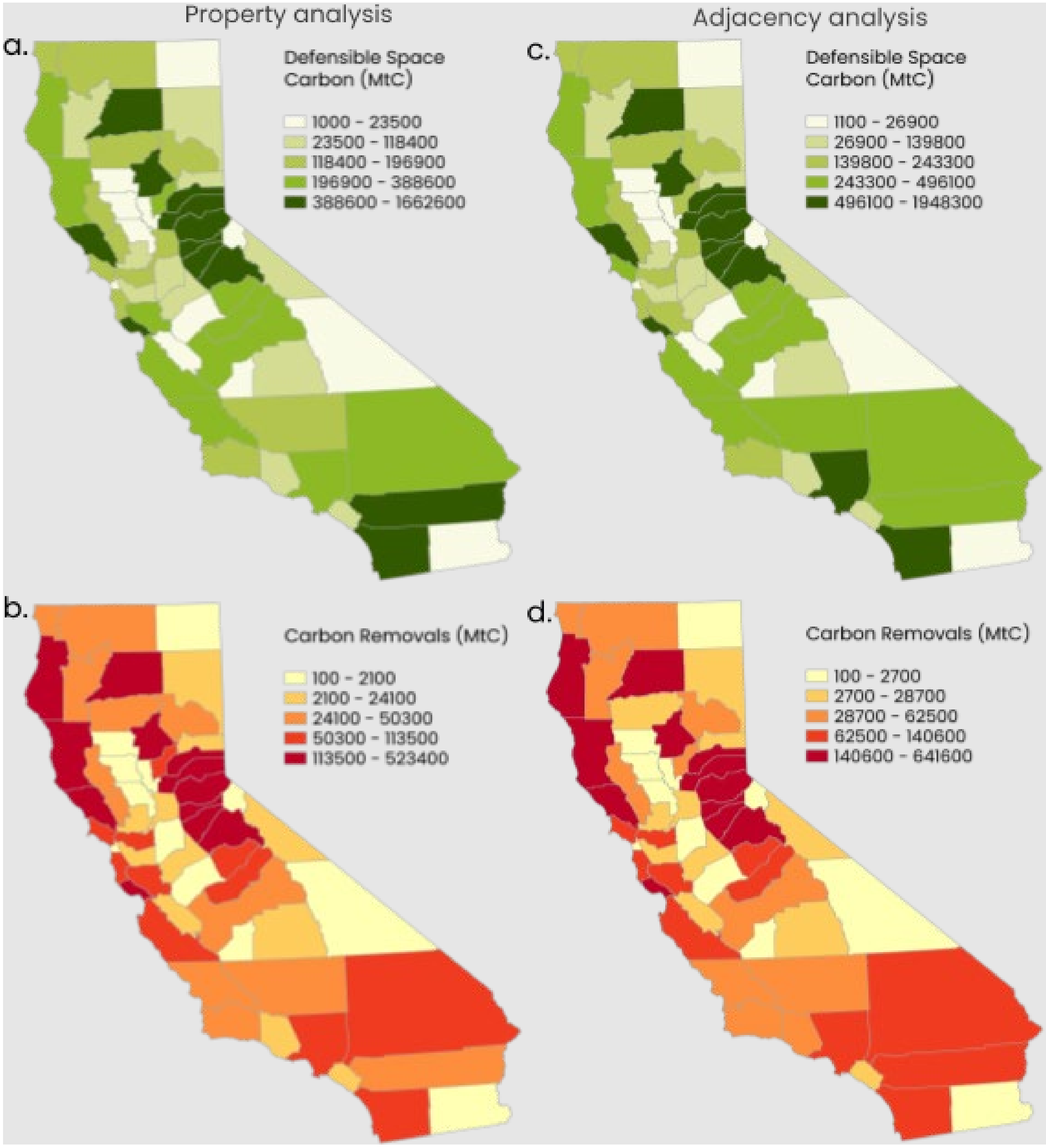

Figure 52: Defensible space carbon stocks and removals by county. Aboveground carbon stocks contained within defensible space zones (a,c). Amount of aboveground carbon stocks that would need to be removed to achieve full compliance with defensible space regulations (b,d).

Table 56: County-level results. CR = Compliance rate. SR = Structures out of compliance. PA = Property Analysis (MT C). AA = Adjacency Analysis (MT C).

County	CR	CR	CR	SR	SR	SR	PA	PA	AA	AA
County	Zone 0	Zone 1	Zone 2	Zone 0	Zone 1	Zone 2	Defensible Space Carbon	Carbon Removals	Defensible Space Carbon	Carbon Removals
Alameda	42.6%	49.7%	71.6%	24,648	17,910	9,547	53795	16655	74786	24176
Alpine	33.6%	35.1%	47.1%	221	144	117	6322	1477	8510	2231
Amador	24.7%	70.9%	85.1%	9,984	2,540	1,293	455822	163349	547421	204622
Butte	32.6%	40.2%	54.4%	26,255	15,330	11,536	688888	191861	868715	258703
Calaveras	29.4%	63.4%	72.8%	15,158	5,492	4,062	532431	152034	682845	210579
Colusa	57.9%	51.7%	54.7%	311	180	163	3214	307	3850	357
ContraCosta	36.3%	55.8%	75.7%	41,547	25,757	13,652	163666	50873	210510	68298
DelNorte	27.8%	55.9%	76.6%	5,220	1,892	997	142644	45425	175599	59118
ElDorado	20.9%	61.1%	77.2%	51,482	17,859	10,352	1662644	523393	1948326	641608
Fresno	52.8%	44.2%	48.1%	4,973	2,856	2,626	229961	36374	269184	44076
Glenn	61.4%	51.6%	53.9%	420	207	197	5881	443	6979	358
Humboldt	28.9%	49.5%	71.9%	19,529	8,212	4,496	379707	130940	457063	163844
Imperial	68.8%	51.4%	70.0%	1,926	1,563	900	6634	260	8168	313
Inyo	47.9%	45.4%	62.9%	3,240	1,814	1,203	7157	847	9042	1084
Kern	68.4%	57.3%	67.1%	13,742	11,618	8,796	196123	24341	249510	32725
Kings	76.5%	58.6%	68.5%	477	150	111	1328	57	1513	67
Lake	37.4%	52.3%	66.9%	14,101	7,004	4,711	120870	28382	158967	39753
Lassen	47.0%	45.9%	55.6%	3,482	1,994	1,619	62735	14779	77010	18864
LosAngeles	48.6%	47.8%	65.8%	169,580	131,674	82,911	376365	87015	498594	125202
Madera	38.1%	50.1%	58.2%	8,323	3,743	3,135	313452	74307	379538	93786
Marin	25.5%	60.5%	80.2%	27,224	11,449	5,615	192485	65353	252521	92058
Mariposa	29.8%	51.7%	65.9%	6,458	2,193	1,548	322681	85018	364826	98013
Mendocino	28.4%	56.0%	76.2%	15,177	4,893	2,636	346087	118344	405746	144466
Merced	70.7%	59.2%	64.5%	683	486	384	9375	596	11201	713
Modoc	57.8%	38.4%	41.3%	704	464	439	9118	1532	10655	1772
Mono	34.8%	38.7%	52.6%	3,517	2,166	1,661	46585	9260	65649	14612
Monterey	40.0%	50.8%	71.8%	22,935	12,128	6,651	244356	72215	294907	92562
Napa	38.4%	57.3%	71.8%	9,610	3,664	2,360	150555	39644	174164	47698
Nevada	15.0%	70.4%	84.0%	39,200	9,784	5,274	1404774	476467	1636557	578584
Orange	49.2%	38.6%	61.4%	53,513	47,027	24,858	31483	7179	53122	13900
Placer	31.6%	60.4%	76.8%	44,270	18,148	10,024	1138290	334003	1366753	422574
Plumas	25.9%	49.0%	68.3%	5,788	2,650	1,638	134525	41107	181636	59034
Riverside	66.2%	48.3%	62.4%	65,750	70,471	47,200	394607	50182	492446	68168
Sacramento	55.4%	52.2%	62.5%	13,214	8,433	6,201	119946	10102	140450	11997
SanBenito	59.4%	46.0%	52.5%	1,409	931	810	22872	4159	26157	4171
SanBernardino	67.7%	62.5%	74.2%	71,150	62,676	41,483	346814	70033	481573	113533
SanDiego	49.7%	40.6%	55.0%	96,664	74,584	52,865	553149	106144	665045	134766
SanFrancisco	41.5%	42.5%	77.3%	585	46	17	3970	1257	4153	1329
SanJoaquin	60.7%	47.1%	51.1%	2,406	1,434	1,303	26772	1721	30730	1991
SanLuisObispo	54.1%	52.2%	64.9%	23,674	13,210	9,542	229194	41521	269281	51167
SanMateo	34.3%	55.6%	76.7%	21,709	11,336	5,605	157306	53525	196252	70582
SantaBarbara	35.3%	51.9%	68.9%	20,330	9,318	5,917	173872	49307	204879	61040
SantaClara	39.9%	53.7%	72.4%	24,962	14,630	8,379	200069	62138	241770	78952
SantaCruz	31.0%	59.9%	80.9%	24,576	8,773	4,058	702996	268676	855476	340910
Shasta	35.2%	45.8%	59.1%	31,716	17,447	13,061	621664	156754	727628	191779
Sierra	29.0%	56.8%	66.0%	1,037	384	300	29230	8525	38328	11682
Siskiyou	39.4%	48.3%	60.9%	8,480	4,354	3,251	167551	44954	200912	56178
Solano	61.4%	51.8%	66.7%	7,041	5,909	3,677	74859	9532	88599	8716
Sonoma	39.0%	57.4%	74.0%	35,137	13,456	8,015	705376	175472	822664	216316
Stanislaus	52.1%	46.4%	58.2%	1,777	960	706	24331	2776	28130	3345
Sutter	65.0%	48.8%	61.3%	233	169	125	977	72	1146	81
Tehama	43.1%	47.6%	59.8%	6,270	3,371	2,558	155501	27933	180140	25712
Trinity	28.9%	54.0%	67.9%	3,898	1,395	974	73552	24609	88791	30908
Tulare	53.8%	42.9%	47.7%	2,846	1,616	1,470	110983	17665	132423	22238
Tuolumne	17.7%	70.7%	82.7%	16,890	3,910	2,296	541449	174467	704469	243655
Ventura	50.7%	48.8%	70.2%	34,469	26,718	14,784	112006	23303	136975	29420
Yolo	57.3%	51.0%	63.6%	1,084	643	434	10731	1006	12167	1159
Yuba	44.9%	46.1%	61.0%	4,745	2,425	1,746	206331	50614	231519	47097

Delta Wetlands Modeling

Background

The Sacramento San Joaquin Delta is a diverse wetland that contains millions of metric tons of carbon stored in its peat, soils, and vegetation. Years of draining of these wetlands for agricultural use has highly degraded these wetlands and led to a high level of subsidence, or loss of top soil, to wind erosion. This subsidence in the drained portions of these wetlands are leading to the sinking of the croplands within the delta. This sinking leads to higher costs for maintaining these lands for crops through pumping and bolstering of the levy system. These wetlands also provide much of the water that communities all through California depend upon for both drinking and irrigation. The lands also provide innumerable ecological and societal co-benefits from recreation to wildlife habitat. For this reason, these lands were the focus of the 2022 Scoping Plan Update modeling for wetlands.

Method

The overall method for estimating the emissions and sequestration rates of wetland restoration in the Delta was to use literature and previous modeling results to derive emissions and sequestration factors for various types of sub-wetlands that exist in the Delta. In this way, acres could be transferred from one type of land use to another, and new emissions or sequestration factors could be applied.

Data

Historic and Present-day Land Use

Land use in the early 2000s to present day (as represented by 2016 in this analysis) was determined using two datasets: the NOAA C-CAP database [100] for comparison with more detailed San Francisco Estuary Institute (SFEI) datasets based on the Bay Area Aquatic Resources Inventory (BAARI), Delta Aquatic Resources Inventory (DARI), and CDFW's VegCAMP mapping. Steps to create the land use determination were as follows:

1. The 2001 C-CAP datasets were used to correspond to the 2002/2003 SFEI dataset based on Delta 2002 and Suisun 2003 VegCAMP mapping, and the 2016 C-CAP dataset for the 2015/2016 SFEI dataset based on Delta 2016 and Suisun 2015 mapping from DARI and BAARI.
2. All spatial datasets were clipped according to the MHHWS tidal boundary from Brophy et al. 2019 [101].
3. Brackish water was delineated from freshwater areas at the midpoint between Browns Island and Sherman Lake.

4. From the SFEI datasets tidal and non-tidal areas were extracted and used as masks to separate the C-CAP rasters. This resulted in four rasters for each C-CAP year:
    a. Brackish tidal
    b. Brackish non-tidal
    c. Freshwater tidal
    d. Freshwater non-tidal
5. All attribute tables were exported into Excel and calculated areas in acres. Pivot tables were used to summarize each dataset and year according to the land-use classes.

Data provided by the Delta Stewardship Council was used to identify modern restored wetlands and impounded marshes; with the exception of the 14-acre experimental wetland on Twitchell Island, no wetland restoration projects were identified during the early 2000s. There was generally good agreement in acreages of each land use type between C-CAP and the SFEI datasets, with existing differences likely due to greater detail and accuracy in the SFEI datasets (Table 57).

.

Table 57: Areas of land use types for early 2000s and modern. * Total area of historic tidal wetland currently drained. Within this, peat remains on 151,181 acres that are mapped as organic soils or highly organic mineral soils [102, 103]. 43,601 acres of the total historic tidal wetland extent is classified as urban. The land use on the remaining mineral soil acreage is agricultural. **Acreage based on DSC data.

Land use types	Early 2000s Area (acres)	Early 2000s Area (acres)	Present day Area (acres)	Present day Area (acres)
Land use types	**2001 C-CAP**	**2002/3 SFEI**	**2016 C-CAP**	**2015/16SFEI**
a. Brackish – tidal (Suisun)	9,314	7,900	11,295	9,169
b. Brackish – managed seasonal wetlands, Suisun Marsh, organic or highly organic mineral soils c Brackish - managed seasonal wetlands, mineral soils, Suisun Marsh	52,989	50,340	50,711	43,159
d. Drained wetlands used for ag	327,767	317,163	326,334	305,720*
e. Wetlands recently converted to agricultural lands.	N/A		N/A	
f. Rice				3,860
g. Freshwater tidal wetlands	7,534	7,792	9,842	9,319
h. Delta seasonal wetlands, organic and highly organic mineral soils		16,784		6,854
j. Delta seasonal wetlands, mineral soils				9,867
k. Rewetted or restored wetlands (impounded marshes), Sherman and Twitchell Islands owned by DWR				1,700**

Greenhouse gas emissions and removal coefficients

The sources listed in Table 58 were used to estimate the coefficients for CO_2e, CO_2 and CH_4 for the land uses delineated in Table 57. There were insufficient nitrous oxide data to report.

Table 58: Emissions coefficients for land use types. 1) Average factor for CO2 also includes contribution from N2O which is proportional to CO2 where N2O (tCO2e) = 0.153 * CO2 based on methods and data presented in Deverel et al. (2017). 2) Calculation of MT C only includes CO2 and CH4.

Land use types	Emission factor MT CO_2e/acre/yr, (t C/acre yr)	Range MT CO_2e/acre/yr (t C/acre yr)	CO_2 (MT CO_2e/acre/yr) (t C/acre yr)	CH_4 (MT CO_2e/acre/yr) [GWP-28] (t C/acre/yr)	References and notes
a. Brackish – tidal (Suisun)	-3.3 (-0.90)	-3.7 to -2.9	-3.30 (-0.90)	0.015 (0.0004)	Knox et al. (2018) used the eddy covariance technique at Rush Ranch in Suisun Marsh to estimate the emission factor and Lisamarie Windham-Meyers, USGS, Menlo Park provided the methane estimate [104].
b. Brackish – managed seasonal wetlands, Suisun Marsh, organic or highly organic mineral soils	4.0[1] (0.90)[2]	2 to 5.2	3.8[1] (0.90)[2]	0.2 (0.005)	Using the SUBCALC model [102], we estimated a range of fluxes in accordance with the variation in soil organic matter content. Preliminary eddy covariance data provided by Dr. Dennis Baldocchi are generally consistent with the numbers in the table estimated by SUBCALC. The value of 0.2 tons CO_2e CH_4 was estimated from eddy covariance data provided by Dr. Dennis Baldocchi.
c. Brackish – managed seasonal wetlands, mineral soils, Suisun Marsh	NA	NA	NA	NA	no relevant data available
d. Drained wetlands used for ag	9.6[1] (2.15)[2]	-2.5 to 23.2	9.00[1] (2.13)[2]	0.60 (0.016)	Hemes et al. (2019) summarized data for drained agriculture on organic and highly organic mineral soils [105]. SUBCALC [102] provides estimates of spatially variable emissions for these soils. Shaffer and Thompson (2015) and Li et al. (2014) were used to estimate emissions and removals for agriculture on mineral soils [106, 107].
e. Agricultural lands with potential to be converted to tidal wetlands (long ago drained wetlands,	same as d.	NA	NA	NA	We could not find any evidence that there have been wetlands recently drained for agriculture anywhere in the Delta.

basically agricultural lands).					
f. Rice	7.02 (1.47)	5.30 to 8.76	5.21 (1.42)	1.81 (0.05)	Hemes et al. (2019) summarized eddy covariance data for rice on Twitchell Island [105].
g. Freshwater tidal wetlands	0.33 (-0.45)	-0.81 to 2.2	-1.86 (-0.51)	2.19 (0.06)	CO_2 uptake estimated from mean vertical soil accretion rates reported in Callaway et al. (2012) and peat carbon densities from a synthesis of peat core data from remnant tidal marsh sites in the Delta (in prep) [108]. CH_4 emission factors are IPCC tier 1 values.
h. Delta seasonal wetlands, organic and highly organic mineral soils	3.60[1] (0.98)[2]	1.7 to 5.5	3.60[1] (0.98)[2]	Deverel et al. (1998) reported minimal CH_4 fluxes from seasonal wetland on Twitchell Island.	Based on data presented for Twitchell Island in Deverel et al. (1998) [109], we assumed that seasonal wetlands on organic soils and highly organic mineral soils will emit CO_2 similarly to agriculture. This is due to drainage of these wetlands during spring, summer and fall which facilitates oxidation of the soil organic matter. Some areas designated as seasonal wetlands are too wet to farm due to poor drainage conditions [102]. Inability to adequately drain these areas for farming results in these areas behaving like seasonal wetlands. Deverel et al. (1998) presented data indicating the impounded seasonal wetlands are net sources [109]. Values were estimated using the SUBCALC model [102].
k. Rewetted or restored wetlands (impounded marshes)	1.35 (-1.38)	0.42 to 2.28	-5.75 (-1.57)	7.10 (0.19)	Hemes et al. 2019 (vegetated years) [105].
j. Delta seasonal wetlands, mineral soils	NA	NA	NA	NA	no relevant data available in the literature

Estimated Present-day emissions

Table 59 shows the estimated present-day emissions and removals based primarily on the acreage in Table 57 and coefficients in Table 58. The largest source of emissions are the organic and highly organic mineral soils drained for agriculture in the area delineated as historic emergent tidal wetlands. About 151,818 acres of this area are mapped as organic and highly organic mineral soils that still contain peat. The emissions for these soils was estimated using the SUBCALC model, which was calibrated using eddy covariance data. For the remaining acreage within the area delineated as historic emergent tidal wetlands, the emissions and removals were estimated based on data presented in Shaffer and Thompson (2015) and Li et al. (2014) [106, 107]. The total emissions were estimated for the Delta and Suisun Marsh of about 1.3 million tons of CO_2e per year.

Table 59: Estimated emissions and removals for Delta land uses. 2016 C-CAP and SFEI acreages were based on data provided in Table 57. Estimated present and planned acreages were determined by adjusting SFEI acreages to include present-day completed and planned EcoRestore tidal wetland restoration not captured in the 2015/16 habitat type mapping. For agricultural lands on drained emergent tidal wetlands, emissions due to the oxidation of organic and highly organic mineral soils that were quantified based on SSURGO data and data sources cited in Table 58. For mineral soils within the area delineated as drained former emergent tidal wetlands, emissions and removals were estimated from Shaffer and Thompson (2015) and Li et al. (2014) [106, 107]. For all other land use types, emissions and removals are based on data provided in Table 58. Negative CO2e values represent removals and positive CO2e values represent emissions. The MT C values were calculated by summing the component species (CH4, CO2 and N2O).

Land use types	2016 C-CAP (ac)	2016 SFEI (ac)	Est. Present (ac)	Planned (ac)	2016 tCO_2e C-CAP (MT C)	2016 tCO_2e SFEI (MT C)	tCO_2e Est. Present (MT C)	tCO_2e Planned (MT C)
a. Brackish – tidal (Suisun)	11,295	9,169	9,684	12,382	-37,274 (-10,167)	-30,258 (-8,253)	-31,959 (-8,717)	-40,676 (-11,146)
b and c. Brackish – managed seasonal wetlands, Suisun Marsh, organic or highly organic mineral soils and mineral soils	50,711	43,159	42,644	39,946	202,844 (52,858)	172,636 (44,986)	170,576 (44,450)	159,782 (41,637)
d. Drained emergent tidal wetlands used for agriculture in the Delta	326,334	305,720	301,941	293,040	1,015,538 (240,311)	1,053,062 (235,818)	1,050,859 (248,718)	980,334 (232,026)
f. Rice		3,860	3,860	9,000		27,101 (5,675)	27,101 (5,675)	63,180 (13,232)
g. Freshwater tidal wetlands	9,842	9,319	12,080	16,892	3,248 (-4,419)	3,075 (-4,184)	3,986 (-5,424)	5,574 (-7,585)
h Delta seasonal wetlands, organic and		6,854	6,821	6,788	NA	24,675 (6,733)	24,556 (6,701)	24,437 (6,669)

highly organic mineral								
j Delta seasonal wetlands, mineral soils		9,867	8,980	8,005	NA	?	?	?
k. Rewetted or restored wetlands (impounded marshes), Sherman and Twitchell Islands	NA	1,700	3,702	3,702	NA	2,292 (-2,345)	4,998 (-5,106)	4,998 (-5,106)
Total	398,182	389,648	389,712	389,755	1,184,356 (278,583)	1,252,583 (278,430)	1,250,109 (286,297)	1,197,629 (269,727)

Table 60: Estimated total emissions and removals based on 2016 SFEI acreages (business-as-usual). The MT C values were calculated by summing the component species (CH4, CO2 and N2O).

Land use types	Business as usual (ac)	Annual tCO_2e (MT C)	2030 Total tCO_2e (MT C)	2035 Total tCO_2e (MT C)	2045 Total tCO_2e (MT C)
a. Brackish – tidal (Suisun)	9,169	-30,120 (-8,253)	-271,081 (-74,281)	-421,682 (-115,548)	-722,884 (-198,082)
b and c. Brackish – managed seasonal wetlands, Suisun Marsh, organic or highly organic mineral soils and mineral soils	43,159	172,636 (39,047)	1,553,724 (351,427)	2,416,904 (546,664)	4,143,264 (937,138)
d. Drained emergent tidal wetlands used for agriculture	305,720	1,056,800 (241,806)	9,533,996 (2,181,647)	14,843,914 (3,396,811)	25,483,306 (5,831,766)
f. Rice	3,860	27,097 (5,675)	243,875 (51,074)	379,361 (79,448)	650,333 (136,197)
g. Freshwater tidal wetlands	9,319	3,075 (-4,184)	27,677 (-37,659)	43,054 (-58,581)	73,806 (-100,425)
h Delta seasonal wetlands, organic and highly organic mineral soils	6,854	24,674 (5,840)	222,070 (52,560)	345,442 (81,759)	592,186 (140,159)
j Delta seasonal wetlands, mineral soils	9,867	?	?	?	?
k. Rewetted or restored wetlands (impounded marshes)	1,700	2,295 (-2,345)	20,655 (-21,103)	32,130 (-32,827)	55,080 (-56,274)
Total	389,648	1,256,457 (277,586)	11,330,915 (2,503,664)	17,639,122 (3,897,726)	30,275,091 (6,690,478)

Scenario Development

Three scenarios in which current land uses would be converted to wetlands or rice were quantified as follows.

Current Commitments

Tidal wetlands

- Suisun – 2,698 acres
- Delta – 5,044 acres

Rice and Permanently Flooded Wetlands

- Rice on Delta organic soils currently farmed: 9,000 acres
- Managed Wetlands – 2,300 acres in the Delta

Aggressive

Tidal wetlands:

- Suisun – 35,781 acres

Rice and Permanently Flooded Wetlands

- Rice on Delta organic soils currently farmed: 34,484 acres
- Managed permanently flooded wetlands on organic soils: 41,993 acres

Climate resilience

Tidal Wetlands

- Suisun – 14,164 acres

Rice and Permanently Flooded Wetlands

- Rice on Delta organic soils currently farmed: 18,582 acres
- Managed permanently flooded wetlands on organic soils: 19,512 acres

GHG Emissions and Removals Estimates

Present-day and future GHG emissions and removals were calculated for agricultural lands in the Delta and managed wetlands in Suisun Marsh using an updated version of the SUBCALC [102]. The model accounts for the spatial variability of soil organic matter, depth-to-groundwater, and organic soil thickness to simulate subsidence and the associated GHG emissions. SUBCALC produced results for areas that are mapped as organic soils or highly organic mineral soils and fall within the estimated remaining present-day extent of peat. Emissions were simulated from 2022 through 2045. The output of the SUBCALC model is a grid with 90-ft spatial resolution. One grid was produced for each 2022, 2030, 2035, and 2045 where the values in each grid cell represented the cumulative $tCO_2e\ ac^{-1}$ for the model time series up to the target year.

For each scenario, grid cells were selected for conversion to rice cultivation where the emissions were more than 10 $tCO_2e\ ac^{-1}$, up to the desired acreage (the minimum baseline emissions needed to produce a net GHGs benefit). Grid cells with the next highest fluxes were selected to convert to permanently flooded wetlands up to the desired acreage.

Land-use changes were assumed to be completed in 2025. Estimated emissions from rice were 7.0 $tCO_2e\ ac^{-1}$ and the emissions from permanently flooded impounded wetlands were 1.4 $tCO_2e\ ac^{-1}$ [105].The research team assumed constant annual emissions from rice and wetlands for each year and calculated the net emissions by 2030, 2035, and 2045 by subtracting the cumulative baseline emissions at those time steps from the project emissions.

In Suisun Marsh, the SUBCALC model was used to estimate the emissions for managed wetlands on organic soils. The areas for conversion were selected in descending order of baseline emissions until the acreage was filled. The weighted average annual fluxes in Suisun Marsh managed wetlands on organic soils, 3.8 tCO2e ac-1 (Table 58), compared well with measured using the estimated flux of 3.1 tCO2e ac-1 using preliminary eddy covariance data provided by University of California Berkeley Professor Dennis Baldocchi (email communication with Steven Deverel, February 2022).

Results

Scenarios for the Delta wetlands were developed as three alternative scenarios, a current commitments, climate resilience, and an aggressive scenario. These scenarios relate to the 2022 Scoping Plan Update scenarios as: Aggressive = Scenario 1, Current Commitments = Scenario 2, Climate resilience = Scenario 3, Current Commitments = Scenario 4.

Current Commitment

Table 61 shows the estimated emissions from existing and planned permanently flooded wetlands on Sherman and Twitchell islands and the current and near-future rice cultivation on peat soils. Since these are the present land uses, the current emissions represent part of the 2022 baseline.

Table 61: Estimated emissions and removals for current commitments. MT C estimates were calculated using the sum of the CO2, CH4 and N2O.

Land use types	Current commitments (ac)	Current annual tCO_2e (MT C)	2030 Total tCO_2e (MT C)	2035 Total tCO_2e (MT C)	2045 Total tCO_2e (MT C)
a. Brackish – tidal (Suisun)	12,382	-40,676 (-11,146)	-366,087 (-100,314)	-569,469 (-156,044)	-976,233 (-267,504)
b and c. Brackish – managed seasonal wetlands, Suisun Marsh, organic or highly organic mineral soils and mineral soils	39,946	159,782 (36,140)	1,438,039 (325,261)	2,236,950 (505,961)	3,834,772 (867,362)
d. Drained emergent tidal wetlands used for agriculture	293,040	980,334 (223,960)	8,845,434 (2,020,948)	13,772,463 (3,146,750)	23,645,302 (5,402,799)
f. Rice (Delta Conservancy estimate)	9,000	63,180 (13,232)	568,620 (119,084)	884,520 (185,242)	1,516,320 (317,557)
g. Freshwater tidal wetlands	16,892	5,574 (-7,585)	50,168 (-68,262)	78,040 (-106,185)	133,782 (-182,032)
h Delta seasonal wetlands, organic and highly organic mineral soils	6,788	24,437 (5,784)	219,931 (52,053)	342,115 (80,972)	586,483 (138,809)
j Delta seasonal wetlands, mineral soils	8,005	?	?	?	?
k. Rewetted or restored wetlands (impounded marshes), Sherman and Twitchell Islands (DWR wetlands on Sherman and Twitchell)	3,702	4,998 (-5,106)	44,979 (-45,955)	69,968 (-71,485)	119,945 (-122,545)
Total	389,755	1,197,629 (255,279)	10,801,085 (2,302,816)	16,814,586 (3,585,211)	28,860,371 (6,154,446)

Aggressive

Table 62 shows the estimated total emissions and removals for the aggressive scenario. The selected areas in the Delta for rice and wetlands would replace areas currently drained for agriculture within the historic emergent tidal wetland for which acreage is provided in Table 57 which is the baseline condition. The scenario covers almost every area where the baseline emissions due to oxidation of organic soils are about 4.6 tCO_2e $year^{-1}$ ac^{-1} and higher. The tidal wetlands in Suisun in this scenario would cover almost all the organic soils that are not already tidal marsh and are currently managed wetlands. The total emissions in the Delta and Suisun Marsh by 2045 would be about 15 million tCO_2e.

Table 62: Estimated total emissions (tCO2e) and removals for the aggressive conversion to rice and wetlands in the Delta and Suisun Marsh. MT C estimates were calculated using the sum of the CO2, CH4 and N2O.

Land use types	Aggressive (ac)	2030 Total tCO_2e (MT C)	2035 Total tCO_2e (MT C)	2045 Total tCO_2e (MT C)
a. Brackish – tidal (Suisun)	48,163	-1,071,331 (-293,562)	-1,862,416 (-510,333)	-3,444,585 (-943,873)
b and c. Brackish – managed seasonal wetlands, Suisun Marsh, organic or highly organic mineral soils and mineral soils	4,165	579,295 (131,027)	662,586 (149,866)	829,168 (187,544)
d. Drained emergent tidal wetlands used for agriculture	216,563	4,877,087 (1,081,718)	6,319,209 (1,382,711)	9,229,225 (1,990,796)
f. Rice	43,484	2,092,321 (438,187)	3,618,609 (757,831)	6,671,186 (1,397,121)
g. Freshwater tidal wetlands	16,892	50,168 (-68,262)	78,040 (-106,185)	133,782 (-182,032)
h Delta seasonal wetlands, organic and highly organic mineral soils	6,788	219,931 (52,053)	342,115 (80,972)	586,483 (138,809)
j Delta seasonal wetlands, mineral soils	8,005	?	?	?
k. Rewetted or restored wetlands (impounded marshes)	45,695	385,123 (-393,473)	693,564 (-708,601)	1,310,446 (-1,338,858)
Total	389,755	7,132,594 (947,688)	9,851,708 (1,046,261)	15,315,705 (1,249,506)

Climate resilience

Table 63 present the estimated total emissions and emissions reductions from a climate resilience land use scenario where current agriculture is replaced with rice and wetlands, and managed wetlands in Suisun Marsh are replaced by tidal wetlands. The selected areas for conversion to wetlands and rice would cover all areas where baseline emissions are 13.2 tCO_2e ac^{-1} and higher. The total emission from these land uses in the Delta and Suisun Marsh by 2045 would be about 21 million tCO_2e.

Table 63: Estimated total emissions and emissions reductions (tCO2e) for the climate resilience scenario in the Delta and Suisun Marsh. MT C estimates were calculated using the sum of the CO2, CH4 and N2O.

Land use types	Climate resilience (ac)	2030 Total tCO_2e (MT C)	2035 Total tCO_2e (MT C)	2045 Total tCO_2e (MT C)
a. Brackish – tidal (Suisun)	26,546	-645,260 (-176,812)	-1,081,285 (-296,290)	-1,953,337 (-535,246)
b and c. Brackish – managed seasonal wetlands, Suisun Marsh, organic or highly organic mineral soils and mineral soils	25,782	1,098,103 (248,373)	1,613,734 (365,000)	2,644,996 (598,254)
d. Drained emergent tidal wetlands used for agriculture	254,946	6,421,205 (1,447,181)	9,149,798 (2,052,656)	14,628,475 (3,268,692)
f. Rice	27,582	1,422,528 (297,915)	2,390,657 (5000,666)	4,319,644 (904,646)
g. Freshwater tidal wetlands	16,892	50,168 (-68,262)	78,040 (-106,185)	133,782 (-182,032)
h Delta seasonal wetlands, organic and highly organic mineral soils	6,788	219,931 (52,053)	342,115 (80,972)	586,483 (138,809)
j Delta seasonal wetlands, mineral soils	8,005	?	?	?
k. Rewetted or restored wetlands (impounded marshes)	23,214	203,027 (-207,428)	359,721 (-367,520)	673,110 (-687,704)
Total	389,755	8,769,703 (1,593,019)	12,852,780 (2,229,298)	21,033,153 (3,505,420)

Annual Emissions

Table 64 presents a summary of restored acreage and emissions for each scenario during 2030, 2035, and 2045 with the average annual emissions from 2022 to the time point. The annual emissions would be reduced by about 35% in the climate resilience scenario by 2045. In the aggressive scenario, the annual net emission would be reduced by about 57%.

Table 64: Summary of annual emissions for each scenario during each time point. The average annual emissions are calculated as the average emissions from 2022 to 2030, 2035, and 2045.

Scenario	Year	Total acres restored	Annual emissions (Metric Tons C)	Annual emissions (t CO2e)	Avg. annual emissions (t CO2e)
BAU	2022	0	277,585	1,256,458	1,256,458
BAU	2030	0	278,712	1,261,216	1,258,991
BAU	2035	0	2278,917	1,262,083	1,259,937
BAU	2045	0	279,094	1,262,833	1,261,462
Current Commitments	2030	17,928	256,386	1,202,306	1,200,121
Current Commitments	2035	17,928	256,579	1,203,122	1,201,042
Current Commitments	2045	17,928	256,732	1,203,768	1,202,515
Climate resilience	2030	60,000	127,198	816,373	974,411
Climate resilience	2035	60,000	127,341	816,974	918,056
Climate resilience	2045	60,000	126,186	811,257	876,381
Aggressive	2030	120,000	19,638	543,499	792,510
Aggressive	2035	120,000	19,820	544,268	703,693
Aggressive	2045	120,000	20,344	546,482	638,154

Sparsely Vegetated Lands - Desert Modeling

Background

Deserts represent a large portion of California's land area and includes many of the State's endemic vegetation species. These lands are already vulnerable to climate change, as they exist on the extreme edge of climate that is hospitable to vegetation [110]. These lands contain many culturally and socially important areas, and provide many ecosystem services to both nature and society. Because these lands are globally unique and regionally important, and because they are already at risk from climate change, it is important to preserve as much of this land area as possible. For this reason, CARB focused on land conservation as the primary climate action on these lands.

Objective

The objective of this assessment is to quantify the impact that different levels of future projected land use change has on the organic carbon in California's desert ecosystems.

Methods

The method used for this assessment is to use previously modeled future land use change to assess how different land use change rates reduce existing carbon stocks. As land use change transitions lands into a different land types, it is assumed that any carbon that existed in deserts is completely lost to deserts. Using GIS tools, the land use change from 2014 to 2045 was coupled with the existing carbon stocks to estimate what is lost.

This method assumes that the lands that don't experience land use change do not further degrade through time, and that the carbon stocks that existed in 2014 remain unchanged. It is unknown if more complex modeling over the entire landscape would lead to further carbon losses or sequestration. Further, inorganic carbon was not modeled, and again it is unknown how this carbon pool if modeled would add to the emissions or sequestration potential of these lands. Previous modeling of inorganic carbon on small scales in the Mojave Desert project net loss of the top layer of inorganic carbon under increasing CO_2 concentrations and increased wind erosion [111]. As higher temperature further stresses the vegetation in these lands previous research estimates future expansion of barren land and a subsequent degradation of existing carbon stocks [112]. This change however, is not taken into account in this analysis.

Land use change modeling

The 4th climate change assessment included various modeling exercises, one of which being future land use change [113]. This assessment used a model called the Land Use and Carbon Scenario Simulator (LUCAS) model [114]. This model used historic rates of land use and land cover change to parameterize a spatially and temporally explicit simulation of how land use change may occur into the future. The results of this modeling are provided publically and freely [115]. As randomness exists within this modeling 10 monte carlo simulations were performed, the first of which was used for the 2022 Scoping Plan Update modeling. Further, this modeling includes a BAU projection, as well as scenarios with various demographic change scenarios. For the 2022 Scoping Plan Update modeling, only the BAU projection was used.

Existing Carbon Stocks

The existing carbon stocks from CARB's NWL carbon inventory for 2014 were used to estimate the carbon in this system. This dataset is a spatially explicit data set that includes all live and dead biomass carbon, both above and below ground. In this exercise, carbon stocks do not change through time, except from land use change.

Scenarios

The BAU rate of land use change was used as a basis off which alternative scenarios were developed. The BAU land use change rate was assumed to be the highest rate of change, and the carbon stock loss associated with the BAU rate of change is the highest loss of any scenario. The other scenarios then scaled that stock loss down by 100% 75%, 50%, and 25%. That is to say that in scenario 1 no land use change occurs and all carbon stocks in deserts remain. In scenario 2 only 25% of the BAU land use change rate occurs, and 75% of the land use change is avoided, and so on for the other scenarios.

Results

The results of the carbon stock change modeling demonstrate little change in carbon stocks at 2045 between the BAU scenario, and Scenario 1 with no land use change. The land use change modeling estimates about 2607 acres of land use change per year and this change radiates from population centers. These results do not assume any random land use change away from already existing population centers. The carbon stocks between 2014 and 2045 were then annualized (Table 65).

Table 65: Total biomass carbon stocks in sparsely vegetated ecosystems in California under five different scenarios.

Year	BAU	Scenario 1	Scenario 2	Scenario 3	Scenario 4
2014	0.06602	0.06602	0.06602	0.06602	0.06602
2015	0.06602	0.06602	0.06602	0.06602	0.06602
2016	0.06601	0.06602	0.06602	0.06602	0.06601
2017	0.06600	0.06602	0.06602	0.06601	0.06601
2018	0.06600	0.06602	0.06602	0.06601	0.06600
2019	0.06599	0.06602	0.06601	0.06601	0.06600
2020	0.06599	0.06602	0.06601	0.06600	0.06600
2021	0.06598	0.06602	0.06601	0.06600	0.06599
2022	0.06598	0.06602	0.06601	0.06600	0.06599
2023	0.06597	0.06602	0.06601	0.06600	0.06599
2024	0.06597	0.06602	0.06601	0.06599	0.06598
2025	0.06596	0.06602	0.06601	0.06599	0.06598
2026	0.06596	0.06602	0.06600	0.06599	0.06597
2027	0.06595	0.06602	0.06600	0.06599	0.06597
2028	0.06595	0.06602	0.06600	0.06598	0.06597
2029	0.06594	0.06602	0.06600	0.06598	0.06596
2030	0.06594	0.06602	0.06600	0.06598	0.06596
2031	0.06593	0.06602	0.06600	0.06598	0.06595
2032	0.06593	0.06602	0.06600	0.06597	0.06595
2033	0.06592	0.06602	0.06600	0.06597	0.06595
2034	0.06592	0.06602	0.06599	0.06597	0.06594
2035	0.06591	0.06602	0.06599	0.06597	0.06594
2036	0.06591	0.06602	0.06599	0.06596	0.06594
2037	0.06590	0.06602	0.06599	0.06596	0.06593
2038	0.06590	0.06602	0.06599	0.06596	0.06593
2039	0.06589	0.06602	0.06599	0.06596	0.06592
2040	0.06589	0.06602	0.06599	0.06595	0.06592
2041	0.06588	0.06602	0.06599	0.06595	0.06592
2042	0.06588	0.06602	0.06598	0.06595	0.06591
2043	0.06587	0.06602	0.06598	0.06595	0.06591
2044	0.06587	0.06602	0.06598	0.06594	0.06590
2045	0.06586	0.06602	0.06598	0.06594	0.06590

Economic Analysis

This section presents the analysis of the economic impact of the proposed Natural and Working Lands management practice alternatives. Direct costs of implementing each management strategy were estimated using a combination of academic literature, survey data, and existing subsidy programs. These estimated direct costs were used as inputs into the REMI model. This model evaluates how increases in economic activity in the affected industries and changes in government and private spending change macro-economic measures like employment, economic growth, and personal income as compared to the reference scenario.

Direct Costs

Direct costs of each management strategy were estimated using available academic literature, monitoring and reporting data, survey data, as well as cost data from existing subsidy programs. Costs for each management strategy were estimated on a per acre basis and were assumed to be consistent across the different management alternatives. The total cost of each alternative was then calculated from these per acre costs. The cost of increasing the urban forest was estimated as a proportional increase to the current level of spending on urban forests. The total cost of improving defensible space around structures in the wildlife urban interface was estimated using reports on the cost per property of achieving defensible space and satellite data, which was used to estimate the number of properties that required increased management.

This cost data, in combination with the acreage of each management strategy for each alternative, were used to estimate the overall direct cost to either the government or private sector. The direct costs are estimated so that they are independent of the policy lever used to implement the management strategies. These costs only estimate the labor and capital implementation costs of the action itself, and not any of the pre or post cost that would be needed to practically execute action at scale, such as cost to increase and train a workforce, or environmental assessments as required by law.

The estimated direct costs do not include many important benefits and externalities of the actions, many of which are difficult to quantify. As such, a full quantitative cost benefit analysis of these actions is outside the scope of this document. The NWL actions outlined in the 2022 Scoping Plan Update provide many economic benefits. However, this analysis was only focused on estimating the costs needed to execute action, and not on the subsequent economic co-benefits that would surely outweigh the implementation costs. Such a full accounting of NWL climate action co-benefits was prohibited by time, resources, and a lack of available science, data, and models.

Table 66 shows the estimated cost per acre of each management strategy. Descriptions of the method used to estimate the cost of each management strategy can be found below.

Table 66: Cost/Acre of Management Actions

Landtype	Management Action	Dollars per Acre
Forest/Shrublands/Grassland	Biological, Chemical, and Herbaceous Treatments	$135
Forest/Shrublands/Grassland	Clearcut	$6618
Forest/Shrublands Grassland	Harvesting	$1626
Forest/Shrublands/Grassland	Thinning	$1457
Forest/Shrublands/Grassland	Mastication	$800
Forest/Shrublands/Grassland	Other Mechanical	$555
Forest/Shrublands/Grassland	Prescribed Burning	$412
Annual Croplands	Cover cropping (legumes)	$378
Annual Croplands	Cover cropping (non-legumes)	$378
Annual Croplands	No Till	$95
Annual Croplands	Reduced Till	$85
Annual Croplands	Compost Amendment	$200
Annual Croplands	Transition to organic farming	$3482
Annual Croplands	Conservation of Annual Cropland	$7000
Annual Croplands	Riparian Forest Buffers	$9054
Annual Croplands	Alley Cropping	$2107
Annual Croplands	Windbreaks/Shelterbelts	$30492
Annual Croplands	Tree and Shrubs in Croplands	$1024
Annual Croplands	Hedgerows	$29969
Perennial Croplands	Hedgerows in Perennial Croplands	$29969
Perennial Croplands	Windbreak/Shelterbelts in Perennial Croplands	$30492
Developed Lands	Urban Forest Investment	4.2 billion in Reference
Developed Lands	Defensible Space in WUI Communities	2,500 per property
Wetlands	Wetland Restoration	$2500
Sparsely Vegetated	Avoided Conversion	$3242

Estimates of Direct Costs:

Forest/Shrublands/Chaparral/Grassland Treatments

Costs per acre for the non-commercial management strategies (Biological, Chemical, and Herbaceous Treatments, Thinning, Mastication, Other Mechanical, Prescribed Burning) were estimated from survey data collected by the U.S. Forest service on hazardous fuel treatment projects where entities self-report costs of implementing the management strategies [116]. A crosswalk was used to map the management strategies as they appear in the survey to the management strategies as they are described in the Management and Treatment Modeling section (Table 67).

Table 67: Crosswalk between USFS reported silvicultural activities to Scoping Plan management actions for cost estimation purposes.

USFS FACTS silvicultural practice	Scoping Plan management action
Chipping of Fuels	Mastication
Commercial Thin	Thinning
Compacting/Crushing of Fuels	Mastication
Control of Understory Vegetation	Other Mechanical
Coppice Cut (w/leave trees) (EA/RH/FH)	Other Mechanical
Fuel Break	Clearcut
Grazing and Range Mgt. for Hazardous Fuels Reduction	Mastication
Group Selection Cut (UA/RH/FH)	Harvest
Harvest Without Restocking	Harvest
Improvement Cut	Thinning
Invasives Pesticide Application	Mastication
Patch Clearcut (w/ leave trees) (EA/RH/FH)	Clearcut
Permanent Land Clearing	Clearcut
Piling of Fuels, Hand or Machine	Other Mechanical
Pre-commercial Thin	Thinning
Prune	Other Mechanical
Pruning to Raise Canopy Height and Discourage Crown Fire	Other Mechanical
Range Control Vegetation	Biological
Range Cover Manipulation	Other Mechanical
Range Piling Slash	Other Mechanical
Rearrangement of Fuels	Other Mechanical
Recreation Removal of hazard trees and snags	Thinning
Right of Way Maintenance	Other Mechanical
Road Maintenance	Other Mechanical
Salvage Cut (intermediate treatment, not regeneration)	Clearcut
Sanitation Cut	Clearcut
Seed tree Final Cut (EA/NRH/FH)	Harvest
Shelterwood Removal Cut (EA/NRH/FH)	Harvest
Single tree Selection Cut (UA/RH/FH)	Harvest
Site Preparation for Natural Regeneration Mechanical	Other Mechanical
Site Preparation for Planting Manual	Thinning
Site Preparation for Planting Mechanical	Other Mechanical
Slashing Presite Preparation	Other Mechanical
Stand Clearcut (EA/RH/FH)	Clearcut
Stand Clearcut (w/ leave trees) (EA/RH/FH)	Clearcut
Thinning for Hazardous Fuels Reduction	Thinning
Tree Release and Weed	Thinning
Wildlife Habitat Precommercial thinning	Thinning
Yarding Removal of Fuels by Carrying or Dragging	Harvest

The implementation costs associated with an increased level of commercial harvests (harvests and clear-cuts) were estimated from a special data request to the U.S. Department of Agriculture, Forest Service Transaction Evidence and Appraisal (TEA) System that was fulfilled on behalf of CARB and Cal Fire [117].

Results of the macro-economic modeling in Table 72 show that some of the alternative management scenarios would require a large increase in the number of workers in the Forestry and Logging sector to achieve the desired level of management. This might require significant training costs to achieve these levels of forest management and these costs are not quantified as part of our estimates.

Healthy Soils Practices

Implementation costs for the healthy soils practices (Table 66), were estimated as the dollar value of existing subsidy programs in the state of California, which are posted on the CDFA website [118]. The subsidy values of some management practices were converted to a dollar per acre figure. The current program is reportedly oversubscribed, so increasing the level of management at current subsidy dollar values is plausible.

Transition to Organic

The cost of transitioning to organic agriculture from conventional was estimated as the cost of increased inputs plus forgone revenue that a farm operator would incur during the required three-year organic certification process. During this three-year transition period, farmers must adopt organic agricultural practices, which requires them to pay for changes in input requirements and face decreased yields. However, during this transition period they do not receive organic premiums for their produce.

The estimated input cost differences between organic and conventional produce for several specific crops in California were taken from academic literature [119] which estimated cost differences using extensive survey data and interviews with California farmers, as well as a model of agricultural practices that translates differences in practices to differences in input requirements.

Estimates of yield differences between conventional and organic practices for specific crops were taken from the relevant academic literature [120] [121]. This was combined with data on average revenue per acre from the California Agricultural Statistics Review [122] to produce estimates of the forgone revenue associated with switching to organic practices.

Total cost difference for each crop was then estimated by adding the increased cost of inputs to the forgone revenue. The final cost per acre number was calculated as a weighted average of the total cost difference for each crop, weighted by the number of organic acres in cultivation for that crop as reported in the 2020 California Agricultural Organic Report [123].

Avoided Development on Annual Croplands

The cost of avoiding development on an acre of annual croplands was estimated as the cost of placing a conservation easement on an acre of land. The average cost per acre of a conservational easement was obtained from the Department of Conservation and was estimated based on 20 annual cropland easement projects in Contra Costa, Monterey, Madera, Merced, Placer and Yuba county.

Urban Forests

The cost of urban forest expansion required to reach the proposed levels of coverage in the alternatives was calculated as a percent increase of the levels of current spending on urban forests. This was estimated as the sum of spending by all groups including developers, governments, and private citizens. The number of trees in California was taken from academic literature that combines plot level survey data with satellite imagery to estimate the total canopy coverage in the state and the total number of trees per acre of canopy cover [124]. This literature estimates that there are approximately 173.2 million urban trees in California. Data on the cost of urban trees was also taken from academic literature and reports [125] [126] [127] [128] [129]. Annualized costs were estimated over the entire lifecycle of a tree and were estimated separately for trees on private and public lands. Estimated costs included the cost of planting, pest control, pruning, cleanup, repairs, removal irrigation and administration. The literature estimates that the annualized cost of a private tree is approximately $22 while the annualized cost of a public tree is approximately $34. Trees on public land were estimated to be more expensive due to higher costs of pruning and repairs associated with damage to roads and sidewalks. Multiplying these costs per trees by the number of trees in California, we estimated that at present Californians spend approximately 4.2 Billion dollars annually on all aspects of planting, maintaining, and disposing of the 173 million public trees. Academic literature that seeks to quantify all costs and benefits of urban trees finds that on average benefits of urban trees tend to outweigh these costs [128]. Urban forests require a high level of maintenance compared to wildland forests. Whereas wildland forests may receive a treatment every decade, urban forests always have to be irrigated, pruned, leaves racked, and dead wood and trees disposed of. This leads to the much higher cost of urban forests compared to wildland forests.

Wetlands

Rice conversion costs per acre were based on current State rice cultivation. A value of $500/ac was provided by Conservation Farms and Ranches Farm Director Dawit Zeleke in personal communication.

For permanently flooded wetlands, the construction costs from DWR were estimated for wetlands on Sherman Island and Twitchell Island. The cost of $2,500/ac was determined as the cost for the wetland construction component of the projects.

For tidal wetlands, total acreage for current commitments were taken from publicly available documents provided through EcoAtlas and DWR. Costs for 4 planned projects were acquired from DWR documentation (Dutch Slough Tidal Habitat Restoration, Lookout Slough Tidal Habitat Restoration and Flood Improvement, McCormack Williamson Tract, Hill Slough Tidal Habitat Restoration, and Liberty Island). The average per-acre cost of all these projects was used to estimate the expected cost for new tidal wetland. The average cost was $20,882/ac. If cost information was available for a particular project, that cost was used instead (e.g. Hill Slough Tidal Habitat Restoration has $10mil listed in project documents).

Avoided conversion on Sparsely Vegetated Lands

The Cost of avoiding conversion on Sparsely Vegetated Lands was estimated as the cost of purchasing the land. A report on undeveloped desert land values in the California Desert, which was created for the purpose of estimating the cost of desert conservation, reported the average value for an acre of land to be $3,432 [130].

WUI Defensible Space

The cost of creating defensible space around California properties in the Wildland Urban Interface was estimated by multiplying the number of properties that would require more defensible space by the cost of improving landscaping so that it met defensible space requirements. The cost of improving properties to meet defensible space requirements was taken from a report produced by an economics consulting firm [131] while estimates of the number of properties that required improvement was calculated as described in the Wildland Urban Interface Modeling section.

Total costs

Table 68 shows the direct annual costs aggregated by land type for each alternative and the total annual implementation costs for each alternative. These were calculated by multiplying the per acre costs of each management action by the proposed management scale as described in the Alternative Scenario Development section.

Alternative 1 is the most expensive with a projected annual cost of $84 billion per year. This is almost entirely due to the large cost of spending on urban forests. Alternative 2, Alternative 3, and Alternative 4 would cost $5.65, $3.35 and $4.79 billion dollars per year respectively. The cost of Alternative 1 and 2 is dominated by urban forestry spending; the cost of Alternative 4 is dominated by spending on forests, shrublands and grasslands, while the cost of Scenario 3 is predominantly a mix of urban forests and forests, shrubland and grasslands spending.

These estimates of total cost do not consider the numerous benefits that would occur if the management scenarios were implemented. These benefits include but are not limited to, increased carbon sequestration described in the different land type modeling sections, reduced health impacts from wildfire smoke, as described in the Wildfire Emissions, Health, and Health Economic Impact section, reduced use of pesticides, aesthetic value of urban forests, improved temperature regulation in cities from urban forests, improved soil health, increased recreational opportunities in wetlands, and decreased damage to structures from wildfires from improving defensible space.

Alternative 1 targeted the theoretical maximum urban tree cover by 2045. All groups within the state, including private individuals, developers, and governments, were estimated to currently spend approximately $4.5 billion dollars annually on planting, maintenance, sidewalk repair, tree removal, and other expenses related to urban forests and that reaching the theoretical maximum tree cover would require increasing that spending by a factor of twenty.

In Alternative 2, 12% of the total direct cost of forest, grassland, and shrubland management cost is the cost of increases in commercial harvests while in Alternatives 3 and 4, approximately 20% of forest, grassland and shrubland costs. Based on survey data, it is expected that costs associated with increased commercial harvests would be offset by the revenue generated from the commercial harvest.

The total estimated cost of implementing the actions on Annual and Perennial Croplands ranges from approximately 563 million for Alternative 1, to 141 million for Alternative 4. Of these costs, approximately 80 percent are costs associated with transitioning to organic, 6% are associated with increasing healthy soils practices, and 14% are associated with purchasing easements on annual croplands.

Table 68: Aggregate Annual Direct Costs

Category	A1	A2	Scoping Plan Scenario	A4
Forest/Shrublands/Grasslands	(418,265,721)	538,141,014	1,777,554,428	4,224,937,743
Annual Croplands	555,591,439	416,677,756	303,914,650	138,916,747
Perennial Croplands	7,919,556	5,932,175	3,974,763	1,987,381
Urban Forests	83,655,253,060	4,562,053,306	4,562,053,306	255,867,986
Wildland Urban Interface	114,000,000	114,000,000	114,000,000	145,000,000
Sacramento/San Joaquin Delta	53,477,868	8,276,725	27,699,884	8,276,725
Sparsely Vegetated Lands/Other Lands	8,453,224	6,339,107	4,228,233	2,114,117
Total	83,976,429,426	5,651,420,083	6,457,451,958	4,777,100,699

Macro-Economic Impacts

REMI Model Description

After estimating the direct cost of each management strategy in each scenario, macro-economic impacts of each Alternative were estimated using the Regional Economic Models, Inc. (REMI), Policy Insight Plus (PI+) Version 2.5.0. CARB uses a single-region, 160-sector version of the PI+ model configured to the population, demographics, and employment of California. REMI is a structural economic forecasting and policy analysis model that relies on four methodologies in its framework. The methodologies include:

- Input/output modeling: I/O modeling outlines the connection between different industries and households in the economy and is represented by multipliers that track the flow of goods and services between firms, sales to household, and wages paid to and spent by individuals. This data is sourced from the Bureau of Labor Statistics (BLS) and modified to reflect the California economy.
- Econometrics: The REMI model includes statistical parameters representing the behavior of households and firms based on historical data. This includes how industries and consumers respond to changes in prices or wages.
- Computable General Equilibrium (CGE): Aspects of CGE modeling, including market concepts, market shares, and competitiveness for businesses, are included in the REMI model. Inclusion of these concepts allows the REMI model to adjust the flow of goods and services over time in response to changing economic conditions.
- Economy geography: The REMI model represents the spatial dimension of the California economy and allows for clustering of industry and labor by geographic region.

Figure 53 presents the overall structure of the REMI model, which consists of five major blocks: (1) output and demand, (2) labor and capital demand, (3) population and labor supply, (4) compensation, prices, and costs, and (5) market share.

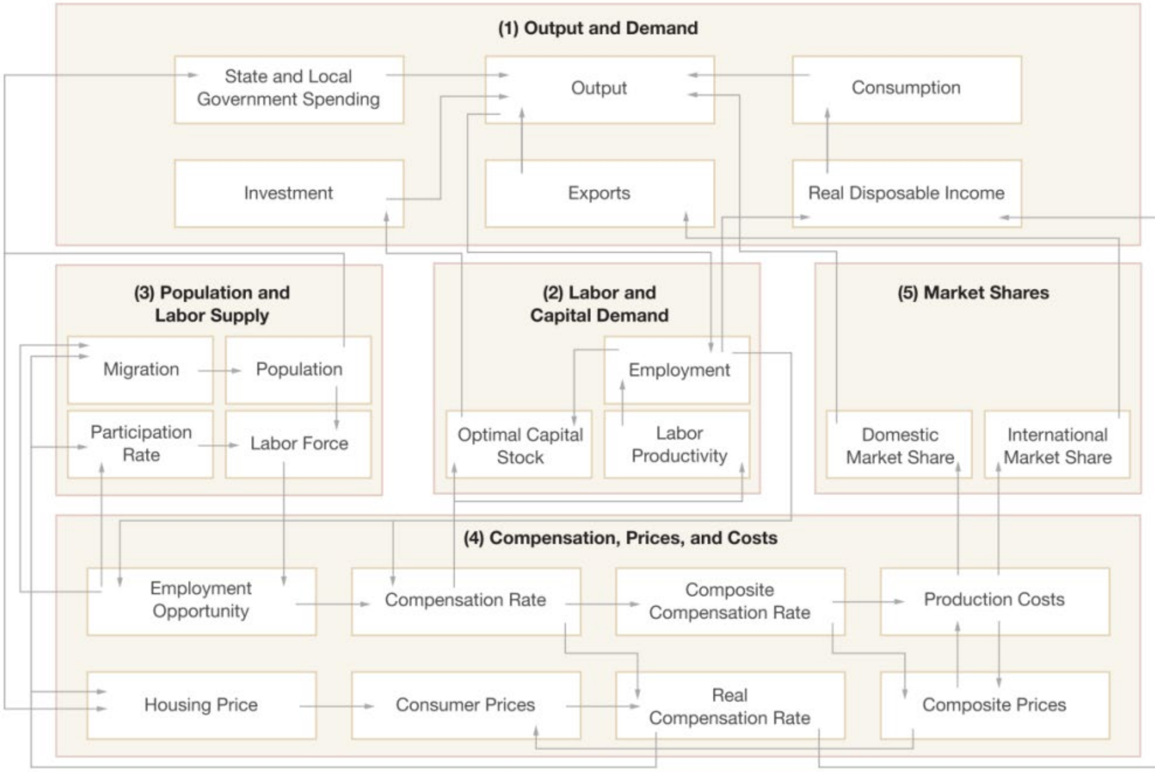

Figure 53: Diagram of the REMI model.

Within Figure 53 the rectangles represent a variable with arrows representing the equations that link the pieces of the model together. Block 1 represents macroeconomic impacts and includes components of Gross Domestic Product (GDP) often used as a proxy for economic growth. Block 2 contains firm and industry related elements. Changes in demand for goods from block 1 require firms in block 2 to adjust through changes in labor and capital. Block 3 includes demographic modeling components including population and the labor force. Within block 4, households and businesses evaluate the markets for labor, housing, fuels, and energy prices and make decisions about consumption and location. Block 5 quantifies regional impacts and competitiveness and determines any exports from the region. For a more detailed description of the equations linking the different blocks see [132].

The REMI model provides year-by-year estimates of the total impacts of the alternative management strategies relative to the Reference, or no action, Scenario. The Reference Scenario modeled in REMI includes a forecast of the California economy through 2045 based on current conditions that are adjusted for forecasted population and projected economic growth in the future.

Modeling Approach

For each alternative, the macroeconomic impact was modeled by assuming that economic activity in the relevant industries grows in proportion to the proposed implementation spending in that industry as shown in Table 68. All funds for implementing the actions are assumed to be sourced from within the state. For urban forests, the funds were modeled as being sourced from a combination of state government and private property owners in proportion to the current estimated private/public spending ratio. For all other actions, funds were assumed to be sourced from the state government. Commercial harvests, which make up between 12% and 20% of the implementation costs of management of forests, shrubland and grasslands, were assumed to be self-financing. In each modeled scenario, government spending and income to property owners were reduced relative to the Reference Scenario in proportion to the annual costs of implementation. None of the proposed spending was modeled as being sourced from increased taxes. As such, the modeling inputs and results reflect just one of many potential real-world strategies for financing the implementation the proposed alternatives.

While the macro-economic model does count the increased economic activity in the affected industries as part of gross state product, it does not quantify many of the important economic, health, and environmental benefits that would occur if these actions were implemented. While these benefits, like the reduced use of pesticides, amenity value of Urban Trees, and increased recreational opportunities would be very significant, they are outside the scope of the macro-economic modelling at this time. While spending on these management strategies would produce benefits, it does imply that the affected governments, businesses, and consumers would have less income to spend elsewhere in the economy. The model represents how that reallocation of resources is projected to affect the economy, dynamically through time.

Results

The model returns results in the form of estimates of the projected difference in levels of various macro-economic aggregates between the reference scenario and the modeled alternative. It also returns differences in the level of employment for each industry in the model. Projected differences between the reference scenario and the alternative are estimated for every year from the beginning of implementation, 2025, and the last year being modeled, 2045.

Table 69 shows the projected difference in total employment, gross state product, and personal income per capita in the year 2035 while Table 70 shows the difference in 2045. Projected differences in 2035 are qualitatively similar to those in 2045

Table 69: Percent Changes in 2035

Category	A1	A2	Scoping Plan	A4
Total Employment	3.668%	0.180%	0.12%	-0.069%
Gross Domestic Product	0.975%	0.039%	0.00%	-0.029%
Real Disposable Personal Income per Capita	-3.244%	-0.179%	-0.044%	-0.022%

Table 70: Percent Changes in 2045

Category	A1	A2	Scoping Plan	A4
Total Employment	3.313%	0.116%	-0.010%	-0.075%
Gross Domestic Product	0.915%	0.011%	-0.01%	-0.029%
Real Disposable Personal Income per Capita	-3.078%	-0.17%	-0.14%	-0.012%

The largest impacts on the macro-economy are observed in Alternative 1 with a projected increase in the level of total employment of 3.3% and a projected increase in the level of gross state product of 1% relative to the Reference Scenario in the year 2045. Besides Alternative 1, impacts on the macro-economy of the state are projected to be modest with no more than a .03% change in GSP in Alternative 1, Alternative 2, and the Proposed Scenario by 2045. The Scoping Plan Scenario is projected to have the smallest impact on the economy with almost no change in GDP in the year 2045.

Because of the high cost of urban forests, much of which is borne by individuals rather than governments, Alternative 1 is projected to decrease the level of personal income per capita by 3.1% in the year 2045. Other alternatives are projected to have a more modest effect on personal income.

The macro-economic model also makes projections about the total level of employment in the State. The model forecasts that Alternatives 1 and 2, which channel economic activity towards labor-intensive industries like landscaping for urban forests, would increase total employment while Alternative 4, which channel economic activity towards capital intensive industries like forestry, would lead to a slight decrease in total employment. The Scoping Plan Scenario is a combination of both harnessing labor intensive and capital intensive industries. While the model does aim to accurately represent many labor market dynamics, including adjustments of wages and migration rates, it does not account for many costs and frictions that might be associated with dramatically scaling up employment in a particular industry, such as the cost of job training.

Table 71 shows the projected percent difference in employment by Industry in 2035 and Table 72 shows the same for 2045. Results are qualitatively similar across the two different years but projected differences from the reference scenario are generally predicted to attenuate over time. Changes to employment in industries not listed tend to be very small and negative as labor is reallocated towards the affected industries. Employment is expected to increase in the alternatives and industries where economic activity increases. In this model, landscaping services are a subset of the industry “Services to Buildings and Dwellings”. Therefore, dramatic increases are seen in that sector in alternatives that direct economic activity towards urban forestry. Employment in state and local government is projected to decrease in all scenarios roughly in proportion to the amount of government spending that is required to be redirected away from other areas to implement the various management actions.

Alternative 1 and 2, which reallocate economic activity towards landscaping services, a relatively labor-intensive industry, tend to increase total levels of projected employment. Alternative 4, which re-allocates economic activity towards a relatively capital-intensive industry, Forestry and Logging, leads to a small projected decrease in total employment.

Alternatives 2 and 4, and the Scoping Plan Scenario, lead to significant projected increases in employment in the "Forestry and Logging" sector. Alternative 2, which involves approximately 1 million acres of action is projected to lead to a 24% increase in 2035, The Scoping Plan Scenario, which involves 2.5 million acres of action, is projected to lead to a 78% increase in 2035, and Alternative 4 which involves 5 million acres of action is projected to lead to a 183% increase in forestry employment in 2035.

Table 71: Percent Changes to Employment by Industry in 2035

Industry	A1	A2	Scoping Plan	A4
All Industries	3.67%	0.13%	0.12%	-0.07%
Forestry and Logging	-19.50%	23.98%	78.25%	182.66%
Support activities for agriculture and forestry	-0.41%	0.36%	1.05%	2.43%
Construction	0.14%	-0.13%	-0.19%	-0.27%
Sawmills and wood preservation	-0.81%	0.17%	0.63%	1.30%
Retail trade	-0.47%	-0.05%	-0.06%	-0.06%
Transit and ground passenger transportation	0.10%	-0.06%	-0.09%	-0.14%
Services to buildings and dwellings	213.05%	11.28%	11.26%	0.49%
State and Local Government	-2.28%	-0.60%	-0.82%	-0.97%
Farm	0.09%	0.37%	0.25%	0.12%

Table 72: Percent Changes to Employment by Industry in 2045

Industry	A1	A2	Scoping Plan	A4
All Industries	3.31%	0.12%	0.10%	-0.07%
Forestry and Logging	-18.80%	23.09%	75.22%	175.22%
Support activities for agriculture and forestry	-0.33%	0.30%	0.87%	2.02%
Construction	0.03%	-0.12%	-0.17%	-0.23%
Sawmills and wood preservation	-0.87%	0.25%	0.86%	1.74%
Retail trade	-0.11%	-0.03%	-0.04%	-0.06%
Transit and ground passenger transportation	0.38%	-0.04%	-0.07%	-0.12%
Services to buildings and dwellings	174.77%	9.30%	9.28%	0.41%
State and Local Government	-1.92%	-0.55%	-0.76%	-0.91%
Farm	0.07%	0.30%	0.21%	0.10%

Overall NWL Results

Background

As results are brought together from all of the various NWL land types and analyses, it becomes clear the overall trajectory of this sector, and the contributions that each land type makes to that trajectory. The NWL modeling for the 2022 Scoping Plan Update is designed to make large-scale long-term projections, not predictions. Projections are focused on trajectories and relative magnitudes of change. Whereas, predictions make forecasts of exactly what will occur, where, and when. This is to say that the NWL projections should not be considered CARB's prediction of what will occur into the future, but instead the use of the best available science, data, and models, to quantify the likely future outcomes of the State's NWL on large scales. It is very likely that between now and 2045 events will occur that cannot now be predicted that will alter the overall trajectories quantified here. However, it is likely that any unforeseen events will have negative impacts on NWL carbon stocks. Carbon stocks are like savings account, in that they can quickly be depleted, but take a long time to build up.

Further, carbon stocks in the 2022 Scoping Plan Update modeling were calibrated based on the 2014 carbon stock estimates in the 2018 edition of CARB's NWL carbon inventory. CARB is continually making refinements to the NWL carbon inventory as more data are collected, measurement science advances, and new quantification methodology and models are developed over time. Updates to the 2014 carbon stock estimates are expected in future inventory editions. For this reason, the absolute values of the 2022 Scoping Plan Update modeling are less significant than the trajectories and relative magnitude of change. Setting targets as relative change to a retrospective baseline allows opportunity to incorporate new data and science into quantification of the baseline number and continual progress in tracking in the future. Every effort to improve the NWL inventory will be made, and that will not affect the relative carbon stock target set by the Scoping Plan.

Results

For a detailed spreadsheet of all of the final results, please refer to 2022 Scoping Plan-NWL-Data.xlsx in the 2022 Scoping Plan Appendix.

References

[1] California State Senate, *SB-27 Carbon sequestration: state goals: natural and working lands: registry of projects.,* Sacramento: State of California, 2021.

[2] California State Senate, *SB-859 Public resources: greenhouse gas emissions and biomass.,* Sacramento: State of California, 2016.

[3] California State Assembly, *AB-1504 Forest resources: carbon sequestration,* Sacramento: State of California, 2010.

[4] California State Senate, *SB-1386 Resource conservation: working and natural lands.,* Sacramento: State of California, 2016.

[5] California Air Resources Board, "2017 CLIMATE CHANGE SCOPING PLAN UPDATE Resolution 17-46," State of California, Sacramento, 2017.

[6] IPCC, "IPCC Good Practice Guidance for LULUCF - Ch. 2 Basis for Consistent Representatino of Land Areas," IPCC, 2019.

[7] California Air Resources Board Scoping Plan Environmental Justice Advisory Committee, " Recommendations, N2," State of California, Sacramento, 2022.

[8] The State of California, "California's Fourth Climate Change Assessment - Key Findings," California Energy Comission, 2018. [Online]. Available: https://www.climateassessment.ca.gov/state/overview/. [Accessed 22 April 2022].

[9] J. Sanderman and J. Baldock, "Accounting for soil carbon sequestration in national inventories: a soil scientist's perspective," *Environmental Research Letters,* vol. 5, no. 3, p. 034003, 2010.

[10] IPCC, "Good Practice Guidance for Land Use, Land-Use Change and Forestry," IPCC, 2021.

[11] N. Tautges, J. Chiartas, A. Gaudin, A. O'Geen, I. Herrera and K. Scow, "Deep soil inventories reveal that impacts of cover crops and compost on soil carbon

sequestration differ in surface and subsurface soils.," *Global change biology,* vol. 25, no. 11, pp. 3753-3766, 2019.

[12] S. J. Deverel and D. A. Leighton, "Historic, recent, and future subsidence, sacramento-san Joaquin delta, California, USA," *San Francisco Estuary and Watershed Science,* vol. 8, no. 2, 2010.

[13] D. Nowak and E. Greenfield, "US urban forest statistics, values, and projections," *Journal of Forestry,* vol. 116, no. 2, pp. 164-177, 2018.

[14] State of California, *PUBLIC RESOURCES CODE - PRC 4291 - DIVISION 4. FORESTS, FORESTRY AND RANGE AND FORAGE LANDS - PART 2. PROTECTION OF FOREST, RANGE AND FORAGE LANDS,* Sacramento: State of California, 2021.

[15] C. Li, "The DNDC model.," *Evalution of soil organic matter models,* pp. 263-267, 1996.

[16] W. Parton, M. Hartman, D. Ojima and D. Schimel, "DAYCENT and its land surface submodel: description and testing," *Global and Planetary Change,* vol. 19, pp. 35-48, 1998.

[17] State of California, United States Forest Service, "Agreement for shared stewardship of California's forests and rangelands," State of California, Sacramento, 2020.

[18] M. Rollins, "LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment.," *Journal of Wildland Fire,* vol. 18, no. 3, pp. 235-249, 2009.

[19] USGS, "Water resources of the United States: Hydrological Unit Maps.," [Online]. Available: https://water.usgs.gov/GIS/huc.html. [Accessed 1 December 2020].

[20] Z. Zhu, J. Vogelmann, D. Ohlen, J. Kost, X. Chen, B. Tolk and M. Rollins, "Mapping existing vegetation composition and structure for the LANDFIRE prototype project.," The LANDFIRE prototype project: nationally consisten and locally relevant geospatial data and tools for wildland fire management, 1998.

[21] M. Rollins, "LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment.," *International Journal of Wildland Fire,* vol. 18, no. 3, pp. 235-249, 2009.

[22] J. Abatzoglou, S. Dobrowski, S. Parks and K. Hegewisch, "Terraclimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015," *Scientific Data,* vol. 5, pp. 170-191, 2018.

[23] J. Omernik and G. Griffith, "Ecoregions of the conterminous United States: evolution of a hierarchical spatial framework," *Environmental Management,* vol. 54, no. 6, pp. 1249-1266, 2014.

[24] California Air Resources Board, "An Inventory of Ecosystem Carbon in California's Natural & Working Lands," State of California, Sacramento, 2018.

[25] R. Bart, M. Kennedy, C. Tague and McKenzie, "Integrating fire effects on vegetation carbon cycling within an ecohydrologic model," *Ecological Modeling,* vol. 416, p. 108880, 2020.

[26] C. L. Tague and L. E. Band, "RHESSys: Regional Hydro-Ecologic Simulation System—An Object-Oriented Approach to Spatially Distributed Modeling of Carbon, Water, and Nutrient Cycling," *Earth Interactions,* vol. 8, no. 19, p. 1–42, 2004.

[27] G. D. Farquhar and S. v. Caemmerer, "Modelling of Photosynthetic Response to Environmental Conditions," in *Physiological Plant Ecology II (pp. 549–587)*, Springer Berlin, 1982.

[28] M. G. Ryan, "Effects of Climate Change on Plant Respiration," *Ecological Applications,* vol. 1, no. 2, p. 157–167, 1991.

[29] M. G. Tjoelker, J. Oleksyn and P. B. Reich, "Modelling respiration of vegetation: Evidence for a general temperature-dependent Q10," *Global Change Biology,* vol. 7, no. 2, p. 223–230, 2001.

[30] M. C. Kennedy, D. McKenzie, C. Tague and A. L. Dugger, "Balancing uncertainty and complexity to incorporate fire spread in an eco-hydrological model," *International Journal of Wildland Fire,* vol. 26, no. 8, p. 706–718, 2017.

[31] R. R. Bart, M. C. Kennedy, C. L. Tague and D. McKenzie, "Integrating fire effects on vegetation carbon cycling within an ecohydrologic model," *Ecological Modelling,* vol. 416, p. 108880, 2020.

[32] C. L. Tague, N. G. McDowell and C. D. Allen, "An Integrated Model of Environmental Effects on Growth, Carbohydrate Balance, and Mortality of Pinus ponderosa Forests in the Southern Rocky Mountains," *PLoS ONE,* vol. 8, no. 11, p. e80286, 2013.

[33] B. Livneh, T. J. Bohn, D. W. Pierce, F. Munoz-Arriola, B. Nijssen, R. Vose, D. R. Cayan and L. Brekke, "A spatially comprehensive, hydrometeorological data set for Mexico, the U.S., and Southern Canada 1950–2013," *Scientific Data,* vol. 2, no. 1, p. 150042, 2015.

[34] D. W. Pierce, D. R. Cayan and B. L. Thrasher, "Statistical Downscaling Using Localized Constructed Analogs (LOCA)," *Journal of Hydrometeorology,* vol. 15, no. 6, p. 2558–2585, 2014.

[35] D. W. Pierce, J. F. Kalansky and D. R. Cayan, "Climate, Drought, and Sea Level Rise Scenarios for California's Fourth Climate Change Assessment," California Energy Commission., Sacramento, 2018.

[36] D. Schwede and G. Lear, "A novel hybrid approach for estimating total deposition in the United States," *Atmospheric Environment,* vol. 92, pp. 207-2020, 2014.

[37] Total Deposition Science Committee, "Hybrid approach to mapping total deposition," National Atmospheric Deposition Program, Madison, 2021.

[38] IPCC, "Annex II: Climate System Scenario Tables," Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, New York, 2013.

[39] M. Zhao, F. Heinsch, R. Nemani and S. Running, "Improvements of the MODIS terrestrial gross and net primary production global data set," *Remote sensing of Environment,* vol. 95, no. 2, pp. 164-176, 2005.

[40] M. Simard, N. Pinto, J. B. Fisher and A. Baccini, "Mapping forest canopy height globally with spaceborne lidar," *Journal of Geophysical Research: Biogeosciences,* vol. 116, p. G04021, 2011.

[41] J. C. Refsgaard, "Parameterisation, calibration and validation of distributed hydrological models," *Journal of Hydrology,* vol. 198, no. 1-4, p. 69–97, 1997.

[42] H. V. Gupta, H. Kling, K. K. Yilmaz and G. F. Martinez, "Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling," *Journal of Hydrology,* vol. 377, no. 1, p. 80–91, 2009.

[43] M. G. Rollins, "LANDFIRE: A nationally consistent vegetation, wildland fire, and fuel assessment," *International Journal of Wildland Fire,* vol. 18, no. 3, p. 235–249, 2009.

[44] A. Moreno, M. Neumann and H. Hasenauer, "Climate limits on European forest structure across space and time," *Global and Planetary Change,* vol. 169, pp. 168-178, 2018.

[45] R. Knutti, R. Furrer, C. Tebaldi, J. Cermak and G. Meehl, "Challenges in combining projections from multiple climate models," *Journal of Climate,* vol. 23, no. 10, pp. 2739-2758, 2010.

[46] D. Pierce, J. Kalansky and D. Cayan, "Climate, Drought, and sea level rise scenarios for California's fourth climate change assessment," State of California, Sacramento, 2018.

[47] G. Christensen, A. Gray, O. Kuegler, N. Tase and R. M, "AB 1504 California Forest Ecosystem and Harvested Wood Product Carbon Inventory: 2019 Reporting Period Data update. U.S. Forest Service agreement no. 18-CO-11052021-214," California Department of Forestry and Fire Protection and California Board of Forestry and Fire Protection, Sacramento, 2019.

[48] D. Wang, D. Guan, S. Zhu, M. Kinnon, G. Geng, Q. Zhang, H. Zheng, T. Lei, S. Shao, P. Gong and S. Davis, "Economic footprint of California wildfires in 2018," *Nature Sustainability,* vol. 4, no. 3, pp. 252-260, 2021.

[49] C. Wiedinmyer, S. Akagi, R. Yokelson, L. Emmons, J. Al-Saadi, J. Orlando and A. Soja, "he Fire INventory from NCAR (FINN): A high resolution global model to estimate the emissions from open burning," *Geoscientific Model Development,* vol. 4, no. 3, pp. 625-641, 2011.

[50] California Air Resources Board, "Wildfire Emissions & Burned Area Estimates 2000-2020," State of California, Sacramento, 2021.

[51] California Air Resources Board, "CARB's Methodology for Estimating the Health Effects of Air Pollution," The State of California, [Online]. Available: https://ww2.arb.ca.gov/resources/documents/carbs-methodology-estimating-health-effects-air-pollution. [Accessed 19 4 2022].

[52] Forest Management Task Force, "California's Wildfire and Forest Resilience Action Plan," 2021.

[53] State of California, "Agreement for Shared Stewardship of California's Forest and Rangelands," 12 August 2020. [Online]. Available: https://www.gov.ca.gov/wp-content/uploads/2020/08/8.12.20-CA-Shared-Stewardship-MOU.pdf.

[54] California Energy Commission, "Potential Positive and Negative Environmental Impacts of Increased Woody Biomass Use for California," 2011.

[55] D. Sandalow, R. Aines, J. Friedmann, C. McCormick and D. Sanchez, "Biomass Carbon Removal and Storage (BiCRS) Roadmap," Innovation for Cool Earth Forum, Tokyo, 2021.

[56] California Energy Commission, "Biomass Energy in California," 26 April 2022. [Online]. Available: https://www.energy.ca.gov/data-reports/california-power-generation-and-power-sources/biomass/biomass-energy-california.

[57] California Public Utilities Commission, "Bioenergy Feed-in Tariff Program (SB 1122)," 26 April 2022. [Online]. Available: https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/electric-power-procurement/rps/rps-procurement-programs/rps-sb-1122-biomat.

[58] Sierra Club California, "Moving Beyond Incineration," 2019.

[59] J. Carman, M. Severy, C. Barrientos, M. Blasdel, C. Geronimo, A. Harris, C.-W. Hsu, J. Kane, S. Rios-Romero, M. Wright and K. Fingerman, "California Biomass Residue Emissions Characterization (C-BREC) Model Framework," Schatz Energy Research Center and Humboldt State University Department of Environmental, Arcata, 2021.

[60] Y. Zhang and M. Goldberg, "Jobs and Economic Development Impact (JEDI) User Reference Guide: Fast Pyrolysis Biorefinery Model," National Renewable Energy Laboratory, Golden, 2015.

[61] S. Holland, E. Mansur, N. Muller and A. Yates, "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors.," *American Economic Review,* pp. 3700-3729, 2016.

[62] Oak Ridge National Laboratory, "2016 Billion Ton Report," U.S. Department of Energy, Oak Ridge, 2016.

[63] ICF for the American Gas Foundation (AGF), "Renewable Sources of Natural Gas: Supply and Emissions Reduction Assessment," 2019.

[64] R. B. Williams, B. M. Jenkins and S. Kaffka, "An Assessment of Biomass Resources in California, 2013," California Energy Commission, 2015.

[65] Katherine A. Mitchell, California Biomass Collaborative, UC Davis; Nathan C. Parker, Institute of Transportation Studies, UC Davis; Benktesh Sharma, Center for Forestry, UC Berkeley; Stephen Kaffka, Director, California Biomass Collaborative, UC Davis, "Potential for Biofuel Production from Forest Woody Biomass (Report)," Biomass Collaborative, UC Davis, Davis, CA, January 2015.

[66] B. Cabiyo, B. M. Collins, J. S. Fried, W. Stewart, J. Wong and D. L. Sanchez, "Innovative wood use can enable carbon-beneficial forest management in California," *PNAS,* 22 November 2021.

[67] S. E. Baker, J. K. Stolaroff, G. Perid and et al., "Getting to Neutral: Options for Negative Carbon Emissions in California," 2020.

[68] CalRecycle, "SB 498 Biomass Conversion Facility Reporting," 2021. [Online]. Available: https://calrecycle.ca.gov/swfacilities/rdreporting/biomass/#.

[69] University of Montana Bureau of Business and Economic Research, "Energy Use and Emissions by the California Sawmill Sector, 2016," California Department of Forestry and Fire Protection, Sacramento, CA, 2019.

[70] California Governor's Office of Planning and Research, "Sustainable Woody Biomass Industry Development in California," 2022.

[71] California Air Resources Board, "Natural and Working Lands Carbon Inventory," The State of California, Sacramento, 2018.

[72] California Department of Food and Agriculture, "2019 Califronia Almond Acreage Report," The State of California, Sacramento, California, 2020.

[73] United States Department of Agriculture National Agricutural Statistics Service, "2017 California Walnut Acreage Report," Pacific Regional Office, Sacrament, California, 2018.

[74] B. Sleeter, T. Wilson, E. Sharygin and J. Sherba, "Future scenarios of land change based on empirical data and demographic trends," *Earth's Future,* vol. 5, no. 11, pp. 1068-1083, 2017.

[75] USDA, Colorado State University, "COMET-Planner," [Online]. Available: http://www.comet-planner.com/.

[76] B. Parton, D. Ojima, S. Del Grosso and C. Keough, "CENTURY tutorial. Supplement to Century User's manual," 2001.

[77] S. Del Grosso, D. Ojima, W. Parton, A. Mosier, G. Peterson and D. Schimel, "Simulated effects of dryland cropping intensification on soil organic matter and greenhouse gas exchanges using the DAYCENT ecosystem model.," *Environmental pollution,* vol. 116, pp. S75-S83, 2002.

[78] L. Bedsworth, J. Anderson, G. A. M. Franco and S. Wilhelm, "Projected climate scenarios selected to represent a range ofpossible futures in California. California Energy Commission, ClimateAction Team Research Working Group, docket number16-IEPR-04, TN# 215798," 2017. [Online]. Available: https://efiling.energy.ca.gov/GetDocument.aspx?tn=215798.

[79] NRCS, "Soil Survey Geographic (SSURGO) Database," USDA Natural Resources Conservation Service. , edited, 2009.

[80] K. E. Saxton, W. J. Rawls, J. S. Romberger and R. I. Papendick, "Estimating generalized soil-water characteristics from texture," *Soil Science Society of America Journal,* vol. 50, no. 4, pp. 1031-1036, 1986.

[81] B. Basso, P. K. O. Gargiulo, G. P. Robertson, C. Porter, P. R. Grace and J. W. Jones, "Procedures for Initializing Soil Organic Carbon Pools in the DSSAT-CENTURY Model for Agricultural Systems," *Soil Science Society of America Journal,* vol. 75, no. 1, pp. 69-78, 2011.

[82] NASS, "Agricultural Chemical Usage: 2002 Field Crops Summary," National Agricultural Statistics Service. USDA, 2003.

[83] NASS, "Field Crops: Usual Planting and Harvesting Dates," National Agricultural Statistics Service. USDA, 2010.

[84] USDA, Colorado State University, "A companion report to www.comet-planner.com," 2015.

[85] A. Gattinger, A. Muller, M. Haeni, C. Skinner, A. Fliessbach, N. Buchmann, P. Mäder, M. Stolze, P. Smith, N. Scialabba and U. Niggli, "Enhanced top soil carbon stocks under organic farming," *Proceedings of the National Academy of Sciences,* vol. 109, no. 44, pp. 18226-18231, 2012.

[86] K. Gravuer, "Compost Application Rates for California Croplands and Rangelands for a CDFA Healthy Soils Incentives Program," California Department of Food and Agriculture, Sacramento, 2016.

[87] K. Hughes and A. Dusault, "Achieving Economic and Environmental Benefit through Agricultural and Municipal Cooperation in Co-composting Green Waste with Animal Manure," 2003 OSWER Innovations Pilot Project, San Francisco, 2003.

[88] R. Rynk, M. v. d. Kamp, G. Willson, M. Singley and e. al, "On-Farm Composting Handbook," Northeast Regional Agricultural Engineering Service Cooperative Extension, Ithaca, 1992.

[89] J. Owen and W. Silver, "Greenhouse gas emissions from dairy manure management in a Mediterranean environment," *Ecological applications,* vol. 27, no. 2, pp. 545-559, 2017.

[90] US EPA, "Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2018 – Annex 3 Part B," USA, 2021.

[91] D. Pierce, D. Cayan and B. Thrasher, "Statistical downscaling using Localized Constructed Analogs (LOCA)," *Journal of Hydrometeorology,* vol. 15, pp. 2558-2585, 2014.

[92] E. McPherson, Q. Xiao, N. van Doorn, J. de Goede, J. Bjorkman, A. Hollander, R. Boynton, J. Quinn and J. Thorne, "The structure, function and value of urban

forests in California communities.," *Urban Forestry & Urban Greening,* vol. 28, pp. 43-53, 2017.

[93] CAL FIRE, "Defensible Space," The State of California, [Online]. Available: https://www.fire.ca.gov/programs/communications/defensible-space-prc-4291/. [Accessed 29 April 2022].

[94] California State Assembly, "AB-38 Fire safety: low-cost retrofits: regional capacity review: wildfire mitigation.," The State of California, Sacramento, 2019.

[95] California State Assembly, "AB-3074 Fire prevention: wildfire risk: defensible space: ember-resistant zones.," The State of California, Sacramento, 2020.

[96] CALFIRE - FRAP, "GIS Data," [Online]. Available: https://frap.fire.ca.gov/mapping/gis-data/. [Accessed 27 April 2022].

[97] Microsoft, "Github," [Online]. Available: https://github.com/microsoft/USBuildingFootprints. [Accessed 27 April 2022].

[98] Salo Sciences, "The California Forest Observatory," [Online]. Available: https://forestobservatory.com/. [Accessed 27 April 2022].

[99] Salo Sciences, "California Forest Observatory: Introduction Webinar," YouTube, 2020.

[100] NOAA, "C-CAP Regional Land Cover and Change," NOAA Office for Coastal Management, 2016. [Online]. Available: https://coast.noaa.gov/digitalcoast/data/ccapregional.html. [Accessed 28 April 2022].

[101] L. Brophy, C. Greene, V. Hare, B. Holycross, A. Lanier, W. Heady, K. O'Connor, H. Imaki, T. Haddad and R. Dana, "Insights into estuary habitat loss in the western United States using a new method for mapping maximum extent of tidal wetlands," *PloS one,* p. e0218558, 2019.

[102] S. Deverel, T. Ingrum and D. Leighton, "Present-day oxidative subsidence of organic soils and mitigation in the Sacramento-San Joaquin Delta, California, USA.," *Hydrogeology Journal,* pp. 569-586, 2016.

[103] Soil Survey Staff, "Soil Survey Geographic (SSURGO).," Natural Resources Conservation Service, United States Department of Agriculture. .

[104] S. H. Knox, L. Windham-Myers, F. Anderson, C. Sturtevant and B. Bergamaschi, "Direct and indirect effects of tides on ecosystemscale CO2 exchange in a brackish tidal marsh in Northern California," *Journal of Geophysical Research: Biogeosciences,* pp. 787-806, 2018.

[105] K. S. Hemes and e. al, "Assessing the carbon and climate benefit of restoring degraded agricultural peat soils to managed wetlands," *Agricultural and Forest Meteorology* , pp. 202-214, 2019.

[106] S. Schaffer and T. E. Jr, "A New Comparison of Greenhouse Gas Emissions from California Agricultural and Land Use," American Farmland Trust, 2015.

[107] C. Li, J. Six, W. Horwath and W. Salas, "Calibrating, Validating, and Implementing Process Models for California Agriculture Greenhouse Gas Emissions, Final Report to the Air Resources Board," California Air Resources Board, Sacramento, 2014.

[108] J. Callaway, E. Borgnis, R. Turner and C. Milan, "Carbon Sequestration and Sediment Accretion in San Francisco Bay Tidal Wetlands," *Estuaries Coasts* , p. 1163–1181, 2012.

[109] S. Deverel, B. Wang and S. Rojstaczer, "Subsidence in the Sacramento-San Joaquin Delta, in Borchers, JW, (ed.)," *Proceedings of the Joseph Poland Subsidence Symposium, Association of Engineering Geologists, Special Publication No. 8,* pp. 489-502, 1998.

[110] D. Bachelet, K. Ferschweiler, T. Sheehan and J. Strittholt, "Climate change effects on southern California deserts.," *Journal of Arid Environments,* vol. 127, pp. 17-29, 2016.

[111] D. Hirmas, C. Amrhein and R. Graham, "patial and process-based modeling of soil inorganic carbon storage in an arid piedmont.," *Geoderma,* vol. 154, no. 3-4, pp. 486-494, 2010.

[112] D. Bachelet, K. Ferschweiler, T. Sheehan and J. Strittholt, "Climate change effects on southern California deserts," *Journal of Arid Environments,* vol. 1, no. 127, pp. 17-29, 2016.

[113] B. Sleeter, T. Wilson, E. Sharygin and J. Sherba, "Future scenarios of land change based on empirical data and demographic trends.," *Earth's Future,* vol. 5, no. 11, pp. 1068-1083, 2017.

[114] B. Sleeter, J. Liu, C. Daniel, L. Frid and Z. Zhu, " An integrated approach to modeling changes in land use, land cover, anddisturbance and their impact on ecosystem carbon dynamics: A case study in the sierra Nevada Mountains of California.," *AIMS Environmental Science,* vol. 2, no. 3, p. 577–606, 2015.

[115] U. S. G. Survey, "ScienceBase-Catalog," [Online]. Available: https://www.sciencebase.gov/catalog/item/587fb408e4b085de6c11f389. [Accessed 19 April 2022].

[116] 2. US Department of Agriculture Forest Service, "S_USA.Activity_HazFuelTrt_PL," 2020.

[117] US Department of Agriculture, Forest Service, "Special data request from Transaction Evidence Appraisal (TEA) System.," 2022.

[118] California Department of Food and Agriculture, "Healthy Soils Program," [Online]. Available: https://www.cdfa.ca.gov/oefi/healthysoils/incentivesprogram.html.

[119] K. Klonsky, "Comparison of Production Costs and Resource Use for Organic and Conventional Production Systems.," *Amererican Journal of Agricultural Economics,* no. 94, pp. 314-321, 2012.

[120] L. E. Drinkwater, D. K. Letourneu, F. Workneh, A. H. C. van Bruggen and C. Shennan, "Fundamental Differences Between Conventional and Organic Tomato Agroecosystems in California," *Ecological Applications,* pp. 1098-1112, 1995.

[121] J. W. Reganold, "Organic Agriculture in the twenty-first century," *Nature Plants,* 2016.

[122] California Department of Food and Agriculture, "California Agricultural Statistics Review," 2020.

[123] California Department of Food and Agriculture, "California Agricultural Organic Report," 2020.

[124] J. Bjorkman, J. Thorne, A. Hollander, N. Roth, R. Boynton, J. de Goede, Q. Xiao, K. Beardsley, G. McPherson and J. Quin, "Biomass, Carbon Sequestration, and Avoided Emissions: Assesing the Role of Urban Trees in California," Information Center for the Enviornment, University of California, Davis., 2015.

[125] A. Kunsch and R. Parks, " Tree Planting Cost-Benefit Analysis: A Case Study for Urban Forest Equity in Los Angeles," Tree People, 2021.

[126] E. G. McPherson, K. I. Scott, J. R. Simpson, Q. Xiao and P. J. Peper, "Tree Guidelines for Coastal Southern California Communities," Western Center for Urban Forest Research and Education, USDA Forest Service Pacific Southwest Research Station, 2000.

[127] E. G. McPherson, J. R. Simpson, P. J. Peper, S. L. Gardner, K. E. Vargas, S. E. Maco and Q. Xiao, "Piedmont community tree guide; benefits, costs, and strategic planting.," US Department of Agriculture, Forest Service, Pacific Southwest Research Station, 2006.

[128] E. G. McPherson, Q. Xiao, N. S. van Doorn, J. de Goede, J. Bjorkman, A. Hollander, R. M. Boynton, J. F. Quinn and J. H. Thorne, "The structure, function and value of urban forests in California communities," *Urban Forestry & Urban Greening,* vol. 28, pp. 43-53, 2017.

[129] E. G. McPherson,, J. R. Simpson, P. J. Peper, A. M. Crowell and Q. Xiao, "Northern California coast community tree guide: benefits, costs, adn strategic planting," U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station, 2010.

[130] C. R. Analysis, "A Market Study of Land Values Related to Several Areas of Prospective Acquisition, Associated with the Coachella Valley Multiple Species Habitat Conservation Plan," 2010.

[131] S. L. Quarles and K. Pohl, "Building a Wildfire-Resistant Home:," 2018.

[132] Regional Economic Models Inc., "Model Equations," 2017.

[133] California Natural Resources agency, "Expanding Nature-Based Solutions," State of California, 2022. [Online]. Available: https://resources.ca.gov/Initiatives/Expanding-Nature-Based-Solutions. [Accessed 21 April 2022].

[134] J. Dingman, L. Guo, M. Miranda, A. Moreno, K. Scott and A. Huang, "Technical Support Document for the Natural & Working Lands Inventory," Air Quality Planning and Science Division of The California Air Resources Board, Sacramento, CA, 2018.

[135] California Natural Resources Agency, "Expanding Nature-Based Solutions," State of California, 2022. [Online]. Available: https://resources.ca.gov/Initiatives/Expanding-Nature-Based-Solutions. [Accessed 21 April 2022].

[136] C. Knight, L. Anderson, M. Bunting, M. Champagne, R. Clayburn, J. Crawford, A. Klimaszewski-Patterson, E. Knapp, F. Lake, S. Mensing and D. Wahl, "Land management explains major trends in forest structure and composition over the last millennium in California's Klamath Mountains," *Proceedings of the National Academy of Sciences*, vol. 119, no. 12, p. 2116264119, 2022.

[137] M. J. S. a. D. C. C. D. o. F. a. F. P. Rosenberg, "Biomass potentials from California forest and shrublands including fuel reduction potentials to lessen wildfire threat," 2005.

Appendix I.1 – NWL Synthesis

Background

The NWL sector includes a vast array of ecosystem types, each with their own particular environmental conditions, management practices and climate regimes. The complexity of estimating future statewide sequestration and emissions rates results from this ecosystem diversity and each system's response to climate and management change. Increasing interest in the NWL sector's essential role in climate change mitigation and carbon neutrality have led to a growing number of studies examining this topic, though modeling efforts to estimate the future of Californian ecosystems, and actions to alter them, have been performed for decades. These existing efforts help with CARB's objective of integrating the NWL sector into statewide targets for climate mitigation and gaining an understanding to how current and past science has quantified this sector's future.

Staff conducted a synthesis of existing literature and studies on 1) BAU projections and 2) action outcome estimates. Each of these syntheses produced a range of BAU projection and action outcome estimates across different land types and actions. A meta-analysis, which involves collating results from many disparate studies to answer a new question, was conducted on the BAU projection studies and on the action outcome studies for forests. For the action outcome studies on all other land types, a simpler synthesis of the literature was conducted due to time and resource constraints. The systematic compilation and analysis of quantitative data from multiple studies enables CARB to utilize more robust information that avoids relying on any single study. The results of the syntheses provide context for CARB's strategies for the NWL sector and help ensure a feasible, scientifically informed target is set.

The BAU synthesis will assess the state of the science regarding how California ecosystems are expected to change in the future without any adjustments to existing policies and practices. The main question was: *Given all current research, what is California NWL's future climate benefit or liability?* This synthesis informs CARB of whether the NWL sector is expected to gain or lose carbon in the future, the approximate magnitude of gain or loss, and highlight which ecosystems have the largest potential for loss or gain.

The synthesis of action outcome estimates examines the outcomes of individual NWL management practices that are expected to produce climate benefits. The main questions were: *What are the most promising combinations of actions to explore? What is the best possible theoretical carbon outcome given NWL trajectory and most beneficial actions?* This synthesis shows the predicted magnitude and range of carbon impacts CARB can expect from the practices included in the modeling efforts. CARB uses the impact estimates to compare with the modeled results to validate modeling processes. These estimates are focused solely on carbon benefits and provide only limited insight into feedbacks between practices, co-benefits, or tradeoffs. CARB acknowledges that there are many other management strategies that could be implemented on NWLs to benefit the State and the climate, and the fact that a particular practice was not included in the modeling conducted for the Scoping Plan does not mean CARB does not consider that practice to be beneficial.

Methods

The procedures for the literature syntheses are outlined below:

Staff identified keywords to define the literature search in order to capture all pertinent studies. Keyword categories included geographic, ecosystem/cover type, climate, and outcome related descriptors(Table 73, Figure 73).

1. Staff identified seed papers, which represent known studies that exemplify the type of research that is pertinent to this search, to include its' citations and any papers that cited the seed paper in the synthesis (Table 74, Table 76).
2. Keyword search parameters were used to conduct the Web of Science search. All results were compiled into a database.
3. Titles were screened to eliminate results that were unrelated.
4. Abstracts were screened to eliminate results that were unrelated.

5. The following criteria were used to eliminate results:
    a. Geographic location not relevant to California
    b. Land or vegetation type not relevant to California
    c. Management action not relevant to California
6. Papers were perused for useful data and eliminated if no data was provided.
7. Study attributes such as location of study, land cover type, vegetation type, type of study, model used in the study, practice evaluated, duration of study, timing of data collection, climate assumptions, data/results provided, plus other attributes were extracted from studies and compiled into an attribute database.
8. Attribute database was evaluated to determine the types of syntheses that could be conducted with the available data. Staff considered study scale, location, vegetation type, output data, climate change assumptions, and sample size. Studies were eliminated that could not be used in a synthesis.
9. BAU projection and action outcome data, and uncertainty where available, from select papers were extracted and compiled in an extracted data database. Data points were extracted from tables or from figures using the Web Plot Digitizer tool.
10. Compiled data was synthesized for land types, by region, and for management actions. The level and detail of synthesis depended on the quantity of studies and data points that were compiled for a certain land type or action. See more detailed discussion of each synthesis below.

Table 73. Keywords and Seed Papers used for the literature search in the BAU synthesis. * is a wildcard search character to capture similar terms, e.g. Agricultur* captures terms such as agriculture and agricultural.

Geographic	Ecosystem/Cover Type	Climate	Outcome
California	Agricultur*	Drought	Carbon
Sierra Nevada	Forest	Warm*	Biomass
Central Valley	Wetland	Future	Greenhouse Gas
Mojave	Desert	21st Century	Producti*
Sacramento Valley	Woodland	Precipitation	Flux
Southern California	Grassland	Rain*	Stocks
Northern California	Shrubland	Temperature	Sequest*
San Francisco Bay	Rangeland	Snow*	Methane
West Coast	Chaparral	CO2	Nitrous Oxide
Pacific Coast	Redwood	Fire	Radiative Forc*
Western United States	Temperate Rainforest	VPD	Decompos*
Mediterranean	Urban Forest	Arid*	NA
Klamath	Soil	Fog	NA
SSJD	Five needle pine	Climate	NA
San Joaquin	Riparian	NA	NA
Northwest	Sequoia	NA	NA
Southwest	Farm	NA	NA
Colorado Desert	NA	NA	NA
Great Basin	NA	NA	NA

Table 74: Seed papers for the BAU synthesis.

Sleeter, B. M., Marvin, D. C., Cameron, D. R., Selmants, P. C., Westerling, A. L., Kreitler, J., ... & Wilson, T. S. (2019). Effects of 21st-century climate, land use, and disturbances on ecosystem carbon balance in California. *Global change biology*, *25*(10), 3334-3353.
Liang, S., Hurteau, M. D., & Westerling, A. L. (2017). Potential decline in carbon carrying capacity under projected climate-wildfire interactions in the Sierra Nevada. *Scientific reports*, *7*(1), 1-7.
Lenihan, J. M., Drapek, R., Bachelet, D., & Neilson, R. P. (2003). Climate change effects on vegetation distribution, carbon, and fire in California. *Ecological Applications*, *13*(6), 1667-1681.
Lenihan, J. M., Bachelet, D., Neilson, R. P., & Drapek, R. (2008). Response of vegetation distribution, ecosystem productivity, and fire to climate change scenarios for California. *Climatic Change*, *87*(1), 215-230.
Shaw, M. R., Pendleton, L., Cameron, D. R., Morris, B., Bachelet, D., Klausmeyer, K., ... & Haunreiter, E. (2011). The impact of climate change on California's ecosystem services. *Climatic Change*, *109*(1), 465-484.
Underwood, E. C., Hollander, A. D., Safford, H. D., Kim, J. B., Srivastava, L., & Drapek, R. J. (2019). The impacts of climate change on ecosystem services in southern California. *Ecosystem Services*, *39*, 101008.
Reeves, Matthew C., et al. "Estimating climate change effects on net primary production of rangelands in the United States." *Climatic Change* 126.3-4 (2014): 429-442.

Table 75: Keywords and Seed Papers used for the literature search in the Actions synthesis * is a wildcard search character to capture similar terms, e.g. Agricultur* captures terms such as agriculture and agricultural.

Geographic	Ecosystem/Cover Type	Management Action	Outcome
California	Agricultur*	Management	Carbon
Sierra Nevada	Forest	Reforestation	Biomass
Central Valley	Wetland	Restoration	Greenhouse Gas
Mojave	Desert	Fire	Producti*
Sacramento Valley	Woodland	Fuels reduction	Flux
Southern California	Grassland	Thin*	Stocks
Northern California	Shrubland	Treatment	Sequest*
San Francisco Bay	Rangeland	Avoided conversion	Methane
West Coast	Chaparral	Biomass Utilization	Nitrous Oxide
Pacific Coast	Redwood	Conserv*	Radiative Forc*
Western United States	Temperate Rainforest	Compost addition	Decompos*
Mediterranean	Urban Forest	Agroforestry	NA
Klamath	Soil	Graz*	NA
SSJD	Five needle pine	Till*	NA
San Joaquin	Riparian	Cover crop*	NA
Northwest	Sequoia	Mulch*	NA
Southwest	Farm	Nutrient manag*	NA
Colorado Desert	NA	Biochar	NA
Great Basin	NA	Whole orchard recycl*	NA
NA	NA	Compost application	NA
NA	NA	Windbreak	NA
NA	NA	Hedgerow	NA

Table 76: Seed papers for the actions synthesis.

Cameron, D. R., Marvin, D. C., Remucal, J. M., & Passero, M. C. (2017). Ecosystem management and land conservation can substantially contribute to California's climate mitigation goals. *PNAS,* 114(48) 12833-12838.
Griscom, B. W., Adams, J., Ellis, P. W., Houghton, R. A., Lomax, G., Miteva, D. A., … & Fargione, J. (2017). Natural climate solutions. *PNAS*, 114(44), 11645-11650.
Hurteau, M. D., Robards, T. A., Stevens, D., Saah, D., North, M., & Koch, G. W. (2014). Modeling climate and fuels reduction impacts on mixed-conifer forest carbon stocks in the Sierra Nevada, California. *Forest Ecology and Management*, 315, 30-42.
Lian, S., Hurteau, M. D., & Westerling, A. L. (2018). Large-scale restoration increases carbon stability under projected climate and wildfire regimes. *Frontiers in Ecology and the Environment,* 16(4), 207-212.
Jahanzad, E., Holtz, B. A., Zuber, C. A., Doll, D., Brewer, K. M., Hogan, S., & Gaudin, A. C. M. (2020) Orchard recycling improves climate change adaptation and mitigation potential of almond production systems. *PLoS ONE,* 15(3).
Lal, R. (2004). Soil carbon sequestration to mitigate climate change. *Geoderma*, *123*(1-2), 1-22.

Results

BAU Synthesis

Literature Results

Figure 54 shows the number of studies at each stage of our methodology for the BAU and action outcomes synthesis. First, key words and seed papers resulted in thousands of papers. Then the process of manually filtering papers to develop a body of literature that answers the Scoping Plans questions. The two primary questions of these two syntheses was, 1) what is the future of California's NWL carbon stocks, and 2) how might these outcomes change given climate action.

A screening process is the labor-intensive process of filtering papers from an initial search to result in a relevant body of literature that can be used for an informative meta-analysis. The papers that resulted from the search were then screened by title to ensure that the paper was potentially appropriate. The resulting papers were then filtered by reading every abstract. Once filtered by abstract, papers were filtered after reading the entire text. The resulting papers were then filtered by if relevant data could be extracted from the paper for a meta-analysis. See the Methods section for more details.

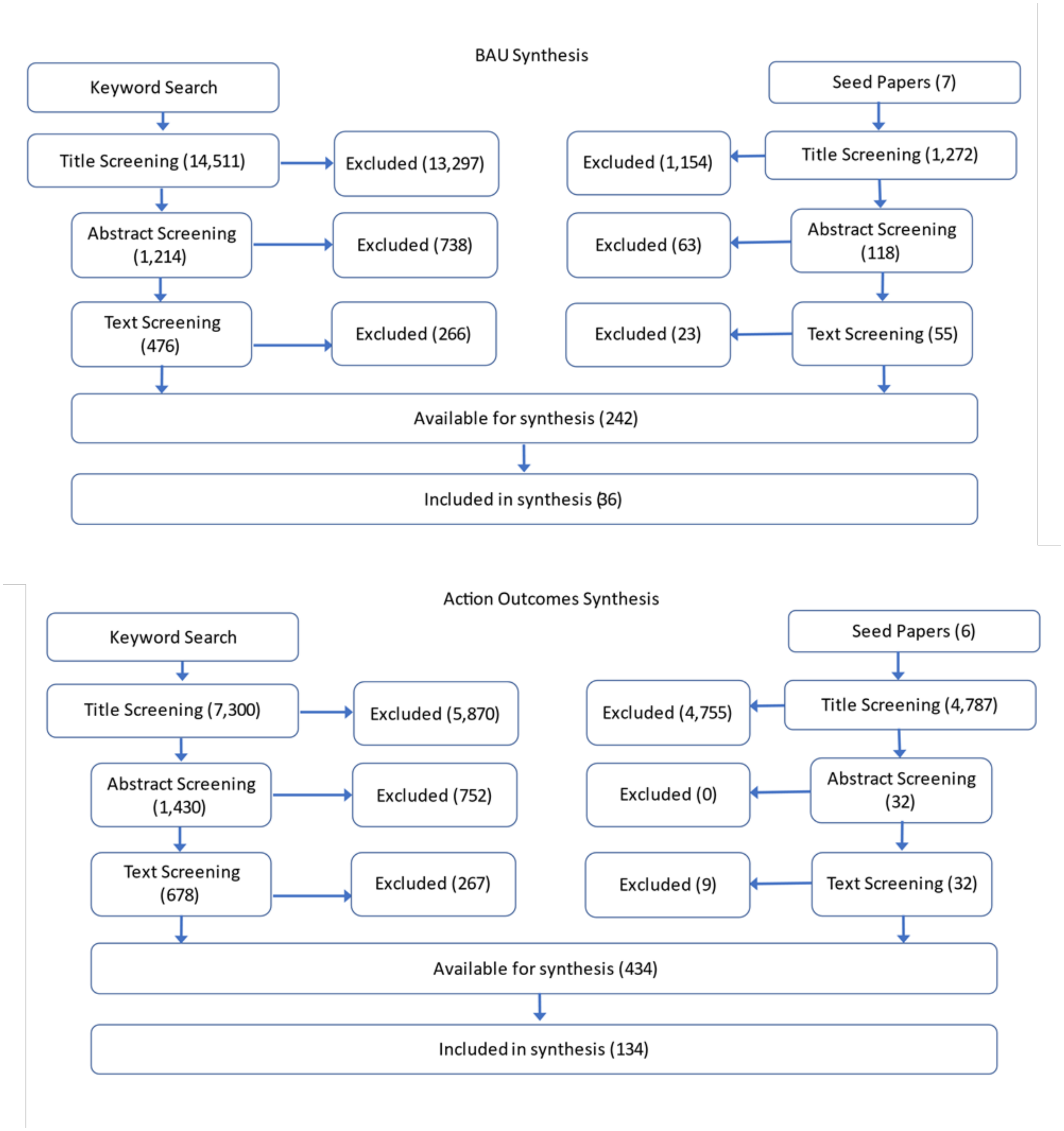

Figure 54: BAU (top) and action outcomes (bottom) synthesis literature count results for the Keywords and Seed Papers identified in Table 73, following the methodology described in the Methods section. Each box includes in parentheses the number of articles at that step of the methodology. "Excluded" boxes indicate how many papers were excluded at that screening stage based on screening criteria described in the Methods section.

Statewide

Four publications (Lenihan et al. 2003, Lenihan et al. 2008, Sleeter et al. 2019, Dass 2018) projected carbon stocks over the entire State, including all land types. However, Lenihan 2008 is an update to Lenihan 2003, so for this assessment only Lenihan 2008 was used. These studies included multiple projection runs, for a total of 15 results, under various climate change projections. The weighted average of all results was calculated by weighting the 15 results proportionally so that the papers have equal weight no matter the number of scenarios modeled. To normalize the results, they were compared to 2001 carbon stocks levels (Figure 55). On average, the projections indicate a decline in statewide carbon stocks into the future. This decline is driven by climate change, land conversion, and increased wildfire activity.

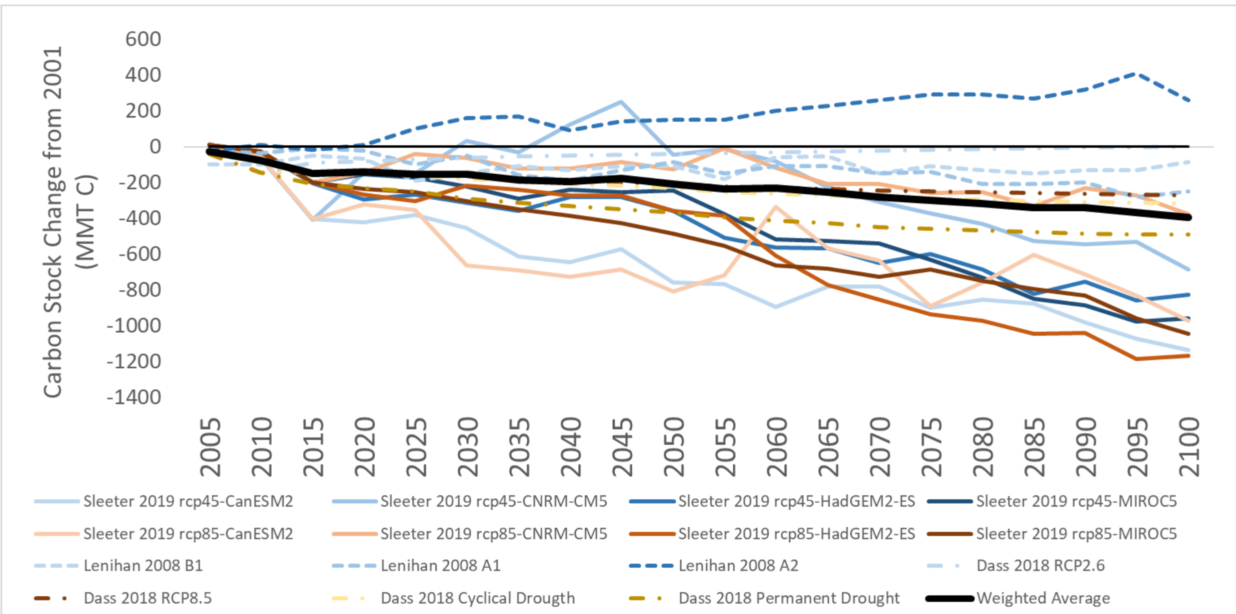

Figure 55: BAU projected statewide California All NWL Carbon Stock change from 2001. Each line represents a different result from a study. Studies have the same line type (e.g. solid line, dashed line, dash-dot line). Lines are labeled with the first author name, and the emissions scenario and global climate model used. Lines below the zero line are a projected loss of carbon stocks. A weighted average (in black) was used to weight all three studies equally, regardless of the number of results from each study.

Land Cover Changes

Three studies modeled changes in statewide vegetation cover types over the course of the 21st century (Lenihan et al, 2003, Hayhoe et al., 2004, Lenihan et al. 2008), including nine different scenarios (. Averaged across all scenarios, large decreases in area are expected to occur by late century (2070-2099) for alpine/subalpine forests, evergreen conifer forests, and shrublands. Mixed evergreen forests, and grasslands are expected to greatly increase in extent (Figure 56). While alpine/subalpine forest decreases, grassland and mixed evergreen forest increases occurred in all scenarios, changes in shrubland, desert, and evergreen conifer forest were more variable and ranged from increases to decreases.

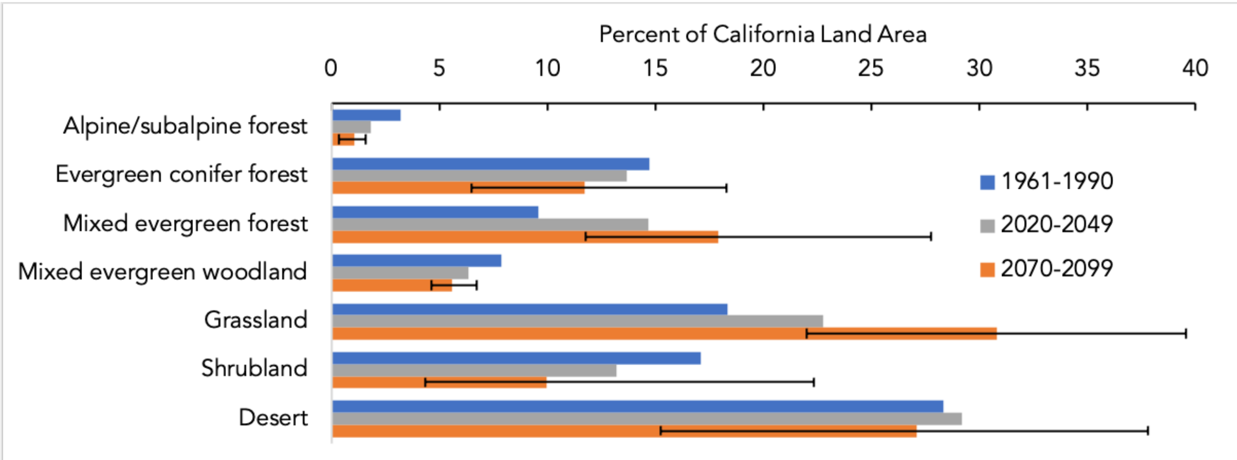

Figure 56: Vegetative land cover types in California during the late 20th century (from Lenihan et al. 2003), during the early 21st century (Hayhoe et al., 2004), and during the late 21st century (Lenihan et al., 2003, Hayhoe et al., 2004, Lenihan et al., 2008). Error bars for the late 21st century data points represent the range of modeled outcomes.

Regional Forests

This assessment uses articles that were filtered by forestland type, located in California, applicable at the regional scale, and containing carbon stock data. This resulted in 21 articles, 5 of which were determined to be not applicable. The papers were mostly focused on the Sierra Nevada region (including Lake Tahoe Basin), with 3 articles located in the Klamath Siskiyou region. 5 articles contained pertinent, extractable data (Liang et al., 2017a, 2017b; Loudermilk et al., 2013; Maxwell, 2018; Scheller et al., 2018). This analysis focuses on Net Ecosystem Carbon Balance (NECB), which represents the change in carbon stocks per unit area per year and accounts for growth, respiration, and carbon loss from disturbance. Several papers included multiple scenarios; this assessment used only the scenarios that the authors considered business-as-usual or baseline. The articles handled fire and insect/disease mortality differently; however, general trends are apparent when combining article results.

Under all Sierra Nevada region articles, total ecosystem carbon (TEC) continues to increase to the end of the 21st century (indicated by the positive NECB, Figure 57), even with increases in wildfire and disturbance where management is held to baseline levels (Liang et al., 2017a, 2017b; Loudermilk et al., 2013; M. Sleeter et al., 2015; Scheller et al., 2018). However, towards the later decades of the century, NECB slows down and the annual increase in carbon stocks decreases. More of the landscape turns from a carbon sink to a source as TEC curve flattens out. This effect is exacerbated by climate change and its impacts on wildfire and mortality.

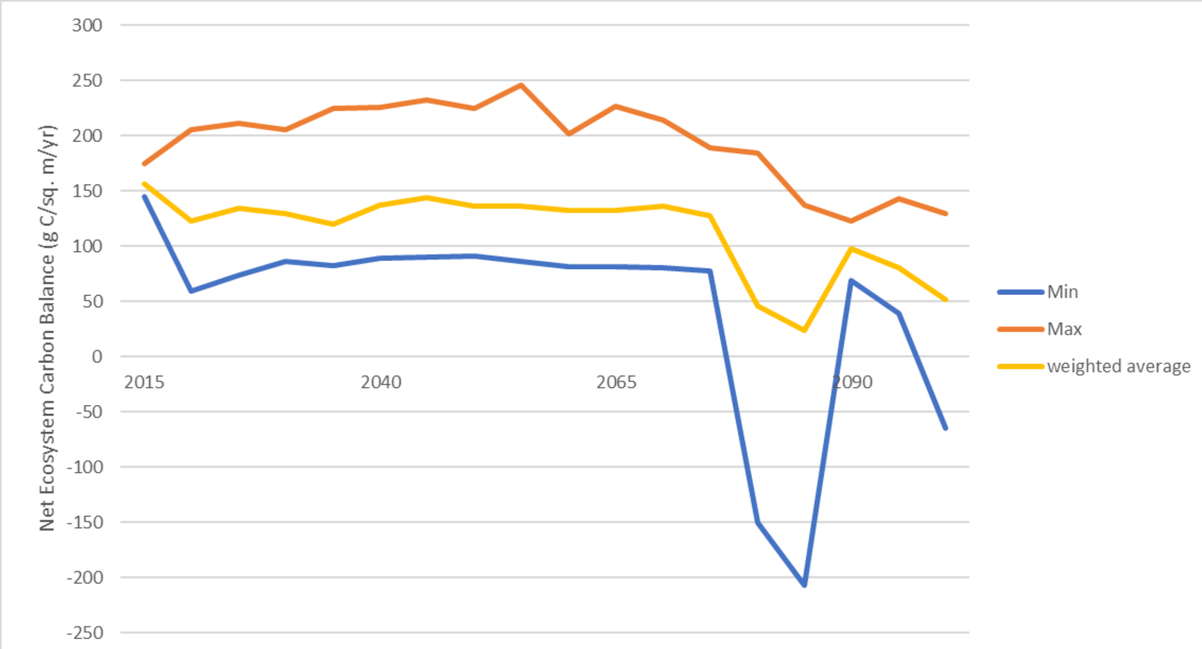

Figure 57. Projected Net Ecosystem Carbon Balance of the Sierra Nevada region from 2015 through 2100, from Liang et al. 2017a & 2017b, Loudermilk et al. 2013, Scheller et al. 2018. A positive NECB indicates a net increase in carbon stocks each year. Min and Max represent minimum and maximum values projected in each year; a weighted average (in yellow) was used to weight all four studies equally, regardless of the number of results from each study. N=21 cases.

The authors of these papers explain this finding as a result of the legacy of past forest management in the Sierras going back to the 19th century. Over a century of intensive harvesting and clearcutting has left the forests relatively young, dense, and fast-growing. The projected growth of this forest landscape remains high even under the negative impacts of climate change. Not until the latter half of the 21st century does the effects of climate change begin to materialize in the projected forest growth. This lag time between ecosystem response and environmental change can vary depending on extreme events such as prolonged drought, bark beetle outbreaks, widespread mortality, and catastrophic wildfire. Without extreme events, species shifts are slow and thus forest productivity is maintained. These extreme events are difficult to model, and authors note that their occurrence can reduce the lag time, i.e. the reduction in NECB could occur earlier than predicted in their models if extreme events occur. Note that all of these papers were published before 2020, the largest wildfire year ever recorded in California. Many papers used conservative model estimates, e.g. wildfire activity and shrub dynamics, and note that the reduction in NECB most likely would be accelerated. Other studies noted that the BAU rate of fuels reduction treatment implementation does not have a significant effect on fire activity, and future fire activity under climate change can be expected to increase under BAU management conditions (Hurteau et al., 2019; Spencer et al., 2015).

The one paper on the Klamath Siskiyou region found that NECB declines (but remains positive) throughout the 21st century under a BAU scenario, and in fact under all management scenarios modeled (Maxwell, 2018). The authors found that future forest management accounts for carbon dynamics more than climate, and that harvested material accounts for more carbon removal than release from wildfire. The harvesting legacy and fire regime in this region is different from the Sierras, and therefore requires a different management approach, i.e. the suggestion that fuels reduction treatments can enhance carbon storage on the landscape in the long run through reductions in fire severity might not hold true for this region with its mixed severity fire regime.

Several articles project changes in forest type distributions, with increases in shrubs and grasses, and oak woodlands in response to higher temperatures and lower precipitation (Liang et al., 2017b; Loudermilk et al., 2013; Maxwell et al., 2020; Parks et al., 2018). High elevation mixed conifer may decrease, as well as general conifer growth across the Sierras (J. J. Battles et al., 2007; Das et al., 2014) which leads to species shifts (Liang et al., 2017a; Scheller et al., 2018), though one study found ponderosa pine productivity could increase in the future (Battles et al., 2009). One article predicted that mountain meadow conifer encroachment is expected to increase under climate change (Lubetkin et al., 2017). Studies in the Klamath region predicted Brewer spruce will decrease in occurrence in the future due to changing climate conditions and will shift from conifer dominance to shrub/hardwood communities (Serra-Diaz et al., 2018; Ledig et al., 2012). The pace at which these forest type and species composition changes occur can be slow due to regeneration dynamics, residual species availability, and variable disturbance regimes. However, if extreme disturbance events like large high severity wildfire or widespread drought mortality occur more frequently or with higher severity, it could hasten the forest type/species change. The carbon stock implications of species composition changes are not clear. The carbon stock implications of cover type changes are also not clear, though shifts to shrubs and grasslands may result in lower carbon stocks in some cases.

Urban Forests

Research on urban forest projections is limited. Assessing the current carbon stocks in urban forests is challenging due to data limitations and uncertainties. Currently, estimates for California's urban forest range from storage of 56.9 million tons of carbon stored and 2.9 million tons sequestered per year (Nowak et al. 2021) across 343 million trees (Nowak et al. 2018) to 103 million tons of CO2e stored and 7.2 million tons sequestered per year across 173 million trees (Bjorkman et al. 2015; McPherson et al. 2017). CARBs NWL Inventory estimates 30 MMT C in 2016. These ranges highlight the impact that varied assumptions on delineating urban areas and how tree data is collected has on overall carbon stocks.

California urban land area increased by 0.3% of state land area between 2000-2010, or about 257,000 acres; this was below the national average of 0.4% increase (Nowak and Greenfield 2018). Using imagery from 2014, tree canopy covered approximately 31.5% of this urban area (Nowak and Greenfield 2018a).

California urban land area is projected to expand by 9.2% by 2060 (Nowak et al. 2021), while the percentage of urban land under tree cover will remain essentially consistent (+0.0%). These are empirical projections based National Land Cover Database (NLCD) imagery from circa 2011 to establish trends in existing urban land and rural land converted to urban. Corrections were applied for systematic undercounting of urban trees previously noted in the NLCD dataset (e.g., Nowak and Greenfield 2010) through comparison with 2014 imagery to create a decadal projection of land use change, which was then extrapolated again for each subsequent decade to 2060. The projected change in rate of urban tree coverage is also based on an extrapolation of current trends established through use of 2010 data. Notably, this stable urban tree cover percentage places California among only 13 states projected not to experience declining urban tree cover percentages by 2060 (Nowak et a. 2021).

Total urban forest carbon storage in California is projected to increase by 77,760,000 tons from 2010 levels by 2060 (Nowak et al. 2021). Over the same period, annual carbon sequestration will increase by 3,934,000 tons. This estimate was made by applying the national-scale mean 7.69kg C/m2 carbon storage factor and California's state-specific sequestration factor (Nowak et al. 2013) to projections of urban area growth, based on current rates of change.

Wetlands

No relevant future projections on wetland carbon outcomes were found based on the screening criteria CARB staff utilized. Research on short-term impacts of wetland restoration and inventories of existing wetlands exist, but no future projections of wetland carbon stock changes were found. This may be partially due to the challenge in projecting the multiple factors that heavily influence wetland restoration/conversion rates, such as economic markets for agricultural products, water policy, levee failure, water yield, and others.

CARB held discussions with wetland experts, including the San Francisco Estuary Institute, San-Joaquin Delta Conservancy, and Hydrofocus who confirmed that while future projections are currently being worked on, there are no existing BAU projections for wetlands. For mountain meadows, CARB confirmed with The University of Nevada - Reno researchers that mountain meadow maps and carbon dynamic studies are currently being developed, but that future modeling capabilities do not yet exist.

This research gap is important to highlight as wetlands, including mountain meadows, are critical to California's water supply and provide numerous benefits to the state. Improved data and tools for these land types would allow California to further incorporate them into strategies and plans.

Croplands

Research on cropland projections were limited as most studies focused on short-term effects from specific management actions, which were more appropriate for the Actions Outcomes synthesis. One study (Sleeter et al. 2018) was identified that projected soil organic carbon content in California agricultural lands into the future, and 2 papers that projected soil carbon in agricultural lands and orchard productivity in the Mediterranean region of Europe were used. Sleeter et al. 2018 projected that total California agricultural carbon stocks have been declining for the past two decades and will continue to decline in the future (Figure 59). One of the European studies (Jebari et al. 2018) projected that soil carbon stocks per hectare will likely experience diminishing increases (Figure 58) under climate change. The remaining paper (Brilli et al. 2019) examined Mediterranean orchards and projected a general decline in net ecosystem exchange (carbon sequestration) under changing climate conditions though this varied by site and degree of temperature change. Carbon stocks were not projected in this study.

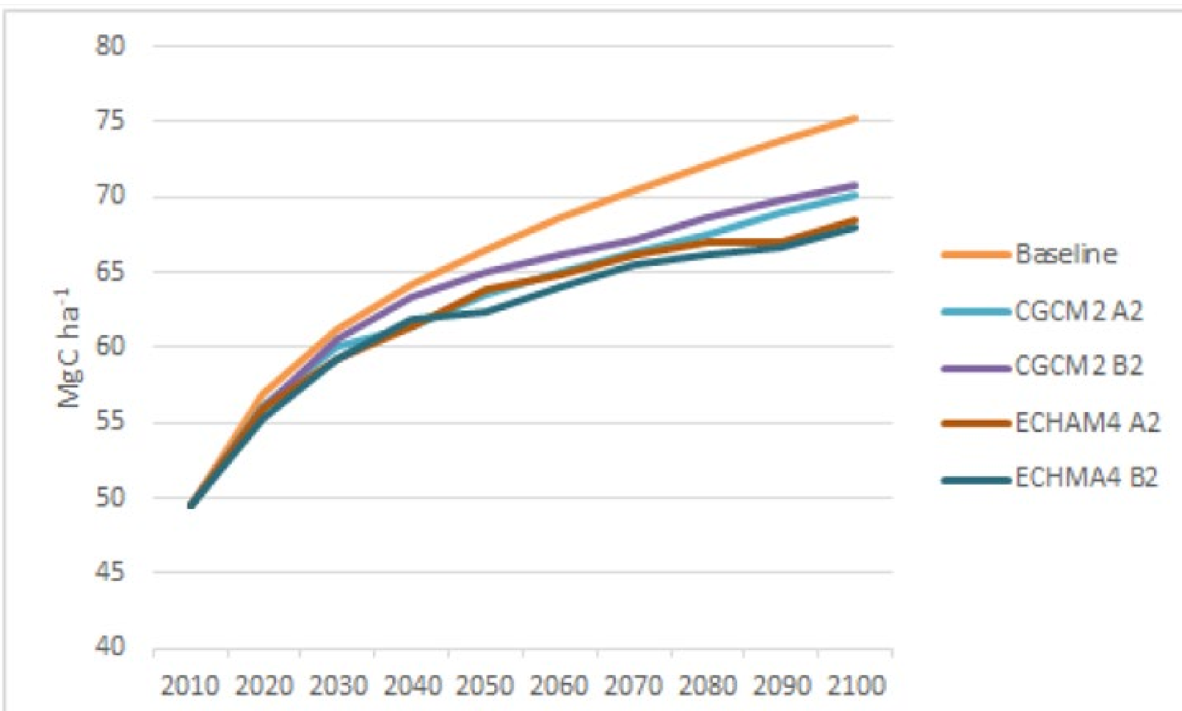

Figure 58: Soil carbon stock projections for croplands copied from Jebari et al. 2018. Full caption: Soil organic carbon (SOC) content evolution under the Baseline scenario and the four climate scenarios tested (CGCM2 A2, CGCM2 B2, ECHAM4 A2, ECHAM4 B2) during the 2010-2100 period at the 0-30 cm soil layer in the agricultural surface of the Aragon region.

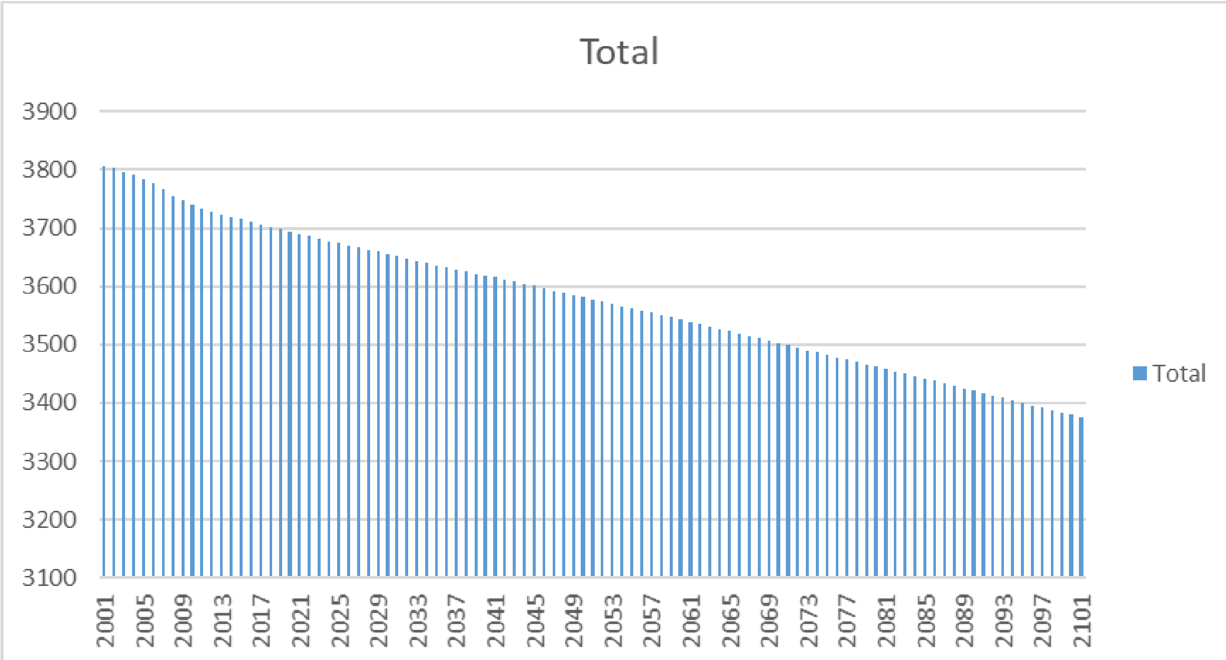

Figure 59: Total Ecosystem Agriculture Carbon stock (in Tg C) projections copied from Sleeter et al. 2018 dataset. California Total Ecosystem Agriculture Carbon, including aboveground biomass carbon and soil carbon, projected under BAU land use change rates, RCP8.5, and averaged across all four GCMs.

Sparsely Vegetated Lands

Research on carbon stocks on sparsely vegetated lands were limited to plant or small scale studies. No future projections were found. This research gap is important to highlight as sparsely vegetated lands make up a large portion of the state and are critical to California's coastlines. They provide numerous benefits to the state, such as recreation opportunities, protection from sea level rise, and contain many unique habitats and species. Improved data and tools for these land types would allow California to further incorporate them into strategies and plans.

Grasslands

Research on grassland projections were limited as studies were generally limited in scale and experimental in nature. Two studies were found that projected grassland soil carbon (Owen et al. 2015, Byrd et al. 2015) and one that projected net biome productivity of grasslands (Dass et al. 2018). Figure 60 shows grassland soil carbon stocks per area are projected to slightly increase or remain relatively steady in the future. Byrd et al. 2015 projected that land use change plays a major role in the future total carbon stocks of grasslands. They projected that under a series of IPCC-SRES land use change scenarios, California grassland total carbon stocks would decrease by approximately 14-26%, depending on the scenario, though they did not estimate carbon stock per area changes. Dass et al. 2018 projected that net biome productivity of grasslands would remain positive (i.e. grasslands are a net carbon sink and carbon stocks continue increasing) throughout the century under a variety of climate conditions, except for persistent drought conditions (Figure 61). Grasslands have the potential to continue accruing carbon stocks but land use changes will be an important driver of total statewide carbon stocks.

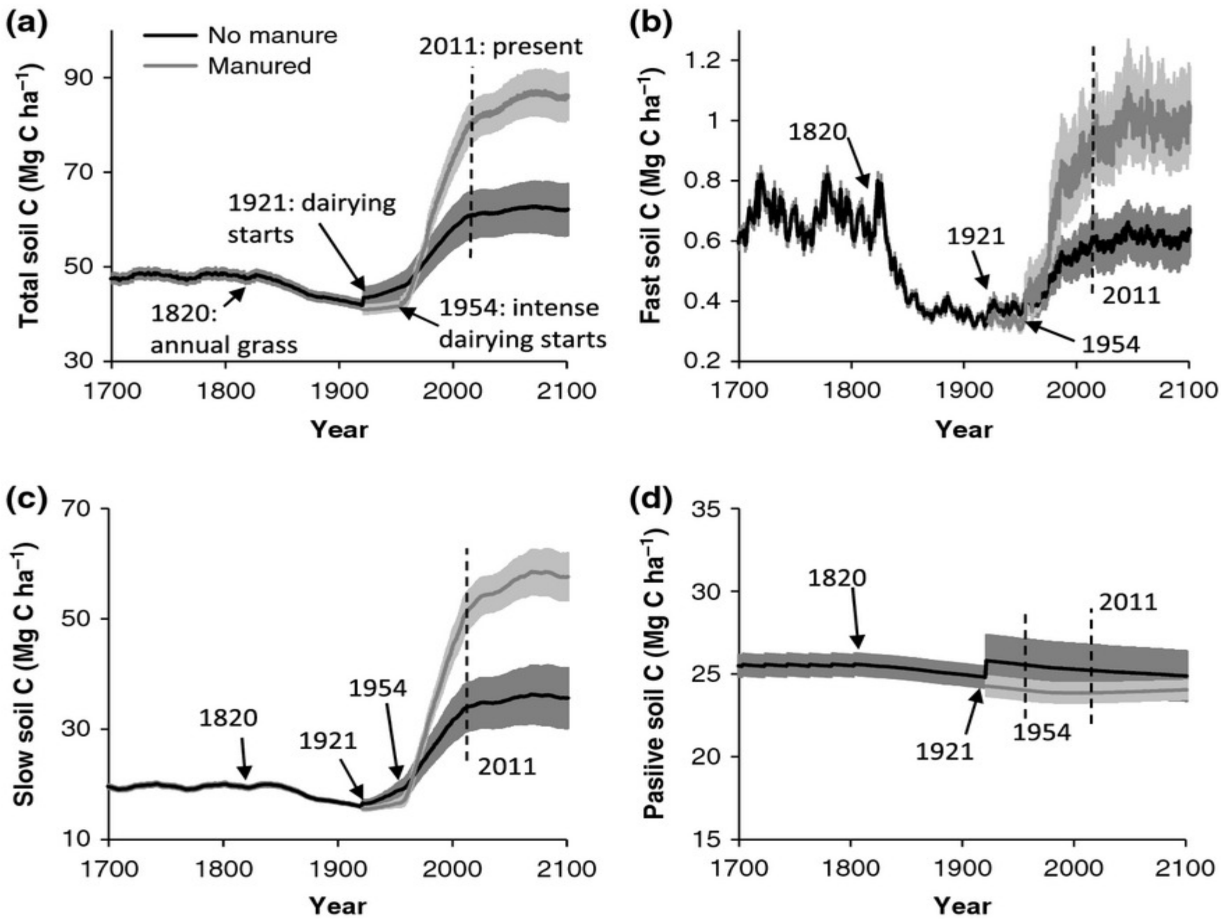

Figure 60: Grassland carbon stocks projections through 2100 copied from Owen et al. 2015. Full caption: Modeled soil C content for (a) total C, (b) fast pool, (c) slow pool, and (d) passive pool. Shaded areas around the data lines are standard errors. Vertical dashed lines denote years with important changes to management parameters. The apparently abrupt split in passive soil C pools (d) between manured and non-manured fields in 1921 is an artifact of the model parameterization and data analysis.

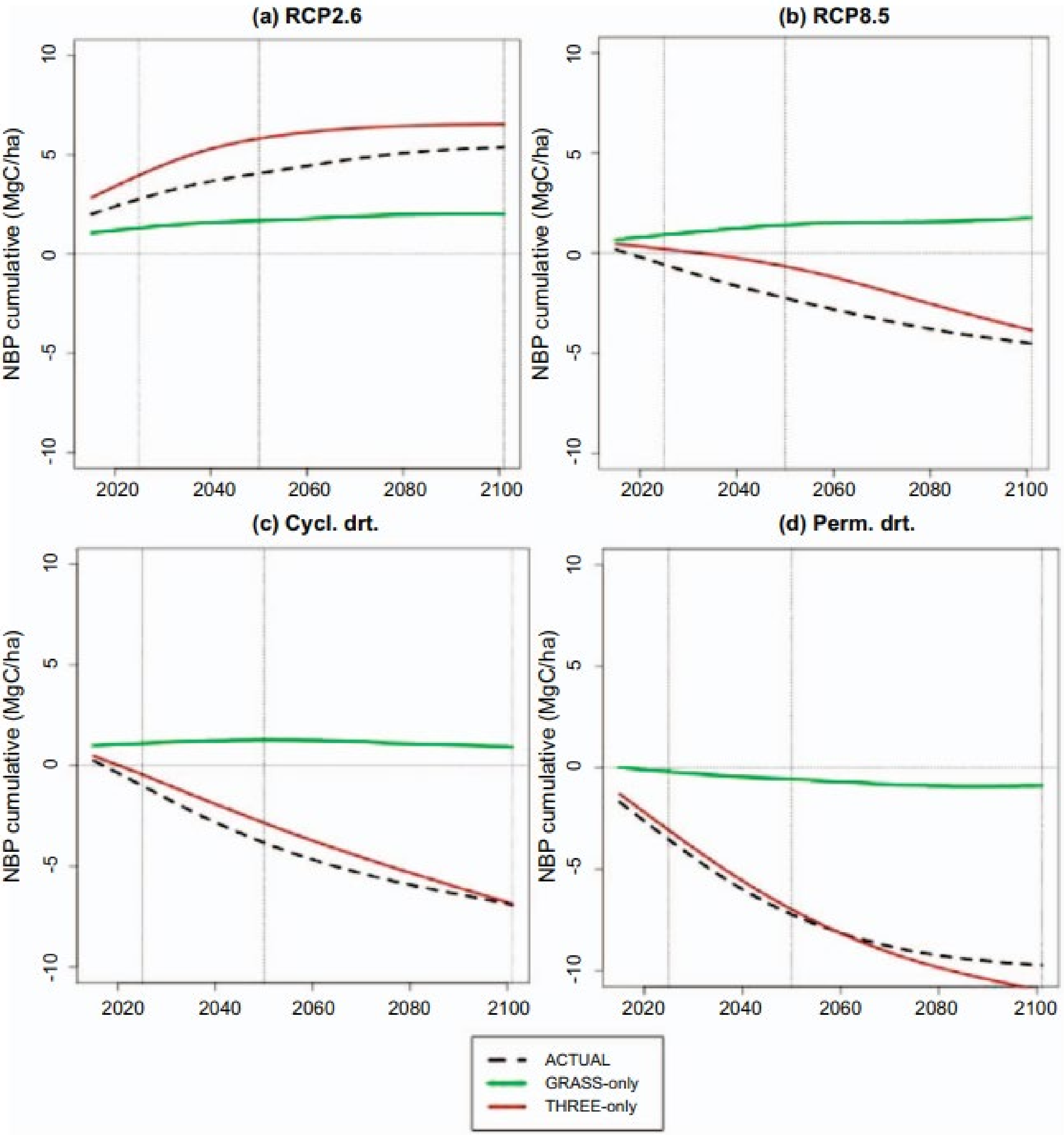

Figure 61: Net Biome Productivity projections of forests and grasslands copied from Dass et al. 2018. Full caption: Net C storage change calculated as cumulative NBP after 2015 is used to compare the robustness of the respective ecosystems as net C sinks from the short to long term (shown by vertical lines). Positive NBP represents net C sequestration while negative values for net C emissions. The difference between the net C sequestration by grassland ecosystems increases progressively from the short-term to long-term. Results presented as smoothened lines for comparison (using a 'Spar' value of 1). Apart from the environmental factors and wildfires, vegetation shifts also impact NBP.

Shrublands

Research on carbon stocks on shrublands were limited to plant or small scale studies. No future projections were found. This research gap is important to highlight as shrublands make up a large portion of the state, especially in southern California. They provide numerous benefits to the state such as recreation opportunities and contain many unique habitats and species. Improved data and tools for these land types would allow California to further incorporate them into strategies and plans.

Wildfire Activity

There were five studies with available data on modeled changes in statewide burned area during some or all of the 21st century (Figure 62 and Figure 63). Among these five studies, two (Lenihan et al., 2003, Lenihan et al., 2008) modeled burned area as part of comprehensive earth systems modeling; these two studies suggested modest increases in burned area of 1.5-10% by mid century (2030-2059, Figure 63) and 5-12% by late century (2060-2089 mean; not shown) relative to average 20th century (1895-2003) burned area. Three studies were specifically focused on predicting changes in fire activity resulting from climate change. Mann et al. (2016) predicted increases in burned area of 2.3-5% by the second quarter of the 21st century (2026-2050; Figure 63) relative to the second half of 20th century (1951-2000). Westerling et al. (2011) and Westerling (2018) predicted the largest increases in fire activity, with mid-century increases of 17-43% (Figure 63). Westerling (2018) include within their published model output data showing large interannual variability in burned area, with single years later in the 21st century showing more than a 400% increase in burned area relative to the late 20th century in some climate model/emissions scenario combinations. Notably, the actual observed contemporary increase in burned area relative to the late 20th century (1987-2000) already far exceeds all model predictions for the entire 21st century.

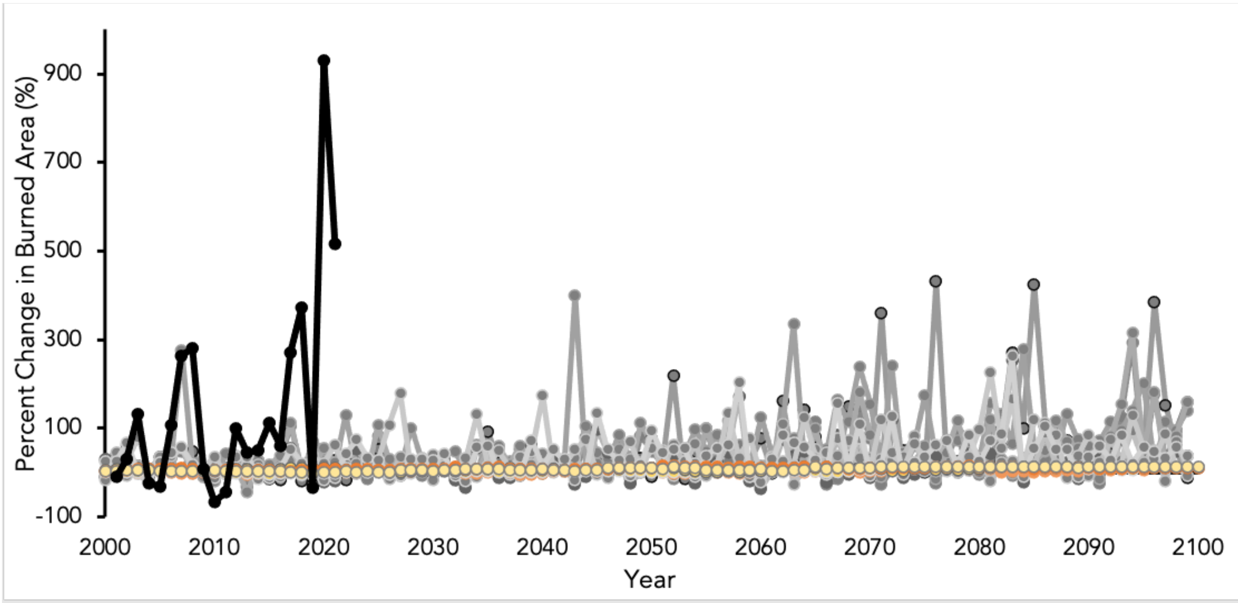

Figure 62: Annual burned area: Modeled changes in relative burned area (% increase from baseline) in years 2000 to 2100. Grey symbols are data from Westerling (2014), including four climate models and two emissions scenarios with "business as usual" California land use patterns, with percent change in burned area relative to 1953-1999. Orange symbols are data from Lenihan et al., (2003) and Lenihan et al., (2008). The black line shows observed statewide fire activity relative to mean burned area 1987-2000.

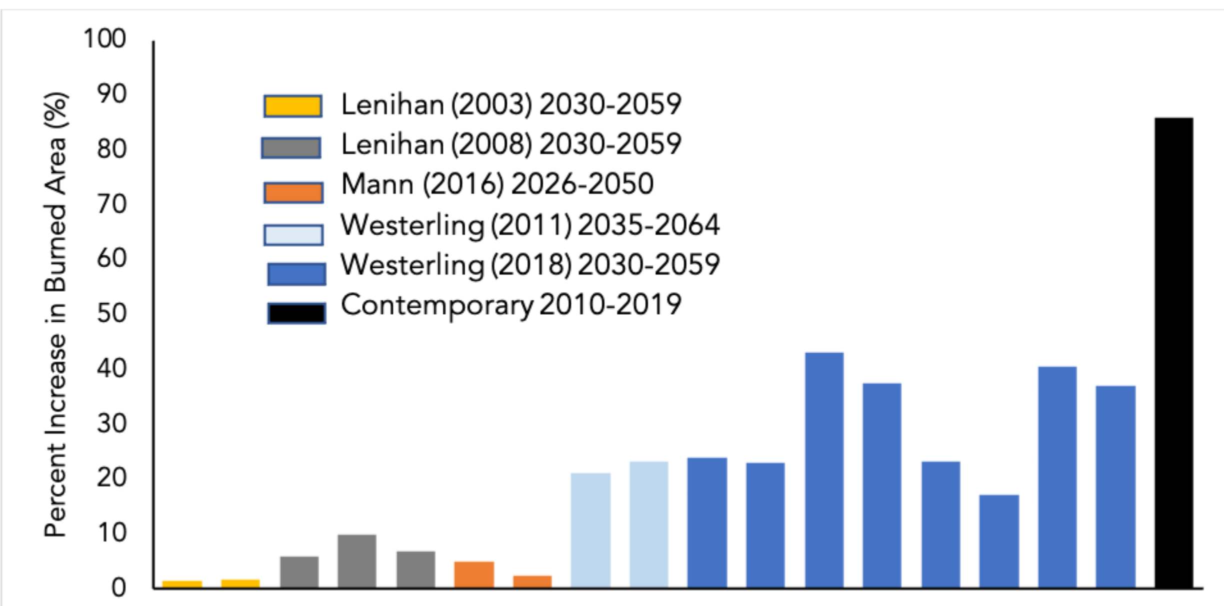

Figure 63: Midcentury burned area: Modeled change in relative burned area (% increase from 20th century baseline) during the middle of the 21st century. Bars shown for each study represent a different climate model/emissions scenario combination. Note that the midcentury averaging period differs somewhat among the studies. Also included is contemporary wildfire burned area, calculated relative to the late 20th century (1987-2000).

Action Outcomes Synthesis

This synthesis effort focused on actions that were being modeled by CARB for the Scoping Plan. Studies examining actions that were not modeled in CARB's Scoping Plan analysis were included where there was sufficient sample size.

Forests

Methods

The literature search and screening process of steps 1-6 from above resulted in a large number of studies on forest management actions. The work to extract the data and synthesize the results for these papers was contracted out to UC Merced, and a separate report was created titled "Impacts of forest management on carbon outcomes: A meta-analysis", the findings of which are included here. Supplemental materials can be found in that report. The types of forest management actions and carbon pools found in the literature were aggregated into fewer categories. This aggregation created sufficient sample sizes of case studies to allow for subsequent meta-analysis while preserving the major differences among categories. Specifically, the forest management actions were categorized into the same 7 LANDFIRE disturbance categories as were used in the RHESSys modeling: Thinning, Prescribed fire, Biological/herbicide/chemical, Harvesting, Mastication, Clearcuts, and Other mechanical. For carbon pools, five categories were defined, namely live aboveground carbon, dead aboveground woody carbon, forest floor, mineral soil carbon, and fine and coarse root carbon. We also identified articles that record carbon flux-related outcomes (e.g., soil respiration rate, annual increase in aboveground biomass, and wildfire carbon emissions). To unify carbon outcomes, we converted carbon pools to carbon fluxes by dividing the carbon pools with the corresponding years after forest management.

Based on the extracted forest management action and carbon outcome information, the following articles were further excluded. First, the articles which recorded tree radial growth, and the growth of diameter at breast height and tree height as the articles typically provided insufficient information to convert them into carbon density measurements. Second, the articles which reported carbon outcomes (e.g., tree mortality rates, carbon sequestration rates, net primary productivity, soil inorganic carbon, and soil GHG flux) that have too few case studies to allow for the meta-analysis. Third, the articles which reported forest management actions (e.g., road decommissioning, and rainfall exclusion) that have too few case studies to allow for the meta-analysis.

The effect size was calculated by referencing to the control group. Specifically, two effect sizes were calculated: the difference between treatment group mean and control group mean (absolute effect size) and the ratio between treatment group mean and control group mean (relative effect size). If the articles employed paired-sites study design, the control groups were typically defined as adjacent untreated plots, or plots with similar conditions as treated plots; if the chrono sequence design was employed, the control groups referred to the initial values of the same plots before forest management actions.

Additional articles were identified that employed factorial experiment designs to examine the impacts of the combinations of forest management actions on carbon outcomes. For these studies, the control group was designated in a dynamic way, and one example was given in Figure 64. For example, if “Thinning & prescribed fire” (the treated group) was referenced to “Thinning” (the control group), the impact of “Prescribed fire” on carbon outcomes was examined. To differentiate the disparate impacts of forest management actions on different time-scales, the years post-treatment were classified into three categories: short-time (< 5 years), medium-time (>=5 & < 15 years), and long-term (>= 15 years). The effect sizes were then calculated separately for different time-scales.

Factorial experiment design	
1 Untreated	2 Thinning
3 Prescribed fire	4 Thinning & Prescribed fire

Treated group	Control group	Targeted management
2	1	2
3	1	3
4	1	4
4	2	3
4	3	2

Figure 64: The dynamic approach for designating control group that was used in forest action outcomes synthesis. An example is shown here for a study with a factorial experiment design (left). The targeted management for which carbon outcomes are quantified, shown on the right, depend on the treated group and control group being evaluated.

In addition to articles that employ field observation data, several articles use modeling approaches to examine the impact of forest management on carbon outcomes. For those articles, a separate meta-analysis was performed from the field observation articles because the modeling articles tend to project into the future rather than being based on historical data. Therefore, 2020 was used as the baseline year because it was the most employed starting year for simulations and calculated the effect sizes by referencing to this baseline year. Again, the absolute effect size is the difference between any future year and the baseline year, while the relative effect size is the ratio between those two. All identified modeling articles were further aggregated into four regions: Sierra Nevada (e.g., Lake Tahoe Basin, Southern Sierra Nevada, and Northern Sierra Nevada), California's northern coast, Pacific west (e.g., Oregon Coast Range, Western Oregon, Western Washington, and Northern Idaho), and Southwest (e.g., Northern Arizona, Kaibab Plateau in Arizona, and Northern New Mexico). Each scenario was also classified into low (e.g., control and business-as-usual scenarios), moderate (e.g., exceed historical efforts, but feasible through increased current funding), and aggressive (e.g., accelerated, require substantial increases in funding and policy support) categories based on the intensity and implementation rates of forest management.

Results

We identified 66 relevant papers and 936 case studies that employed field measurement approaches over the time period 2000-2021. The distribution of case studies was uneven among forest management actions, with a majority of studies examining the impacts of "thinning" and "prescribed fire" (Figure 65). Together, these two forest management categories occupied up to 74.6% of case studies. This was followed by the category "biological/herbicide/chemical", with a percentage of 9.3%. There were comparatively few studies that examined "soil amendment", "harvesting", "other mechanical" and "mastication", and their occupied percentages ranged between 2.6%-5.1%. Last, the percentage of the case studies that reported the carbon impacts of "clearcut" was < 1%.

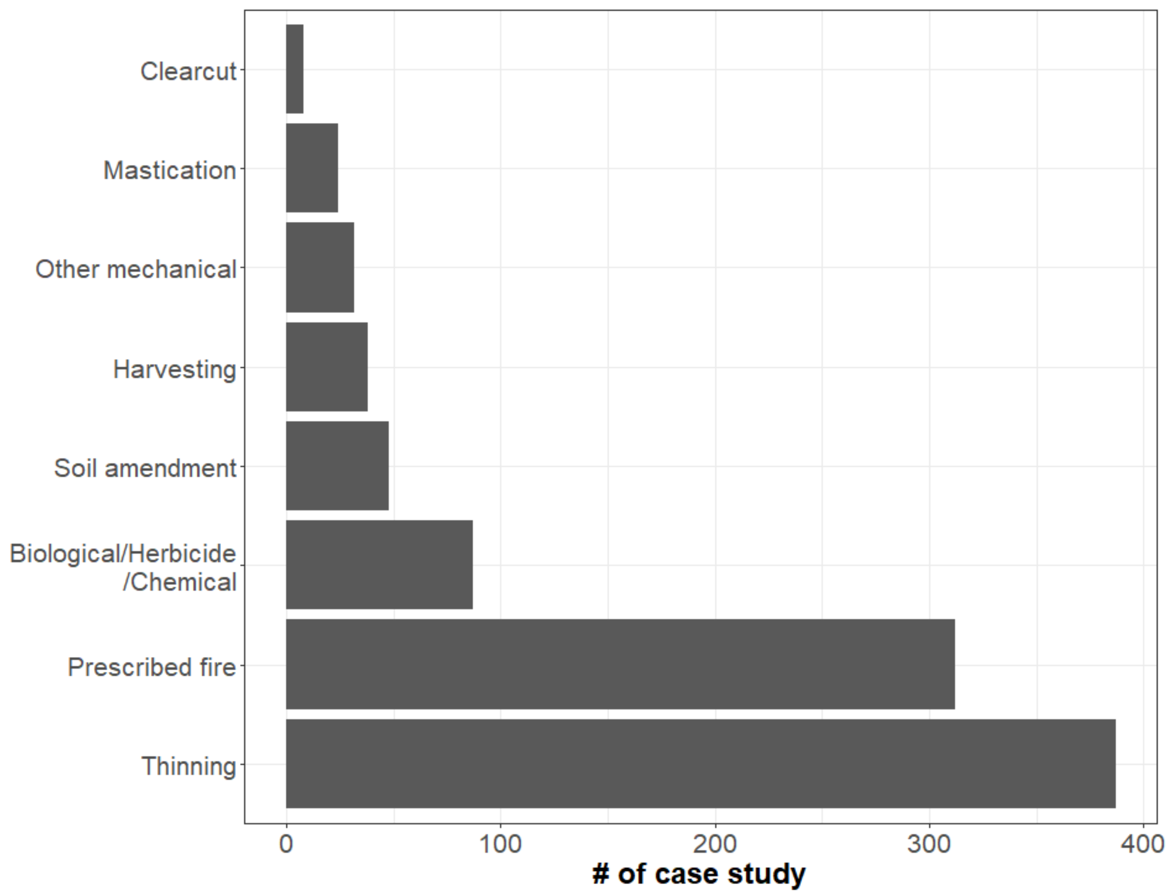

Figure 65: Distribution of case studies among eight forest management categories from the relevant studies identified in the forest action outcomes synthesis, following the procedures discussed in the Methods sections. Each study contains multiple case studies that were considered for this synthesis.

With regards to carbon outcomes, the percentages of case studies were 87.7% for carbon pools and 12.3% for carbon fluxes (Figure 66). Among the carbon pools, the ranking of the numbers of case studies was forest floor carbon (24.5%) > live aboveground carbon (23.5%) > dead aboveground woody C (19.3) > mineral soil carbon (13.2%) > root carbon (7.1%). For carbon fluxes, the percentage of case studies that examined soil respiration rate was the largest (6.6%), followed by increase in aboveground biomass (3.6%), and wildfire carbon emissions (2.1%).

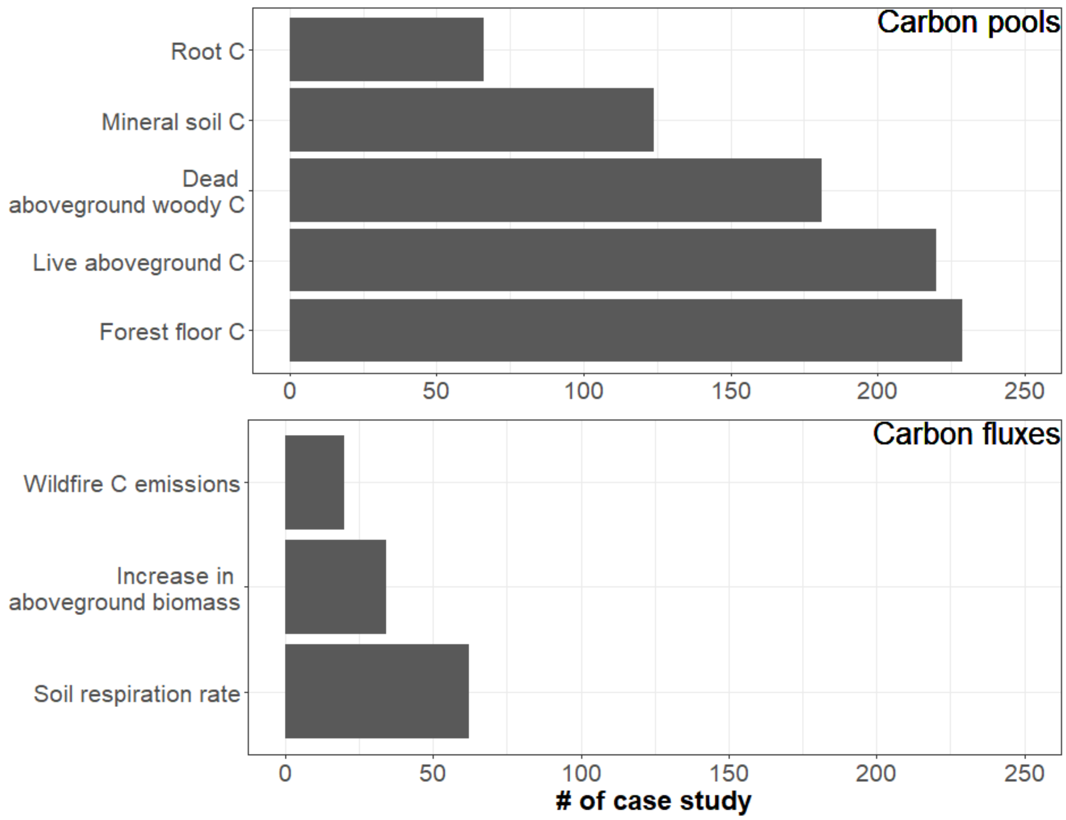

Figure 66: Distribution of carbon outcomes from case studies considered in the forest action outcomes synthesis. Case study counts related to carbon pools and fluxes are shown above and below, respectively.

The boxplot summaries of effect sizes were presented for each pair of forest management action and carbon outcome. Figure 67 shows the measures for the relative effect size while Figure 68 is for the absolute effect size. Several patterns were observed from these figures. First, the ranges and variabilities of the effect sizes were large, indicating that the effects of forest management on carbon outcomes were highly variable. This is probably due to impacts of forest management on carbon outcomes that were mediated by many other factors (e.g., forest types, location, management practices, and study periods). Second, when comparing with control groups, forest management tended to reduce live aboveground carbon (except for soil amendment) and root carbon over the time period of these studies. Third, prescribed fire was generally decreased subsequent carbon fluxes. Fourth, soil amendment had positive effects on live aboveground carbon, forest floor carbon, and mineral soil carbon; thinning has immediate negative effects for live aboveground carbon, root carbon, and wildfire-derived carbon emissions over the time period of these studies, while positive effects for mineral soil carbon and soil respiration rate. Fifth, forest management actions tended to reduce the loss of live tree carbon after subsequent wildfire, when compared with untreated sites at 1 or 2 years post-treatment. Wildfire carbon emissions are the carbon loss resulted from wildfire-induced tree mortality, and their values were derived by applying field observation data to a fire effect model ([FOFEM](#)) at six sites across the western US. Last, for other activity actions, their impacts on carbon outcomes were complex with both negative and positive values reported for the same pair of management action and carbon outcome.

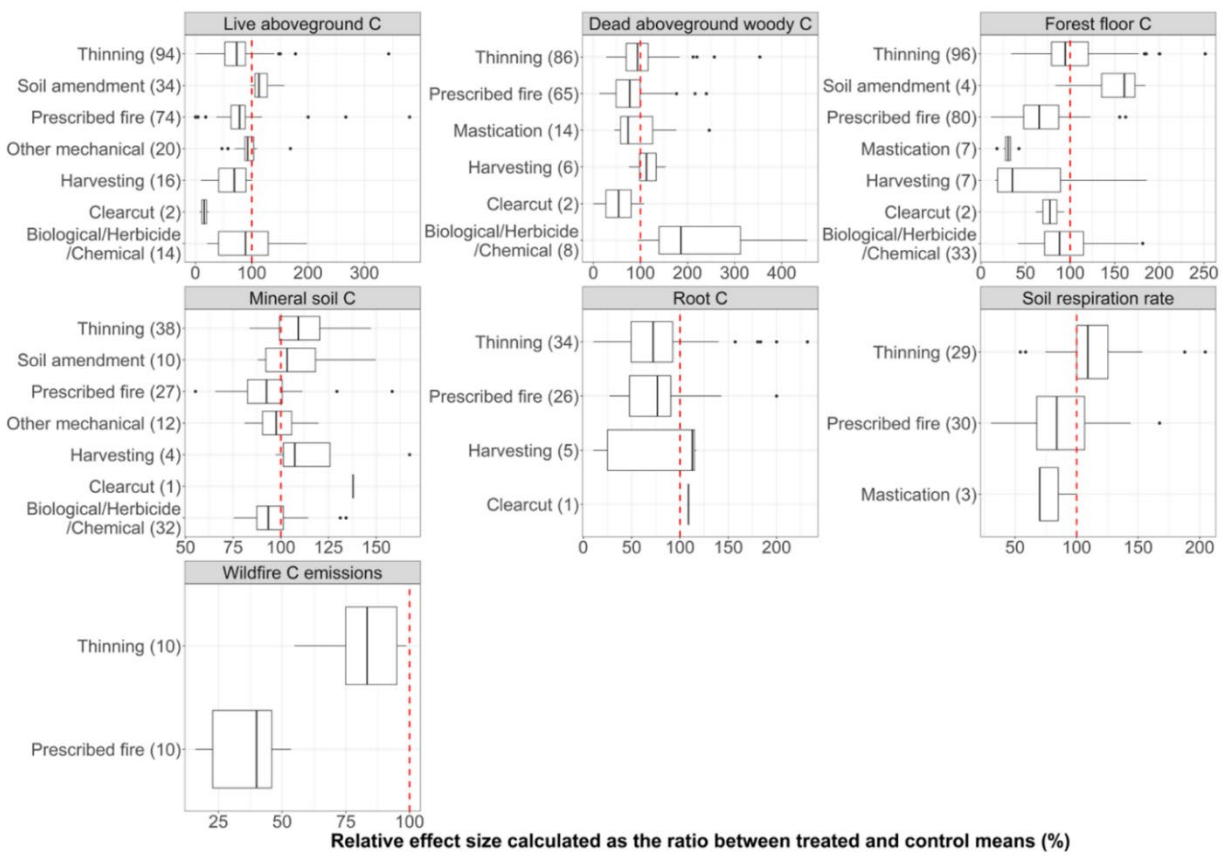

Figure 67: The boxplot summary for the relative effect of forest management action on carbon outcomes. The numbers in the y-axis represent the numbers of case studies for the pairs of forest management and carbon outcomes. The red dash lines (x-axis: 100%) serve as no-effect reference points, where left side indicates that forest management reduced carbon when comparing with control group, while the right side indicates the opposite results. For the "Live aboveground C" panel, two outliers (850 for Biological/Herbicide /Chemical and 500 for Thinning) were removed to enhance the visualization of the results.

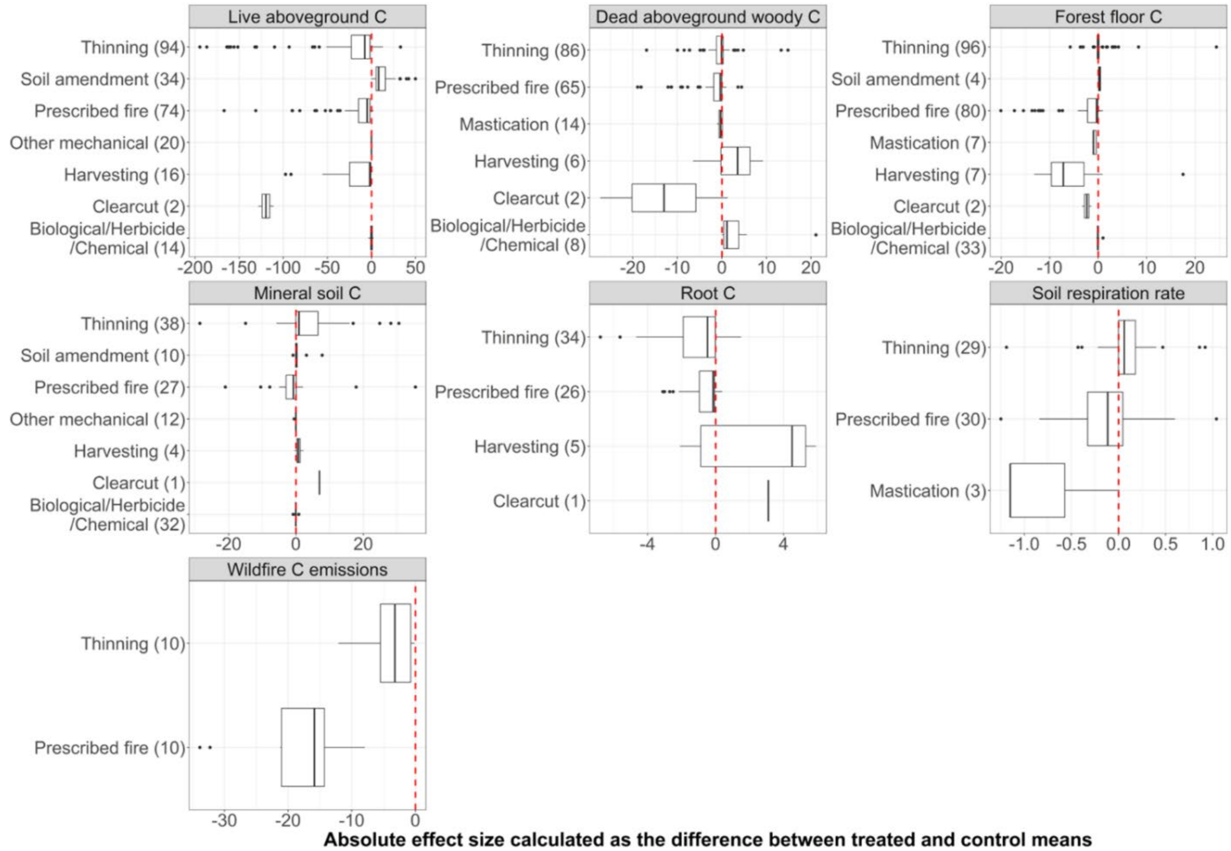

Figure 68: The boxplot summary for the absolute effect of forest management action on carbon outcomes: unit is MgC/ha/yr, except for soil respiration rate (gCO2 /m2/h). The numbers in the y-axis represent the numbers of case studies for the pairs of forest management and carbon outcomes. The red dash lines (x-axis: 0) serve as no-effect reference points, where left side (negative values) indicates that treated group reduce carbon when comparing with control group, while the right side (positive values) indicates the opposite results.

We disaggregated the overall impacts by three time-scales: short-time (< 5 years), medium-time (>=5 & < 15 years), and long-term (>= 15 years) (Figure 69 & Figure 70). The thinning operations tended to increase unstable carbon pools (e.g., dead aboveground woody carbon, and forest floor carbon) and mineral soil carbon in the short-term, while these carbon pools decreased in the medium- and long-term time periods. Thinning tended to decrease live aboveground carbon and increased soil respiration rate, regardless of time periods. For prescribed fire, the disparate impacts across time-scales varied for different carbon outcomes: (1) only small changes were observed for mineral soil carbon in the short- and medium-term groups when compared with the long-term group, while the opposite was observed for forest floor carbon; (2) it decreased soil respiration rate in the short time period while increasing soil respiration rate in the medium time period; and (3) for the other carbon outcomes, there were no clear patterns for the impacts of prescribed fire. Regarding other forest action categories, there were not enough case studies or either no clear patterns.

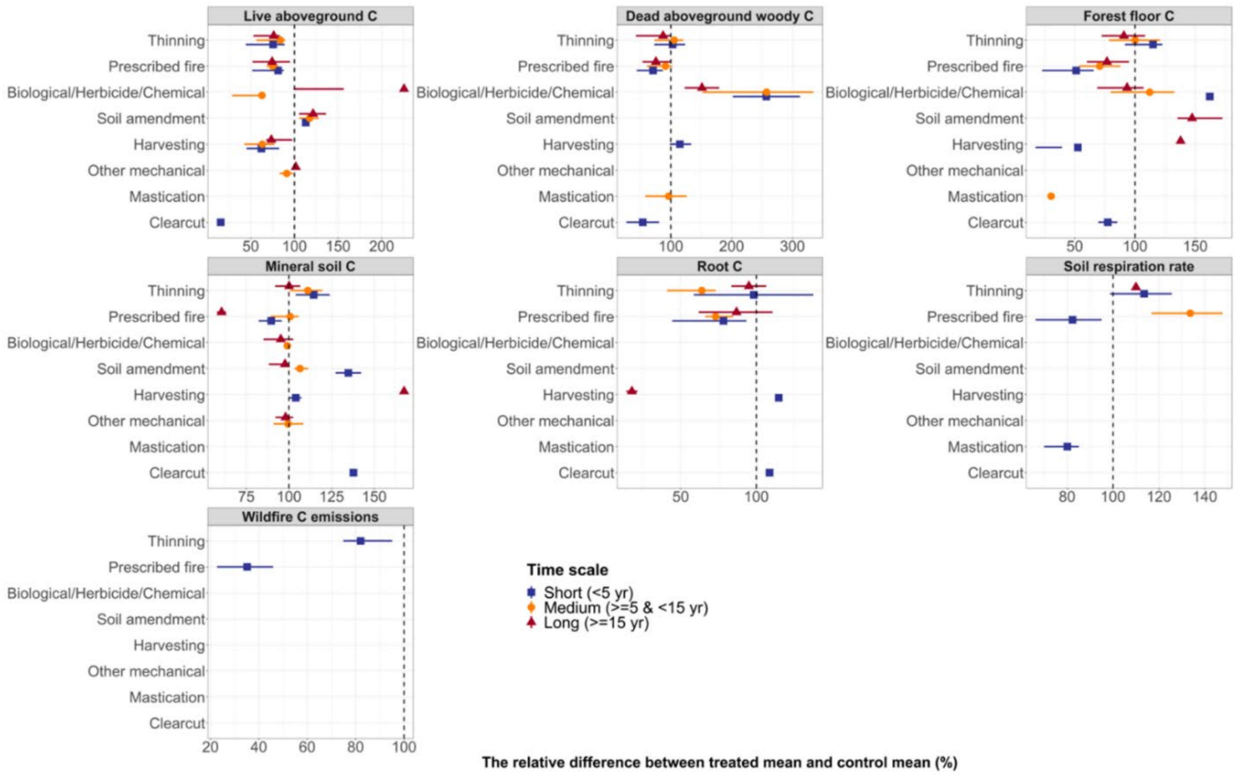

Figure 69: The disparate impacts of forest management actions on carbon outcomes (measured by the relative effect size). Graphs show mean estimates with the interquartile ranges. The black dash lines (x-axis: 100%) serve as no-effect reference points, where left side indicates that forest management reduced carbon when comparing with control group, while the right side indicates the opposite results.

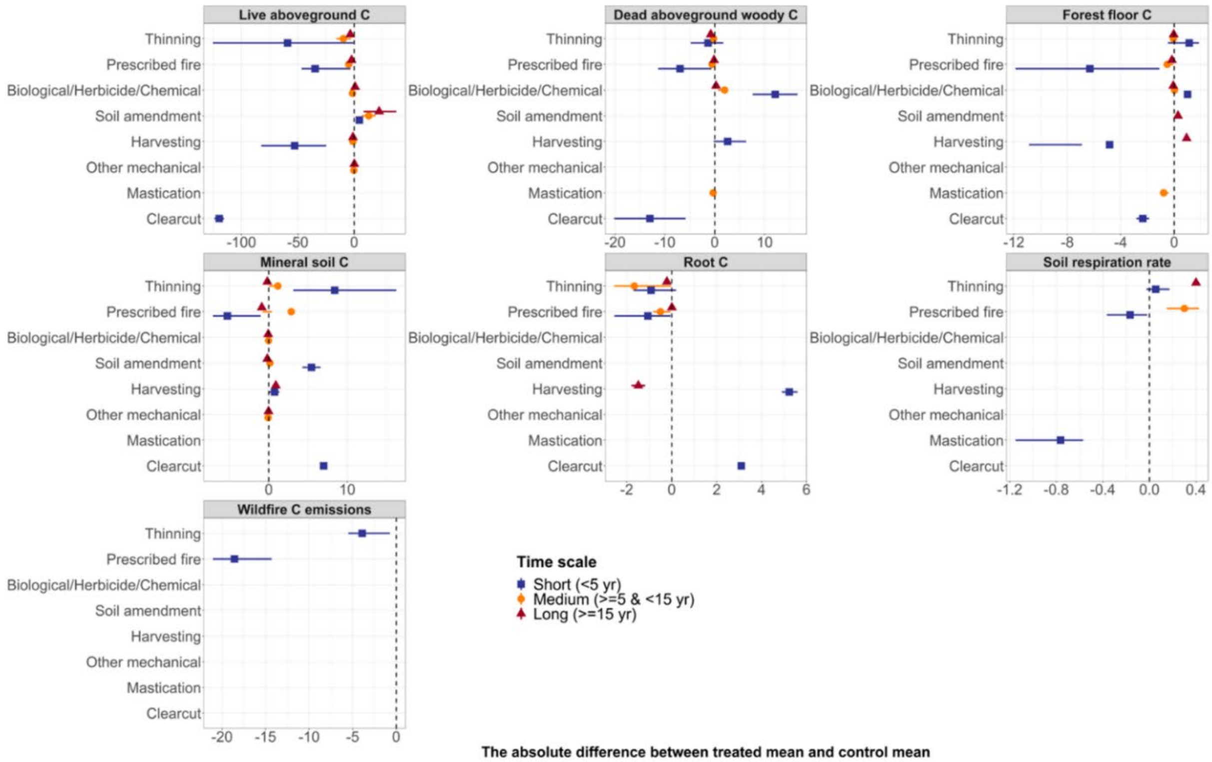

Figure 70: The disparate impacts of forest management action on carbon outcomes (measured by the absolute effect size; unit is MgC/ha/yr, except for soil respiration rate (gCO2 /m2/h)). Graphs show mean estimates with the interquartile ranges. The black dash lines (x-axis: 0) serve as no-effect reference points, where left side (negative values) indicates that treated group reduce carbon when comparing with control group, while the right side (positive values) indicates the opposite results.

We included 13 articles and 70 scenarios into our meta-analysis of articles that utilized modeling. Unlike the field observation articles that examined the impacts of individual forest management actions, the modeling papers were typically organized by scenarios, and a scenario could be a portfolio of forest management actions lumped together and implemented at different rates. Figure 71, Figure 72 and Figure 73 were analyzed based on scenarios, and were not specific to any forest management actions. The effect sizes in California's northern coast showed much higher variations than the other three regions (Figure 71). Note that the scenarios in California's northern coast were all from Berrill and Han 2017. The large variations were likely due to different nature of scenarios (from “no treatment” to “group selection combined with individual-tree selection with high-density management”), regardless of the site characteristics. In California's northern coast (Figure 71), the relative effect sizes were clearly above one, and their median values increased over time. This indicated that the model projections predicted the positive effects of forest management, and their long-term carbon benefits exceeded the short-term benefits.

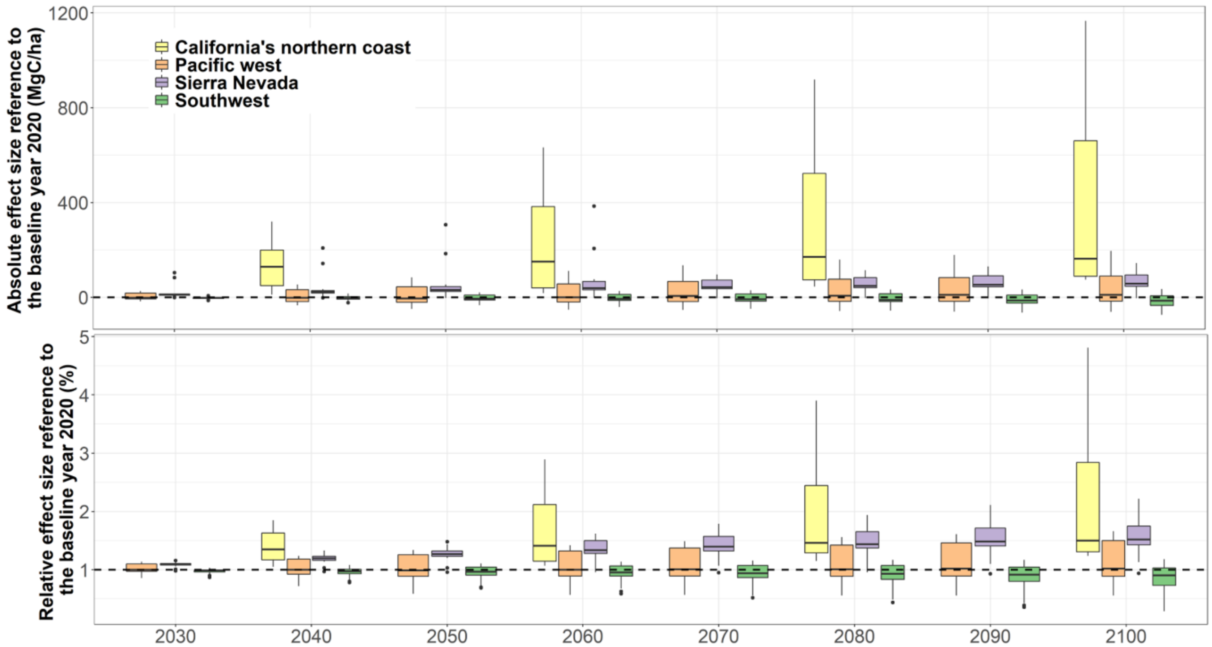

Figure 71: The absolute (top panel) and relative effect (bottom panel) sizes of total ecosystem carbon by referencing to the year 2020, aggregated by the geographic regions (Sierra Nevada: Lake Tahoe Basin, Southern Sierra Nevada, and Northern Sierra Nevada; California's northern coast; Pacific west: Oregon Coast Range, Western Oregon, Western Washington, and Northern Idaho; and Southwest: Northern Arizona, Kaibab Plateau in Arizona, and Northern New Mexico). The black dash lines indicate on-effect reference lines. Each boxplot was aggregated based on scenarios. A scenario could be a portfolio of forest management actions lumped together and implemented at different rates, and therefore was not specific to any forest management action. The numbers of scenarios were 7 for California's northern coast, 11 for Pacific west, 18 for Sierra Nevada, and 34 for Southwest US.

When California's northern coast is excluded, the patterns in the other three regions becomes clear (Figure 72). In Sierra Nevada, forest management increased carbon stocks relative to the baseline in 2020 and the effect sizes increased over time, reaching maximum levels at the end of the simulations (the year 2100). In contrast, the opposite pattern was observed for the Southwestern U.S. region. In this southwest region, forest management tended to decrease carbon stocks and the magnitude of the decrease became larger over time. Regarding the Pacific west, there was no clear patterns as their boxplot came across the reference lines (the horizontal line of 0 for the absolute effect and the line of 1 for the relative effect), and their median values were close to the reference lines. Although there were no time-series trends for the Pacific west, they showed larger variations as indicated by the wider boxplots (Figure 72).

Figure 72: 10 The absolute (top panel) and relative effect (bottom panel) sizes of total ecosystem carbon by referencing to the year 2020, aggregated by the geographic regions (excluding the California's northern coast) (Sierra: Lake Tahoe Basin, Southern Sierra Nevada, and Northern Sierra Nevada; Pacific west: Oregon Coast Range, Western Oregon, Western Washington, and Northern Idaho; and Southwest: Northern Arizona, Kaibab Plateau in Arizona, and Northern New Mexico). The black dash lines indicate on-effect reference lines. Each boxplot was aggregated based on scenarios. A scenario could be a portfolio of forest management actions lumped together and implemented at different rates, and therefore was not specific to any forest management action. The numbers of scenarios were 11 for Pacific west, 18 for Sierra Nevada, and 34 for Southwest US.

For all the 70 scenarios, we were able to distinguish 31 scenarios into different levels of intensities. When aggregating the scenarios into three categories of intensities, several patterns can be observed (Figure 73). The majority of low-intensity scenarios lay below the reference lines, regardless of the time periods. This indicated that continuing current business-as-usual scenarios or scenarios with similar levels of intensity would be more likely to turn forest lands into carbon sources. This is probably due to increased pressures from climate warming and more severe natural disturbances. In contrast, the moderate and aggressive scenarios tended to increase forest carbon stocks over time, and their median values were above the reference lines after 2050. This indicated that it took decades to realize the carbon benefits of forest management. Another main difference between three categories of scenarios was that higher intensity scenarios were associated with larger variations, and the variations increased over time. The variations may be due to factors such as characteristics of study region, different future climatic projections, and different definitions of scenarios across the studies.

Overall, higher intensity and longer time periods were associated with more carbon benefits. However, aggressive scenarios may not be feasible due to the lack of funding and resources, and the need to balance carbon considerations with impacts on other objectives (e.g., biodiversity conservation). One thing to note here is that increased magnitudes of carbon benefits were larger when changing from low to moderate scenarios, than changing from moderate to aggressive scenarios (Figure 73).

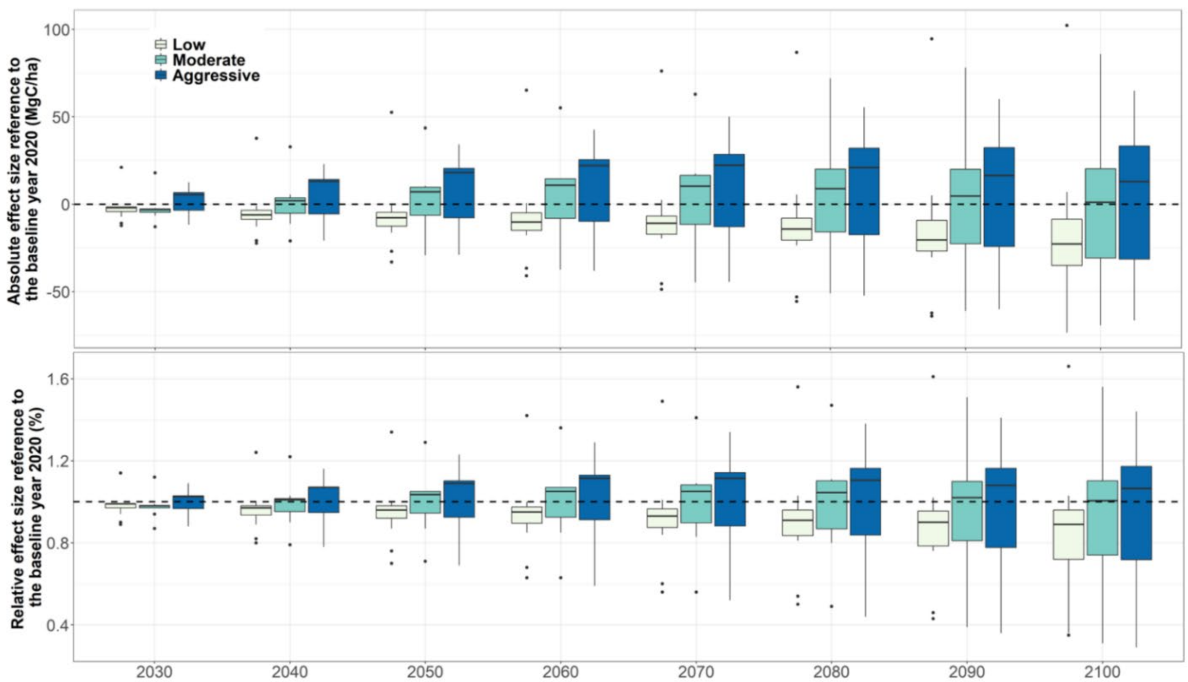

Figure 73: The absolute (top panel) and relative effect (bottom panel) sizes of total ecosystem carbon by referencing to the year 2020, aggregated by management intensities. The black dash lines indicate on-effect reference lines. Each boxplot was aggregated based on scenarios. A scenario could be a portfolio of forest management actions lumped together and implemented at different rates, and therefore was not specific to any forest management action. The numbers of scenarios were 15 for Low, 8 for Moderate, and 8 for Aggressive.

Discussion

For this study, we conducted a comprehensive literature review to identify the relevant papers extracted forest management and carbon outcome related attributes, and then performed a meta-analysis to examine the impacts of forest management on carbon outcomes. It is worth noting several limitations of the study, which provide directions for future exploration. First, the definitions and practices of forest management actions change from papers to papers, even if they are under the same name. For example, thinning in Lopez et al. 2003 denotes the extraction of 79% of basal area, while thinning in Burton et al. 2013 is measured by residual tree densities. Therefore, the characteristics of forest management action (e.g., treatment intensities) are likely different. Second, we aggregate a diverse set of forest management actions into fewer categories to allow for a more valid meta-analysis. This aggregation, such as combining overstory thinning and understory thinning into thinning, and initially one-time herbicide and annually over-year herbicide into vegetation control, creates large variability and uncertainty which makes the generalization of the findings challenging. Third, we treat case studies equally in the meta-analysis. Some case studies may have higher plot numbers and smaller standard deviations, and therefore are more accurate than the case studies with larger standard deviations. However, not all studies report standard deviations to allow a weighted pooling of effect sizes. Fourth, we pool together effect sizes under the same pair of forest management action and carbon outcome, and calculate overall impacts. However, the impacts could be potentially moderated by confounders (e.g., forest type, disturbance history, elevation, and latitude). Incorporating these factors in the future exploration is necessary but requires more case studies. Fifth, it takes years for trees to recover and sequester carbon, and some studies regard "less than 25 years" as a short time-scale. Indeed, most of the experimental studies were conducted for a shorter time period than this. A robust time-series analysis is needed for better determining long-term benefits of forest management.

For woodlands, papers on land conversion and vegetation clearing were found, but were excluded because of insufficient sample sizes.

Croplands

Thirty-seven studies on agricultural practice impacts on carbon outcomes in California were identified. The synthesis here focused on those practices which were modeled by CARB for the Scoping Plan Update process. For annual crop studies, time periods for treatment effect were categorized as follows: 0 - <5 years post-treatment is short term, 5 – 10 years post-treatment is medium term, and >10 years post-treatment is long term. No and reduced till resulted in increased soil carbon in the short, medium, and long term, with greater increases in soil carbon over the long term. Cover cropping also increased soil carbon over all time periods, but was greater in the medium term.

Perennial studies were limited in number and were not separated based on time since treatment. Results from Garland et al. 2011 and Steenwerth and Belina 2008 indicated that the average annual increase in N2O emissions under cover cropping and no tillage in perennial crops increased slightly, but not significantly. This was attributed to the dry growing season allowing for well-aerated conditions that are less susceptible to N2O changes from tilling. For cover cropping, the timing of the mowing of cover crops was crucial in determining N2O emissions impacts. Steenwerth et al. 2010 found that soil respiration decreased significantly under cover crop and no till practices after 2 years; by 3.3 mt CO2e/ha/year and 5.7 mt CO2e/ha/yr, respectively. Biomass and soil carbon stocks increased 0.3 Mt CO2e/ha/yr over 22 years following cover cropping and no tilling under another study (Belmonte et al. 2018). When compost was added, soil carbon increased 7.2 Mt CO2e/ha/yr over the first 2 years (Lepsch et al. 2019). The uncertainty from these studies are high due to the limited number of data points and the high variability of soil characteristics throughout the state.

Three additional synthesis studies in the Mediterranean region were included here. Aguilera et al. 2013 examined herbaceous crops, and Morugan et al. 2019 and Vicente-Vicente 2016 examined orchards/vineyards. These studies conducted meta-analysis on previous literature, and key figures are copied in Figure 74, Figure 75, and Figure 76. They found that the effect on soil carbon and carbon sequestration varied depending on the agricultural practice and can be a significant positive impact.

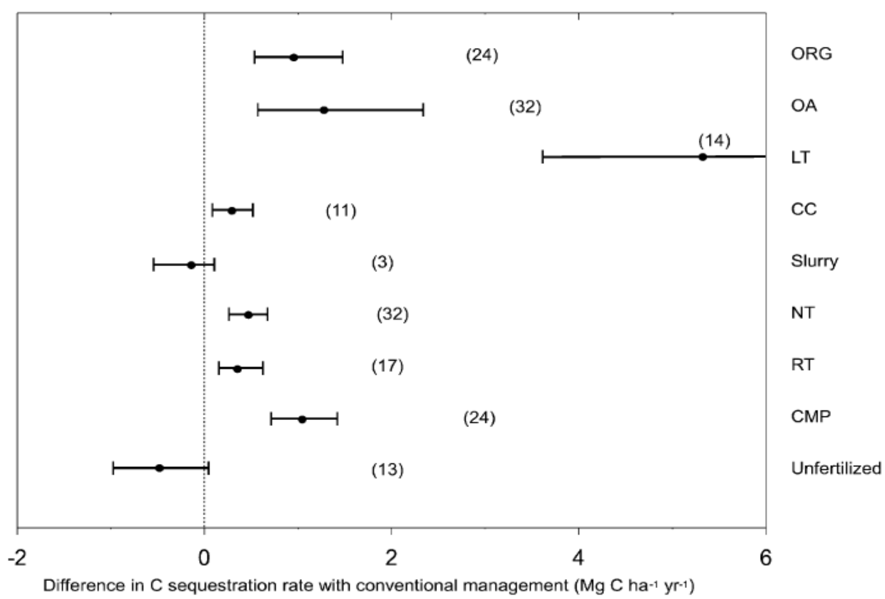

Figure 74. Comparison of soil organic carbon (top) and carbon sequestration rates (bottom) under various cropland management actions compared to conventional management, copied from Aguilera et al. 2013. Values to the left of the dotted line (zero) represent a decrease in SOC or sequestration rate for that action compared to conventional management, while values to the right indicate higher SOC or sequestration rate. Full caption (top): Effect of different recommended management practices (RMPs) on soil organic carbon (SOC) in units of percent change from the control (conventional management). ORG: organic management; LT: land treatment (urban wastes and C inputs exceeding 10 Mg C ha−1 yr−1); OA: organic amendments; CC: cover crops; Slurry: liquid manures; NT: no tillage; RT: reduced tillage; CMP: combined man-agement practices (OA combined with CC, CR, RT or NT); Unfertilized: no organic or synthetic fertilizers are applied. Error bars represent confidence intervals at 95%. Number of data sets is given in parentheses. Full caption (bottom): Effect of different recommended management practices (RMPs) on C seques-tration rate, compared to conventional management. ORG: organic management; LT: land treatment (urban wastes and C inputs exceeding 10 Mg C ha−1 yr−1); OA: organic amendments; CC: cover crops; Slurry: liquid manures; NT: no tillage; RT: reduced tillage; CMP: combined management practices (OA combined with CC, CR, RT or NT); Unfertilized: no organic or synthetic fertilizers are applied. Error bars represent confidence intervals at 95%. Number of data sets is given in parentheses.

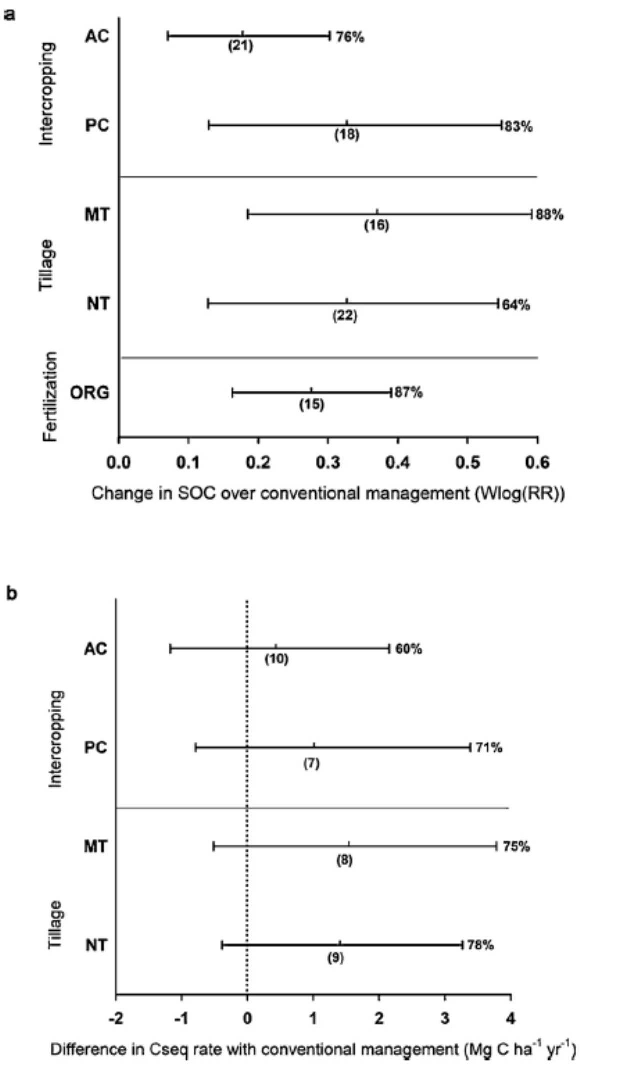

Figure 75. Comparison of soil organic carbon (a) and carbon sequestration rates (b) under various cropland management actions compared to conventional management, copied from Morugan et al. 2020. Values to the left of the dotted line (zero) in (b) represent a decrease in sequestration rate for that action compared to conventional management, while values to the right indicate higher SOC or sequestration rate. In (a), all actions resulted in greater SOC compared to conventional management. Full caption: Effects of intercropping, conservation tillage and organic fertilization on soil organic carbon (shown as weighted log response ratio: Wlog(RR)) (A) and differences in Carbon sequestration rates with conventional management (Mg C ha−1 yr−1) (B). The "|" denotes the mean, and the horizontal bar represents the confidence interval at 95%. The number below each bar indicates the size of the sample. AC: annual crops in intercropping; PC: permanent crops in intercropping; MT: minimum tillage; NT: no-tillage; ORG: organic fertilization.

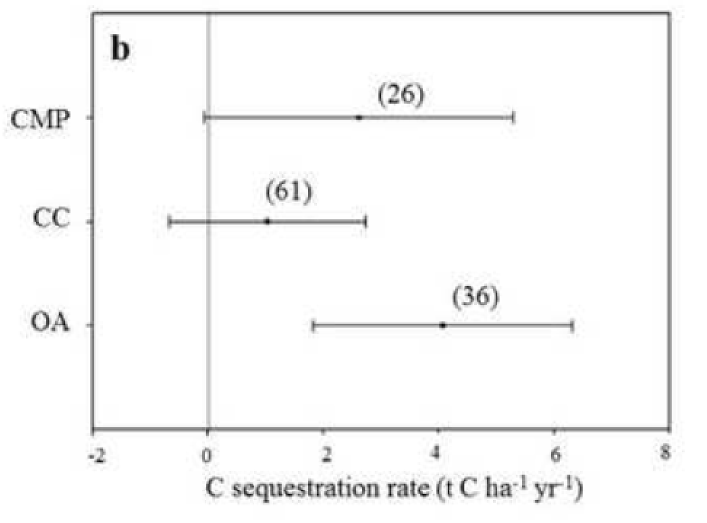

Figure 76. Carbon sequestration rate under various cropland management strategies, copied from Vicente-Vicente 2016. Full caption: Annual carbon sequestration rate under different management: CMP=combined management practices (cover crop + organic amendment/crop residues + reduced tillage/no tillage mowing/no tillage grazing), CC=cover crops (cover crop + no till mowing/no till grazing/reduced tillage), OA=organic amendment (organic amendment + tillage with herbicides/no tillage with herbicide).

Urban Forests

No studies examining specific urban forest management actions were found. Two papers were found that pertained to actions in urban areas to increase carbon stocks. One was related to grass turf management and another at mining site restoration. These studies were not included in this synthesis.

Wetlands

Several studies were identified that evaluated delta wetland restoration carbon outcomes. These studies examined GHG flux in wetlands after restoration treatment (i.e. inundation). Most of the studies did not measure pre-treatment (control), making estimates of GHG emissions reductions uncertain. Two studies included control measurements. The restoration treatments resulted in emissions reductions in the short duration of the studies (<2 years) (Figure 77, Figure 78).

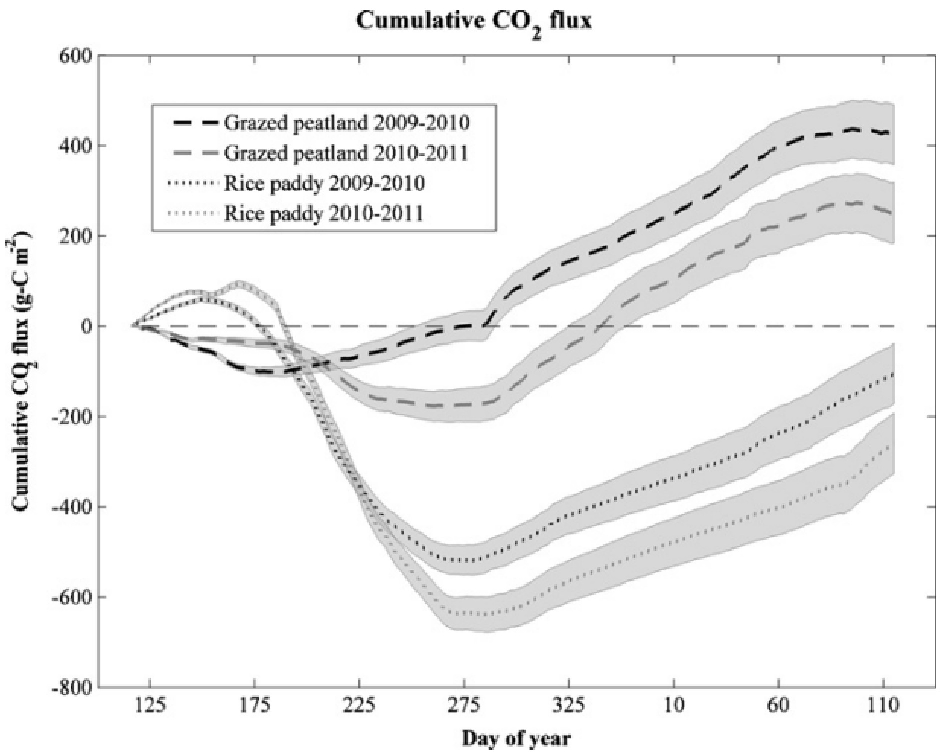

Figure 77. Cumulative GHG flux following delta wetland restoration treatment (Rice paddy) and the control (Grazed peatland), copied from Hatala et al. 2012. Full caption: Cumulative NEE. Cumulative NEE is plotted for the grazed degraded peatland (dashed lines) and rice paddy sites (dotted lines) for the two years of this study. Gray shaded areas represent the 95% confidence interval from bootstrapping the half-hourly fluxes. Due to the large uptake of CO2 during the growing season at the rice paddy and lower rates of wintertime respiration, much less CO2 is released to the atmosphere on an annual basis. Conversely, the lower photosynthetic CO2 uptake and high wintertime respiration at the grazed degraded peatland make it an annual CO2 source to the atmosphere. More favorable growing conditions in the 2010–2011 season cause greater photosynthetic uptake at both sites compared with 2009–2010.

Site	NEE	GEP	ER	CH_4		Harvest	C budget	GHG budget
	$g\,C\,m^{-2}$	$g\,C\,m^{-2}$	$g\,C\,m^{-2}$	$g\,C\,m^{-2}$	$g\,CO_2eq\,m^{-2}$	$g\,C\,m^{-2}$	$g\,C\,m^{-2}$	$g\,CO_2eq\,m^{-2}$
Pasture*	341±73	−1438±10	1762	5.84±1.51 to 11.4±2.66	194±51 to 381±88	N/A	347±75 to 352±76	1444±319 to 1631±356
Corn	278±24	−1356±9	1619	N/A	N/A	293	571±24	2094±88
Rice	−50±76	−1159±14	1203	5.30±0.80	177±27	162	117±77	588±306
Young wetland	−368±46	−2106±16	1834	53.0±0.78	1769±26	N/A	−315±47	420±194
Old wetland	−397±20	−1506±7	1108	38.7±1.10	1293±36	N/A	−358±21	−162±109

*The upper and lower bounds for the CH_4 budget at the Pasture are representative of different field conditions. Additional details are given in the body of the article.
N/A, not applicable.

Figure 78: GHG effects from various land uses of wetlands, copied from Knox et al. 2014. Full caption: Annual sums of net and partitioned CO2 fluxes, CH4 fluxes, harvest, and total ecosystem carbon and greenhouse gas budgets. Error bounds reflect the 95% confidence interval for the gap-filling procedure. Note that there are no error bounds for ecosystem respiration since it is modeled based on the relationship between nighttime net CO2 exchange and air temperature and is independent of the gap-filling procedure.

Sparsely Vegetated Lands

No studies examining specific land management actions on sparsely vegetated landscapes were found.

Grasslands

Compost addition to rangelands was identified as an action to consider for the Scoping Plan through public comment, stakeholder feedback, and interagency collaboration. Modeling of long-term carbon outcomes from this action are primarily driven by the 3-year field data collected in Ryals and Silver 2013 study. The 4th Climate Change Assessment Report "CARBON SEQUESTRATION AND GREENHOUSE GAS MITIGATION POTENTIAL OF COMPOSTING AND SOIL AMENDMENTS ON CALIFORNIA'S RANGELANDS" (Silver et al. 2018), which also drew from the Ryals and Silver 2013 data, modeled the net CO2e flux from rangelands with compost amendments over 85 years. Accounting for increased emissions resulting from the compost amendment, the modeling found that the net CO2e flux (net climate benefit) increased immediately after compost addition and decreased over time (Figure 79).

Other publications that looked at statewide projections of NBS also evaluated rangeland compost application carbon outcomes. DiVittorio et al. 2021 utilized CALAND and estimated that over 33 years, the average annual sequestration increase resulting from compost amendment ranged between 0.25 and 0.97 metric tons CO2/hectare, though N2O emissions were not accounted for. Cameron et al. 2017 used the assumption of a 2.35 MT CO2e/hectare annual emissions reduction rate, though they did not include any changes to CH4 and N2O emissions resulting from the compost addition. The LLNL Getting to Neutral report (Baker et al. 2020) used Comet Planner and estimated a 0.24 MT CO2e/hectare annual sequestration rate. The

4th Climate Change Assessment Report projections yielded a net climate benefit of 0.32 MT CO2e/hectare annually through year 20 post-treatment.

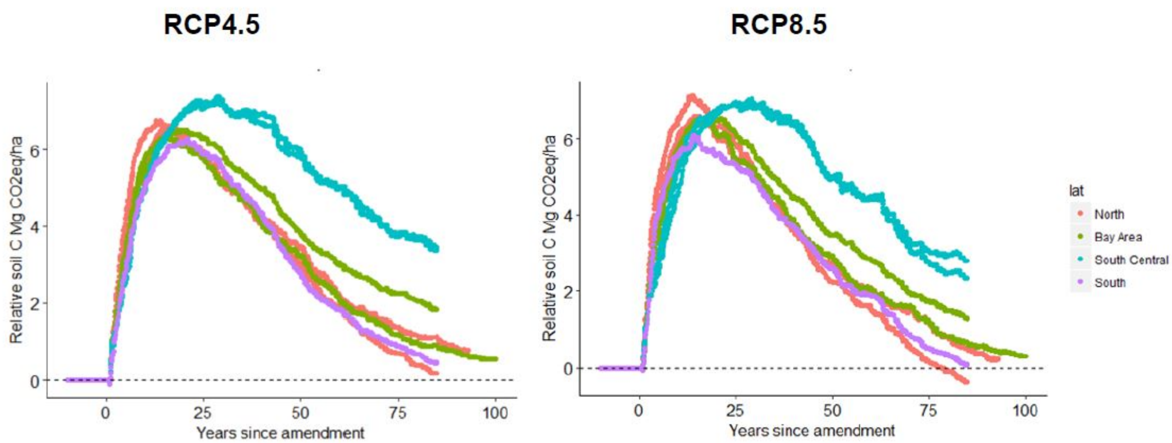

Figure 79: Projected net climate benefit in increased soil carbon of grassland compost amendment for seven grassland sites throughout California, copied from Silver et al. 2018. Full caption: Net climate benefit (Gross soil C inputs minus greenhouse gas emissions) for all seven sites were positive through the end of the century under RCP 4.5. The two northern sites (red), had a similar decreasing net climate benefit as San Diego County in the south (purple), while the Bay Area sites (green) had a slightly longer lasting climate benefit. The two driest sites of Santa Barbara and Tulare Counties in South Central California (blue) had the largest and longest climate benefit due to compost. With greater climate change in the RCP 8.5 scenario, all sites exhibited reduced climate benefit in the latter half of the century, and even a net loss of C from the system by the end of the century in the wet, Mendocino County site.

Gravuer et al. 2019 noted this benefit from compost amendment comes with harms as well. These harms depend on the local conditions where compost is added, such as the climate and water availability, proximity to watercourses, soil chemistry, and the C:N ratio of the compost. They include changes to soil chemistry and species diversity, changes to water runoff quantities, and potential changes to nutrient runoff. The authors conclude that careful consideration of local conditions is needed when determining appropriate site strategies for compost amendment.

Shrublands

A wide variety of actions on shrublands were studied; however, they were either examining an action that was not modeled in CARBs Scoping Plan analysis or did not comprise a sufficient sample size to be included in this synthesis.

References

BAU Synthesis

Battles, JJ; Robards, T; Das, A; Waring, K; Gilless, JK; Biging, G; Schurr, F., 2008. Climate change impacts on forest growth and tree mortality: a data-driven modeling study in the mixed-conifer forest of the Sierra Nevada, California. CLIMATIC CHANGE. 43(7), pp.1474-1481. doi:10.1016/j.soilbio.2011.03.020

Battles, John J; Robards, Timothy; Das, Adrian; Waring, Kristen; Gilless, J Keith; Schurr, Frieder; LeBlanc, John; Biging, Gregory; Simon, Clara, 2006. Climate change impact on forest resources. California Climate Change Center White Paper. 77, pp.767-780. doi:10.1016/j.atmosenv.2013.06.003

Battles, John; Robards, Timothy; Das, Adrian; Stewart, William, 2009. Projecting climate change impacts on forest growth and yield for California's Sierran mixed conifer forests. California Climate Change Center paper CEC-500-2009-047-D. Available at www.energy.ca.gov/2009publications/CEC-500–2009–047/CEC-500–2009–047-F. PDF. 109(1-3), pp.63-83. doi:10.1007/s10533-011-9654-3

Brilli, L; Lugato, E; Moriondo, M; Gioli, B; Toscano, P; Zaldei, A; Leolini, L; Cantini, C; Caruso, G; Gucci, R; Merante, P; Dibari, C; Ferrise, R; Bindi, M; Costafreda-Aumedes, S., 2019. Carbon sequestration capacity and productivity responses of Mediterranean olive groves under future climates and management options. MITIGATION AND ADAPTATION STRATEGIES FOR GLOBAL CHANGE. 30(17), pp.6883-6904. doi:10.1175/JCLI-D-17-0005.1

Byrd, KB; Flint, LE; Alvarez, P; Casey, CF; Sleeter, BM; Soulard, CE; Flint, AL; Sohl, TL., 2015. Integrated climate and land use change scenarios for California rangeland ecosystem services: wildlife habitat, soil carbon, and water supply. LANDSCAPE ECOLOGY. 138(3-4), pp.655-666. doi:10.1007/s10584-016-1762-6

Dass, P; Houlton, BZ; Wang, YP; Warlind, D., 2018. Grasslands may be more reliable carbon sinks than forests in California. ENVIRONMENTAL RESEARCH LETTERS. 20(2), pp.935-952. doi:10.5194/hess-20-935-2016

Hayhoe, K; Cayan, D; Field, CB; Frumhoff, PC; Maurer, EP; Miller, NL; Moser, SC; Schneider, SH; Cahill, KN; Cleland, EE; Dale, L; Drapek, R; Hanemann, RM; Kalkstein, LS; Lenihan, J; Lunch, CK; Neilson, RP; Sheridan, SC; Verville, JH., 2004. Emissions pathways, climate change, and impacts on California. PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA. 51(2), pp.131-172. doi:10.1023/A:1012297314857

Hurteau, MD; Liang, S; Westerling, AL; Wiedinmyer, C., 2019. Vegetation-fire feedback reduces projected area burned under climate change. SCIENTIFIC REPORTS. 33(2), pp.236-253. doi:10.1080/15427528.2019.1578712

Hurteau, MD; Robards, TA; Stevens, D; Saah, D; North, M; Koch, GW., 2014. Modeling climate and fuel reduction impacts on mixed-conifer forest carbon stocks in the Sierra Nevada, California. FOREST ECOLOGY AND MANAGEMENT. 63(4), pp.841-865. doi:10.1111/1467-8489.12330

Jebari, A; del Prado, A; Pardo, G; Martin, JAR; Alvaro-Fuentes, J., 2018. Modeling Regional Effects of Climate Change on Soil Organic Carbon in Spain. JOURNAL OF ENVIRONMENTAL QUALITY. 54(3), pp.2152-2182. doi:10.1002/2017WR020954

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. 5 doi:10.3389/fevo.2017.00020

Krofcheck, DJ; Hurteau, MD; Scheller, RM; Loudermilk, EL., 2017. Restoring surface fire stabilizes forest carbon under extreme fire weather in the Sierra Nevada. ECOSPHERE. 111(1-2), pp.173-182. doi:10.1007/s00704-012-0655-5

Ledig, FT; Rehfeldt, GE; Jaquish, B., 2012. PROJECTIONS OF SUITABLE HABITAT UNDER CLIMATE CHANGE SCENARIOS: IMPLICATIONS FOR TRANS-BOUNDARY ASSISTED COLONIZATION. AMERICAN JOURNAL OF BOTANY.

Lenihan, James M; Bachelet, Dominique; Neilson, Ronald P; Drapek, Raymond, 2008. Response of vegetation distribution, ecosystem productivity, and fire to climate change scenarios for California. Climatic Change. 220(2), pp.213-225. doi:10.1007/s11258-018-0843-1

Lenihan, JM; Drapek, R; Bachelet, D; Neilson, RP., 2003. Climate change effects on vegetation distribution, carbon, and fire in California. ECOLOGICAL APPLICATIONS. 131, pp.28-39. doi:10.1016/j.soilbio.2018.12.022

Liang, S; Hurteau, MD; Westerling, AL., 2017a. Potential decline in carbon carrying capacity under projected climate-wildfire interactions in the Sierra Nevada. SCIENTIFIC REPORTS. 76(2). doi:10.1007/s13595-019-0843-x

Liang, S; Hurteau, MD; Westerling, AL., 2017b. Response of Sierra Nevada forests to projected climate-wildfire interactions. GLOBAL CHANGE BIOLOGY. 59(1-2), pp.263-282. doi:10.1023/A:1024427803359

Loudermilk, EL; Scheller, RM; Weisberg, PJ; Kretchun, A., 2017. Bending the carbon curve: fire management for carbon resilience under climate change. LANDSCAPE ECOLOGY. 20(12), pp.2331-2346. doi:10.1175/JHM-D-19-0055.1

Loudermilk, EL; Scheller, RM; Weisberg, PJ; Yang, J; Dilts, TE; Karam, SL; Skinner, C., 2013. Carbon dynamics in the future forest: the importance of long-term successional legacy and climate-fire interactions. GLOBAL CHANGE BIOLOGY. 124(10).

Lubetkin, KC; Westerling, AL; Kueppers, LM., 2017. Climate and landscape drive the pace and pattern of conifer encroachment into subalpine meadows. ECOLOGICAL APPLICATIONS. 266, pp.173-183. doi:10.1016/j.agrformet.2018.12.016

Maxwell, Charles J; Serra-Diaz, Josep M; Scheller, Robert M; Thompson, Jonathan R, 2020. Co-designed management scenarios shape the responses of seasonally dry forests to changing climate and fire regimes. Journal of Applied Ecology. 22(4), pp.1365-1388. doi:10.1890/11-1269.1

Maxwell, Charles Jeffrey, 2018. Climate Change on the Forests of the Klamath-Siskiyous and Potential Management Strategies. . 114 doi:10.1029/2008JD010966

Nowak, D., Greenfield, E., 2018. US urban forest statistics, values, and projections. Journal of Forestry. 116(2), pp.164-177.

Nowak, D., Greenfield, E., 2018. Declining urban and community tree cover in the United States. Urban forestry & urban greening. 32, pp.32-55.

Nowak, D., Greenfield, E., Ellis, A., 2021. Climate Change and Urban Forests: Part 1: Urban Forest Projections with Urban Expansion. USDA Forest Service and Davey Institute.

Nowak, D., Greenfield, E., Hoehn, R., Lapoint, E., 2013. Carbon storage and sequestration by trees in urban and community areas of the United States. Environmental pollution. 32, pp.229-236.

Parks, Sean A; Holsinger, Lisa M; Miller, Carol; Parisien, Marc-André, 2018. Analog-based fire regime and vegetation shifts in mountainous regions of the western US. Ecography. 11(10), pp.2803-2816. doi:10.5194/nhess-11-2803-2011

Scheller, RM; Kretchun, AM; Loudermilk, EL; Hurteau, MD; Weisberg, PJ; Skinner, C., 2018. Interactions Among Fuel Management, Species Composition, Bark Beetles, and Climate Change and the Potential Effects on Forests of the Lake Tahoe Basin. ECOSYSTEMS. 33(5), pp.863-875. doi:10.1111/j.1365-3040.2009.02112.x

Serra-Diaz, JM; Maxwell, C; Lucash, MS; Scheller, RM; Laflower, DM; Miller, AD; Tepley, AJ; Epstein, HE; Anderson-Teixeira, KJ; Thompson, JR., 2018. Disequilibrium of fire-prone forests sets the stage for a rapid decline in conifer dominance during the 21st century. SCIENTIFIC REPORTS. , pp.135-149-.

Sleeter, B. M., Liu, J., Daniel, C., Frid, L., & Zhu, Z. ., 2015. An integrated approach to modeling changes in land use, land cover, and disturbance and their impact on ecosystem carbon dynamics: a case study in the Sierra Nevada Mountains of California. . AIMS Environmental Science. 142(3), pp.465-473. doi:10.1007/s00442-004-1713-1

Sleeter, BM; Marvin, DC; Cameron, DR; Selmants, PC; Westerline, AL; Kreitler, J; Daniel, CJ; Liu, JX; Wilson, TS., 2019. Effects of 21st-century climate, land use, and disturbances on ecosystem carbon balance in California. GLOBAL CHANGE BIOLOGY. 338(1-2), pp.261-272. doi:10.1007/s11104-010-0304-7

Syphard, AD; Scheller, RM; Ward, BC; Spencer, WD; Strittholt, JR., 2011. Simulating landscape-scale effects of fuels treatments in the Sierra Nevada, California, USA. INTERNATIONAL JOURNAL OF WILDLAND FIRE. 201(2), pp.498-504. doi:10.1111/nph.12546

Weinstein, DA; Laurence, JA; Retzlaff, WA; Kern, JS; Lee, EH; Hogsett, WE; Weber, J., 2005. Predicting the effects of tropospheric ozone on regional productivity of ponderosa pine and white fir. FOREST ECOLOGY AND MANAGEMENT. 101(1), pp.27-32. doi:10.1073/pnas.0305746101

Westerling, A.L., Bryant, B.P., Preisler, H.K. et al. ., 2011. Climate change and growth scenarios for California wildfire. Climatic Change. 185(4), pp.763-774. doi:10.1007/s00442-017-3976-3

Westerling, Anthony Leroy, 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. 252, pp.53-61. doi:10.1016/j.plantsci.2016.07.004

Action Outcome Synthesis

Aban, CL; Verdenelli, R; Gil, SV; Huidobro, DJ; Meriles, JM; Brandan, CP., 2021. Service crops improve a degraded monoculture system by changing common bean rhizospheric soil microbiota and reducing soil-borne fungal diseases. FEMS MICROBIOLOGY ECOLOGY. 97(2). doi:10.1093/femsec/fiaa258

Agbede, TM; Adekiya, AO., 2020. Influence of Biochar on Soil Physicochemical Properties, Erosion Potential, and Maize (Zea mays L.) Grain Yield under Sandy Soil Condition. COMMUNICATIONS IN SOIL SCIENCE AND PLANT ANALYSIS. 51(20), pp.2559-2568. doi:10.1080/00103624.2020.1845348

Aguilera, E; Lassaletta, L; Gattinger, A; Gimeno, BS., 2013. Managing soil carbon for climate change mitigation and adaptation in Mediterranean cropping systems: A meta-analysis. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 168, pp.25-36. doi:10.1016/j.agee.2013.02.003

Akbarian, MM; Mojaradi, T; Shirzadi, F., 2021. Effects of Hedysarum coronarium L. (sulla) as a Green Manure along with Nitrogen Fertilizer on Maize Production. AGRITECH. 41(1), pp.95-106. doi:10.22146/agritech.58944

Amami, R; Ibrahimi, K; Znouda, A; Abrougui, K; Sayed, C., 2021. Influence of tillage systems on soil bulk density and carbon dioxide emissions in the Mediterranean context. Ecounit. RO-MEDITERRANEAN JOURNAL FOR ENVIRONMENTAL INTEGRATION. 6(1). doi:10.1007/s41207-020-00229-0

Angst, TE; Six, J; Reay, DS; Sohi, SP., 2014. Impact of pine chip biochar on trace greenhouse gas emissions and soil nutrient dynamics in an annual ryegrass system in California. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 191, pp.17-26. doi:10.1016/j.agee.2014.03.009

Baker, S. E., Stolaroff, J. K., Peridas, G., Pang, S. H., Goldstein, H. M., Lucci, F. R., .. & McCormick, C. 2020. Getting to neutral: Options for negative carbon emissions in California (No. LLNL-TR-796100). Lawrence Livermore National Lab.(LLNL), Livermore, CA (United States); Univ. of California, Berkeley, CA (United States); Negative Carbon Consulting, Half Moon Bay, CA (United States); Univ. of Calgary, AB (Canada); Univ. of Queensland, Brisbane, QLD (Australia); Univ. of California, Davis, CA (United States); Worcester Polytechnic Institute, MA (United States); Georgetown Univ., Washington, DC (United States); Valence Strategic, Washington, DC (United States).

Banerjee, T; Heilman, W; Goodrick, S; Hiers, JK; Linn, R., 2020. Effects of canopy midstory management and fuel moisture on wildfire behavior. SCIENTIFIC REPORTS. 10(1). doi:10.1038/s41598-020-74338-9

Baughman, OW; Griffen, J; Kerby, J; Davies, KW; Clenet, D; Boyd, C., 2021. Herbicide protection pod technology for native plant restoration: one size may not fit all. RESTORATION ECOLOGY. 29(3). doi:10.1111/rec.13323

Bell, DM; Acker, SA; Gregory, MJ; Davis, RJ; Garcia, BA., 2021. Quantifying regional trends in large live tree and snag availability in support of forest management. FOREST ECOLOGY AND MANAGEMENT. 479. doi:10.1016/j.foreco.2020.118554

Belmonte, SA; Celi, L; Stahel, RJ; Bonifacio, E; Novello, V; Zanini, E; Steenwerth, KL., 2018. Effect of Long-Term Soil Management on the Mutual Interaction Among Soil Organic Matter, Microbial Activity and Aggregate Stability in a Vineyard. PEDOSPHERE. 28(2), pp.288-298. doi:10.1016/S1002-0160(18)60015-3

Billman, ED; Williamson, JA; Soder, KJ; Andreen, DM; Skinner, RH., 2020. Mob and rotational grazing influence pasture biomass, nutritive value, and species composition. AGRONOMY JOURNAL. 112(4), pp.2866-2878. doi:10.1002/agj2.20215

Bogunovic, I; Telak, LJ; Pereira, P; Filipovic, V; Filipovic, L; Percin, A; Durdevic, B; Birkas, M; Dekemati, I; Comino, JR., 2020. Land management impacts on soil properties and initial soil erosion processes in olives and vegetable crops. JOURNAL OF HYDROLOGY AND HYDROMECHANICS. 68(4), pp.328-337. doi:10.2478/johh-2020-0033

Brennan, EB; Acosta-Martinez, V., 2017. Cover cropping frequency is the main driver of soil microbial changes during six years of organic vegetable production. . 109, pp.-188.

Brodt, SB; Fontana, NM; Archer, LF., 2020. Feasibility and sustainability of agroforestry in temperate industrialized agriculture: preliminary insights from California. RENEWABLE AGRICULTURE AND FOOD SYSTEMS. 35(5), pp.513-521. doi:10.1017/S1742170519000140

Brown, S; Cotton, M., 2011. Changes in Soil Properties and Carbon Content Following Compost Application: Results of On-farm Sampling. COMPOST SCIENCE & UTILIZATION. 19(2), pp.87-96.

Burger, M; Jackson, LE; Lundquist, EJ; Louie, DT; Miller, RL; Rolston, DE; Scow, KM., 2005. Microbial responses and nitrous oxide emissions during wetting and drying of organically and conventionally managed soil under tomatoes. BIOLOGY AND FERTILITY OF SOILS. 42(2), pp.109-118. doi:10.1007/s00374-005-0007-z

Callegary, JB; Norman, LM; Eastoe, CJ; Sankey, JB; Youberg, A., 2021. Preliminary Assessment of Carbon and Nitrogen Sequestration Potential of Wildfire-Derived Sediments Stored by Erosion Control Structures in Forest Ecosystems, Southwest USA. AIR SOIL AND WATER RESEARCH. 14. doi:10.1177/11786221211001768

Cameron, DR; Marvin, DC; Remucal, JM; Passero, MC., 2017. Ecosystem management and land conservation can substantially contribute to California's climate mitigation goals. . 44528(114), pp.-12833.

Campi, P; Gaeta, L; Mastrorilli, M; Losciale, P., 2020. Innovative Soil Management and Micro-Climate Modulation for Saving Water in Peach Orchards. FRONTIERS IN PLANT SCIENCE. 11. doi:10.3389/fpls.2020.01052

Campos, V; Sanchis, JR; Talavera, C., 2021. The Importance of Social Value in Agroecological Farms: Adjusting the Common Good Balance Sheet to Improve Their Sustainable Management. SUSTAINABILITY. 13(3). doi:10.3390/su13031184

Chalkia, C; Vavoulidou, E; Koubouris, G; Chatzipavlidis, I; Kalaitzaki, A; Perdikis, D., 2020. Spreading raw olive mill wastewater is compatible with the growth and the beneficial functions of the earthworm Octodrilus complanatus. APPLIED SOIL ECOLOGY. 153. doi:10.1016/j.apsoil.2020.103625

Chamberlain, SD; Anthony, TL; Silver, WL; Eichelmann, E; Hemes, KS; Oikawa, PY; Sturtevant, C; Szutu, DJ; Verfaillie, JG; Baldocchi, DD., 2018. Soil properties and sediment accretion modulate methane fluxes from restored wetlands. GLOBAL CHANGE BIOLOGY. 24(9), pp.4107-4121. doi:10.1111/gcb.14124

Chomphosy, WH; Varriano, S; Lefler, LH; Nallur, V; McClung, MR; Moran, MD., . Ecosystem services benefits from the restoration of non-producing US oil and gas lands. NATURE SUSTAINABILITY. doi:10.1038/s41893-021-00689-4

Crotteau, JS; Keyes, CR., 2020. Restoration Treatments Improve Overstory Tree Resistance Attributes and Growth in a Ponderosa Pine/Douglas-Fir Forest. FORESTS. 11(5). doi:10.3390/f11050574

Curci, M; Lavecchia, A; Cucci, G; Lacolla, G; De Corato, U; Crecchio, C., 2020. Short-Term Effects of Sewage Sludge Compost Amendment on Semiarid Soil. SOIL SYSTEMS. 4(3). doi:10.3390/soilsystems4030048

De Gryze, S; Albarracin, MV; Catala-Luque, R; Howitt, RE; Six, J., 2009. Modeling shows that alternative soil management can decrease greenhouse gases. CALIFORNIA AGRICULTURE. 63(2), pp.84-90. doi:10.3733/ca.v063n02p84

De Gryze, S; Wolf, A; Kaffka, SR; Mitchell, J; Rolston, DE; Temple, SR; Lee, J; Six, J., 2010. Simulating greenhouse gas budgets of four California cropping systems under conventional and alternative management. ECOLOGICAL APPLICATIONS. 20(7), pp.1805-1819.

Deligios, PA; Farina, R; Tiloca, MT; Francaviglia, R; Ledda, L., 2021. C-sequestration and resilience to climate change of globe artichoke cropping systems depend on crop residues management. AGRONOMY FOR SUSTAINABLE DEVELOPMENT. 41(2). doi:10.1007/s13593-021-00680-5

Deng, J; Li, CS; Burger, M; Horwath, WR; Smart, D; Six, J; Guo, L; Salas, W; Frolking, S., 2018. Assessing Short-Term Impacts of Management Practices on N2O Emissions From Diverse Mediterranean Agricultural Ecosystems Using a Biogeochemical Model. JOURNAL OF GEOPHYSICAL RESEARCH-BIOGEOSCIENCES. 123(5), pp.1557-1571. doi:10.1029/2017JG004260

Devkota, M; Yigezu, YA., 2020. Explaining yield and gross margin gaps for sustainable intensification of the wheat-based systems in a Mediterranean climate. AGRICULTURAL SYSTEMS. 185. doi:10.1016/j.agsy.2020.102946

D'Hervilly, C; Marsden, C; Capowiez, Y; Beral, C; Delapre-Cosset, L; Bertrand, I., . Trees and herbaceous vegetation strips both contribute to changes in soil fertility and soil organism communities in an agroforestry system. PLANT AND SOIL. doi:10.1007/s11104-021-04932-x

Di Vittorio, A. V., Simmonds, M. B., & Nico, P. 2021. Quantifying the effects of multiple land management practices, land cover change, and wildfire on the California landscape carbon budget with an empirical model. PloS one, 16(5), e0251346.

Djaman, K; Smeal, D; Koudahe, K; Allen, S., 2020. Hay Yield and Water Use Efficiency of Alfalfa under Different Irrigation and Fungicide Regimes in a Semiarid Climate. WATER. 12(6). doi:10.3390/w12061721

Escobedo-Monge, MA; Aparicio, S; Escobedo-Monge, MF; Marugan-Miguelsanz, JM., 2020. Long-Term Effects of the Application of Urban Waste Compost and Other Organic Amendments on Solanum tuberosum L. AGRONOMY-BASEL. 10(10). doi:10.3390/agronomy10101575

Failla, S; Pirchio, M; Sportelli, M; Frasconi, C; Fontanelli, M; Raffaelli, M; Peruzzi, A., 2021. Evolution of Smart Strategies and Machines Used for Conservative Management of Herbaceous and Horticultural Crops in the Mediterranean Basin: A Review. AGRONOMY-BASEL. 11(1). doi:10.3390/agronomy11010106

Faria, N; Morales, MB, 2020. Farmland management regulates ecosystem services in Mediterranean drylands: Assessing the sustainability of agri-environmental payments for bird conservation. JOURNAL FOR NATURE CONSERVATION. 58. doi:10.1016/j.jnc.2020.125913

Fehmi, JS; Rasmussen, C; Gallery, RE., 2020. Biochar and woodchip amendments alter restoration outcomes, microbial processes, and soil moisture in a simulated semi-arid ecosystem. RESTORATION ECOLOGY. 28, pp.S355-S364. doi:10.1111/rec.13100

Feng, XY; Kebreab, E., 2020. Net reductions in greenhouse gas emissions from feed additive use in California dairy cattle. PLOS ONE. 15(9). doi:10.1371/journal.pone.0234289

Fernandez-Gonzalez, AJ; Wentzien, NM; Villadas, PJ; Valverde-Corredor, A; Lasa, AV; Cabanas, CGL; Mercado-Blanco, J; Fernandez-Lopezo, M., 2020. Comparative study of neighboring Holm oak and olive trees-belowground microbial communities subjected to different soil management. PLOS ONE. 15(8). doi:10.1371/journal.pone.0236796

Foster, DE; Battles, JJ; Collins, BM; York, RA; Stephens, SL., 2020. Potential wildfire and carbon stability in frequent-fire forests in the Sierra Nevada: trade-offs from a long-term study. ECOSPHERE. 11(8). doi:10.1002/ecs2.3198

Garland, GM; Suddick, E; Burger, M; Horwath, WR; Six, J., 2011. Direct N2O emissions following transition from conventional till to no-till in a cover cropped Mediterranean vineyard (Vitis vinifera). AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 144(1), pp.423-428. doi:10.1016/j.agee.2011.11.001

Gavinet, J; Ourcival, JM; Gauzere, J; de Jalon, LG; Limousin, JM., 2020. Drought mitigation by thinning: Benefits from the stem to the stand along 15 years of experimental rainfall exclusion in a holm oak coppice. FOREST ECOLOGY AND MANAGEMENT. 473. doi:10.1016/j.foreco.2020.118266

Gonzalez-Rosado, M; Parras-Alcantara, L; Aguilera-Huertas, J; Lozano-Garcia, B., 2021. Long-term evaluation of the initiative 4 parts per thousand under different soil managements in Mediterranean olive groves. SCIENCE OF THE TOTAL ENVIRONMENT. 758. doi:10.1016/j.scitotenv.2020.143591

Gravuer, Kelly; Gennet, Sasha; Throop, Heather L., 2019. Organic amendment additions to rangelands: A meta-analysis of multiple ecosystem outcomes. Global change biology. 25

Harrington, TB; Slesak, RA; Dollins, JP; Schoenholtz, SH; Peter, DH., 2020. Logging-debris and vegetation-control treatments influence competitive relationships to limit 15-year productivity of coast Douglas-fir in western Washington and Oregon. FOREST ECOLOGY AND MANAGEMENT. 473. doi:10.1016/j.foreco.2020.118288

Hatala, JA; Detto, M; Sonnentag, O; Deverel, SJ; Verfaillie, J; Baldocchi, DD., 2012. Greenhouse gas (CO2, CH4, H2O) fluxes from drained and flooded agricultural peatlands in the Sacramento-San Joaquin Delta. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 150, pp.1-18. doi:10.1016/j.agee.2012.01.009

Hemes, KS; Chamberlain, SD; Eichelmann, E; Knox, SH; Baldocchi, DD., 2018. A Biogeochemical Compromise: The High Methane Cost of Sequestering Carbon in Restored Wetlands. GEOPHYSICAL RESEARCH LETTERS. 45(12), pp.6081-6091. doi:10.1029/2018GL077747

Hernandez, E; Shaw, EA; Aoyama, L; Brambila, A; Niederer, C; Weiss, SB; Hallett, LM., 2021. Fire versus grazing as tools to restore serpentine grasslands under global change. RESTORATION ECOLOGY. 29. doi:10.1111/rec.13353

Hunter, ME; Robles, MD., 2020. Tamm review: The effects of prescribed fire on wildfire regimes and impacts: A framework for comparison. FOREST ECOLOGY AND MANAGEMENT. 475. doi:10.1016/j.foreco.2020.118435

Jackson, LE; Calderon, FJ; Steenwerth, KL; Scow, KM; Rolston, DE., 2003. Responses of soil microbial processes and community structure to tillage events and implications for soil quality. GEODERMA. 114(44259), pp.305-317. doi:10.1016/S0016-7061(03)00046-6

Janousek, CN; Bailey, SJ; Brophy, LS., 2021. Early Ecosystem Development Varies With Elevation and Pre-Restoration Land Use/Land Cover in a Pacific Northwest Tidal Wetland Restoration Project. ESTUARIES AND COASTS. 44(1), pp.13-29. doi:10.1007/s12237-020-00782-5

Jiang, R; Yang, JY; Drury, CF; He, WT; Smith, WN; Grant, BB; He, P; Zhou, W., 2021. Assessing the impacts of diversified crop rotation systems on yields and nitrous oxide emissions in Canada using the DNDC model. SCIENCE OF THE TOTAL ENVIRONMENT. 759. doi:10.1016/j.scitotenv.2020.143433

Johnston, JD; Hagmann, RK; Seager, ST; Merschel, AG; Franklin, JF; Johnson, KN., 2021. Commentary: Large Trees Dominate Carbon Storage in Forests East of the Cascade Crest in the United States Pacific Northwest. FRONTIERS IN FORESTS AND GLOBAL CHANGE. 4. doi:10.3389/ffgc.2021.653774

Kallenbach, CM; Rolston, DE; Horwath, WR., 2010. Cover cropping affects soil N2O and CO2 emissions differently depending on type of irrigation. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 137(3-4), pp.251-260. doi:10.1016/j.agee.2010.02.010

Keightley, KE., 2011. Applying New Methods for Estimating in Vivo Vineyard Carbon Storage. AMERICAN JOURNAL OF ENOLOGY AND VITICULTURE. 62(2), pp.214-218. doi:10.5344/ajev.2010.10081

Kennedy, T; Decock, C; Six, J., 2013. Assessing drivers of N2O production in California tomato cropping systems. SCIENCE OF THE TOTAL ENVIRONMENT. 465, pp.36-47. doi:10.1016/j.scitotenv.2013.04.014

Kennedy, TL; Suddick, EC; Six, J., 2013. Reduced nitrous oxide emissions and increased yields in California tomato cropping systems under drip irrigation and fertigation. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 170, pp.16-27. doi:10.1016/j.agee.2013.02.002

Khorchani, M; Nadal-Romero, E; Tague, C; Lasanta, T; Zabalza, J; Lana-Renault, N; Dominguez-Castro, F; Choate, J., 2020. Effects of active and passive land use management after cropland abandonment on water and vegetation dynamics in the Central Spanish Pyrenees. SCIENCE OF THE TOTAL ENVIRONMENT. 717. doi:10.1016/j.scitotenv.2020.137160

Knox, SH; Sturtevant, C; Matthes, JH; Koteen, L; Verfaillie, J; Baldocchi, D., 2015. Agricultural peatland restoration: effects of land-use change on greenhouse gas (CO2 and CH4) fluxes in the Sacramento-San Joaquin Delta. GLOBAL CHANGE BIOLOGY. 21(2), pp.750-765. doi:10.1111/gcb.12745

Kong, AYY; Fonte, SJ; van Kessel, C; Six, J., 2009. Transitioning from standard to minimum tillage: Trade-offs between soil organic matter stabilization, nitrous oxide emissions, and N availability in irrigated cropping systems. SOIL & TILLAGE RESEARCH. 104(2), pp.256-262. doi:10.1016/j.still.2009.03.004

Kong, AYY; Six, J; Bryant, DC; Denison, RF; van Kessel, C., 2005. The relationship between carbon input, aggregation, and soil organic carbon stabilization in sustainable cropping systems. SOIL SCIENCE SOCIETY OF AMERICA JOURNAL. 69(4), pp.1078-1085. doi:10.2136/sssaj2004.0215

Kroll, AJ; Johnston, JD; Stokely, TD; Meigs, GW., 2020. From the ground up: Managing young forests for a range of ecosystem outcomes. FOREST ECOLOGY AND MANAGEMENT. 464. doi:10.1016/j.foreco.2020.118055

Kroll, AJ; Springford, A; Verschuyl, J., 2020. Conservation and production responses vary by disturbance intensity in a long-term forest management experiment. ECOLOGICAL APPLICATIONS. 30(7). doi:10.1002/eap.2148

Lavoie, A; Wardropper, CB., . Engagement with conservation tillage shaped by good farmer identity. AGRICULTURE AND HUMAN VALUES. . doi:10.1007/s10460-021-10205-1

Lazcano, C; Tsang, A; Doane, TA; Pettygrove, GS; Horwath, WR; Burger, M., 2016. Soil nitrous oxide emissions in forage systems fertilized with liquid dairy manure and inorganic fertilizers. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 225, pp.160-172. doi:10.1016/j.agee.2016.04.009

Lee, J; Hopmans, JW; van Kessel, C; King, AP; Evatt, KJ; Louie, D; Rolston, DE; Six, J., 2009. Tillage and seasonal emissions of CO2, N2O and NO across a seed bed and at the field scale in a Mediterranean climate. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 129(4), pp.378-390. doi:10.1016/j.agee.2008.10.012

Lepsch, HC; Brown, PH; Peterson, CA; Gaudin, ACM; Khalsa, SDS., 2019. Impact of organic matter amendments on soil and tree water status in a California orchard. AGRICULTURAL WATER MANAGEMENT. 222, pp.204-212. doi:10.1016/j.agwat.2019.06.002

Littke, KM; Harrington, TB; Holub, SM; Littke, WR; Harrison, RB; Turnblom, EC., 2020. Douglas-Fir Biomass Allocation and Net Nutrient Pools 15-20 Years after

Organic Matter Removal and Vegetation Control. FORESTS. 11(9). doi:10.3390/f11091022

Littke, KM; Harrington, TB; Slesak, RA; Holub, SM; Hatten, JA; Gallo, AC; Littke, WR; Harrison, RB; Turnblom, EC., 2020. Impacts of organic matter removal and vegetation control on nutrition and growth of Douglas-fir at three Pacific Northwestern Long-Term Soil Productivity sites. FOREST ECOLOGY AND MANAGEMENT. 468. doi:10.1016/j.foreco.2020.118176

Llovet, A; Mattana, S; Chin-Pampillo, J; Otero, N; Carrey, R; Mondini, C; Gasco, G; Marti, E; Margalef, R; Alcaniz, JM; Domene, X; Ribas, A., 2021. Fresh biochar application provokes a reduction of nitrate which is unexplained by conventional mechanisms. SCIENCE OF THE TOTAL ENVIRONMENT. 755. doi:10.1016/j.scitotenv.2020.142430

Loures, L; Chamizo, A; Ferreira, P; Loures, A; Castanho, R; Panagopoulos, T., 2020. Assessing the Effectiveness of Precision Agriculture Management Systems in Mediterranean Small Farms. SUSTAINABILITY. 12(9). doi:10.3390/su12093765

Lucas-Borja, ME; Delgado-Baquerizo, M; Munoz-Rojas, M; Plaza-Alvarez, PA; Gomez-Sanchez, ME; Gonzalez-Romero, J; Pena-Molina, E; Moya, D; de las Heras, J., 2021. Changes in ecosystem properties after post-fire management strategies in wildfire-affected Mediterranean forests. JOURNAL OF APPLIED ECOLOGY. 58(4), pp.836-846. doi:10.1111/1365-2664.13819

Lull, C; Bautista, I; Lidon, A; del Campo, AD; Gonzalez-Sanchis, M; Garcia-Prats, A., 2020. Temporal effects of thinning on soil organic carbon pools, basal respiration and enzyme activities in a Mediterranean Holm oak forest. FOREST ECOLOGY AND MANAGEMENT. 464. doi:10.1016/j.foreco.2020.118088

Mackay, AD; Vibart, R; McKenzie, C; Costall, D; Bilotto, F; Kelliher, FM., 2021. Soil organic carbon stocks in hill country pastures under contrasting phosphorus fertiliser and sheep stocking regimes, and topographical features. AGRICULTURAL SYSTEMS. 186. doi:10.1016/j.agsy.2020.102980

Mancinelli, R; Marinari, S; Allam, M; Radicetti, E., 2020. Potential Role of Fertilizer Sources and Soil Tillage Practices to Mitigate Soil CO2 Emissions in Mediterranean Potato Production Systems. SUSTAINABILITY. 12(20). doi:10.3390/su12208543

Mantino, A; Tozzini, C; Bonari, E; Mele, M; Ragaglini, G., 2021. Competition for Light Affects Alfalfa Biomass Production More Than Its Nutritive Value in an Olive-Based Alley-Cropping System. FORESTS. 12(2). doi:10.3390/f12020233

Marklein, AR; Meyer, D; Fischer, ML; Jeong, S; Rafiq, T; Carr, M; Hopkins, FM., 2021. Facility-scale inventory of dairy methane emissions in California: implications for mitigation. EARTH SYSTEM SCIENCE DATA. 13(3), pp.1151-1166. doi:10.5194/essd-13-1151-2021

Markou, M; Moraiti, CA; Stylianou, A; Papadavid, G., 2020. Addressing Climate Change Impacts on Agriculture: Adaptation Measures For Six Crops in Cyprus. ATMOSPHERE. 11(5). doi:10.3390/atmos11050483

Marouani, E; Zarai, B; Boudabbous, K; Benzina, NK; Ziadi, N; Zoghlami, RI; Bouslimi, B; Koubaa, A., 2021. Short-Term Effects of Biosolid Application on Two Mediterranean Agricultural Soils and Durum Wheat Yield. AGRONOMY-BASEL. 11(4). doi:10.3390/agronomy11040709

Mateo-Marin, N; Isla, R; Guillen, M; Quilez, D., 2020. Agronomic and Environmental Implications of Substituting Pig Slurry for Synthetic Nitrogen in Mediterranean Wheat Systems. AGRONOMY-BASEL. 10(10). doi:10.3390/agronomy10101498

Mateo-Marin, N; Quilez, D; Isla, R., 2020. Utility of stabilized nitrogen fertilizers to reduce nitrate leaching under optimal management practices. JOURNAL OF PLANT NUTRITION AND SOIL SCIENCE. 183(5), pp.567-578. doi:10.1002/jpln.201900561

Medina, J; Calabi-Floody, M; Aponte, H; Santander, C; Paneque, M; Meier, S; Panettieri, M; Cornejo, P; Borie, F; Knicker, H., 2021. Utilization of Inorganic Nanoparticles and Biochar as Additives of Agricultural Waste Composting: Effects of End-Products on Plant Growth, C and Nutrient Stock in Soils from a Mediterranean Region. AGRONOMY-BASEL. 11(4). doi:10.3390/agronomy11040767

Minoshima, H; Jackson, LE; Cavagnaro, TR; Sanchez-Moreno, S; Ferris, H; Temple, SR; Goyal, S; Mitchell, JP., 2007. Soil food webs and carbon dynamics in response to conservation tillage in California. SOIL SCIENCE SOCIETY OF AMERICA JOURNAL. 71(3), pp.952-963. doi:10.2136/sssaj2006.0174

Mitchell, Jeffrey P; Shrestha, Anil; Mathesius, Konrad; Scow, Kate M; Southard, Randal J; Haney, Richard L; Schmidt, Radomir; Munk, Daniel S; Horwath, William R., 2017. Cover cropping and no-tillage improve soil health in an arid irrigated cropping system in California’s San Joaquin Valley, USA. Soil and Tillage Research. 165()

Mitchell, JP; Shrestha, A; Horwath, WR; Southard, RJ; Madden, N; Veenstra, J; Munk, DS., 2015. Tillage and Cover Cropping Affect Crop Yields and Soil Carbon in the San Joaquin Valley, California. AGRONOMY JOURNAL. 107(2), pp.588-596. doi:10.2134/agronj14.0415

Mitchell, JP; Shrestha, A; Mathesius, K; Scow, KM; Southard, RJ; Haney, RL; Schmidt, R; Munk, DS; Horwath, WR., 2017. Cover cropping and no-tillage improve soil health in an arid irrigated cropping system in California's San Joaquin Valley, USA. SOIL & TILLAGE RESEARCH. 165, pp.325-335. doi:10.1016/j.still.2016.09.001

Montemurro, F; Persiani, A; Diacono, M., 2020. Cover Crop as Living Mulch: Effects on Energy Flows in Mediterranean Organic Cropping Systems. AGRONOMY-BASEL. 10(5). doi:10.3390/agronomy10050667

Montoya, M; Vallejo, A; Corrochano-Monsalve, M; Aguilera, E; Sanz-Cobena, A; Gines, C; Gonzalez-Murua, C; Alvarez, JM; Guardia, G., 2021. Mitigation of yield-scaled nitrous oxide emissions and global warming potential in an oilseed rape crop through N source management. JOURNAL OF ENVIRONMENTAL MANAGEMENT. 288. doi:10.1016/j.jenvman.2021.112304

Morugan-Coronado, A; Linares, C; Gomez-Lopez, MD; Faz, A; Zornoza, R., 2020. The impact of intercropping, tillage and fertilizer type on soil and crop yield in fruit orchards under Mediterranean conditions: A meta-analysis of field studies. AGRICULTURAL SYSTEMS. 178. doi:10.1016/j.agsy.2019.102736

Muraina, TO; Jimoh, SO; Ewetola, IA; Ojo, VOA; Amisu, AA; Okukenu, OA; Adebisi, YA; Muraina, HA; Olanite, JA., 2020. Mineral composition of two Stylosanthes species oversown in natural pasture: effect of tillage practice and sowing method. TROPICAL ANIMAL HEALTH AND PRODUCTION. 52(5), pp.2753-2759. doi:10.1007/s11250-020-02305-7

Nepal, S; Eskelson, BNI; Ritchie, M., 2020. Difference in Regeneration Conditions inPinus ponderosaDominated Forests in Northern California, USA, over an 83 Year Period. FORESTS. 11(5). doi:10.3390/f11050581

Nguyen, LTT; Kravchenko, AN., 2021. Effects of cover crops on soil CO2 and N2O emissions across topographically diverse agricultural landscapes in corn-soybean-wheat organic transition. EUROPEAN JOURNAL OF AGRONOMY. 122. doi:10.1016/j.eja.2020.126189

Novara, A; Cerda, A; Barone, E; Gristina, L., 2021. Cover crop management and water conservation in vineyard and olive orchards. SOIL & TILLAGE RESEARCH. 208. doi:10.1016/j.still.2020.104896

Oliveira, M; Castro, C; Coutinho, J; Trindade, H., 2021. Grain legume-based cropping systems can mitigate greenhouse gas emissions from cereal under Mediterranean conditions. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 313. doi:10.1016/j.agee.2021.107406

Omirou, M; Anastopoulos, I; Fasoula, DA; Ioannides, IM., 2020. The effect of chemical and organic N inputs on N2O emission from rain-fed crops in Eastern Mediterranean. JOURNAL OF ENVIRONMENTAL MANAGEMENT. 270. doi:10.1016/j.jenvman.2020.110755

Phillips, CL; Meyer, KM; Hanson, CV; Biraud, SC; Trippe, KM., 2021. Manipulating rangeland soil microclimate with juniper biochar for improved native seedling establishment. SOIL SCIENCE SOCIETY OF AMERICA JOURNAL. . doi:10.1002/saj2.20207

Pi, HW; Webb, NP; Huggins, DR; Sharratt, B., 2020. Critical standing crop residue amounts for wind erosion control in the inland Pacific Northwest, USA. CATENA. 195. doi:10.1016/j.catena.2020.104742

Poudel, DD; Ferris, H; Klonsky, K; Horwath, WR; Scow, KM; van Bruggen, AHC; Lanini, WT; Mitchell, JP; Temple, SR., 2001. The sustainable agriculture farming system project in California's Sacramento Valley. OUTLOOK ON AGRICULTURE. 30(2), pp.109-116. doi:10.5367/000000001101293553

Povak, NA; Churchill, DJ; Cansler, CA; Hessburg, PF; Kane, V; Kane, JT; Lutz, JA; Larson, AJ., 2020. Wildfire severity and postfire salvage harvest effects on long-term forest regeneration. ECOSPHERE. 11(8). doi:10.1002/ecs2.3199

Prats, SA; Malvar, MC; Wagenbrenner, JW., 2021. Compaction and cover effects on runoff and erosion in post-fire salvage logged areas in the Valley Fire, California. HYDROLOGICAL PROCESSES. 35(1). doi:10.1002/hyp.13997

Rallings, AM; Smukler, SM; Mullinix, K., 2020. A novel methodology to characterize and quantify regional farmscape non-production perennial vegetation carbon storage and potential for loss in Southwest British Columbia. AGROFORESTRY SYSTEMS. 94(5), pp.1947-1958. doi:10.1007/s10457-020-00514-5

Reed, WP; Varner, JM; Knapp, EE; Kreye, JK., 2020. Long-term changes in masticated woody fuelbeds in northern California and southern Oregon, USA. INTERNATIONAL JOURNAL OF WILDLAND FIRE. 29(9), pp.807-819. doi:10.1071/WF19156

Ryals, R., & Silver, W. L. 2013. Effects of organic matter amendments on net primary productivity and greenhouse gas emissions in annual grasslands. Ecological Applications, 23(1), 46-59.

Saksa, PC; Conklin, MH; Tague, CL; Bales, RC., 2020. Hydrologic Response of Sierra Nevada Mixed-Conifer Headwater Catchments to Vegetation Treatments and Wildfire in a Warming Climate. FRONTIERS IN FORESTS AND GLOBAL CHANGE. 3. doi:10.3389/ffgc.2020.539429

Serrano, J; Shahidian, S; Costa, F; Carreira, E; Pereira, A; Carvalho, M., 2021. Can Soil pH Correction Reduce the Animal Supplementation Needs in the Critical Autumn Period in Mediterranean Montado Ecosystem? AGRONOMY-BASEL. 11(3). doi:10.3390/agronomy11030514

Severiano, RM; Pierangeli, MAP; Santos, ND; Xavier, V., 2021. Soil organic carbon in no-tillage systems of different ages in Southwest Mato Grosso, Brazils. REVISTA BRASILEIRA DE ENGENHARIA AGRICOLA E AMBIENTAL. 25(4), pp.250-255. doi:10.1590/1807-1929/agriambi.v25n4p250-255

Silver, W. L., Vergara, S. E., & Mayer, A. 2018. Carbon sequestration and greenhouse gas mitigation potential of composting and soil amendments on California's rangelands. California Natural Resources Agency, 62.

Sintim, HY; Bandopadhyay, S; English, ME; Bary, A; Gonzalez, JELY; DeBruyn, JM; Schaeffer, SM; Miles, CA; Flury, M., 2021. Four years of continuous use of soil-biodegradable plastic mulch: impact on soil and groundwater quality. GEODERMA. 381. doi:10.1016/j.geoderma.2020.114665

Smith, OM; Taylor, JM; Echeverri, A; Northfield, T; Cornell, KA; Jones, MS; Latimer, CE; Owen, JP; Snyder, WE; Kennedy, CM., 2021. Big wheel keep on turnin ' : Linking grower attitudes, farm management, and delivery of avian ecosystem services. BIOLOGICAL CONSERVATION. 254. doi:10.1016/j.biocon.2021.108970

Stanton, CY; Mach, KJ; Turner, PA; Lalonde, SJ; Sanchez, DL; Field, CB., 2018. Managing cropland and rangeland for climate mitigation: an expert elicitation on soil carbon in California. CLIMATIC CHANGE. 147(3-4), pp.633-646. doi:10.1007/s10584-018-2142-1

Steenwerth, K; Belina, KM., 2008. Cover crops and cultivation: Impacts on soil N dynamics and microbiological function in a Mediterranean vineyard agroecosystem. APPLIED SOIL ECOLOGY. 40(2), pp.370-380. doi:10.1016/j.apsoil.2008.06.004

Steenwerth, KL; Pierce, DL; Carlisle, EA; Spencer, RGM; Smart, DR., 2010. A Vineyard Agroecosystem: Disturbance and Precipitation Affect Soil Respiration under Mediterranean Conditions. SOIL SCIENCE SOCIETY OF AMERICA JOURNAL. 74(1), pp.231-239. doi:10.2136/sssaj2008.0346

Stumpner, EB; Kraus, TEC; Liang, YL; Bachand, SM; Horwath, WR; Bachand, PAM., 2018. Sediment accretion and carbon storage in constructed wetlands receiving water treated with metal-based coagulants. . 111, pp.-176.

Suddick, EC; Ngugi, MK; Paustian, K; Six, J., 2013. Monitoring soil carbon will prepare growers for a carbon trading system. CALIFORNIA AGRICULTURE. 67(3), pp.162-171. doi:10.3733/ca.v067n03p162

Suddick, EC; Scow, KM; Horwath, WR; Jackson, LE; Smart, DR; Mitchell, J; Six, J., 2010. THE POTENTIAL FOR CALIFORNIA AGRICULTURAL CROP SOILS TO REDUCE GREENHOUSE GAS EMISSIONS: A HOLISTIC EVALUATION. ADVANCES IN AGRONOMY, VOL 107. pp.123-162. doi:10.1016/S0065-2113(10)07004-5

Suddick, EC; Six, J., 2013. An estimation of annual nitrous oxide emissions and soil quality following the amendment of high temperature walnut shell biochar and compost to a small scale vegetable crop rotation. SCIENCE OF THE TOTAL ENVIRONMENT. 465, pp.298-307. doi:10.1016/j.scitotenv.2013.01.094

Tautges, NE; Chiartas, JL; Gaudin, ACM; O'Geen, AT; Herrera, I; Scow, KM., 2019. Deep soil inventories reveal that impacts of cover crops and compost on soil carbon sequestration differ in surface and subsurface soils. GLOBAL CHANGE BIOLOGY. 25(11), pp.3753-3766. doi:10.1111/gcb.14762

Thengane, SK; Kung, K; York, R; Sokhansanj, S; Lim, CJ; Sanchez, DL., 2020. Technoeconomic and emissions evaluation of mobile in-woods biochar production. ENERGY CONVERSION AND MANAGEMENT. 223. doi:10.1016/j.enconman.2020.113305

Veenstra, JJ; Horwath, WR; Mitchell, JP., 2007. Tillage and cover cropping effects on aggregate-protected carbon in cotton and tomato. SOIL SCIENCE SOCIETY OF AMERICA JOURNAL. 71(2), pp.362-371. doi:10.2136/sssaj2006.0229

Venkat, K., 2012. Comparison of Twelve Organic and Conventional Farming Systems: A Life Cycle Greenhouse Gas Emissions Perspective. JOURNAL OF SUSTAINABLE AGRICULTURE. 36(6), pp.620-649. doi:10.1080/10440046.2012.672378

Vicente-Vicente, JL; Garcia-Ruiz, R; Francaviglia, R; Aguilera, E; Smith, P., 2016. Soil carbon sequestration rates under Mediterranean woody crops using recommended management practices: A meta-analysis. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 235, pp.204-214. doi:10.1016/j.agee.2016.10.024

Wang, Y; del Campo, AD; Wei, XH; Winkler, R; Liu, WY; Li, Q., 2020. Responses of forest carbon and water coupling to thinning treatments from leaf to stand scales in a young montane pine forest. CARBON BALANCE AND MANAGEMENT. 15(1). doi:10.1186/s13021-020-00159-y

White, KE; Brennan, EB; Cavigelli, MA., 2020. Soil carbon and nitrogen data during eight years of cover crop and compost treatments in organic vegetable production. DATA IN BRIEF. 33. doi:10.1016/j.dib.2020.106481

White, KE; Brennan, EB; Cavigelli, MA; Smith, RF., 2020. Winter cover crops increase readily decomposable soil carbon, but compost drives total soil carbon during eight years of intensive, organic vegetable production in California. PLOS ONE. 15(2). doi:10.1371/journal.pone.0228677

Wieme, RA; Reganold, JP; Crowder, DW; Murphy, KM; Carpenter-Boggs, LA., 2020. Productivity and soil quality of organic forage, quinoa, and grain cropping systems in the dryland Pacific Northwest, USA. AGRICULTURE ECOSYSTEMS & ENVIRONMENT. 293. doi:10.1016/j.agee.2020.106838

Wilson, SG; Lambert, JJ; Dahlgren, R., 2021. Compost Application to Degraded Vineyard Soils: Effect on Soil Chemistry, Fertility, and Vine Performance. AMERICAN JOURNAL OF ENOLOGY AND VITICULTURE. 72(1), pp.85-93. doi:10.5344/ajev.2020.20012

Yu, OT; Greenhut, RF; O'Geen, AT; Mackey, B; Horwath, WR; Steenwerth, KL., 2017. Precipitation Events and Management Practices Affect Greenhouse Gas Emissions from Vineyards in a Mediterranean Climate. SOIL SCIENCE

SOCIETY OF AMERICA JOURNAL. 81(1), pp.138-152. doi:10.2136/sssaj2016.04.0098

Zeng, HW; Wu, BF; Zhang, M; Zhang, N; Elnashar, A; Zhu, L; Zhu, WW; Wu, FM; Yan, NN; Liu, WJ., 2021. Dryland ecosystem dynamic change and its drivers in Mediterranean region. CURRENT OPINION IN ENVIRONMENTAL SUSTAINABILITY. 48, pp.59-67. doi:10.1016/j.cosust.2020.10.013

Zhang, J; Zhang, JW; Mattson, K; Finley, K., 2020. Effect of Silviculture on Carbon Pools during Development of a Ponderosa Pine Plantation. FORESTS. 11(9) doi:10.3390/f11090997

Zhang, XK; Ferris, H; Mitchell, J; Liang, WJ., 2017. Ecosystem services of the soil food web after long-term application of agricultural management practices. . 111, pp. 36.

Zhu, BW; Huang, MY; Cheng, YY; Xie, XH; Liu, Y; Zhang, XS; Bisht, G; Chen, XY; Missik, J; Liu, HP., 2020. Effects of Irrigation on Water, Carbon, and Nitrogen Budgets in a Semiarid Watershed in the Pacific Northwest: A Modeling Study. JOURNAL OF ADVANCES IN MODELING EARTH SYSTEMS. 12(9). doi10.1029/2019MS001953

Zhu-Barker, X; Easter, M; Swan, A; Carlson, M; Thompson, L; Horwath, WR; Paustian, K; Steenwerth, KL., 2019. Soil Management Practices to Mitigate Nitrous Oxide Emissions and Inform Emission Factors in Arid Irrigated Specialty Crop Systems. SOIL SYSTEMS. 3(4) doi:10.3390/soilsystems3040076