Report

Climate Impacts of Biopower Generation from Forest Residues in California

March, 2021

Prepared by:
Kevin Fingerman and Jerome Carman
Schatz Energy Research Center and Humboldt State University Department of Environmental Science and Management
Humboldt State University
Arcata, CA 95521
(707) 826-4345

About the Schatz Energy Research Center

The Schatz Energy Research Center at Humboldt State University advances clean and renewable energy. Our projects aim to reduce climate change and pollution while increasing energy access and resilience.

Our work is collaborative and multidisciplinary, and we are grateful to the many partners who together make our efforts possible.

Learn more about our work at schatzcenter.org

Acknowledgements

Collaboration and funding for this study were provided by the California Energy Commission under contract agreement number EPC-16-047.

The primary authors would like to thank the California Energy Commission for its support of this research and in particular Commission Agreement Managers Katharina Gerber and David Stoms for their indispensable assistance. This work would not have been possible without the contributions and commitment of the following members of our research team: Cassidy Barrientos, Max Blasdel, Jeff Comnick, Carisse Geronimo, Andrew Harris, Chih-Wei Hsu, Jeffrey Kane, Elaine Oneil, Luke Rogers, Sabrinna Rios-Romero, Mark Severy, and Micah Wright. Finally, this research was much improved by the ongoing input and support of the members of our Technical Advisory Committee and in particular of its chair, Andrea Tuttle.

Fingerman, K. and Carman, J. Climate Impacts of Biopower Generation from Forest Residues in California. EPC-16-047. Humboldt, CA: Schatz Energy Research Center. schatzcenter.org/pubs/2021-biomass-R1.pdf

Contact: kevin.fingerman@humboldt.edu

ABSTRACT

The State of California faces crisis conditions on its forested landscapes. The increased drought and hotter, drier, windier weather conditions brought on by climate change have created increasingly severe wildfire conditions in forests already overstocked with biomass following a century of aggressive logging and fire suppression. In light of this ongoing ecological, climate, economic, and public health emergency, and in view of the potential for sustainable forestry to deliver both climate change mitigation *and* adaptation, the state has prioritized funding for forest management with the goal of treating one million acres of forest per year in the near future.

This aggressive forest management activity, on top of ongoing commercial activity in California's working forestlands, generates millions of tons per year of woody residues that are typically left or burned in the field, impacting air quality, creating wildfire hazard, and leading to further ecosystem disruption. State policymakers have turned to bioelectricity generation as a key market for woody biomass in the hope that it can support sustainable forest management activities while also advancing California's Renewable Portfolio Standard goals. However, many in the state have raised concerns surrounding climate, air quality, and ecosystem health implications of many bioenergy systems. In particular, open questions surrounding the climate performance of electricity generation from woody biomass have made it difficult to determine how best to manage the risks and opportunities posed by forest residues.

The California Biomass Residue Emissions Characterization (C-BREC) model—developed with the support of a grant from the California Energy Commission—offers a Life Cycle Assessment (LCA) framework specific to the use of California forest residues. The C-BREC model rigorously and transparently establishes the climate and air pollution impacts of these systems in California, including the variable emissions from different biomass supply chains as well as the counterfactual emissions from prescribed burn, wildfire, and decay avoided by residue mobilization. This report lays out the findings from a case study application of the C-BREC model across the real-world forest management activities carried out in California from 2016 through 2019, identifying clearly the climate and air quality performance of biopower from woody residues across the varying conditions and supply chains seen in California. These results, and the C-BREC model, can be useful to state policymakers in shaping California's energy and forest management policies and supports going forward. More information about the C-BREC model and related work can be found at schatzcenter.org/cbrec/.

TABLE OF CONTENTS

LIST OF FIGURES

Page

1. Introduction

California faces a forest management crisis. Drought, pest infestation, and wildfire – all exacerbated by climate change – have led to increasingly challenging conditions on the state's forested landscapes. These risks are heightened by the overstocking of biomass on the landscape brought about by a history of intensive logging and aggressive fire suppression (Collins et al., 2014). California's Forest Carbon Plan (Forest Climate Action Team, 2018) identifies insufficient forest management activity rates, limited biomass processing and utilization infrastructure, and unprecedented deterioration of forest health as critical barriers to managing forests for resilience and net carbon sequestration.

Recognizing the significant ecological, economic, and health risks associated with this crisis as well as the potential of sustainable forest management to deliver climate change mitigation and adaptation through a single action, the state has prioritized funding for forest treatment. The California Department of Forestry and Fire Protection (CALFIRE) has spent nearly $1 billion dollars through its California Climate Investments (CCI) program on sustainable forestry and wildfire management projects, since 2014 (California Air Resources Board, 2021). This spending is expected to continue growing, as the state pursues its goal of treating 1 million acres of forestland annually.

This management activity, as well as the commercial harvests carried out annually on California forestlands, creates a new problem in the form of significant residual woody biomass that must be managed on-site. Woody residues from forest harvest and restoration activities in California are typically left or burned in the field, impacting air quality, creating wildfire hazard, and leading to further ecosystem disruption. A related challenge faces the disposal of woody residues from agricultural production in the state. From 2005-2012, open burning of agricultural residue in the San Joaquin Valley had been reduced by over 80%, but drought and the shutdown of six biopower facilities in the region led to a significant increase in open burning, bringing open burning back above 2005 levels. Most of this increase stems from disposal of biomass from pruning and removal of orchard trees. Under business-as-usual projections, open burning of agricultural residues—and the resultant emissions of health harming air pollutants—are expected to increase.

Residues generated by forest thinning and fuels treatment as well as commercial forestry have the potential to be transformed from a waste stream into a renewable energy resource. If managed properly, bioenergy can support sustainable forest management activities while also advancing California's Renewable Portfolio Standard goals. However, there are legitimate concerns surrounding climate, air quality, and ecosystem health implications of many bioenergy systems. In particular, the climate performance of electricity generation from woody biomass residuals can be quite variable, and there has been a great deal of debate in the academic literature as well as in state policy circles as to how to best account for these emissions.

The California Biopower Impacts (CBI) Project, supported by the California Energy Commission under Grant Funding Opportunity 16-306, has sought to rigorously and transparently establish the environmental performance of bioenergy from forest residues. The core of the CBI Project effort has been development and implementation of the California Biomass Residue Emissions Characterization (C-BREC) Model, a life-cycle assessment (LCA) framework specific to the use of California forest residues for electricity generation.

This model, and the simplified webtool version of the forest model that can be found at schatzcenter.org/cbrec/ enables robust, transparent accounting for the GHG and air pollutant emissions associated with residual woody biomass energy systems in California. Users specify the following key project characteristics:

- Location of residue generation
- Type of forest treatment or harvest activity being conducted and baseline residue disposition
- Location of residue utilization
- Reference fate of unremoved biomass (prescribed burn, left in place)
- Key supply chain characteristics such as biomass removal level, any post-harvest treatment, end-use technology, etc.

For a given project profile, the C-BREC model generates an emissions time-series and reports net CO_2-equivalent (CO_2e) emission values for two different time-explicit climate metrics. It quantifies the emissions associated directly with a "use" case in which biomass residuals are mobilized from the field for use in a biomass energy supply chain and a "reference" case in which they are not mobilized. The net emissions of the biopower system is the difference between these two fates for the same material. The use case includes emissions from mobilization, transportation, and end-use where the reference emissions are made up of three distinct processes, applied in probabilistic fashion to any given ton of biomass:

- Pile or broadcast burning of residuals in year 1
- Decay extending for 100 years of material piled/scattered on the forest floor
- Ongoing exposure to wildfire over a 100-year period

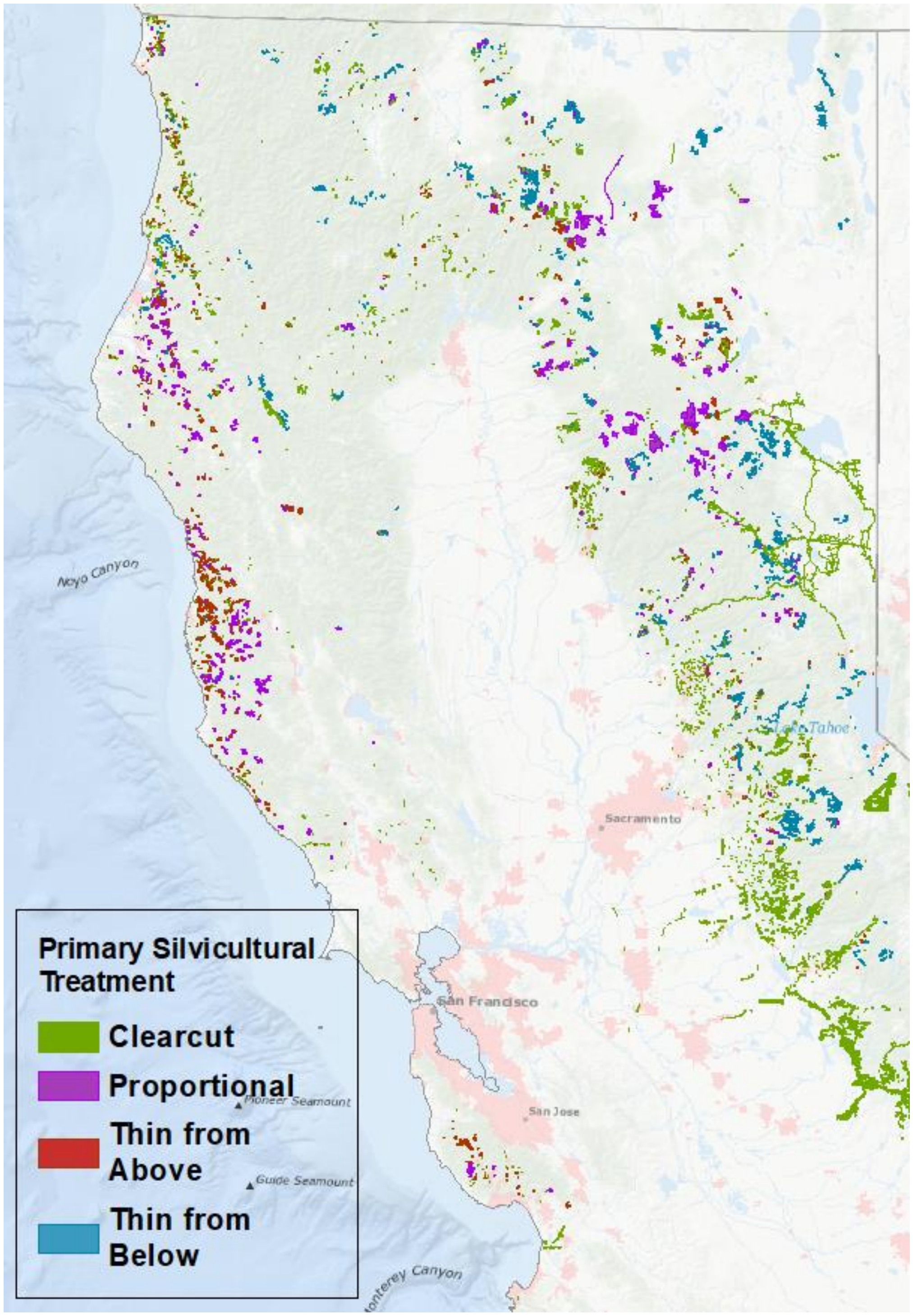
Most early life-cycle assessments (LCAs) of woody bioenergy made the simplifying assumption that CO_2 emissions from combustion of biomass (i.e. "biogenic" emissions) do not contribute to climate change because they represent a closed loop between biomass growth and fuel consumption. Using this assumption, these studies typically found significant net reductions in GHG emissions when bioenergy replaces fossil energy. A recent meta-analysis of 94 LCA studies of bioenergy systems found only one single case study which accounted for the climate change impact of biogenic CO_2 emission (Cherubini & Strømman, 2011). Other recent literature has called this assumption into question by pointing out that near-term emissions lead to increased climate forcing over policy-relevant time frames even if we assume that the CO_2 emitted is eventually re-sequestered in forest regrowth or as in the case of residues would have been emitted later by decay or wildfire (Buchholz et al., 2016; Cornwall, 2017; Duncan Brack, 2017; Sterman et al., 2018).

Emerging from this literature is the consensus that the comprehensive approach to life cycle accounting for biopower from woody residues is to quantify emissions—including biogenic emissions—from both the use of residues and their counterfactual, or "reference," fate. However, while many recent studies have done so, these typically assume that all residues not removed for bioenergy will decay in place (Giuntoli et al., 2016; Gustavsson et al., 2015; Jäppinen et al., 2014; Madsen & Bentsen, 2018; McKechnie et al., 2011) and that this decay will occur at a single rate regardless of residue type or location (Giuntoli et al., 2016; Gustavsson et al., 2015; Madsen & Bentsen, 2018). This ignores the possibility of these residues being burned in place, either through a prescribed burn aimed at waste management or by subsequent wildfire (Buchholz et al., 2016; Ter-Mikaelian et al., 2015). In the few studies that have incorporated a burn counterfactual, it is typical to assume that biomass is completely consumed through prescribed burn, leading to instantaneous emission of all carbon present, plus additional forcing from a fixed amount of methane and nitrous oxide emitted by the fire (Liu & Rajagopal, 2019; Miner et al., 2014; Springsteen et al., 2011). This fails to account for the unconsumed fraction of biomass or the formation of recalcitrant char materials as well as the spatial and material-type variation in the dynamics of combustion (Ter-Mikaelian et al., 2015).

The C-BREC model improves on the existing Life Cycle Assessment approaches by capturing the significant spatial and supply-chain variability in life-cycle emissions where many prior analyses have evaluated a single case and assumed it to be broadly representative. It also assesses emissions transparently, providing a model that can be used to evaluate the sensitivity of results to various key input parameters and assumptions. Finally it is becoming increasingly clear that the timing of emissions must be considered in life cycle GHG accounting (Buchholz et al., 2016; Helin et al., 2013; Reid et al., 2020). Where many prior assessments of bioelectricity climate impact fail to do so, we apply time-explicit climate metrics and report them per guidance by the UNEP / SETAC Global Guidance for Life Cycle Impact Assessment Indicators (Levasseur et al., 2016).

This report offers a detailed look at the results generated by the C-BREC model, applied across a range of forestry treatment activities on California landscapes. While the model is able to evaluate the impact of residue removal from any forestry activity type on any forested landscape in the state, we focus here on a case study of the actual treatment activities conducted in California in the years 2016-2019, characterized by data from Timber Harvest Plans and Non-commercial Timber Management Plans filed with CALFIRE (Figure 1). The results of that analysis shed light on the variable environmental performance of biomass electricity systems in California, and also the drivers of that variation.

Figure 1: Forest Treatments in California from 2016 - 2019



The 11,035 individual forest treatment activities that make up the case study detailed in this report. This map focuses on the northern region of California as it contains the majority of the working forests in the state and therefore almost all of the treatments evaluated for this study.

2. Methods

This section describes the methods deployed in the C-BREC model and its application to the case study evaluated here. Much more detail on every facet of the model, including its structure, assumptions, and underlying data, can be found in the C-BREC model framework, which can be found at schatzcenter.org/cbrec/. The model itself can also be downloaded at https://github.com/schatzcenter/CBREC-LCA.

2.1. Biomass Residue Base

The residual biomass resource base of interest is from forestry activity in the State of California. We categorize forest treatments into thirteen different types, covering most common forestry activities as defined by California Forest Practice Rules. The harvest activities modeled are:

- Clearcut
- Thin from below (i.e. selecting for small-diameter trees) removing 20, 40, 60, and 80% of total tree basal area. A sample of this residue base is shown in Figure 2.
- Thin from above (i.e. selecting for large-diameter trees) removing 20, 40, 60, and 80% of total tree basal area.
- Proportional thin (i.e. select equally across small and large diameter trees) removing 20, 40, 60, and 80% of total tree basal area.

Figure 2: Example of Residue Base

Example residue base data layer across a section of Northern California. This map presents the residue resulting from thinning activity removing 40% of total standing basal area from below (i.e. selecting for small diameter trees). Modeled at 30-meter spatial resolution.

For each of the above forest harvest activity types, we modeled the total recoverable biomass residue resource base at the parcel level, divided by residue type and size class. Forest parcels were characterized based on tree list inventory (GNN) data produced by the Landscape Ecology, Modeling, Mapping and

Analysis (LEMMA) group at Oregon State University. We have updated these data in California with timber harvest, fire, tree mortality events, and growth, occurring between 2012 and 2017 using the Forest Vegetation Simulator. Forest data are combined with parcel and riparian management zone data to create a spatially explicit database of forest condition, owner class, and management zone (Figure 1). Tree component biomass for stems, bark, branches, foliage, and roots are calculated by applying national biomass estimators (Jenkins et al., 2003) and the FIA component ratio method to the tree lists. C-BREC also accounts for the difference in decay and fire behavior between woody biomass that is scattered on the forest floor and that which is piled. A given residue base is therefore modeled at 0%, 30%, 50%, and 70% piled disposition to account for this variability.

2.2. Scope and System Boundary

A central assumption underpinning the C-BREC analytical framework is that the residual material being consumed is a true waste, in that it would not have been used at all were it not mobilized for bioenergy. For example, we assume that primary forest harvest activities are being conducted for the purpose of sawtimber extraction or improving forest health. The branches, treetops, and foliage that comprise the harvest residue base are typically left to decay or are burned on site. As such, we do not allocate any of the primary harvest emissions - nor any of the forest carbon stock and flow implications of the primary harvest - to the bioenergy pathway.

This approach is aligned with common Life Cycle Assessment practice, in which the sawtimber and the residues could be considered co-products. It is common in LCA to assign emissions of upstream activities to different co-products on the basis of the relative value of the different products. If sawtimber represented 50% of the value derived from a landscape and pulpwood the other 50%, one would allocate half of the emissions associated with the primary forest management activity to the lumber and half to the pulp. As the residues represent none of the economic value generated by the primary treatment activity, they are allocated none of the emissions or sequestration associated with that activity.

This is made slightly more complex by the fact that fire risk reduction and forest carbon sequestration are not financial products, meaning that conventional value-fraction-based coproduct allocation is not possible. However, when an entity (usually the government) pays for forest management to reduce the risk of a catastrophic wildfire, it is paying for the "product" of fire risk reduction, not for the residue that will be produced by that activity. In the case of these residues, they currently bear no value as is evidenced by the fact that they are not currently removed from the field. In circumstances where residues are purchased by an entity that has been subsidized to accept this material, we do not consider that a true economic value of the residue, but rather a subsidy for the primary treatment via a different market pathway.

As emissions associated with primary forest management decisions are excluded from this analysis, the life cycle assessment of the harvested residues covers only those emissions directly related to their removal (use case) or to their retention on the landscape (reference case). As indicated in Figure 3, this includes emissions associated with:

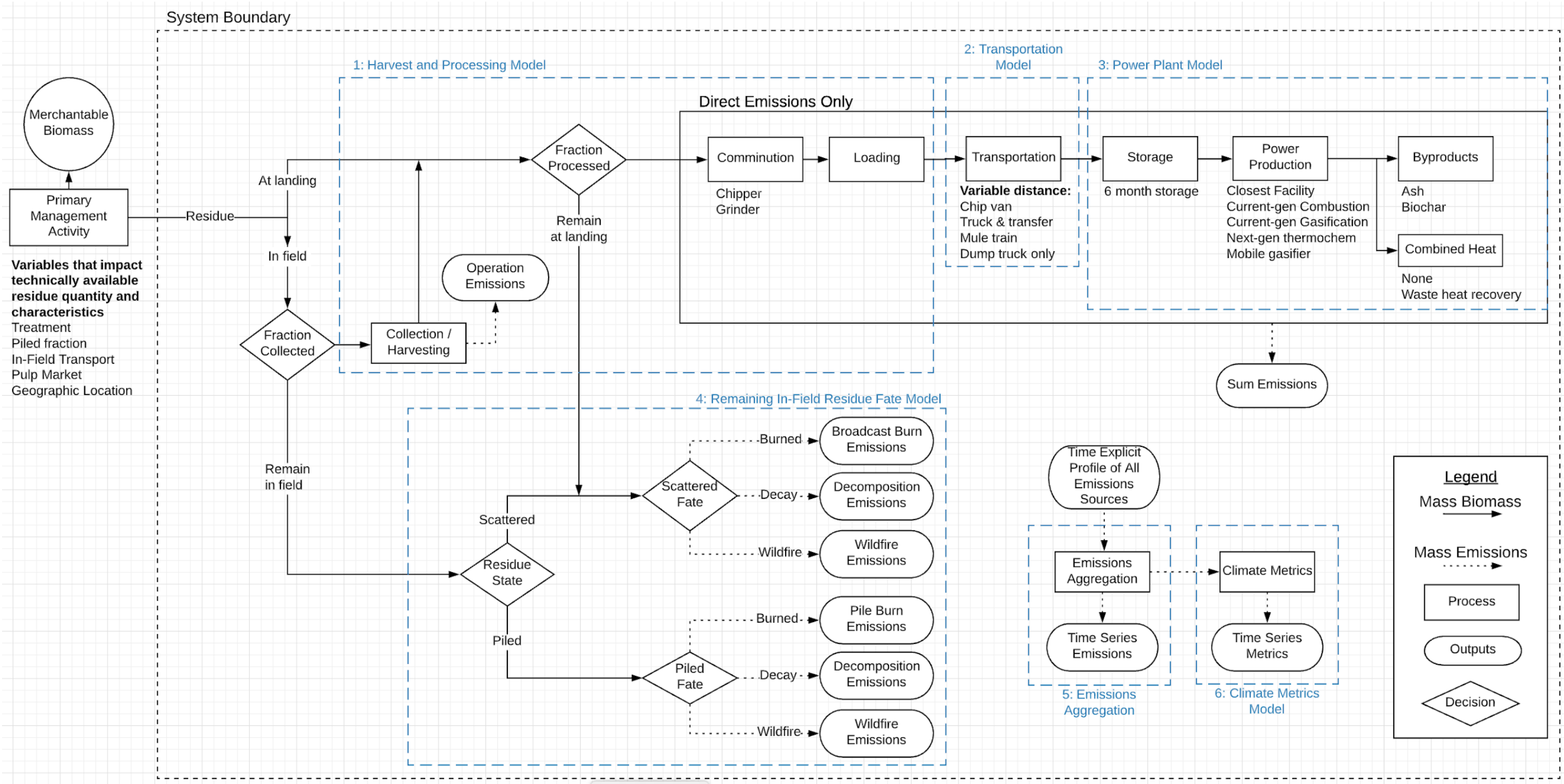
- Collection, transportation, and conversion of biomass residues into electricity
- Controlled burn of residues (pile and broadcast burning)
- Decomposition of any remaining residues out to 100 years
- Exposure of any remaining residues to wildfire (in forest residue cases)

2.3. Emissions from Residue Mobilization and Use

C-BREC users are able to specify treatment type, harvest practices, feedstock collection and handling methods, post-harvest treatments, feedstock management pathways, conversion technologies, and other characteristics. Mobilization and conversion of biomass residues into electricity are covered in the following three steps:

- *Collection and Processing*: This includes gathering, handling, and loading the residues from their initial piled or scattered disposition into the processing stage followed by comminution, hauling to a transfer point, then loading onto chip vans. These steps include both fixed and variable emissions. Fixed emissions are associated with bringing collection and processing equipment to the field and do not vary by treatment size or total residue base. Variable emissions represent the operation of collection and processing equipment and off-road haulers and loaders, and therefore are quantified as mass of emissions per bone-dry metric ton of biomass. All variable emissions are a function of terrain steepness, residue density, and moisture content.
- *Transportation*: Round-trip travel of hauling processed residues between the transfer point and the power plant via chip vans. Emissions from transportation depend on the distance to the power plant and are characterized in C-BREC for either the nearest biomass power facility to a given harvest site or a user-specified distance to the use location. Chip van trips are either volume or weight-limited based on moisture content.
- *Energy conversion*: Operations and production of electricity at a power plant. C-BREC is parameterized with specifications and performance of biomass power plants in California as reported to the California Energy Commission and California Air Resources Board. Emissions are based on a specific existing generator or one of a set of "generic" facility types - current generation combustion plant, next generation integrated gasification/combustion plant, next-generation thermochemical plant, and small (<1MW) mobile generator. Facility performance is also a function of the energy density of the specific biomass type (e.g. tree species) at a given treatment location. Energy content is reduced via dry matter loss over a variable storage period prior to combustion in the power plant.

Figure 3: LCA Boundary and Component Flow Diagram



Mass flow diagram of the C-BREC forestry model analytical framework.

2.4. Reference Biomass Fate

The "reference case" or "counterfactual fate" of the biomass describes the emissions associated with a given ton of biomass residue if it is not removed from the field for energy production.

2.4.1. Modeling Emissions from Fire

We modeled emissions from wildfire and prescribed burns of forest residues using the "activity" fuels equations from the Consume software, version 4.2, created by the US Forest Service (Prichard et al., 2006). The activity fuels equations were developed for fuels that were "resulting from or altered by forestry practices such as timber harvesting or thinning" (Prichard et al., 2006), and are thus directly applicable to this use case. The activity fuels equations calculate consumption and emissions estimates for scattered (i.e. non-piled) fuels. These equations provide estimates of fuel consumption for each fuel size class, weighted by combustion phase: flaming, smoldering, and residual. The consumption estimates are then multiplied by emission factors specific to each emissions species (e.g. CO, CO_2) taken from the Bluesky modeling framework (Larkin et al., 2010).

We use Fuel Characteristic Classification System (FCCS) (Riccardi et al., 2007) data to represent the initial fuel loads. FCCS data are available in raster format through Landfire.gov. Additional fuel loading resulting from treatments is derived from our biomass resource base projections and is added to the original fuel loading data. We estimate the emissions impact of residue removal by running Consume with and without this additional fuel on site. Fuel consumption and emissions estimates are delivered in spatially explicit (raster) format for integration into the C-BREC model framework.

Both emissions and fire behavior models require inputs for fuel moisture and mid-flame wind speed. To estimate these inputs, we use 4 km resolution GRIDMET gridded surface meteorological data set (Abatzoglou, 2013; Abatzoglou & Brown, 2012) augmented with additional fuel moisture parameters (Cohen & Deeming, 1985) and treatment-specific wind adjustment factors (Andrews, 2012). For wildfire simulations, we used the 97th percentile conditions for all climate variables constrained to the months of June through September for all years from 2000 to 2017. For prescribed fire simulations, we used the 37.5th percentile conditions for all climate variables constrained to September and October (the typical fall prescribed fire season) from the same time period.

The approach described above enables us to model the emissions from a wildfire if it were to occur on the landscape at any point in the next 100 years, both with and without forest residues left in the field. However, it is of course not possible to predict when a fire will occur at a given site. C-BREC therefore annualizes emissions from wildfire at each location in each year by taking the product of the expected emissions from a wildfire in that year and the probability of it occurring. Current and projected wildfire probability in California is derived from the Cal-Adapt dataset[1] (Westerling, 2018). For the future wildfire probability projections, C-BREC uses the representative concentration pathway (RCP) 4.5 emissions trajectory and business as usual population growth assumptions.

2.4.2. Decomposition

[1] Cal-adapt.org/tools/wildfire

As is typical in the LCA literature on solid biomass (Giuntoli et al., 2016; Gustavsson et al., 2015; Madsen & Bentsen, 2018) C-BREC characterizes decay using a negative exponential model (Olson, 1963). The literature on biomass decomposition identifies three main drivers for decay rate variability: species composition, size class and disposition of material, and climatic factors. As such, we model these decomposition mechanisms using decay constants that vary across these parameters (Blasdel, 2020). An example of the spatial variability of decay factors for forest material is shown in Figure 4.

Species Composition

We have established a database of decay constants that vary by species and size class. These values come from literature sources and synthesize numerous meta-analyses of decay (Laiho & Prescott, 2004; Mackensen & Bauhus, 1999; Weedon et al., 2009; Yin, 1999). These values are used to vary the rates of average residue decomposition based on the species composition at a given location.

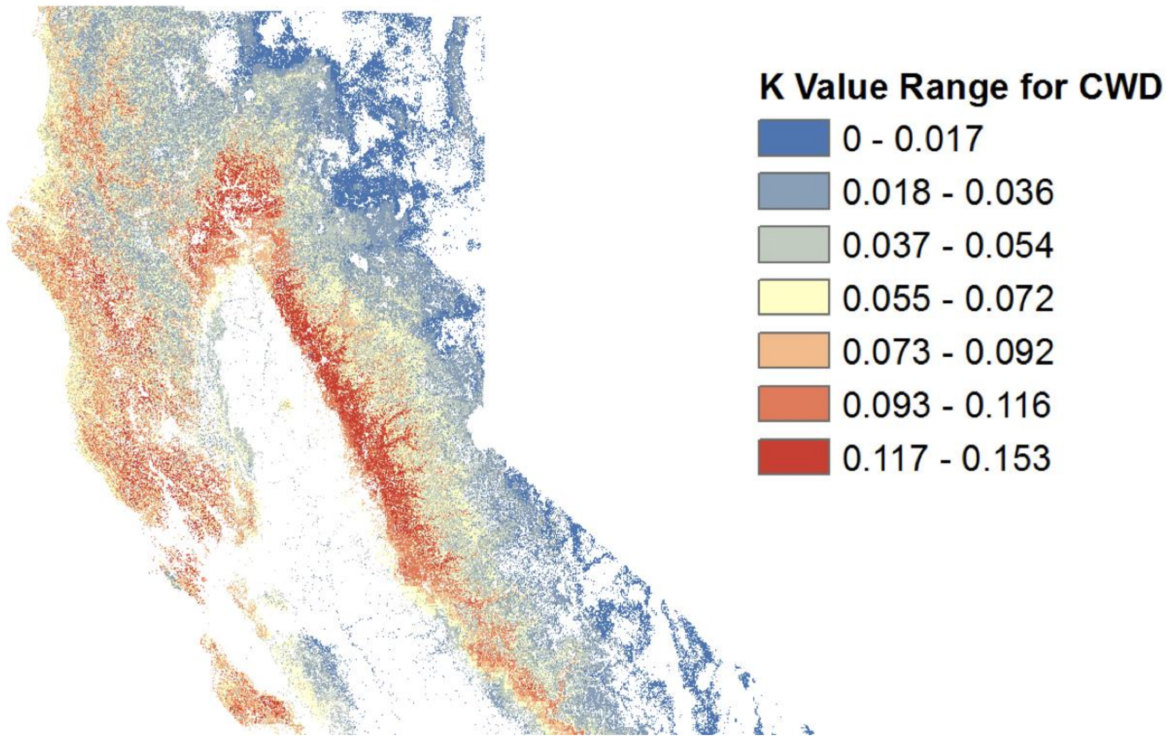
Size Class and Disposition

Decomposition rate of biomass in the forest varies by size class and between scattered and piled material (Edmonds et al., 1986; Erickson et al., 1985; Wagener & Offord, 1972), with material in contact with the ground exposed to conditions and organisms that hasten decay. Where material is piled, we assume a consistent size and geometry for the piles and treat the bottom fraction of the total material as though it were scattered because it is in contact with the ground.

Climate

Temperature and moisture are the two most important climatic factors affecting the decay of biomass (Sierra et al., 2015). Temperature controls the rate of heterotrophic cell respiration while moisture can be a limiting factor for decay if material becomes too dry. To capture these effects in our forestry modeling, we apply a mechanistic model that alters the exponential decay constant in a given area based on the recent historical record of temperature and soil moisture at that site. A variation on the Demeter equations for climate effects (adapted from (Foley, 1995)) was used to derive a climate modifier for decay as a function of temperature and moisture. The decay rate for each 30x30 m grid cell is determined by the average of the climate-modified decay rates for each species present weighted by that species' fraction of total tree biomass in that cell (using the proxy of aggregate trunk diameter by species).

Figure 4: Example Spatial Variability of Decay Constants



Decay rates for coarse woody debris across the forestlands of Northern California. Fine woody debris decay exhibits a similar spatial pattern.

2.4.3. Scenario Case Pairings

As described above, residue from a given forest treatment in C-BREC is modeled at 0%, 30%, 50%, and 70% piled disposition to account for the variability in forest harvest and residue management practices. A forest manager then faces three options: remove the residue for bioelectricity generation, burn it, or leave it on site. In the use case, we model both removal of piles only and removal of all technically recoverable biomass. These pile fraction and removal types also influence the type of burn that occurs in the reference case as we assume the residue removal and the counterfactual prescribed burn are intended to target the same material. Where only piles are removed in the use case, C-BREC assigns a pile burn the as prescribed burn option. Where all technically recoverable material is removed in the use case, C-BREC models pile (if piles are present) and broadcast burn prescription as the reference case. Land managers typically either collect residue or conduct a prescribed burn, and we therefore do not model prescribed burns following collection in the use cases.

2.5. Accounting for Time

A key challenge in the emissions accounting for the framework described here is the fact that bioenergy emissions occur in one pulse at the time of primary treatment (year zero), whereas the emissions associated with the reference fate of the biomass may occur slowly over decades of biomass decay. Just as financial accounting must consider the time value of money in comparing expenses or revenues at different points in time, rigorous LCA must account for the "time value" of emissions or sequestration over time in terms of their differing climate forcing effects on policy-relevant timescales. Our modeling calculates and reports on the basis of two different time-integrated climate metrics: the Global Warming Potential (GWP) and the Global Temperature Potential (GTP).

Life Cycle Impact Assessment in the C-BREC model uses an "emissions scenario" approach as discussed by (Myhre et al., 2013), elaborated on by (Aamaas et al., 2012), and recently implemented in several publications related to the emissions profile of biomass energy (Giuntoli et al., 2015). The result is a time-explicit Absolute GWP and Absolute GTP that approximate the global aggregate radiative forcing and temperature response, respectively, to a time-explicit emissions profile generated by C-BREC. We use these to calculate the CO_2 equivalent emissions for reporting all emissions on a uniform basis - that is the emission mass of CO_2 in year 1 that would yield the same AGWP and AGTP in year 100. This mirrors the approach taken by the Intergovernmental Panel on Climate Change in its calculation of CO_2 equivalent GWP values for different GHGs, except applied across time as well as across emission species.

The GWP-based metric evaluates the aggregate climate forcing experienced by the planet in the 100-year period. Since it is concerned with the total forcing rather than only the end result, we consider this as our short-term metric for climate impact. Since most policy analysis in California is conducted on the basis of 100-year GWP, (though typically only for normalizing across different GHGs, not across emission timings), most of the results in this report use the GWP-based approach. However, the GTP-based metric is also useful, evaluating how much hotter the climate will be 100 years in the future due to a given emission trajectory. As this is concerned with the state of the climate 100 years from now, we consider it as a long-term metric for climate impact. Both of these metrics are useful, as both prioritize different considerations. If we care primarily about the long-term temperature of the climate system, making decisions on the basis of the GTP is rational. However, some impacts of climate change - such as the melting of polar ice caps or the loss of biodiversity - may not be reversible if global temperatures rise and subsequently fall. As such, policy made on the basis of the GWP is also a sensible approach. Rather than choosing one of these metrics, we model both to offer the most possible information and flexibility. This approach is aligned with the guidance put forth by UNEP/SETAC (Levasseur et al., 2016) and taken up by ISO standard for Life Cycle Assessment (ISO 14067:2018, 2018).

2.6. A Note on Electric Power Displacement

The carbon intensity figures presented in this report are total emissions from bioelectricity generation ***net*** of emissions from the counterfactual fate of the same biomass. However, they are ***gross*** emissions for the generation of the bioelectricity as we have chosen not to credit it for the avoided emissions from other sources that might be offset by bioelectricity. Biopower can operate as base load generation and can be ramped in response to intermittent renewable generation causing some analysts to assume that it is displacing natural gas power. Some others point to the fact that biomass can be used in existing stoker power plants to directly displace coal. However, California utilities are also bound by renewable portfolio standard obligations to buy a certain amount of renewable electricity, so biomass could also be said to be displacing other renewables. Ultimately, the marginal power source displaced by biopower generation will be a function of local and regional power system economics and policies, which are shifting constantly. These shifts do not, however, change the emissions associated with biomass mobilization and power generation. As such, we report the emissions from bioelectricity generation absent any assumptions about power grid and market operations, allowing policy makers and other analysts to evaluate these emissions in whatever context they deem appropriate.

3. Results and Discussion

The C-BREC model is capable of evaluating the impact of residue removal from any forestry activity type on any forested landscape in the state. However, in order to investigate the range of results it generates, we ran the model on the actual treatment activities conducted in California in the years 2016-2019 (Figure 1). The results of that analysis shed light on the variable environmental performance of biomass electricity systems in California, and also the drivers of that variation.

In order to evaluate trends, most of the figures in this results section isolate many of the system configuration variables in C-BREC in order to explore the impact of others. For the purposes of this report, except where otherwise noted, we assume the following base case parameters for all of the systems under consideration:

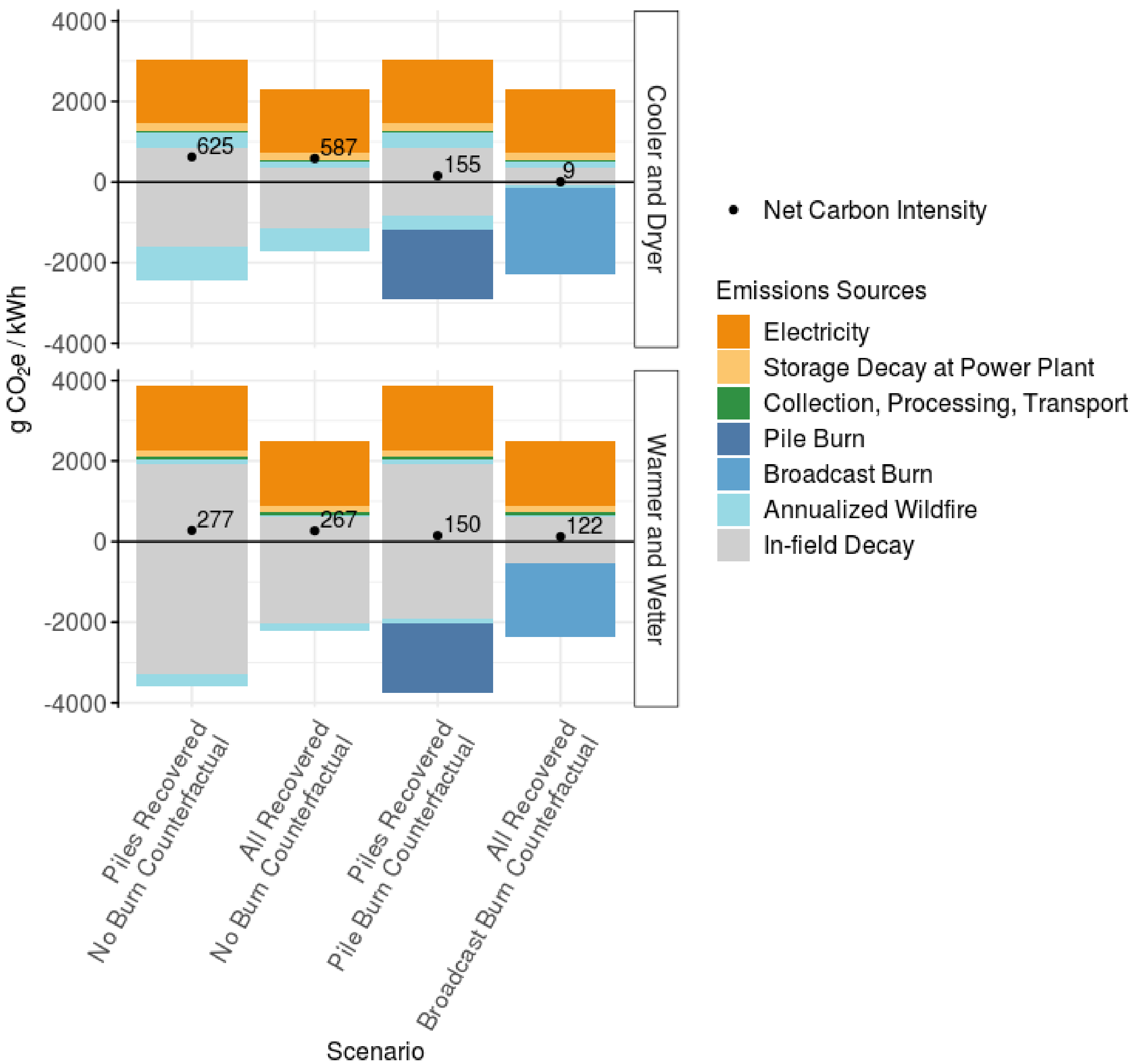
- Biopower is generated using a current-generation combustion plant of statewide average efficiency without combined heat and power (CHP) capability
- Biomass collection is carried out using our large harvest equipment system and comminution conducted on dry wood using a grinder
- Residue is hauled 50 km to the power generation facility
- Emission time series' are normalized to CO_2e using 100-year Global Warming Potential (GWP) equivalencies as discussed above
- Results are filtered to remove unrepresentative outliers, such as treatments in which we estimate <1T of total residue to be present and which are therefore unlikely to be mobilized for bioelectricity generation.

3.1. Net Carbon Intensity of Biopower from Forest Residue Mobilization in California

Figure 5 illustrates the relative roles of the different contributors to both reference and use-case emissions and how these vary by collection and burn scenario as well as across different climate zones in CA. Use-case emissions from residue mobilization and use are arrayed above the x-axis, where reference-case emissions from the counterfactual fate of the same biomass are arrayed below the x-axis as these represent "negative" emissions, avoided by residue mobilization. The difference between the two cases is net emission from bioelectricity generation and is indicated by the black point in each column.

Figure 5 illustrates some expected, and some unexpected, trends that are being quantified by C-BREC. For example, we can see that biomass left in the field in the warmer/wetter climate (below the x-axis for the "no burn counterfactual" scenarios) exhibits more emission from decay but less from wildfire than in the cool/dry climate owing to the climatic drivers of decay rate and fire return interval. In addition, warmer/wetter conditions lead to less complete consumption of scattered residue in a broadcast burn (far right) than is evident in the cooler/drier conditions. In all cases the pile-only collection scenario appears larger in both reference and use cases. This is because these emissions are calculated for the entire residue base and reported per kWh of power generated. Where only piles are collected, there is less total power generation, so the emissions per kWh are larger. The uncollected material is present in both use *and* reference cases, however, so these emissions cancel one another out when calculating net carbon intensity.

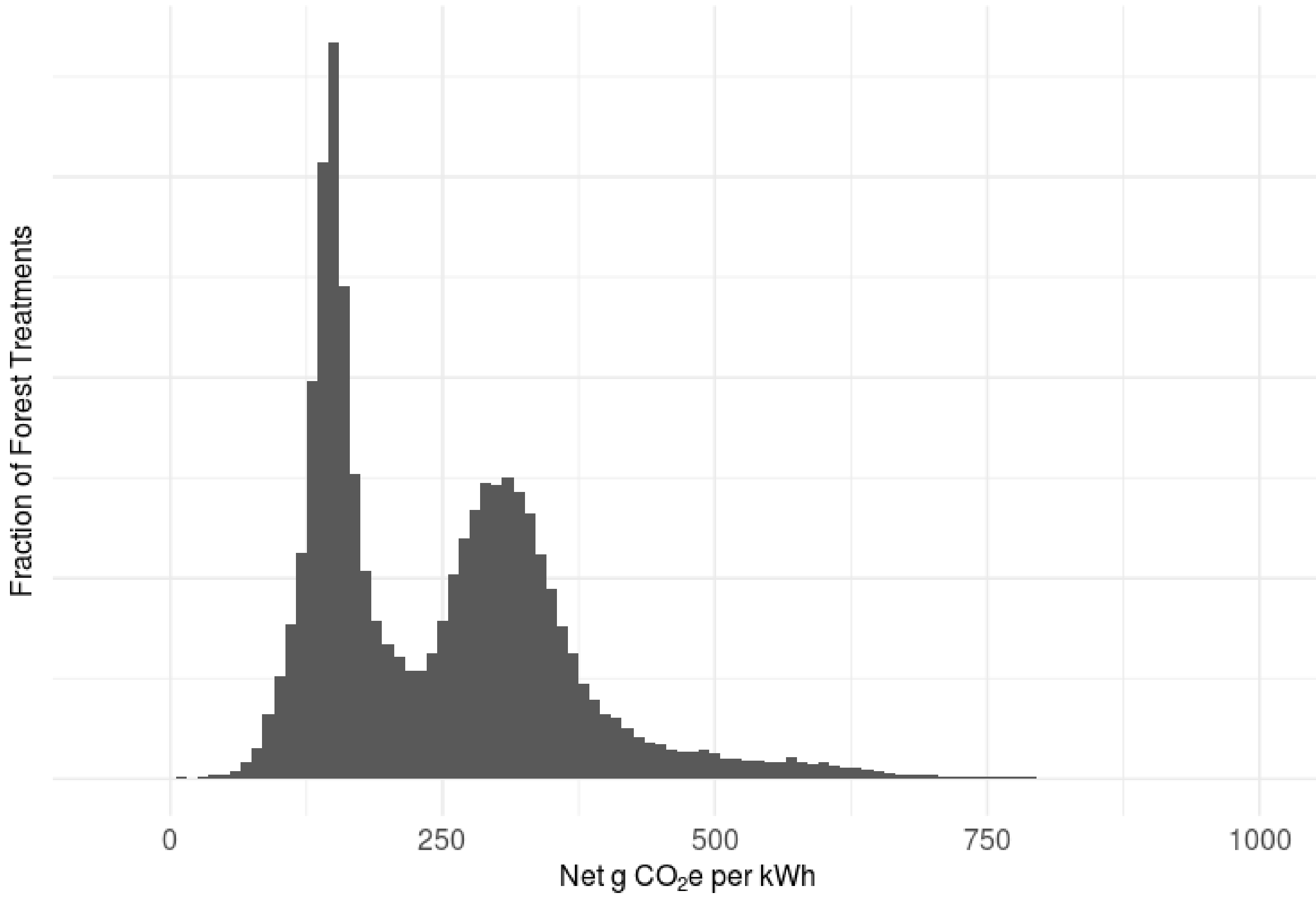
Figure 5: Example of Gross and Net Carbon Emissions by Source



Example emissions from each source for four collection and burn scenarios in both use case (above the x-axis) and reference case (below the x-axis) at two treatment sites in California representing two different climatic zones. Net emissions from biopower generation is the difference between the two cases and is indicated by the black point in each column. All emissions are in present-day CO_2e, normalized based on 100-year GWP.

The emissions displayed in Figure 5 represent a specific and limited set of scenarios to illustrate different emission sources and variations. Our modeled results vary across system characteristics such as forest treatment type, residue disposition, transport distance, and power plant technology as well as geographic characteristics such as residue species, decay rate, and wildfire probability. As such, considering the distribution of carbon intensities across the treatments conducted over the past four years in California allows us to better understand the sources of this variation and the sensitivity of biopower carbon footprint to various system characteristics and model assumptions. This will provide useful insight in shaping forest and bioelectricity policy and industry going forward. Figure 6 displays the distribution of outcomes across the scenarios considered for biopower generation from the residues created by permitted forest harvest and treatment activities conducted in California in the years 2016-2019. In the interest of situating these values in context, we note that the US grid average carbon intensity was 398 g/kWh in 2019 and California's grid average was 160 g/kWh[2].

Figure 6: Aggregate Net CO_2e Intensity Results



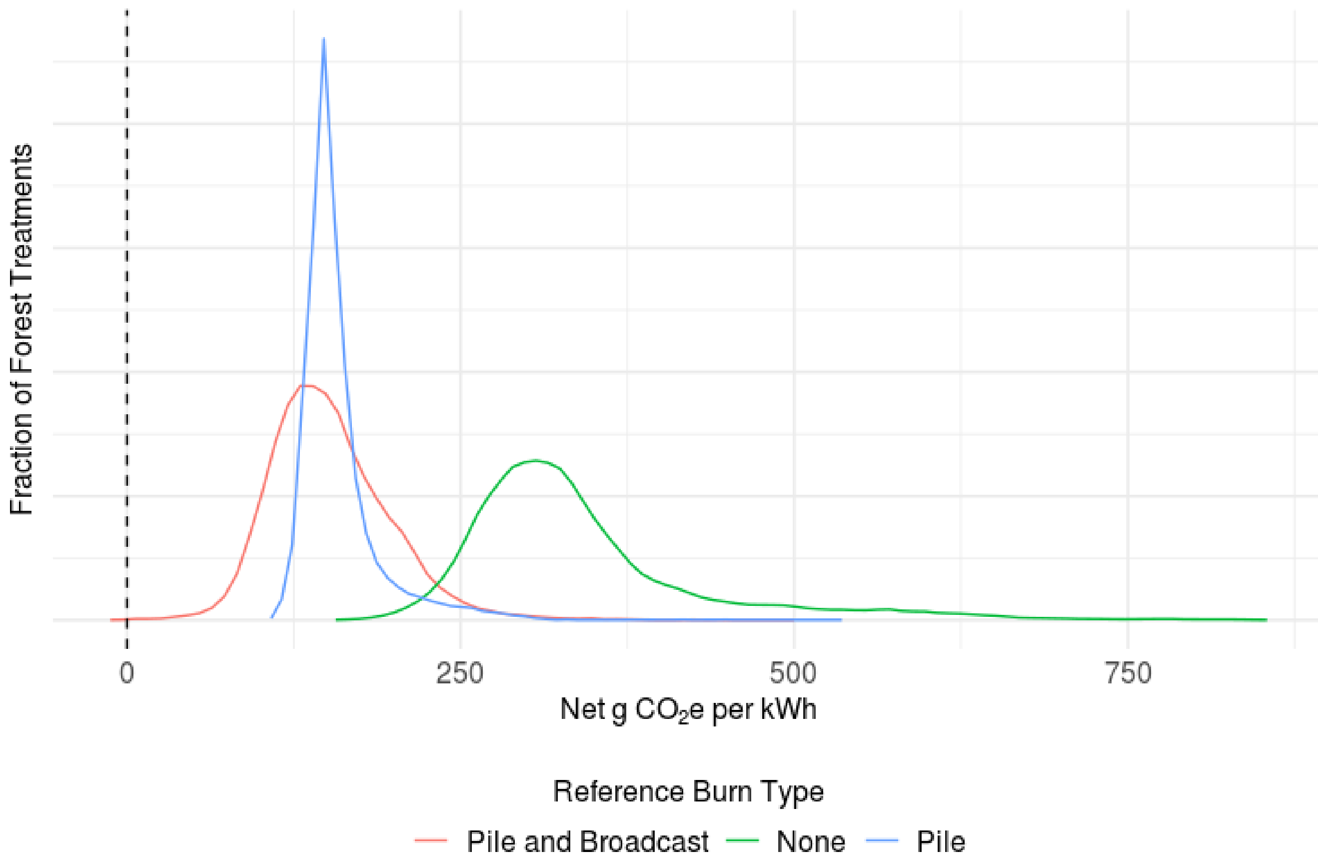
Histogram of net carbon intensity values across the California recent treatments dataset. Represented in this histogram are carbon intensities for all residue disposition, harvest, and counterfactual fate scenarios of biopower generation for each of the 11,035 forest treatments conducted in the years 2016-2019. Some factors are held constant across this distribution and outliers removed as described above. CO_2e uses 100 year time-integrated absolute global warming potential.

The most immediately evident trend in this dataset is the strongly bimodal distribution. This is attributable to the reference scenario considered, as generating electricity from woody biomass that would have been burned in the field if not removed has a much lower net carbon footprint on a 100-year global warming potential (GWP) basis than using biomass that would otherwise have been left in place. Figure 7 shows this clearly by disaggregating the distribution by reference case burn scenario. Figure 7 and many of the

[2] Scott Institute for Energy Innovation. (2017). Power Sector Carbon Index. Carnegie Mellon University, Pittsburgh, PA. Retrieved from https://www.emissionsindex.org.

following distribution figures are smoothed histograms, with carbon intensity displayed on the horizontal axis and relative prevalence of a given range of results represented on the vertical axis.

Figure 7: Net CO_2e Intensity Results Disaggregated by Counterfactual Burn



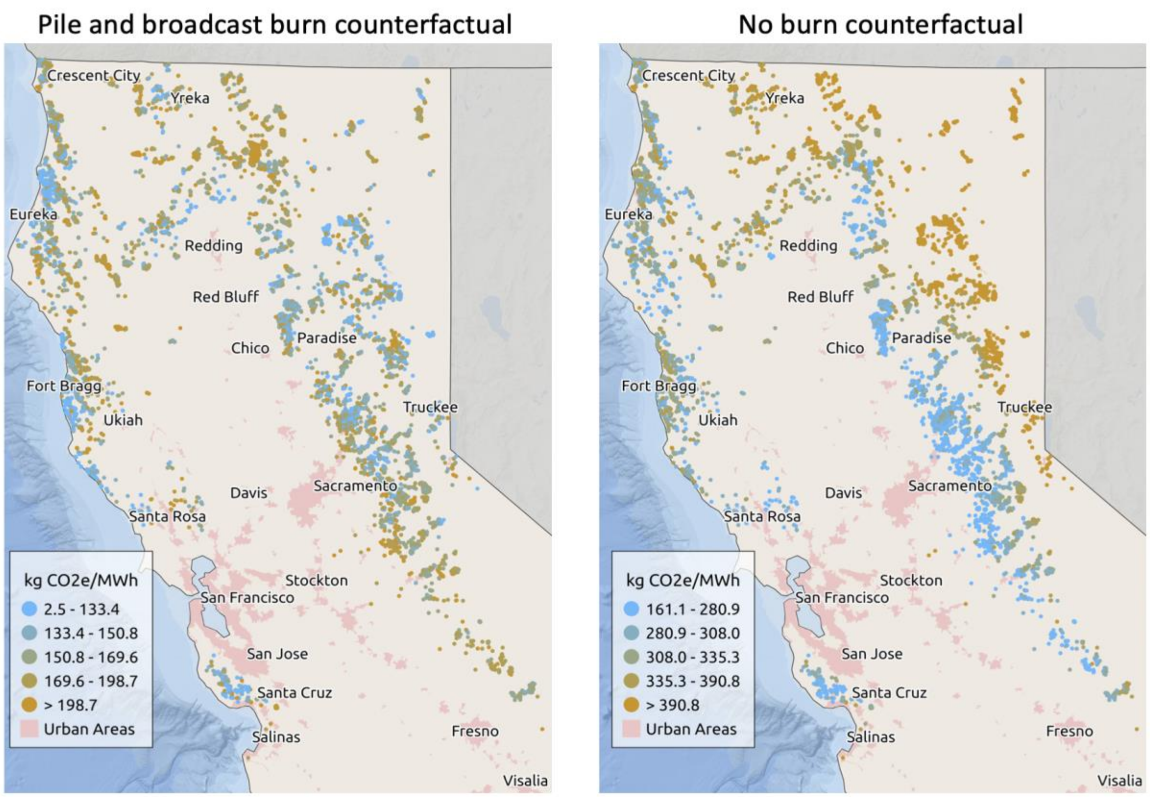
Distribution of carbon intensity results (net g CO_2e/kWh) across the California recent treatments dataset disaggregated to illustrate the difference across reference case burn scenarios.

Because these figures display the net emissions, higher emissions in the reference case lead to lower values here because more of the mobilization and combustion emissions in the use case are "offset" by the counterfactual outcome. It is clear that the prescribed burn scenarios (i.e. those in which residues would be burned if not mobilized for biopower generation) have a lower net biopower carbon intensity than the no-burn cases because they have higher reference-case emissions offsetting those in the use case. We find almost no circumstances in our baseline scenario in which biopower from woody residues has a zero or net negative carbon intensity. This is because the avoided emissions of methane and N_2O that can emerge from prescribed burns are typically more than offset by the fact that those burns do not completely consume the residue, leaving uncombusted wood and char material in the field.

The shapes of the different distributions presented in Figure 7 are also instructive. Scenarios in which only piled material would be collected and a pile burn is therefore the reference fate (blue curve in Figure 7) exhibit the least variability. This is because pile burns are relatively uniform in their combustion dynamics, whereas in broadcast burning (red curve in Figure 7) more wood is exposed to fire but the dynamics of that fire vary significantly across residue types and conditions. At the opposite extreme, the greatest variability is evident in the "no burn" cases where residues would be left in place if not removed (green curve in Figure 7). The climate, species, and treatment-type drivers of decay as well as the conditions and frequency of wildfire lead to variable emissions in the reference case, and therefore a large spread in net emissions for biopower generation.

In addition, long "tails" are evident, especially in the no burn scenario distribution, with a small number of scenarios showing carbon intensities reaching out towards 1000g CO_2e/kWh. These outlier treatments are predominantly those with very low total residue base and/or very low residue density (T/ac). In such cases, the fixed emissions associated with mobilizing collection equipment to field locations can become a dominant source of greenhouse gas emissions since these emissions are distributed across a very small number of total kWh. In addition, these low residue densities tend to occur in areas where climatic factors such as low rainfall rate yield not only low biomass production but also very low decay rates and therefore a larger climate impact from burning wood that would otherwise have been left in situ. These outlier cases are likely not commercially viable for residue mobilization and use, but are worth noting as they may occur where residue removal rather than prescribed burn or scatter is deemed necessary, such as in roadside clearing.

Figure 8: Example Spatial Variability of Biopower Carbon Intensity



Carbon intensity for two specific scenarios mapped across California to illustrate the spatial variation in results in a given scenario (within each map) and how it is influenced by the reference burn scenario (across the two maps). All results assume 50% of residue is piled and all technically recoverable residue is mobilized in the use case.

Even within a single scenario of both use and reference case characteristics, there is significant distribution in the carbon intensity of bioelectricity generated from residues. This is because the many forest treatments being evaluated differ in the species and size class distributions of their residue bases as well as in their climatic drivers of both decay and wildfire emissions. Mapping the net emissions from biomass utilization (Figure 8) allows us to assess these geographic discrepancies.

The map on the left in Figure 8 has lower values across the bins displayed since it assumes a prescribed burn counterfactual fate, where the map on the right is for the scenario in which residue would be left in place if not mobilized for bioelectricity. Each displays the variation across treatments conducted during the 2016-2019 period in California. The spread evident on the left-hand map stems from variation in emissions from prescribed burning owing to residue species, size class distribution, and climate, where that on the right stems from climatic and residue type variables driving differing decay rates and wildfire frequency.

3.2. Criteria Air Pollutants

Beyond greenhouse gases, the C-BREC model also quantifies net emissions of Volatile Organic Compounds (VOCs), carbon monoxide (CO), oxides of nitrogen and sulphur (NO_x and SO_x), and particulates at both 2.5 and 10 micron scales ($PM_{2.5}$ and PM_{10}) including both black[3] and organic carbon. While removing residues from the field for biopower generation almost always leads to a net increase in GHG emissions (though by a variable amount), we found that this diversion can significantly reduce emissions of these health-harming air pollutants when it displaces prescribed burning. Figure 9 shows this effect for the case of $PM_{2.5}$, a particularly harmful atmospheric pollutant. Because these pollutant emissions can't be normalized into a single year as we have done for GHGs, we show only year-1 emissions in this figure.

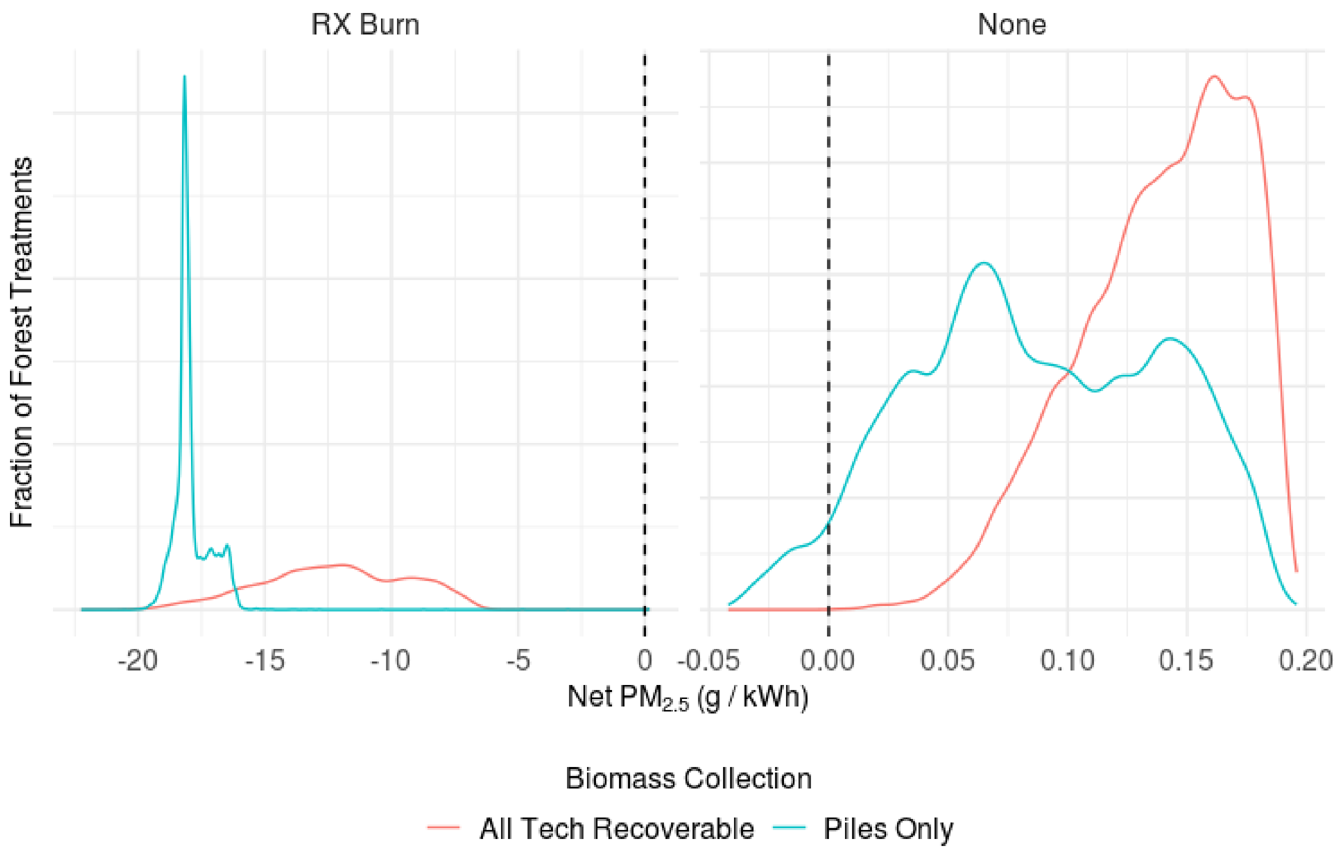
The reduction in emissions from biomass utilization is unsurprisingly strongest where biomass would otherwise have been burned in the field. By removing this material to an engineered combustion chamber, and one where emissions are tightly controlled, we significantly reduce the particulate emissions from a ton of biomass vs burning that same ton in the field. Where residue would have been left in the field rather than subjected to a prescribed burn, mobilization for biopower generation yields generally *slightly* greater emissions, but the results are mixed. However, this is only the expected emissions for the first year and is a product of the very significant emission profile if a wildfire occurs and the relatively small probability of that fire occurring on any given landscape. While the infrequency of wildfire means these expected emissions from a given mass of forest residue are generally lower in one year if left *in situ* vs used for biopower, they could be burned in future years as they decay. As such, the aggregate expected emissions from wood left in place over a decade or more are higher than that from its use in biopower, even if expected emissions in the first year as presented in Figure 9 are lower.

It is worth noting here that while mobilization of this woody biomass may reduce the total mass of particulates emitted per ton of residue, it also aggregates this emission to a point source, and one that may be closer to human populations. We have not evaluated the exposure of humans to these pollutants, nor the

[3] Black carbon has a potentially significant climate forcing effect. However, there is significant uncertainty and variability in the scale, and even the sign of the forcing that results from emissions of black carbon and other short-lived climate pollutants from combustion of woody biomass. Given this, we do not include black carbon in the climate metrics reported above. This issue is discussed in more depth in the Air pollution and soil impacts report available at schatzcenter.org/cbrec/

equity of distribution of that health burden across human populations. This is an important area for future research that will be enabled by the modeling tools and datasets developed under this project.

Figure 9: Net $PM_{2.5}$ Results



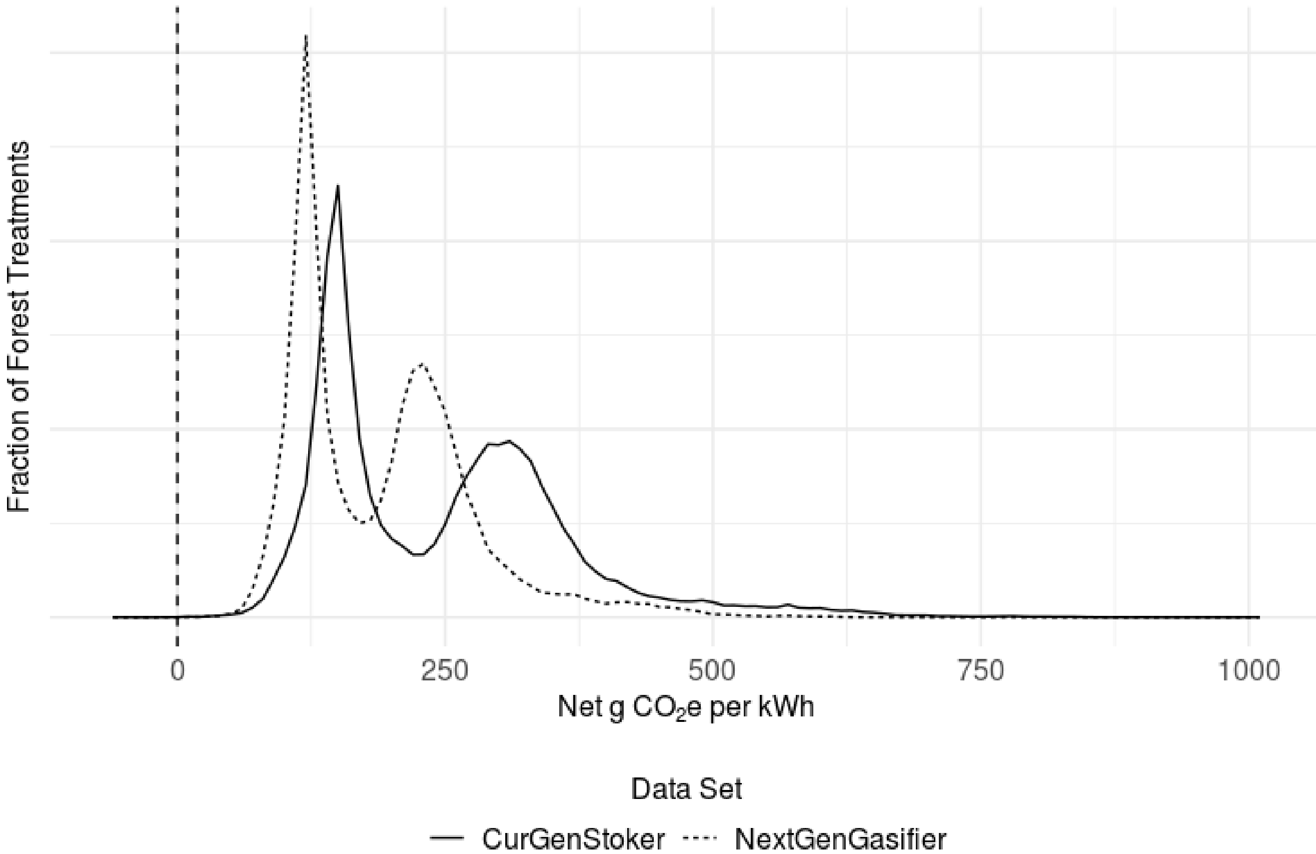
Distribution of first year $PM_{2.5}$ emissions across the California recent treatments dataset.

Further information on the emissions dynamics of particulates and other key criteria pollutants can be found in our companion report on the air quality and soil health effects of woody residue mobilization (available at schatzcenter.org/cbrec/).

3.3. Sensitivity to Key System Characteristics and Assumptions

The C-BREC model also enables us to rigorously evaluate the extent to which those emissions depend on specific characteristics of the system being modeled and the assumptions underlying the model itself. For example, Figure 10 illustrates the impact of upgrading the facility used for power generation from a 20% efficient biomass stoker to a 28% efficient gasifier technology. By improving the generation efficiency, this allows more power generation from a given amount of biomass without influencing either the reference or use-case emissions associated with mobilizing that biomass thereby reducing the emissions per kWh.

Figure 10: Model Sensitivity to Power Plant Efficiency



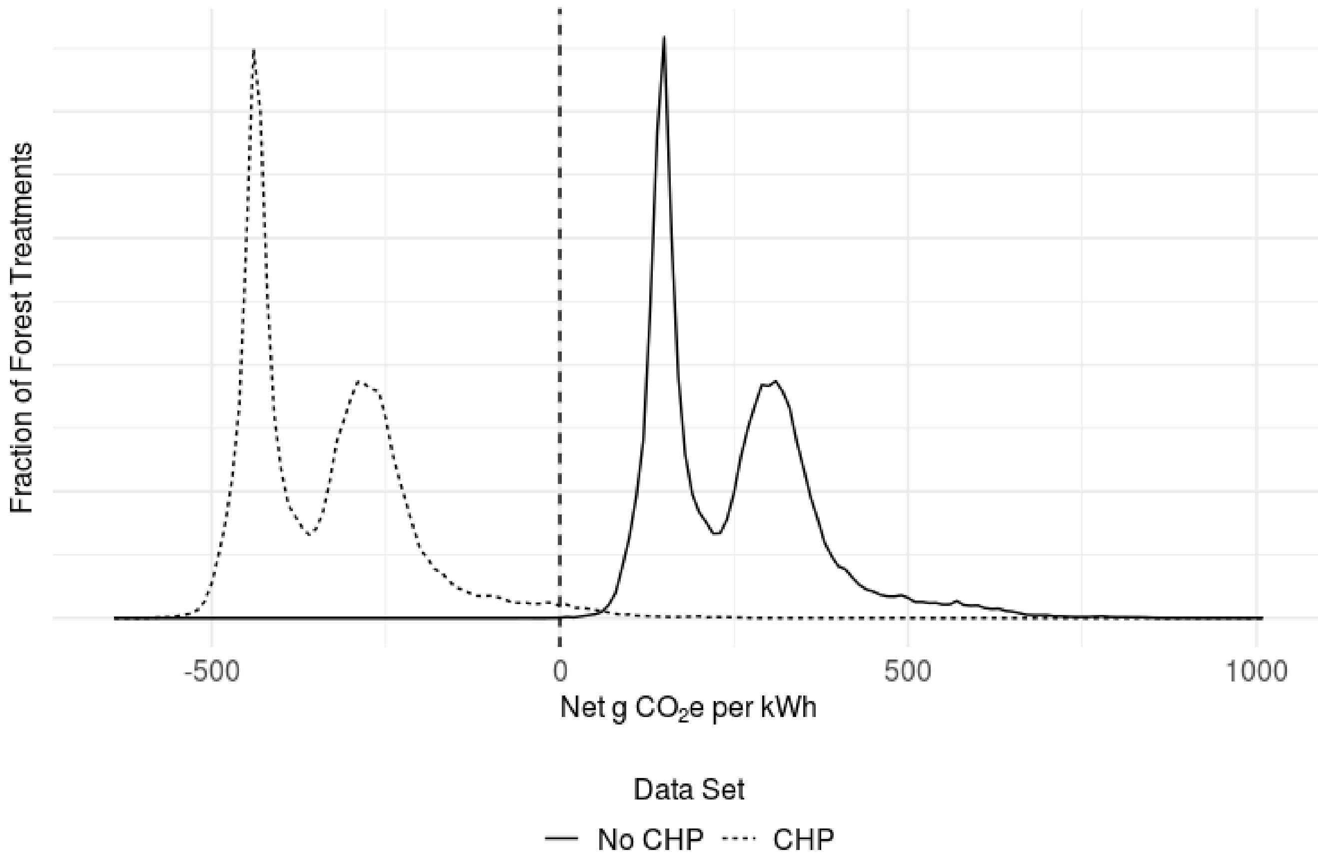
Distribution of carbon intensity results (net g CO_2e/kWh) across the California recent treatments dataset - sensitivity to power plant efficiency assumption.

Another important characteristic of some biopower generation systems is the potential deployment of a combined heat and power (CHP) system. Figure 11 shows the impact of capturing heat from biomass combustion and using that heat to offset heating demand nearby that would otherwise have been satisfied by a natural gas boiler.

It is important to note that several optimistic simplifying assumptions underpin these estimates of the impact of a CHP system. For example, this assumes a state-of-the-art CHP system capable of capturing 80% of the heat energy produced by the power generation. Furthermore, it assumes that 100% of captured heat is able to be used effectively to deliver heat that would otherwise have been provided by natural gas. As a result, the carbon savings from CHP illustrated in Figure 11 should be considered overly optimistic for many existing power plants with CHP, but possible for newer technologies or those facilities that meet these criteria[4].

[4] For example, facilities that participate in the CPUC Quality Facilities and Combined Heat and Power (QF /CHP) Program.

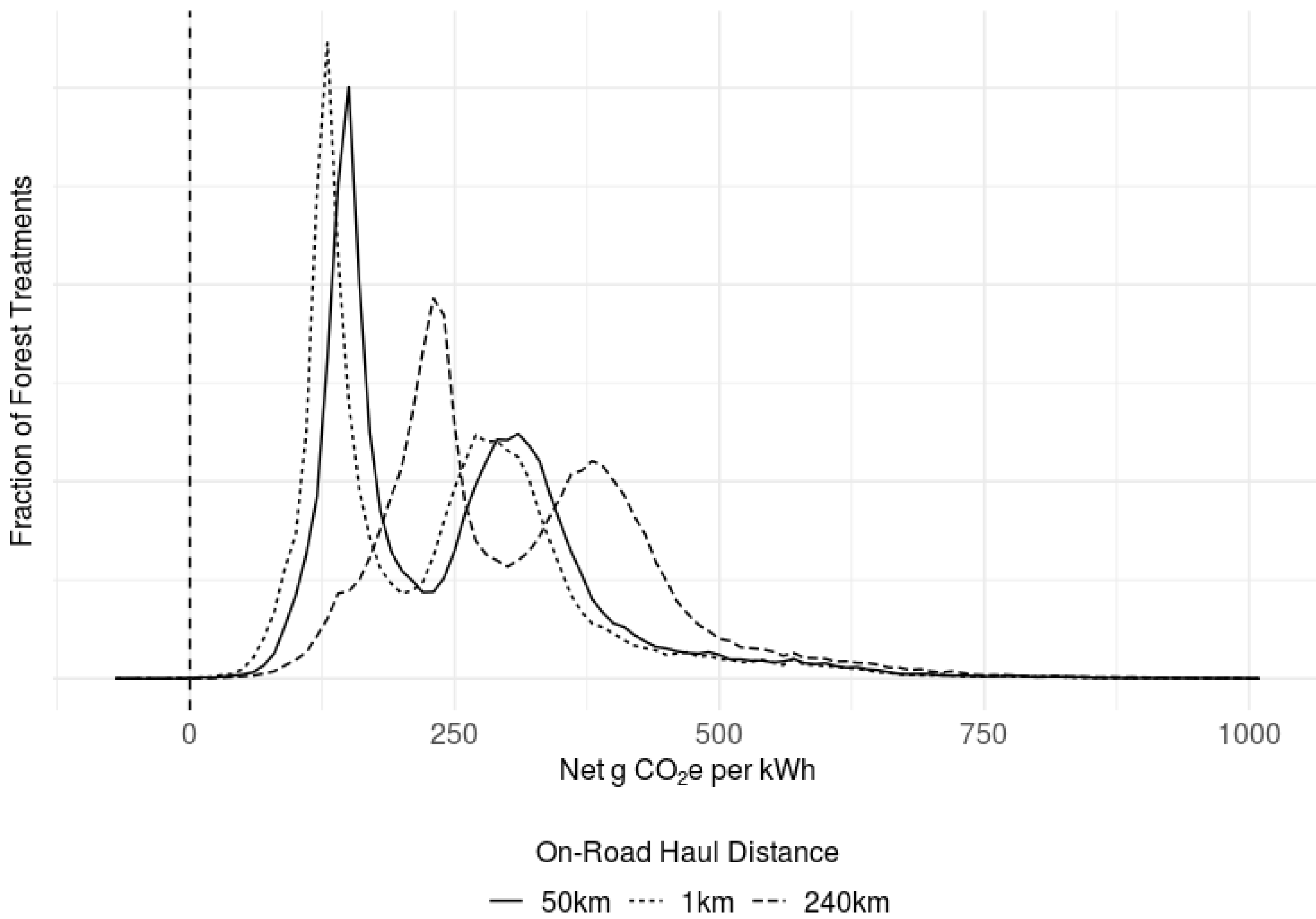
Figure 11: Model Sensitivity to Combined Heat and Power



Distribution of carbon intensity results (net g CO_2e/kWh) across the California recent treatments dataset - sensitivity to offset natural gas with a high-efficiency and fully utilized CHP system at the power generation facility.

After removal of woody residue from the field, it is typically chipped and ground for transport to a biopower generation facility. For most of the figures in this report, we have used a static on-road haul distance of 50km. However, as it is a direct contributor to the use-case carbon emissions that is not present in the reference case, the net carbon intensity of biopower is meaningfully sensitive to this parameter. Figure 12 investigates the sensitivity of the net GHG emissions to on-road transport distance to the power plant, displaying the baseline distribution at the 50km haul distance as well as distributions at two extremes of 1km and 240km.

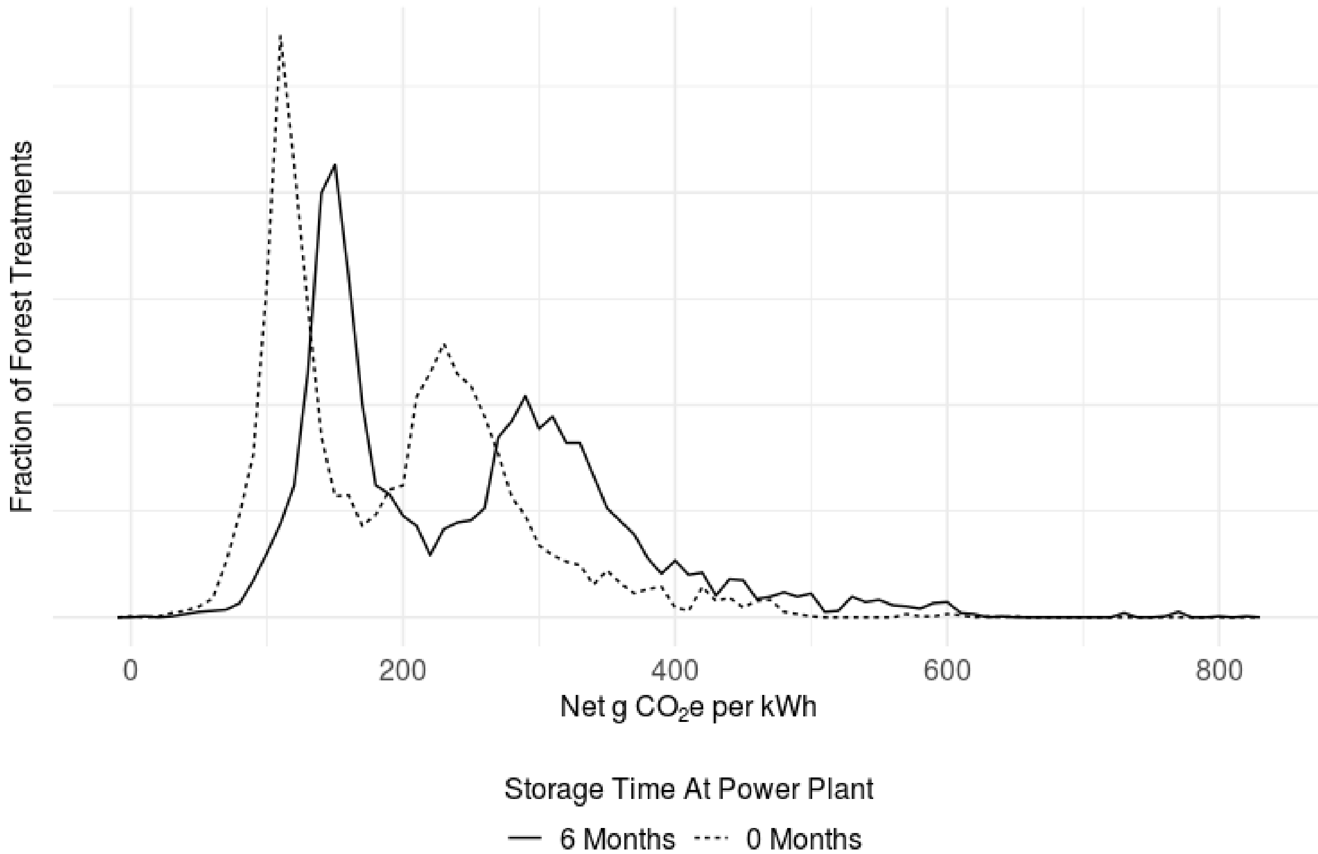
Figure 12: Model Sensitivity to On-Road Chip Van Hauling Distance



Distribution of carbon intensity results (net g CO_2e/kWh) across the California recent treatments dataset - sensitivity to on-road hauling distance from field to biopower facility.

When wood chips arrive at their destination they are then stored until being used for power generation. The baseline C-BREC model assumes that the biomass is stored for 6 months on average based on our own informal field survey. This results in some dry matter loss through decay during storage, leading to GHG emission as well as a loss in heating value. Figure 13 investigates the sensitivity of the biopower CI distribution to this storage period assumption.

Figure 13: Model Sensitivity to Material Storage Period at the Power Plant



Distribution of carbon intensity results (net g CO_2e/kWh) across the California recent treatments dataset - sensitivity to the storage period for chipped biomass at the power plant.

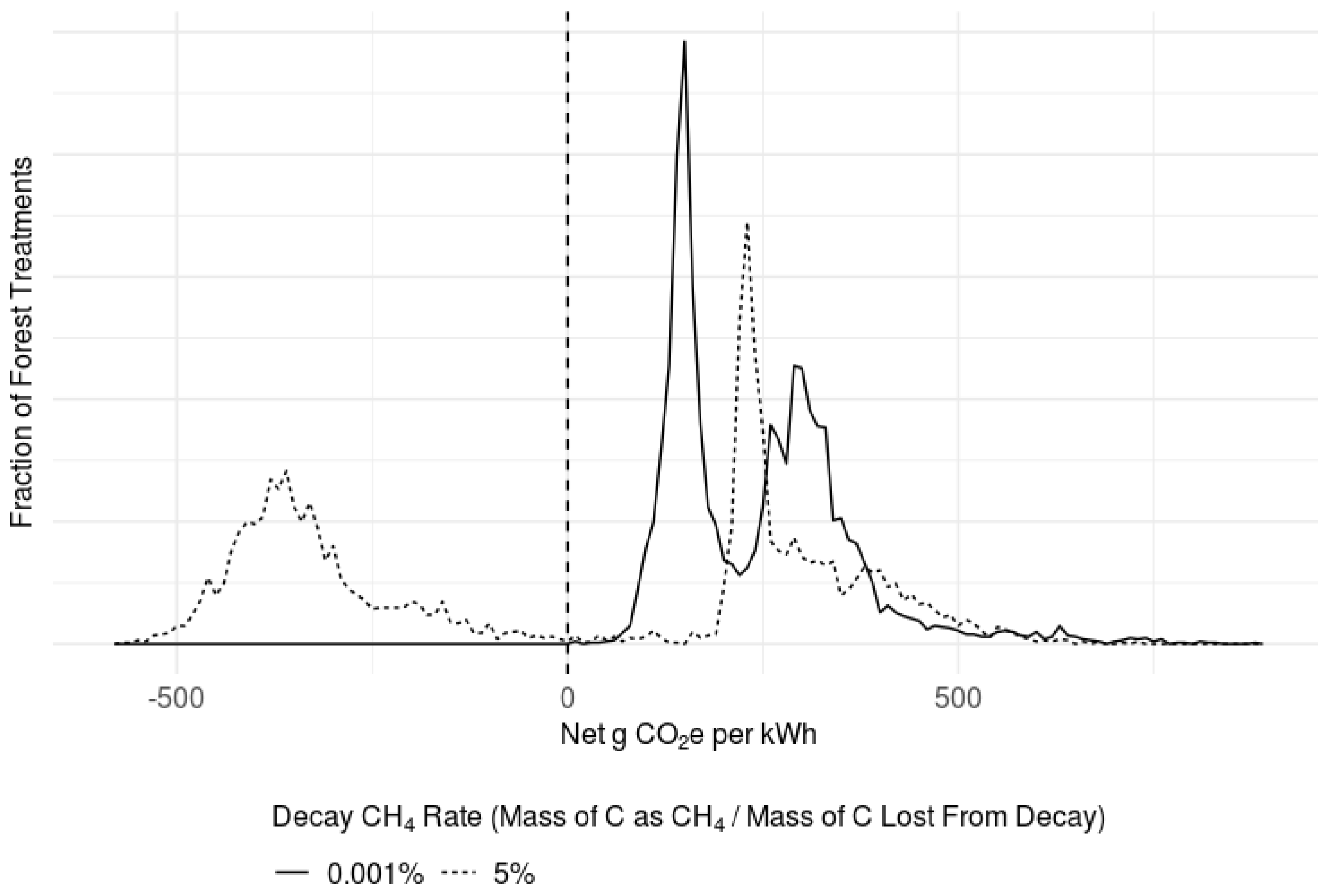
As a pile of biomass decays, anaerobic conditions can develop. Further decay in the absence of oxygen would lead to methane formation. This could occur both in the chip piles present at biopower facilities as well as in residue piles left in the forest. Unfortunately there has been very little empirical field study of this emission source in either of these contexts. As such, we drew on (He et al., 2014) as well as laboratory research by our own research team (Geronimo, 2020) to parameterize the C-BREC model. Our baseline model assumes that approximately .001% of the carbon emitted through decay in both chip piles and field decay is emitted as CH4. As this is potentially an important source of sensitivity and uncertainty in the model, it warrants investigation. Figure 14 shows the carbon intensity of bioelectricity with the baseline assumption of 0.001% methane formation from biomass decay compared against a methane fraction of 5% of total C emission from decay[5]. This 5% case is meant to provide an illustrative bounding sensitivity

---

[5] The California Air Resource Board assumes 0.05 tons CH4 per BDT of residue (California Air Resources Board, 2020) which is based on an assumption that 9% of total residue carbon stock is emitted as CH4 (Placer County Air Pollution Control District, 2013). This roughly translates into 5% - 6% of total carbon emission from decay, depending on assumed carbon content, and assuming 100% degradation of material through decay.

analysis, as no empirical evidence supports an assumption of such a high methane generation rate in woody residues under typical decay conditions.

Figure 14: Model Sensitivity to Decay Methane Fraction



Distribution of carbon intensity results (net g CO_2e/kWh) across the California recent treatments dataset - sensitivity to CH4 fraction from biomass decay.

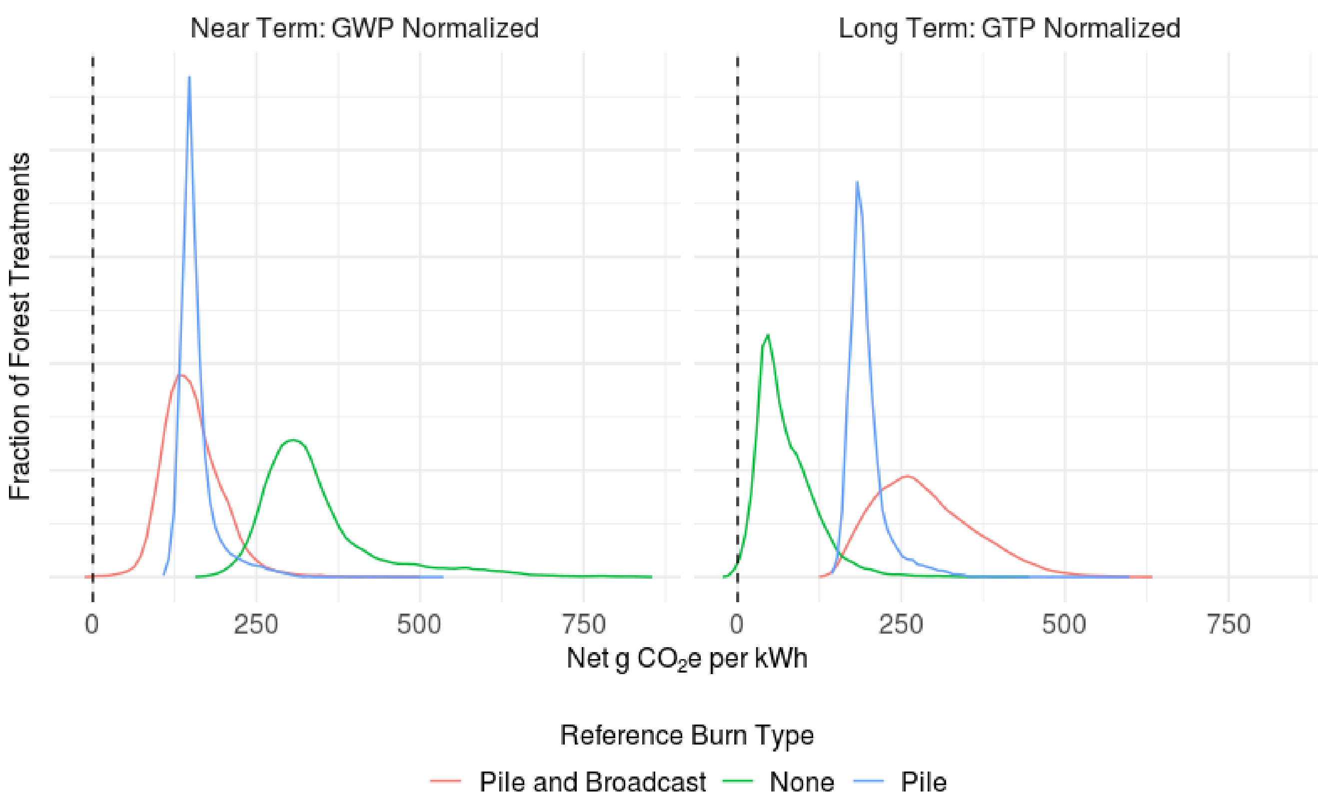
Not only does increasing the assumed fraction of carbon emitted as methane from decay significantly change the result, it also offers key insights into how its importance depends on the scenario under consideration. Note that as elsewhere in these bimodal distributions, the narrow "spike" in carbon intensity represents the less variable prescribed burn counterfactual whereas the wider distribution represents the no burn scenarios. Notably, not only do we see these two scenarios switch their positions when methane fraction from decay is raised to 5%, but the increase in methane emission shifts their carbon intensities in opposite directions.

Where the counterfactual fate of biomass is for it to be left in the field, a 5% methane emission fraction has a very significant impact when normalized on a GWP basis. In this scenario, the CI of biopower would be very negative as there is significant methane emission over a long decay period. Where a prescribed burn is the reference-case outcome for residue, increasing the methane emitted from decay leads to an increase in the net carbon intensity of biopower because there is little residue left in the field to decay, but the decay over the assumed 6-month average storage period at the biopower facility becomes a dominant source of methane.

3.4. Investigating Different Climate Metrics

The C-BREC model is able to calculate carbon intensity values for biopower generation using two different climate metrics. These differ in how they account for the present-day CO_2 equivalent of a modeled emissions time series. The first alternative—and that which is used in the results reported above—is to normalize emissions based on the 100-year Global Warming Potential (GWP). In this case, we calculate the present-day emissions of CO_2 that would yield the same aggregate radiative forcing over a 100-year time period as the emission trajectory in question and report that as the CO_2 equivalent. Because this is an aggregate metric, it is often considered the relevant approach to evaluating *near and medium-term* climate impacts. Another alternative is to normalize emissions using the Global Temperature Potential (GTP). As this approach is an instantaneous metric, and therefore concerned with the state of the climate in 100 years but not any intervening warming, it is often considered the relevant approach for evaluating *long-term* climate impacts (Levasseur et al., 2016). Figure 15 below displays the distribution curves for net carbon intensity across the California recent treatments dataset broken out by reference biomass fate in both GWP and GTP-normalized CO_2e.

Figure 15: Aggregate Net CO_2e Intensity Results for Both GWP and GTP



Distribution of carbon intensity results (net g CO_2e/kWh) across the California recent treatments dataset with emission profile over time normalized to CO_2e on the basis of the 100-year Global Warming Potential (left) and 100-year Global Temperature Potential (right).

Figure 15 warrants further explanation as it offers key insights into the differences between the climate metrics reported. Since these figures display the net emissions, higher emissions in the reference case lead to lower values here because more of the mobilization and combustion emissions in the use case are "offset" by the counterfactual outcome. In the GWP-normalized figure on the left, it is clear that the prescribed burn scenarios (i.e. those in which residues would be burned if not mobilized for biopower generation) have a lower net biopower carbon intensity than the no-burn cases because they have higher reference-case emissions offsetting those in the use case. However, the long-term, GTP-normalized forcing values display the opposite trend, with the "no burn" reference cases having lower carbon intensities than those with prescribed burns. Delaying reference-case emissions by leaving material to decay, means they have less total forcing impact in the 100-year period, bringing the net GWP-normalized carbon intensity of biopower up. However, it also means that more mass of GHGs is present in the atmosphere at year 100 because they were emitted later, driving the net GTP-normalized carbon intensity of biopower today down.

The opposite is true when the alternate outcome for the biomass is a prescribed burn. Field burning emits significantly more methane than controlled combustion in a power plant. Though it is a powerful GHG, methane has a relatively short lifetime in the atmosphere. As a result, the effect of a prescribed burn is smaller on a GTP basis, as it is concerned with temperatures in year-100 when this methane is largely gone from the atmosphere. On the other hand, the effect is greater on a GWP basis which considers the added forcing in the intervening years, thereby capturing the effect of near-term elevated methane levels.

4. Conclusions

Because it is commonly classified as renewable, and is therefore promoted as part of various climate mitigation strategies, biopower—especially when generated from forest wastes and residues—is expected to grow significantly in coming decades. In a 2018 Special Report, the IPCC reviewed eighty-five pathways to achieving a maximum warming of 1.5°C and estimated that bioelectricity systems—in particular those employing carbon capture and sequestration—would need to make up a median of 26% of primary energy supply in 2050 (Rogelj et al., 2018). We highlight these findings not to advocate for the growth of the bioenergy sector *per se*, but in recognition of the fact that it is expected to play a significant role in a climate-constrained energy future, and should therefore be structured to ensure that it delivers the intended climate and environmental performance.

Most policies that support bioenergy are predicated on the assertion that the pathways being promoted offer a climate benefit compared to a scenario in which this bioenergy was not produced. However, as we have shown, the climate performance of biopower from forest residues is highly variable. It is therefore incumbent upon policymakers in California and elsewhere to design bioenergy policies that deliver specifically those pathways offering significant climate and/or other environmental benefits. The C-BREC model offers a useful tool to this end. It improves on the existing Life Cycle Assessment approaches by transparently capturing the significant spatial and supply-chain variability in life-cycle emissions, enabling activities to be targeted to where they offer the greatest benefit.

We find typically net positive emissions from bioelectricity generation, even where there is prescribed burn avoided. However, bioelectricity does not need to have a negative carbon footprint in order to offer a benefit. There are very few products or processes in existence that can make that claim. Biopower from residues that would otherwise have been burned in situ can have a lower carbon intensity than CA grid average electricity on a GWP-normalized basis, though higher than other renewables such as wind and solar power. In addition, the air quality benefits offered by mobilizing residues that would otherwise have been burned are substantial and should be taken into account alongside climate, wildfire, and ecosystem considerations.

This analysis does not account for carbon emissions or sequestration implications of the primary treatment activity that yields the woody residues in question. This is because residue mobilization has not been seen to be a driver of those activities. If biomass removal is a necessary part of forest management activities that reduce fire risk and/or improve the carbon storage on the landscape, bioenergy that facilitates these activities by offering an outlet for residues could provide further climate benefit not quantified here. However, these benefits would not accrue uniquely to bioelectricity, and state policymakers could consider additional uses for the woody biomass in question that may provide stronger climate performance alongside or as an alternative to biopower generation.

While the model results reported here and the tool they introduce offer key insights into the climate and air quality performance of bioelectricity systems in California, they have also identified some important research questions that warrant further investigation:

- *Empirical studies of targeted emissions sources:* C-BREC modeling has identified key system sensitivities that warrant closer evaluation and further study. For example, field measurement of methane generation from biomass piles would aid in stronger empirical parameterization of the model. In addition, the most significant sensitivity in bioelectricity carbon intensity is the counterfactual fate of the biomass being used. There is little organized record-keeping on prescribed burning of forest residues, and further research is needed to rigorously and transparently estimate the fraction of residue that has historically been burned on different working landscapes in California.

- *Air emissions health burden:* C-BREC has generated a substantial, spatially disaggregated database of criteria air pollutant emissions associated with mobilization and use of biomass residues as well as their counterfactual fate in the field. It was beyond the scope of this research to evaluate the human health burden associated with these emissions or the equity of the distribution of this burden. The C-BREC model and output database offer an opportunity to investigate these effects.
- *Expansion to other use-cases for woody biomass:* in addition to electricity, residual biomass could be used as a feedstock for other end uses such as liquid fuels, biochar, or durable wood products. Policy and industry decision-making in the broader wood products space could be better informed if impact assessments were harmonized. Expanding C-BREC to incorporate other pathways for residue utilization would offer key insights and could be accomplished via integration with existing LCA tools such as the GREET model for liquid fuels.
- *Integration of Bioenergy with Carbon Capture and Storage (BECCS) in California:* BECCS is one of the more practical negative emissions electricity generation technologies available. By removing the most significant emission source in the use case of the pathways evaluated here (biomass combustion for electricity generation), it would lead to uniformly negative biopower carbon intensity. C-BREC could be a useful tool in locating and evaluating the potential of BECCS facility development in California.
- *Integration with broader land-use modeling frameworks:* This project considers forest management activities as exogenous to the biomass residue supply chain. As such, C-BREC does not quantify any carbon cycling implication of these activities. There are promising opportunities to integrate C-BREC with forest carbon modeling tools to evaluate the landscape-level climate implications of different land management scenarios including biomass utilization.
- *Incorporation of biomass resource economic modeling:* The C-BREC framework enables us to evaluate the emissions implications of mobilizing residues from notional harvests in California but does not identify where those harvests will occur. By integrating elements evaluating the economics of forest harvest and biomass mobilization, we would be able to robustly evaluate the landscape-scale implications of, for example, new biopower facility construction or subsidies to biomass mobilization in the state.

5. References

Aamaas, B., Peters, G. P., & Fuglestvedt, J. S. (2012). A synthesis of climate-based emission metrics with applications. *Earth System Dynamics Discussions*, *3*(2), 871–934. https://doi.org/10.5194/esdd-3-871-2012

Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, *33*(1), 121–131. https://doi.org/10.1002/joc.3413

Abatzoglou, J. T., & Brown, T. J. (2012). A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology*, *32*(5), 772–780. https://doi.org/10.1002/joc.2312

Andrews, P. L. (2012). Modeling wind adjustment factor and midflame wind speed for Rothermel's surface fire spread model. *Gen. Tech. Rep. RMRS-GTR-266. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 39 p.*, *266*. https://doi.org/10.2737/RMRS-GTR-266

Blasdel, M. (2020). Decay of woody residues as the counterfactual treatment to mobilization for bioelectricity generation. *HSU Theses and Projects*. https://digitalcommons.humboldt.edu/etd/420

Buchholz, T., Hurteau, M. D., Gunn, J., & Saah, D. (2016). A global meta-analysis of forest bioenergy greenhouse gas emission accounting studies. *GCB Bioenergy*, *8*(2), 281–289. https://doi.org/10.1111/gcbb.12245

California Air Resources Board. (2020). *California Climate Investments Quantification Methodology Emission Factor Database Documentation*. https://ww2.arb.ca.gov/resources/documents/cci-quantification-benefits-and-reporting-materials

California Air Resources Board. (2021). *California Climate Investments Funded Programs*. https://ww2.arb.ca.gov/our-work/programs/california-climate-investments/california-climate-investments-funded-programs

Cherubini, F., & Strømman, A. H. (2011). Life cycle assessment of bioenergy systems: state of the art and future challenges. *Bioresource Technology*, *102*(2), 437–451. https://doi.org/10.1016/j.biortech.2010.08.010

Cohen, J. D., & Deeming, J. E. (1985). The national fire-danger rating system: basic equations. *Gen. Tech. Rep. PSW-82. Berkeley, CA: Pacific Southwest Forest and Range Experiment Station, Forest Service, U.S. Department of Agriculture; 16 p*, *082*. https://doi.org/10.2737/PSW-GTR-82

Collins, B. M., Das, A. J., Battles, J. J., Fry, D. L., Krasnow, K. D., & Stephens, S. L. (2014). Beyond reducing fire hazard: fuel treatment impacts on overstory tree survival. *Ecological Applications*, *24*(8), 1879–1886. https://doi.org/10.1890/14-0971.1

Cornwall, W. (2017). The burning question. *Science*, *355*(6320), 18–21. https://doi.org/10.1126/science.355.6320.18

Duncan Brack. (2017, February 23). *The Impacts of the Demand for Woody Biomass for Power and Heat on Climate and Forests*. https://www.chathamhouse.org/2017/02/impacts-demand-woody-biomass-power-and-heat-climate-and-forests

Edmonds, R. L., Vogt, D. J., Sandberg, D. H., & Driver, C. H. (1986). Decomposition of Douglas-fir and red alder wood in clear-cuttings. *Canadian Journal of Forest Research*, *16*(4), 822–831. https://doi.org/10.1139/x86-145

Erickson, H. E., Edmonds, R. L., & Peterson, C. E. (1985). Decomposition of logging residues in Douglas-fir, western hemlock, Pacific silver fir, and ponderosa pine ecosystems. *Canadian Journal of Forest Research*. https://doi.org/10.1139/x85-147

Foley, J. A. (1995). An equilibrium model of the terrestrial carbon budget. *Tellus B: Chemical and Physical Meteorology*, *47*(3), 310–319. https://doi.org/10.3402/tellusb.v47i3.16050

Forest Climate Action Team. (2018). *California Forest Carbon Plan: Managing Our Forest Landscapes in a Changing Climate* (p. 178).

Geronimo, C. (2020). Characterization of greenhouse gas emissions from storage of woody biomass: an incubation study. *HSU Theses and Projects*. https://digitalcommons.humboldt.edu/etd/449

Giuntoli, J., Agostini, A., Caserini, S., Lugato, E., Baxter, D., & Marelli, L. (2016). Climate change impacts of power generation from residual biomass. *Biomass and Bioenergy*. https://doi.org/10.1016/j.biombioe.2016.02.024

Giuntoli, J., Caserini, S., Marelli, L., Baxter, D., & Agostini, A. (2015). Domestic heating from forest logging residues: environmental risks and benefits. *Journal of Cleaner Production*, *99*, 206–216. https://doi.org/10.1016/j.jclepro.2015.03.025

Gustavsson, L., Haus, S., Ortiz, C. A., Sathre, R., & Truong, N. L. (2015). Climate effects of bioenergy from forest residues in comparison to fossil energy. *Applied Energy*, *138*, 36–50. https://doi.org/10.1016/j.apenergy.2014.10.013

He, X., Lau, A. K., Sokhansanj, S., Lim, C. J., Bi, X. T., & Melin, S. (2014). Investigating gas emissions and dry matter loss from stored biomass residues. *Fuel*, *134*, 159–165. https://doi.org/10.1016/j.fuel.2014.05.061

Helin, T., Sokka, L., Soimakallio, S., Pingoud, K., & Pajula, T. (2013). Approaches for inclusion of forest carbon cycle in life cycle assessment - a review. *GCB Bioenergy*, *5*(5), 475–486. https://doi.org/10.1111/gcbb.12016

ISO 14067:2018. (2018). *Greenhouse gases - Carbon footprint of products - Requirements and quidelines for quantification*. International Organization for Standardization. https://www.iso.org/standard/71206.html

Jäppinen, E., Korpinen, O.-J., Laitila, J., & Ranta, T. (2014). Greenhouse gas emissions of forest bioenergy supply and utilization in Finland. *Renewable and Sustainable Energy Reviews*, *29*, 369–382. https://doi.org/10.1016/j.rser.2013.08.101

Jenkins, J. C., Chojnacky, D. C., Heath, L. S., & Birdsey, R. A. (2003). National-Scale Biomass Estimators for United States Tree Species. *Forest Science*, *49*(1), 12–35.

Laiho, R., & Prescott, C. E. (2004). Decay and nutrient dynamics of coarse woody debris in northern coniferous forests: a synthesis. *Canadian Journal of Forest Research*, *34*(4), 763–777. https://doi.org/10.1139/x03-241

Larkin, N. K., O'Neill, S. M., Solomon, R., Raffuse, S., Strand, T., Sullivan, D. C., Krull, C., Rorig, M., Peterson, J., Ferguson, S. A., Larkin, N. K., O'Neill, S. M., Solomon, R., Raffuse, S., Strand, T., Sullivan, D. C., Krull, C., Rorig, M., Peterson, J., & Ferguson, S. A. (2010). The BlueSky smoke modeling framework. *International Journal of Wildland Fire*, *18*(8), 906–920. https://doi.org/10.1071/WF07086

Levasseur, A., Schryver, A. de, Hauschild, M., Kabe, Y., Sahnoune, A., Tanaka, K., & Cherubini, F. (2016). Greenhouse gas emissions and climate change impacts. In *Global guidance for life cycle impact assessment indicators* (Vol. 1). United Nations Environment Programme.

Liu, B., & Rajagopal, D. (2019). Life-cycle energy and climate benefits of energy recovery from wastes and biomass residues in the United States. *Nature Energy*, *4*(8), 700–708. https://doi.org/10.1038/s41560-019-0430-2

Mackensen, J., & Bauhus, J. (1999). *The Decay of Course Woody Debris* (No. 6; National Carbon Accounting System Technical Report). Australian Greenhouse Office, Canberra.

Madsen, K., & Bentsen, N. S. (2018). Carbon Debt Payback Time for a Biomass Fired CHP Plant—A Case Study from Northern Europe. *Energies*, *11*(4), 807. https://doi.org/10.3390/en11040807

McKechnie, J., Colombo, S., Chen, J., Mabee, W., & MacLean, H. L. (2011). Forest Bioenergy or Forest Carbon? Assessing Trade-Offs in Greenhouse Gas Mitigation with Wood-Based Fuels. *Environmental Science & Technology*, *45*(2), 789–795. https://doi.org/10.1021/es1024004

Miner, R. A., Abt, R. C., Bowyer, J. L., Buford, M. A., Malmsheimer, R. W., O'Laughlin, J., Oneil, E. E., Sedjo, R. A., & Skog, K. E. (2014). Forest Carbon Accounting Considerations in US Bioenergy Policy. *Journal of Forestry*, *112*(6), 591–606. https://doi.org/10.5849/jof.14-009

Myhre, G., Shindell, D., Bréon, F.-M., Collins, W., Fuglestvedt, J., Huang, J., Koch, D., Lamarque, J.-F., Lee, D., Mendoza, B., Nakajima, T., Robock, A., Stephens, G., Takemura, T., & Zhang, H. (2013). Anthropogenic and Natural Radiative Forcing. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Doschung, A. Nauels, Y. Xia, V. Bex, & P. M. Midgley (Eds.), *Climate Change 2013 - The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 659–740). Cambridge University Press. http://ebooks.cambridge.org/ref/id/CBO9781107415324A026

Olson, J. S. (1963). Energy Storage and the Balance of Producers and Decomposers in Ecological Systems. *Ecology*, *44*(2), 322–331. https://doi.org/10.2307/1932179

Placer County Air Pollution Control District. (2013). *Biomass Waste to Energy Project Reporting Protocol, Version 6.3* (p. 34). https://www.placerair.org/DocumentCenter/View/2115/Biomass-Waste-For-Energy-Project-Protocol-PDF

Prichard, S. J., Ottmar, R. D., & Anderson, G. K. (2006). Consume 3.0 user's guide. *Pacific Northwest Research Station, Corvallis, Oregon*.

Reid, W. V., Ali, M. K., & Field, C. B. (2020). The future of bioenergy. *Global Change Biology*, *26*(1), 274–286. https://doi.org/10.1111/gcb.14883

Riccardi, C. L., Ottmar, R. D., Sandberg, D. V., Andreu, A., Elman, E., Kopper, K., & Long, J. (2007). The fuelbed: a key element of the Fuel Characteristic Classification System. *Canadian Journal of Forest Research*, *37*(12), 2394–2412. https://doi.org/10.1139/X07-143

Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., Mundaca, L., Séférian, R., & Vilariño, M. (2018). Mitigation pathways compatible with 1.5°C in the context of sustainable development. In V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, & T. Waterfield (Eds.), *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* (pp. 93–174). IPCC/WMO. https://www.ipcc.ch/site/assets/uploads/sites/2/2019/05/SR15_Chapter2_Low_Res.pdf

Sierra, C. A., Trumbore, S. E., Davidson, E. A., Vicca, S., & Janssens, I. (2015). Sensitivity of decomposition rates of soil organic matter with respect to simultaneous changes in temperature and moisture. *Journal of Advances in Modeling Earth Systems*, *7*(1), 335–356. https://doi.org/10.1002/2014MS000358

Springsteen, B., Christofk, T., Eubanks, S., Mason, T., Clavin, C., & Storey, B. (2011). Emission Reductions from Woody Biomass Waste for Energy as an Alternative to Open Burning. *Journal of the Air & Waste Management Association*, *61*(1), 63–68. https://doi.org/10.3155/1047-3289.61.1.63

Sterman, J. D., Siegel, L., & Rooney-Varga, J. N. (2018). Does replacing coal with wood lower CO 2 emissions? Dynamic lifecycle analysis of wood bioenergy. *Environmental Research Letters*, *13*(1), 015007. https://doi.org/10.1088/1748-9326/aaa512

Ter-Mikaelian, M. T., Colombo, S. J., & Chen, J. (2015). The Burning Question: Does Forest Bioenergy Reduce Carbon Emissions? A Review of Common Misconceptions about Forest Carbon Accounting. *Journal of Forestry*, *113*(1), 57–68. https://doi.org/10.5849/jof.14-016

Wagener, W. W., & Offord, H. R. (1972). *Logging Slash: its breakdown and decay at two forests in northern California* [Research Paper]. USDA Forest Service - Pacific Southwest Forest and Range Experiment Station.

Weedon, J. T., Cornwell, W. K., Cornelissen, J. H. C., Zanne, A. E., Wirth, C., & Coomes, D. A. (2009). Global meta-analysis of wood decomposition rates: a role for trait variation among tree species? *Ecology Letters*, *12*(1), 45–56. https://doi.org/10.1111/j.1461-0248.2008.01259.x

Westerling, A. L. (2018). *Wildfire Simulations for California's Fourth Climate Change Assessment: Projecting Changes in Extreme Wildfire Events with a Warming Climate* (No. CCCA4-CEC-2018–014; California's Fourth Climate Change Assessment, California Energy Commission, p. 57). University of California, Merced. cal-adapt.org/tools/wildfire

Yin, X. (1999). The decay of forest woody debris: numerical modeling and implications based on some 300 data cases from North America. *Oecologia*, *121*(1), 81–98. https://doi.org/10.1007/s004420050909