Understanding Impacts of Climate Change, Land Management, and Wildfire on Forest Carbon Cycling in Western US Forests

A Dissertation

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Kristina J. Bartowitz

Approved by:

Major Professor: Tara W. Hudiburg, Ph.D.

Committee Members: Crystal Kolden, Ph.D.; Philip Higuera, Ph.D.,

John Abatzoglou, Ph.D.

Department Administrator: P. Charles Goebel, Ph.D.

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Abstract

Forests play a critical role in climate regulation through their ability to both store a large amount of long-term and persistent terrestrial carbon, and continually sequester carbon from the atmosphere. In addition to carbon storage and sequestration, western US forests provide vital ecosystem services such as wood products, wildlife habitat, recreation, and erosion control. The interactive effects of climate change, land management, and wildfire regimes influence the sustainability of forest growth and stability, biodiversity, and water availability Human and ecological disturbances such as climate change, wildfires, and forest management can significantly decrease forest carbon stocks and sequestration. There is a critical need to better understand and accurately predict the nature and severity of the interactive effects to guide forest management and policy decisions aimed at forest resilience and climate mitigation.

This dissertation addresses the uncertainty associated with impacts of forest disturbances (wildfires and forest management) and climate change on forest carbon dynamics, using data synthesis and ecosystem models. I use publicly available datasets to evaluate how past wildfires and forest management have influenced current forests and use ecosystem models to predict how climate change and future fires will impact forests across space and time. Improved mechanistic predictions of forest conditions will be key to developing relevant management plans at local and regional scales. Here, I clarify the impacts of climate change, wildfires, and land management on forest carbon dynamics across paleo timescales (Chapter 1), the modern historical records (Chapter 2), and the simulated future (Chapter 3).

In Chapter 1, I explored the interactions between fire and carbon dynamics of 14 subalpine forested watersheds in Colorado, USA across 2000 years. Through a modeling experiment, I tested the impact of varying fire frequency over a ~2000 year period on ecosystem productivity and carbon storage using an improved biogeochemical model (Snagged DayCent). The experiment included high-fire, paleo-record fire, and no fire scenarios. High fire frequency simulations had overall lower carbon stocks across all sites compared to scenarios with the paleo-record or no fire frequency scenarios, highlighting the importance of fire frequency and fire timing variability in determining ecosystem carbon storage.

In Chapter 2, I investigated differences in western US forest fire carbon emissions, restoration (understory and small-diameter tree removal, and prescribed burns) and extractive forest management (harvest for timber sale), and fossil fuel emissions over the past decade. Forest fire carbon emissions are on average only 6% of anthropogenic fossil fuel emissions over. Restoration thinning and commercial harvest of mature trees releases a higher density of carbon emissions relative to wildfire (200-1300%). These results show that extractive forest management increases emissions rather than preventing them and suggest that reducing fossil fuel emissions will do more for climate mitigation potential, and subsequent reduction of fire, than increasing extractive harvest to prevent fire emissions. This chapter also discusses policy and management choices to lead to both more resilient forests, and better climate mitigation strategies. Management aimed at fuels reduction to moderate fire behavior and increase forest resilience (such as restoration thinning and prescribed burns) will help to balance reducing catastrophic fire near communities and leave live mature trees on the landscape to continue carbon uptake.

In Chapter 3, I modeled future fire occurrence and carbon dynamics in Northern Rocky forests. Despite the lack of wildfire in some these forests over the last century, it is unclear how fire occurrence and carbon dynamics in these forests will look in the future with continued warming and drying, and how future fire and future climate may impact the carbon balance of the region. I explore the climate-fire-ecosystem interactions in the Northern Rockies through ecosystem modeling. Here, we use an Earth Systems Model with dynamic vegetation (CLM-FATES) and fire module (SPITFIRE) to investigate the future of fire and carbon dynamics in the Northern Rockies over the next century. Future simulations (until 2080) forced with future climate data show an increase in wildfire from the modern record for the wet and cold forest types, while the warm-dry forest type continues to have a shorter mean fire return interval (15-25 years). Fire occurrence in the wet and cold forests is followed by immediate, subsequent decreases in forest carbon (up to 20% loss). However, post-fire recovery of forest carbon stocks occurs for all forest types for the simulation range, with complete AGC recovery seen in as little as 10-20 years following some of the disturbances.

Acknowledgments

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Dedication

I’d like to dedicate this dissertation to

my parents and brother, for always believing in me,

and my partner and dog, for their unwavering support and love.

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Chapter 1: Post-Fire Carbon Dynamics in Subalpine Forests of the Rocky Mountains

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Abstract

Forests store a large amount of terrestrial carbon, but this storage capacity is vulnerable to wildfire. Combustion, and subsequent tree mortality and soil erosion, can lead to increased carbon release and decreased carbon uptake. Previous work has shown that non-constant fire return intervals over the past 4000 years strongly shaped subalpine forest carbon trajectories. The extent to which fire-regime variability has impacted carbon trajectories in other subalpine forest types is unknown. Here, we explored the interactions between fire and carbon dynamics of 14 subalpine watersheds in Colorado, USA. We tested the impact of varying fire frequency over a ~2000 year period on ecosystem productivity and carbon storage using an improved biogeochemical model. High fire frequency simulations had overall lower carbon stocks across all sites compared to scenarios with lower fire frequencies, highlighting the importance of fire-frequency in determining ecosystem carbon storage. Additionally, variability in fire-free periods strongly influenced carbon trajectories across all the sites. Biogeochemical trajectories (e.g., increasing or decreasing total ecosystem carbon and carbon-to-nitrogen (C:N) ratios) did not vary among forest types but there were trends that they may vary by elevation. Lower-elevations sites had lower overall soil C:N ratios, potentially because of higher fire frequencies reducing carbon inputs more than nitrogen losses over time. Additional measurements of ecosystem response to fire-

regime variability will be essential for improving estimates of carbon dynamics from Earth system models.

Introduction

Temperate coniferous forests are significant carbon sinks and are essential for mitigation goals aimed at keeping global warming below 1.5 degrees C (IPCC, 2014; Le Quéré et al., 2018). Western US forests are among the most carbon dense forests in the world (T. Hudiburg et al., 2009) and remain strong carbon sinks (Buotte et al., 2019) despite increases in drought and fire-related mortality (Schwalm et al., 2012). Fire can reduce forest carbon sinks through decreased carbon uptake (due to increased plant stress or mortality), biomass and soil combustion, and/or post-fire soil erosion, creating long-lasting legacies on potential ecosystem carbon storage (T. W. Hudiburg et al., 2017; Kelly et al., 2015). Thus, the ability of forests to continue to store and sequester carbon may decrease as wildfires and area burned increase (Amiro et al., 2010; Berner et al., 2017; Liang et al., 2017; Seidl et al., 2014). These dynamics may create a positive feedback between increased fire activity and reduced carbon storage if the time interval between severe fire events becomes shorter than forest regrowth (Turner et al., 2019). Such feedbacks may be particularly important in slow growing subalpine forests where high-severity fire has historically played an important role (Schoennagel et al., 2004).

Within a broad biome type such as coniferous forests, there is significant variation in plant species composition, but little is known about how species composition interacts with fire regimes to influence carbon and nitrogen dynamics in this region. Spatial differences in plant species distributions, and associated plant traits, have been shown to influence both fire regime characteristics (Pausas et al., 2004) and post-fire ecosystem properties (Clarke et al., 2015). Traditional plant functional traits such as seed size, leaf thickness, and growth rate are also important for determining flammability and post-fire recovery(Archibald et al., 2019; Keeley et al., 2011; Poulos et al., 2018). Recently, a suite of plant traits have been identified that indicate fire adaptations or co-evolution with fire (Archibald et al., 2019; Pausas et al., 2004). These traits, such as bark thickness, seed dispersal distance, and serotiny, vary in subalpine forests of the western US. Finally, nutrient-related plant traits such as foliar N concentration have the potential to create feedbacks with ecosystem primary productivity (Leys et al., 2016; Pompeani et al., 2018) but these are difficult to quantify on decadal or shorter timeframes. Ultimately, regional-scale variation in carbon trajectories will also depend on other site characteristics, such as the local climate. For example, lodgepole pine forests, which comprise a major component of subalpine ecosystems in the western U.S., are experiencing novel climatic conditions in the post-fire recovery phase, leading to decreased post-fire tree regeneration (Davis et al., 2019; Stevens-Rumann et al., 2018).

Fire frequency and area burned are increasing in western U.S. forests due to climate change, past fire suppression (leading to a build-up of fuels), and various other anthropogenic effects (Abatzoglou & Williams, 2016; Balch et al., 2017; Berner et al., 2017; Littell et al., 2009, 2016; Miller et al., 2009; Westerling et al., 2006). Here we focused on documented changes in fire frequency over millennial timescales to evaluate the wide range of possible biogeochemical trajectories that they could produce including increasing, stabilizing, or decreasing carbon storage. It could be hypothesized that increases in fire frequency would increase tree mortality, forest floor carbon pool (e.g., downed woody debris, litter) combustion, and soil erosion, and lead to increased carbon release and decreased carbon sequestration (Berner et al., 2017; Seidl et al., 2016). Alternatively, post-fire forest recovery (i.e., tree growth and regeneration) may quickly re-sequester carbon, creating a near stable long-term ecosystem carbon balance over millennia (Chapin III et al., 2006). A third possibility is that increased fire frequency could increase ecosystem carbon storage over past millennia if fires return a significant portion of stored carbon to soils through dead organic matter inputs (T. W. Hudiburg et al., 2017).

The extent to which climate change and changing fire regimes are affecting forest carbon uptake now and in the future is currently unknown and difficult to predict, especially at spatial and temporal scales relevant to human land-use and management (Bonan & Doney, 2018; Buotte et al., 2019; Fisher et al., 2018; B. E. Law et al., 2018). To evaluate how past fire regimes have influenced forest carbon storage, process-based ecosystem models can be used to quantify fluxes and stocks of ecosystem properties over time. Earth System Modeling of fire events and ecosystem properties has been identified as a research priority in fire ecology (Hantson et al., 2016). Many ecosystem modeling studies use modern forcing data (e.g., modern fire return intervals or climate inputs over approximately the last 30 years) to gain insights into past ecological impacts. Using this short-term, modern data may not accurately portray past ecosystem dynamics because it lacks the full range of potential variability. Recent paleo-informed ecosystem model simulations have shown large differences in output driven by modern vs paleo-fire records (T. W. Hudiburg et al., 2017; Kelly et al., 2015).

Here, we explored how variability in fire activity in subalpine forests of the southern US Rocky Mountains affects carbon and nitrogen dynamics (stocks and fluxes) over centuries to millennia. Building on previous work (T. W. Hudiburg et al., 2017), we inform the biogeochemical model, DayCent, with paleo-fire records to simulate carbon and nitrogen fluxes and stocks over the past ≈2000 years in subalpine forests in northern Colorado. We answer the following questions: (1) How do the long-term (i.e., centennial- to millennial-scale) carbon and nitrogen dynamics of subalpine forests change with varying fire frequency? (2) Does forest type (e.g. species composition) affect carbon dynamics? (3) Does elevation (changes in local temperature and effective moisture) explain any additional regional-scale variation in carbon trajectories? To expand the scope of drivers of carbon trajectories, we examine differences across elevations, which correlate with different absolute climate conditions. We also considered other site-specific factors like the time since the last fire, the range of variation in fire-return intervals, and the mean fire frequency.

Materials and Methods

Using prescribed paleo-reconstructions of fire histories (Calder et al., 2015; Dunnette et al., 2014; Higuera et al., 2014), we simulated carbon and nitrogen dynamics using the biogeochemical model DayCent at 14 watershed study sites (Table 1). DayCent is the daily timestep version of the mechanistic and deterministic model CENTURY, which has been widely used to simulate the effects of climate and fire on ecosystem processes on a multitude of ecosystems worldwide (Bai & Houlton, 2009; Hartman et al., 2007; Savage et al., 2013). DayCent includes three soil carbon pools (active, slow, and passives) that span months to millennia, representing long-term ecosystem change to biogeochemical pools. Detailed DayCent documentation and publication lists can be found on the following website: http://www2.nrel.colostate.edu/projects/daycent-downloads.html. We used the most recent version of DayCent with a new standing dead wood pool (Stenzel et al., 2019).

Table 1. Study sites in the Southern Rocky Mountains. Sub-regions include Rocky Mountain National Park (RMNP) and Medicine Bow-Routt National Forest (MBR-NF).

Study Site	Lat., Long.	Sub-Region	Forest Type	Elevation (m)	Mean FRI (yr) [SD]	Simulation Length
Eileen	40.902, −106.674	MBR-NF	Spruce-fir	3135	220 [142]	2197
Seven	40.896, −106.682	MBR-NF	Upper-treeline spruce-fir	3276	298 [238]	2089
Gold Creek	40.782, −106.678	MBR-NF	Spruce-fir	2917	174 [107]	1909
Hidden	40.771, −106.827	MBR-NF	Spruce-fir	2704	234 [169]	2107
Beaver	40.753, −106.687	MBR-NF	Spruce-fir	3161	283 [266]	1981
Tiago	40.579, −106.613	MBR-NF	Spruce-fir	2700	244 [165]	2197
Whale	40.556, −106.675	MBR-NF	Spruce-fir	3059	240 [141]	2161
Summit	40.545, −106.682	MBR-NF	Upper-treeline spruce-fir	3149	185 [117]	2035
Round	40.473, −106.663	MBR-NF	Spruce-fir	3071	134 [79]	2107
Chickaree	40.334, −105.840	RMNP	Lodgepole	2796	136 [87]	2180
Odessa	40.330, −105.685	RMNP	Spruce-fir	3051	281 [218]	2251
Lonepine	40.232, −105.730	RMNP	Spruce-fir	3016	302 [298]	2416
Thunder	40.221, −105.647	RMNP	Spruce-fir	3231	315 [228]	2206
Sandbeach	40.218, −105.601	RMNP	Lodgepole	3140	243 [152]	2191

The required inputs for DayCent include vegetation cover, daily precipitation and temperature (daily minimum and maximum), soil texture, and disturbance history. DayCent calculates potential plant production as a function of water, light, and soil temperature and limits actual plant growth based on soil nutrient availability. The model includes three soil organic matter (SOM) pools, with different decomposition rates: active, slow, and passive. The active SOM pool (microbial) has short turnover times of 1–3 months. The slow SOM pool (more resistant, structural plant material) has turnover times ranging from 10 to 50 years. depending on the climate. The passive SOM pool includes both physically and chemically stabilized SOM with long turnover times ranging from 400 to 4000 years. In addition, DayCent also includes above and belowground litter pools, and a surface microbial pool (associated with decomposing surface litter). Plant material is split into structural and metabolic material as a function of the lignin-to-nitrogen ratio of the litter (e.g., the structural pool has a higher lignin-to-nitrogen ratios). For this study, DayCent was parameterized to model soil organic carbon to a 30 cm depth using SoilGrids250 (Hengl et al., 2017). Model outputs include soil carbon and nitrogen stocks, live and dead biomass, above- and below-ground net primary productivity (NPP), heterotrophic respiration (Rh), fire emissions, and net ecosystem production.

Disturbance occurrence, such as fire, in DayCent are prescribed. Here, fires were prescribed based on occurrence in the paleo-fire reconstructions (Table S1). Fires can be parameterized to reflect severity through associated impacts to the ecosystem (e.g., biomass killed, carbon and nitrogen lost, soil eroded). The fire model in DayCent is parameterized to include the combusted and/or mortality fraction of each carbon pool (live and dead wood, foliage, coarse and fine roots, etc.) that occurs with each fire event. In addition, DayCent was recently developed to include a standing dead tree (i.e., "snag") pool to more accurately represent forest structure (Stenzel et al., 2019). In previous versions of DayCent, dead trees would immediately enter the coarse woody debris pool with a different rate of decomposition and combustion than standing dead trees have, affecting carbon and nitrogen dynamics for decades to centuries.

Study Sites and Data Collection:

Fourteen subalpine forest watersheds are simulated in this study, each with a single lake-sediment record previously used to reconstruct fire history (Calder et al., 2015; Dunnette et al., 2014; Higuera et al., 2014; T. W. Hudiburg et al., 2017); sites are located in the Rocky Mountain National Park and the Medicine Bow-Routt National Forest (Figure S1, Table 1). Each watershed was simulated for the dominant forest type (Table 1) for approximately the past 2000 years.

Tree inventory, soil, and foliage samples were collected from four (Table S2) of the study sites in June 2018, following standardized terrestrial carbon observation protocols (B. E. Law et al., n.d.; Sampson & Allen, 1995). Samples were collected from three of the modeled sites (Chickaree, Summit, and Gold Creek lakes) and one site that was not modeled (Hinman Lake). Tree species data and foliage C:N ratios were used to parameterize tree characteristics in the model that affect tree growth and organic matter decomposition. Soil samples were analyzed for carbon-to-nitrogen (C:N) ratio as well as soil-texture and classification. Hinman Lake was not modeled because of its shorter paleo-fire history compared to the other lakes in the region. However, because Hinman Lake had a similar vegetation composition to several other lakes that we were unable to sample, Hinman Lake parameter data were used for sites with similar forest composition.

At each of the study sites, samples were collected from four, 15 m-radius circular subplots, located 30 meters in each cardinal direction from the edge of the lake (i.e., N, S, E, W). Tree inventories were taken for each subplot, including species, living or dead status, diameter at breast height (DBH), and height for all trees with a DBH > 10 cm. If the tree was dead, a decay class (1–5) was noted. Foliage samples were taken for each tree species present using a 5-m pruning pole, and the current year's growth on each foliage sample was discarded. Current year's growth was discarded because the C:N ratio of new foliage is usually much lower than the rest of the canopy (less mass, new tissue) and does not represent the bulk of the photosynthetic surface. Four litter and four soil samples were collected at each subplot. Litter was removed and stored and then a soil corer (4.5 cm diameter), was used to collect soil up to a 30 cm depth or to bedrock (whichever was shallower). Ancillary data were recorded at each site, including ground cover, tree seedling and sapling relative abundance and species present, herbaceous and shrub species present, and signs of human disturbance. In addition, photos of ground cover, tree density, and canopy cover measurements were taken at each subplot.

Environmental analyses of C and N content of the foliage, soil, and litter samples were completed at the University of Idaho's Biogeochemistry Core Facility using a Costech ECS 4010. Sediment, plant leaf, and atropine standards were used for carbon and nitrogen analysis. After model parameterization and a 2000-year spin up, we compared modern modeled (end-of-simulation), soil C with our field data to validate model output.

Model Inputs and Parameterization:

DayCent submodels that are associated with tree physiological parameters, site characteristics, soil parameters, and disturbance events were modified using available site-specific observations from both published studies and field work. Three forest types were simulated in DayCent: spruce-fir, lodgepole pine, and upper-treeline spruce-fir (Table 1). The soil properties for the sites that were not sampled were acquired from publicly available soil databases (Hengl et al., 2017). The literature reported that leaf-area-indices for lodgepole pine (Sampson & Allen, 1995), subalpine fir, and Engelmann spruce (Aplet et al., 1989) were used to further parameterize forest type definitions in the model. Climate data required include daily minimum and maximum temperature and precipitation, which were obtained for the 36-year period from 1980 to 2016 from DAYMET (Thornton, P. E., Thornton, M. M., Mayer, B. W., Wilhelmi, N., Wei, Y., Devarakonda, R., & Cook, 2012). All model simulations were forced with these modern climate data but repeated for the duration of each simulation. Thus, for all modeled scenarios, climate was functionally non-varying over the duration of the simulations (beyond the variability within the 30-year dataset).

Model Simulation Scenarios:

We used DayCent to run a series of experiments (hereafter "scenarios") varying the timing and overall frequency of fire events at each site to evaluate the patterns and causes of variations in a suite of model output variables. For each watershed, five DayCent scenarios were completed with varying timing of fire events (Table 2): first, a paleo-fire scenario was run, where the timing of past fires was determined based on the site-specific paleo-fire reconstructions (Calder et al., 2015; Dunnette et al., 2014; Higuera et al., 2014; T. W. Hudiburg et al., 2017). Second, a no-disturbance scenario was run, with no fires or other disturbance over the duration of the simulation for each watershed. In comparison to the paleo-fire scenario, this scenario highlights the effects any amount of fire has on ecosystem stocks and fluxes over millennia. Finally, a high-fire scenario used a fire return interval that was doubled by repeating the paleo-record twice within the same time period (~2000 years). This in effect halved the fire free intervals from the paleo scenario. We also considered an equilibrium scenario with a constant fire return interval determined from the paleo-record (Figure S2), but we focused our discussion on the paleo-fire, no-fire, and high-fire scenarios.

Table 2. Model scenario descriptions.

Scenario	Description	Climate
Equilibrium	Fire prescribed using the mean fire return interval (FRI) of the paleo-fire record	Modern-recycled
Paleo-fire	Fire prescribed using site-specific paleo-fire record	Modern-recycled
High-fire	Fire prescribed by doubling the site-specific paleo-fire record; e.g., fire-history is repeated twice in the 2000-year record	Modern-recycled
No-fire	No disturbance/fire	Modern-recycled

Model Evaluation and Statistical Analyses:

We compared model output with our soil carbon estimates calculated from the field samples for the four lakes. Soil carbon is not parameterized (is not an input) in DayCent; rather, soil carbon is an output of the model and therefore, allows for site-specific model evaluation. Modeled soil carbon estimates were all within one standard deviation of observed estimate means (Figure S3).

Model simulations were analyzed for differences between forest type and model scenarios using two-sample Students *t*-tests and single-factor ANOVAs in R (R Core Team, 2017). The model outputs that were examined include soil carbon, total ecosystem (C:N) ratios, and total ecosystem carbon. Relationships among soil carbon, C:N ratios, fire frequencies, and elevation were examined using simple linear regressions in R (R Core Team, 2017).

Results and Discussion

Impacts of Varying Fire Frequency on Long-Term Carbon and Nitrogen Dynamics of Subalpine Forests:

In all scenarios with fire, wildfire occurrence led to immediate and subsequent depletions in soil carbon (Figure 1); these small declines can be seen in the paleo-fire and high-fire simulations. Spikes in soil C show when fires occurred, as there is immediate loss of soil C (decline) following fire. A portion of soil carbon and nitrogen pools were lost and subsequently recovered at different rates. Consequently, higher fire frequencies over centennial time scales (shorter fire-free intervals) led to incremental reductions in carbon and nitrogen stocks (Figures 1, 2, and S5). Total ecosystem and soil carbon were lower at the end of the simulation period (i.e., in 2012) in simulations with high fire occurrence (e.g., at lakes with frequent paleo-fires and in high-fire scenarios compared to paleo-fire scenarios, Figures S6 and S7).

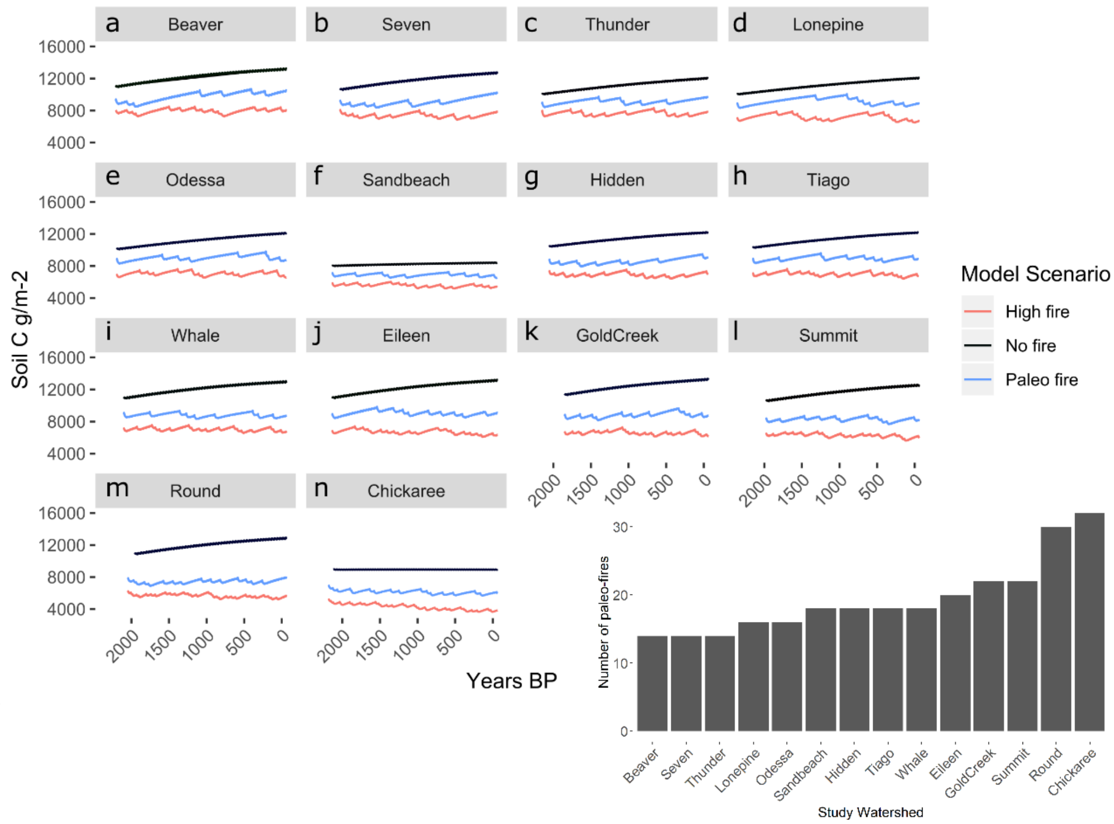

Figure 1. Soil carbon stocks over the simulation period for each watershed. Plots are ordered from low (**a**) to high (**n**) paleo-fire frequency (i.e., Beaver has the lowest fire frequency and Chickaree has the highest), as shown by the bar graph inset. The bar graph inset shows the number of paleo-record fires during the simulation length of each scenario for that study location.

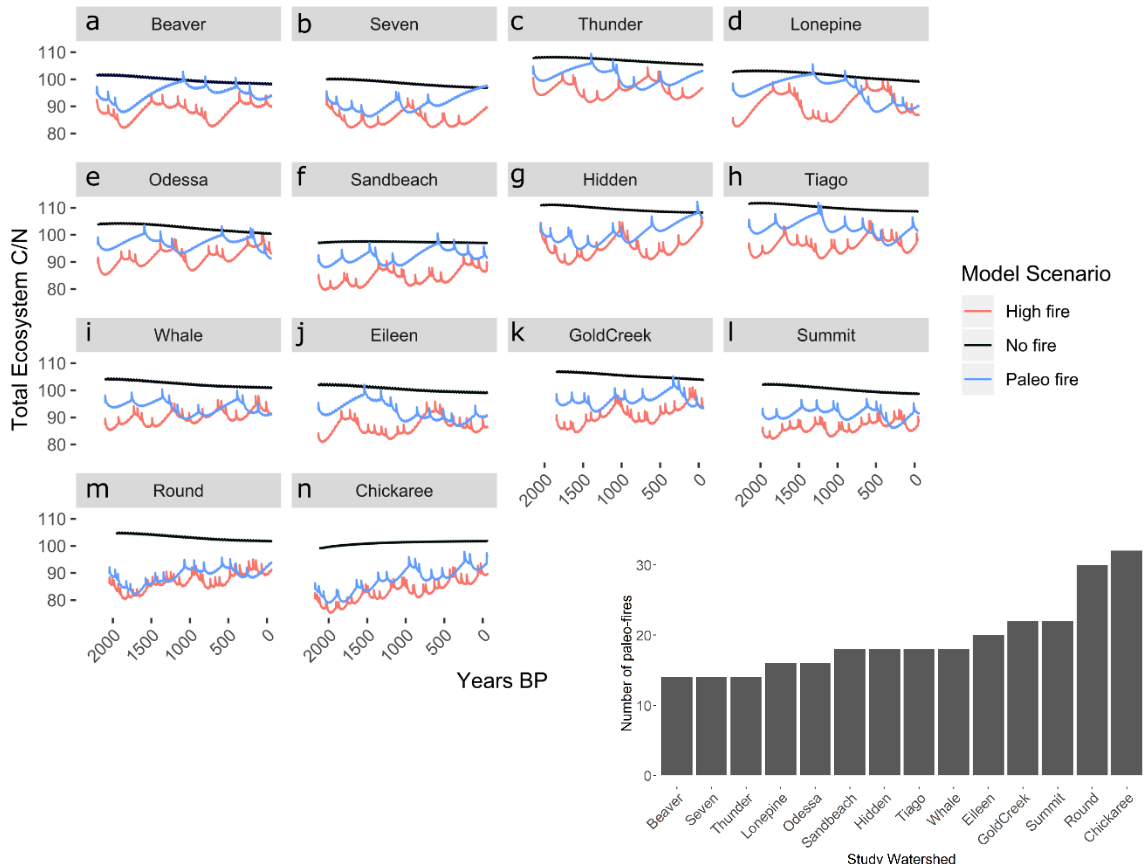

Figure 2. Simulated total (all aboveground and belowground biomass and soil pools) C:N ratio over simulation length. The plots are ordered from low (**a**) to high (**n**) paleo-fire frequency (i.e., Beaver has the lowest fire frequency and Chickaree has the highest), as shown by the bar graph inset. The bar graph inset shows the number of paleo-record fires during the simulation length of each scenario for that study location

In addition to the changes in the soil carbon pool (Figure 1), the simulations also indicate substantial differences in ecosystem C:N among scenarios (Figure 2). Ecosystem C:N ratios for the no-fire scenario decline during the entire simulation period for all study sites, but fires substantially alter this trajectory. However, at each study site, even though soil carbon was lower for all high-fire scenarios than the paleo-fire scenarios, overall trajectories of ecosystem C:N were similar for high-fire and paleo-fire scenarios (Figure 2). The watersheds with high-frequency paleo-fire records (e.g., Chickaree and Round) had C:N ratios that were very similar for both high-fire and paleo-simulations (Figure 2).

In all the scenarios, fewer, or no, fires for more than a century led to slow but steady increases in both ecosystem C and N stocks. Post-fire recovery of different carbon and nitrogen pools varied based on fire frequency. The high-fire scenario lead to a decline of soil carbon across all sites, whereas the paleo-fire scenarios showed a range of soil carbon values, either decreasing or staying at equilibrium values of soil carbon.

Comparing all study watersheds, regardless of forest type, final (end-of-simulation) total ecosystem carbon was significantly different between the three experimental simulations (Figure 3). No-fire scenarios had the highest values of ecosystem C stocks, followed by the paleo-fire and high-fire scenarios ($F = 86.64$, $df = 2$, $p < 0.01$). Final ecosystem C:N ratios were also significantly different between the three experimental simulations. No-fire scenarios had the highest C:N values, followed by paleo-fire and high-fire scenarios ($F = 14.97$, $df = 2$, $p < 0.01$).

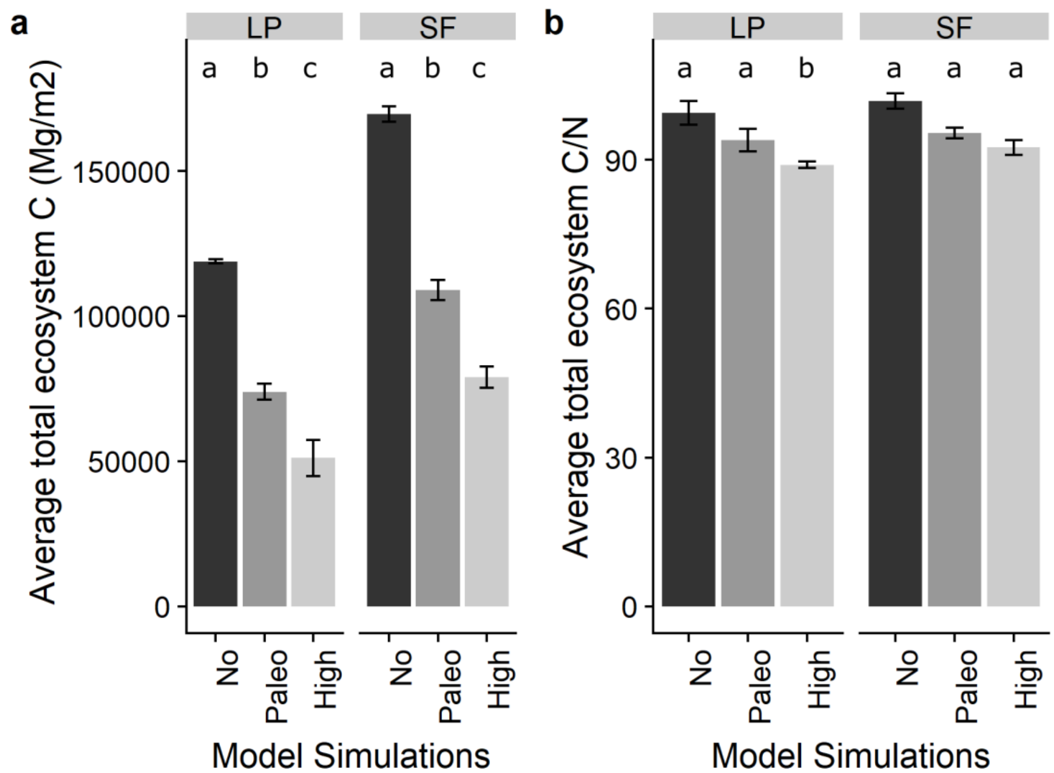

Figure 3. Forest-type variation in final ecosystem carbon and C:N ratios by model scenario. (**a**) Forest-type final (end of simulation) ecosystem carbon by forest types, lodgepole pine (LP) and spruce-fir (SF). (**b**) Forest type final (end of simulation) C:N by lodgepole pine and spruce-fir forests. The error bars represent the standard error in each scenario-forest type combination.

Impacts of Forest Type on Carbon and Nitrogen Dynamics:

Total ecosystem carbon was significantly lower in lodgepole forests than in spruce-fir forests (Figure 3a, dark grey bars, $t = -2.62$, $df = 8$, $p = 0.03$). C:N ratios were not significantly different between lodgepole and spruce-fir forests (Figure 3b, $t = -1.05$, $df = 7$, $p = 0.32$).

Total ecosystem carbon was significantly lower in the high-fire and paleo-fire scenarios compared to the no-fire scenarios in the spruce-fir forest watersheds (Figure 3a, $F = 192$, $df = 2$, $p < 0.01$), and in the lodgepole forest watersheds (Figure 3a, $F = 33.18$, $df = 2$, $p < 0.01$).

C:N ratios were not significantly different in high-fire scenarios than in paleo-fire scenarios for spruce-fir forests (Figure 3b, $F = 7.31$, $df = 2$, $p = 0.07$). High-fire total ecosystem C:N ratios were significantly lower than paleo-fire scenarios in lodgepole pine forests (Figure 3b, $F = 11.38$, $df = 2$, $p < 0.02$).

Influence of Fire Frequency and Site Characteristics on C and N Dynamics:

Influence of fire frequency (FF; number of fires over simulation length), fire return interval standard deviation (FRISD; the standard deviation of average time between fire events over simulation length), time since last fire (TSLF), and elevation (ELEV) were evaluated for their impact on model outputs from the paleo-fire scenario on all study sites. Total ecosystem and total soil carbon stocks were significantly lower in watersheds with higher paleo-fire occurrence than in other watersheds (Figure 4a,e, Table 3). Total C:N ratios did not significantly change with increase in FF, while soil C:N ratios were negatively correlated with fire frequency (Figure 4m, Table 3). Total ecosystem carbon, total soil carbon, and soil C:N ratios were highly correlated with increased FRISD (Figure 4b,f,n, Table 3). TSLF and ELEV were not correlated with carbon and nitrogen dynamics in the paleo-fire simulations (Figure 4, Table 3). There was no correlation relationship between FF and study site elevation (Figure S4), although there is a trend of decreasing FF with increasing elevation.

Table 3. Correlation coefficients comparing paleo-fire scenarios in all the study sites. Relationships determined between total ecosystem carbon (TEC), soil carbon (Soil C), total C:N ratios, and soil C:N ratios in spruce-fir forests by fire frequency (number of fires over the simulation period), fire return interval standard deviation, time since last fire, and elevation (m). The bold values denote significant linear correlations.

		FF	FRISD	TSLF	ELEV
TEC	r^2	**0.4043**	**0.2671**	0.1696	0.0101
Soil C	r^2	**0.5293**	**0.4259**	0.0128	0.176
Total C:N	r^2	0.0182	0.0033	0.0704	0.1822
Soil C:N	r^2	**0.2835**	**0.3278**	0.1489	0.0779

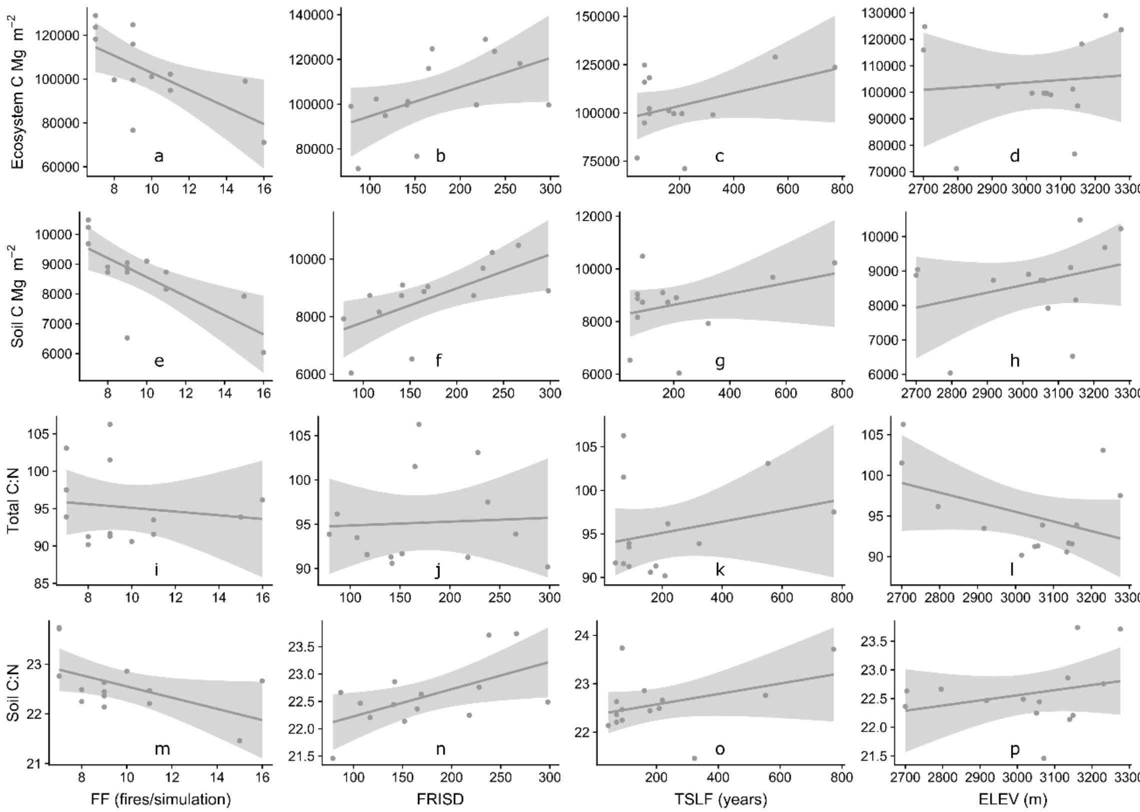

Figure 4. Variation in total ecosystem carbon (Mg m^{-2}), soil carbon (Mg m^{-2}), total C:N ratios, and soil C:N ratios in by fire frequency (number of fires over the simulation period, FF), fire return interval standard deviation (FRISD), time since last fire (TSLF), and elevation (m, ELEV). Figure panels are labeled a-p to refer to panels in text.

Discussion

Using DayCent forced with paleo-fire records, we found several new aspects of simulated carbon and nitrogen fluxes and stocks over the past 2000 years in subalpine forests. Ecosystem carbon trajectories were strongly dependent on fire frequency and timing of fire events. The length of fire-free intervals determined if a watershed gained or lost ecosystem carbon and nitrogen by the end of the simulation period. The occurrence of long fire-free periods led to ecosystem carbon gains whereas frequent fires led to large carbon losses. These results are broadly consistent with empirical work from boreal forests demonstrating that fire-free periods lead to substantial C sequestration in aboveground biomass and upper soil layers (Brown & Johnstone, 2011; Kelly et al., 2015).

Overall, increases in fire frequency substantially decreased soil carbon across all sites over time (Figure 3a). These results have important biogeochemical implications for periods of elevated fire activity in the past (Calder et al., 2015), and in the future (Buotte et al., 2019; Kelly et al., 2015). In this study, the repetition (through doubling the paleo-record fire history) of both fire occurrence and variability in the high-fire scenarios resulted in anew equilibria of overall lower carbon-carrying capacity compared to the paleo-fire scenarios. For example, in watersheds that had a long fire-free period at the end of the simulation, soil carbon increased for both the paleo and high-fire scenario (e.g., Seven Lake), but this increase is compressed in time and smaller in magnitude for the high-fire scenario. A long-term high-fire frequency may lower the overall carbon carrying capacity of subalpine forest, but this trend saturates (i.e., stops declining) as seen in a few of the watersheds with higher paleo fire frequency (e.g., Chickaree and Thunder). Reductions in total ecosystem carbon and soil carbon that result from increases in fire frequency may be predictive of future carbon storage in forested ecosystems in the current era of elevated wildfire activity (B. Law et al., 2015), although many other factors contribute to soil carbon values including vegetation type and elevation (Jobbágy & Jackson, 2000).

High variability in fire return intervals (fire return interval standard deviation) significantly increased total and soil carbon, and raised soil C:N ratio, compared to low variability or no-fire scenarios. Long fire-free intervals in many high-variability simulations likely drove this set of results, because long fire-free periods led to a build-up of carbon and an increase in the soil C:N ratio. Although total ecosystem carbon stocks increased across the study sites in the no-fire scenario, nitrogen stocks also increased, leading to an overall decrease of C:N over time. In no-fire scenarios, nitrogen is being ‘locked up’ in biomass as it accumulates over millennia and not being lost to fire or post-fire impacts. In paleo-fire scenarios, soil C:N ratios decrease with increased fire frequency, which may be due to carbon lost during or after fires, and the return of bioavailable nitrogen to the ecosystem, thereby decreasing the soil C:N ratio. There have been few site-scale studies examining post-fire C:N ratios (Knicker, 2007); however, studies on small time scales (years to decades) and spatial scales (site-specific) may represent processes that differ from the drivers of patterns in our study, which examines C:N ratios across a study region (Southern Rockies) on a millennial timescale. During forest stand development, increases in total C usually occurs with increases in N (Yang et al., 2011). In addition, forest floor C and N losses during prescribed fires can be large, and N volatilization during prescribed fires can be larger than N deposition in forests of the Sierra Nevada (Caldwell et al., 2002). Post-fire C:N ratios can be indicative of the ability of the forest to recover, or availability of N for primary production to drive post-fire growth.

Both plant traits, such as foliar C:N, and potentially limiting nutrients, such as nitrogen, were found to be influenced by fire frequency. For example, variability in fire frequency led to high variability in ecosystem C:N ratios (Figure 2, 3) because of variation in the allocation of N among soil and plant pools. Doubling fire frequency (high-fire scenarios) lowered C:N ratios as compared to the paleo-fire scenarios. As paleo-fire frequency increases, the differences in C:N ratios between paleo and high-fire scenarios decreases. This suggests that there is a point of saturation with the amount of fire occurring, where the C:N ratios for the paleo- and high-fire scenarios are nearly equal (i.e., for Round and Chickaree Lakes) there is already a relatively high amount of fire occurring during the paleo-fire simulation. The lower C:N ratio also suggests that regrowth (or carbon carrying capacity) is not being limited by nutrient availability (nitrogen in DayCent) and is actually being limited by disturbance interval.

We found that no-fire simulations led to the highest total ecosystem carbon stocks for all the study sites. Some of the most carbon dense places in the world (e.g., tropical and temperate rainforests) (Pan et al., 2011) do not (or very rarely) naturally burn. Most tropical forest fires are human-caused (Juárez-Orozco et al., 2017) and these forests are not fire-adapted. Carbon carrying capacity is higher in places with no fire, although fire occurrence in fire-adapted ecosystems has other benefits in these ecosystems. Current trends of increased fire-frequency in fire-prone areas of the US (Westerling et al., 2006) (including the Southern Rockies study region) may lead to lower carbon-carrying capacities, as shown by the decrease in total ecosystem carbon in the high-fire scenario (Figure 2). Further simulations with predictive and fully coupled ecosystem models will help elucidate the potential changes in forest carbon sink potential.

Forest type seems to play a role in total ecosystem carbon storage. Our distribution of forest types among study sites is not ideal for making broad comparisons (n = 2 for lodgepole pine and n = 12 for spruce-fir forests) and it would be a more robust analysis if more forest types had been represented equally. However, this study relied on previously collected paleo-fire reconstructions, of which there were 12 spruce-fir forests and two lodgepole pine forests. We parameterized model runs based on forest type because these species are different physiologically. Model output for the two forest types proved to be significantly different, making the results important to report.

A limitation of this study is the lack of paleoclimate forcing data in the DayCent simulations. Using paleoclimate forcing data would allow for the model scenarios to test the impact of climate, in addition to fire regime variability. However, because our fire events are completely prescribed, they are decoupled from climate in the model simulations. We cannot easily acquire the proper scale of paleoclimate data for these study locations, making these impacts beyond the capability of the current study. Rather than introduce the additional uncertainty of downscaled paleoclimate data (both temporal and spatial), we chose to use climate data that was more specific to each site (Daymet; nearest weather station). As fires are prescribed (not predicted based on climate or vegetation type), our study tested the impact of fire regime variability and fire occurrence variability on carbon and nitrogen dynamics. Paleoclimate data is at such a large timestep and coarse spatial resolutions that downscaling it to use in a daily-timestep model for individual study sites would mask any results that could be interpreted from it.

The biogeochemical model DayCent allowed for the exploration of how known past fire events affected forested watersheds in Colorado. However, DayCent is not currently coupled with a predictive fire, vegetation, or climate model. Because of this limitation of the model, DayCent cannot predict fire or vegetation changes that result from changing climate and disturbance regimes. The results here provide a benchmark for comparison in future research utilizing fully coupled ecosystem model that includes a dynamic vegetation component (e.g., DGVM ecosystem models) and a prognostic fire model (e.g., SPITFIRE (Lasslop et al., 2014)). Simulating Southern Rockies forests with a DGVM coupled with a climate and fire model will allow for predictions of C and N dynamics in forests with altered fire regimes under climate change.

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Supporting Information

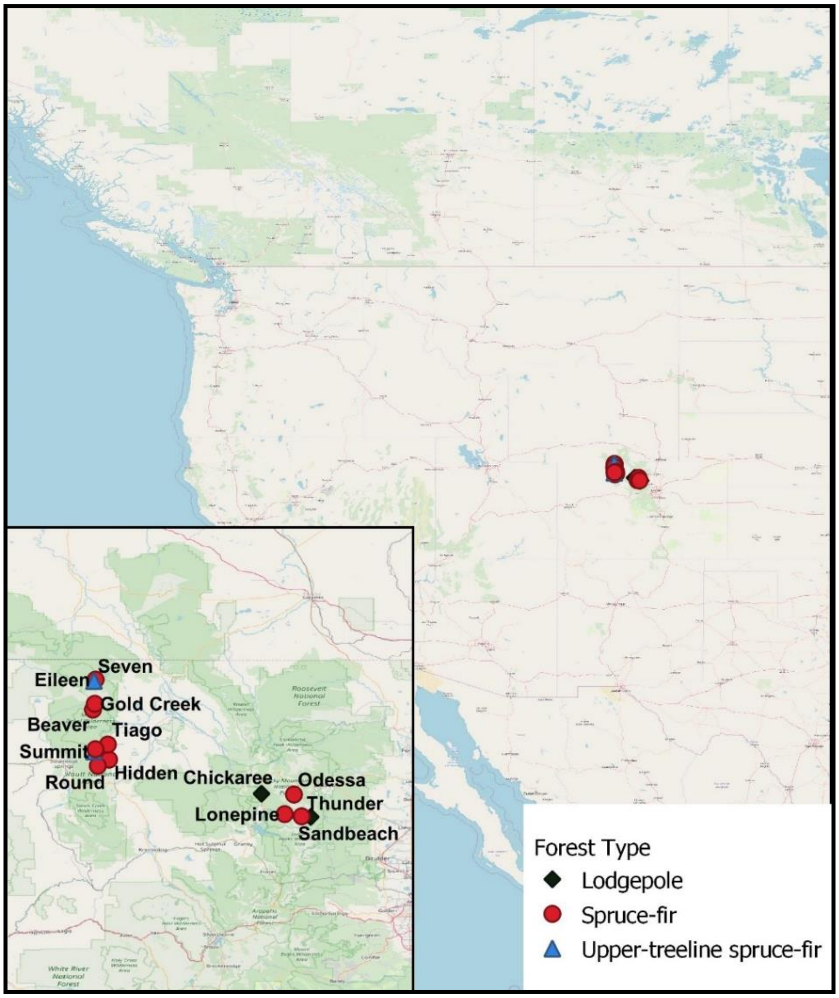


Figure S1. Study site locations in Colorado, USA. The northern sites are in the Medicine Bow-Routt National Forest and the southern sites are in Rocky Mountain National Park.

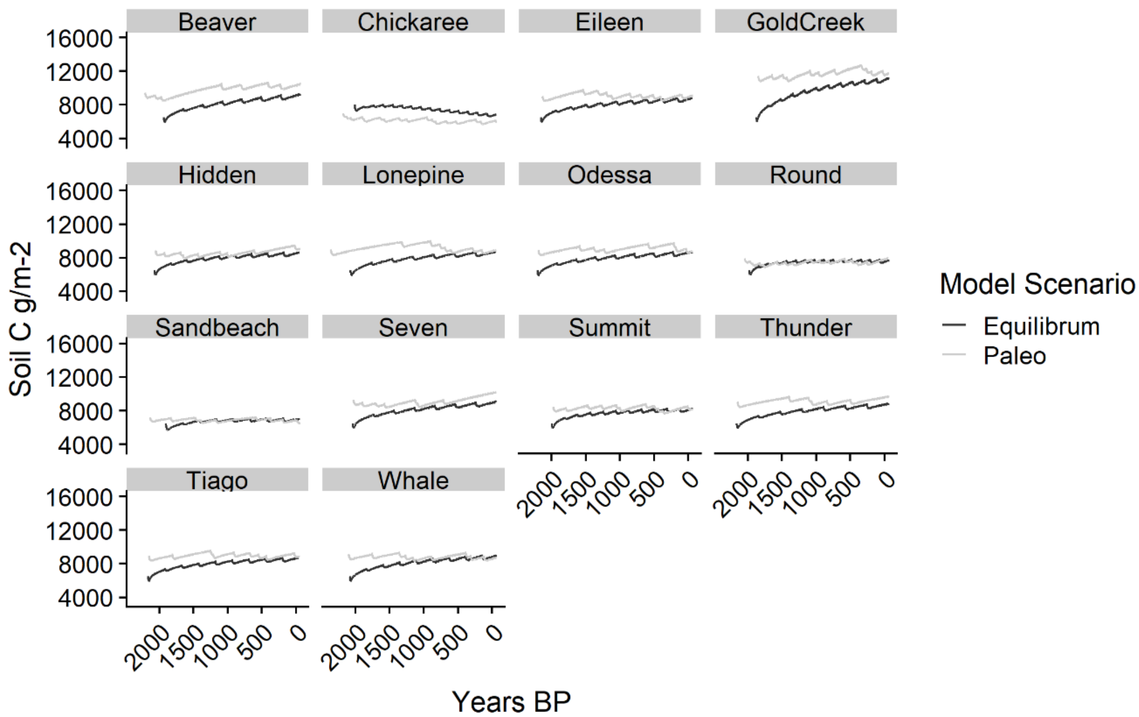


Figure S2. Soil carbon stocks over simulation lengths for paleo-fire (grey) simulations and equilibrium (black) simulations. Equilibrium simulations were run with the average fire return interval.

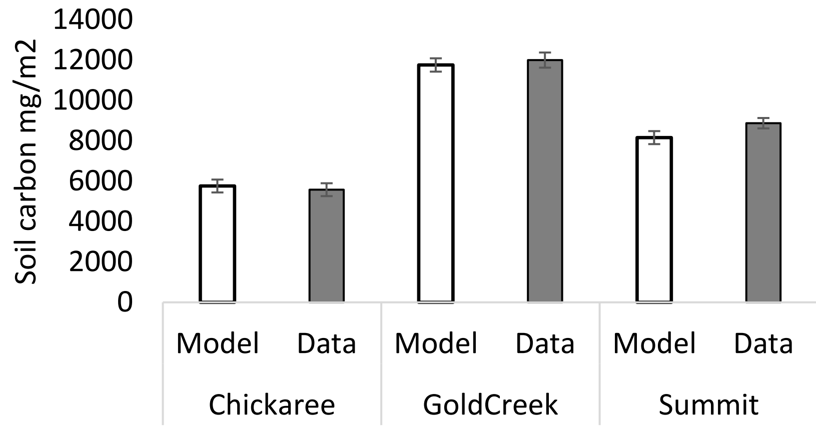


Figure S3. Modeled soil carbon validation. Modeled soil carbon is not significantly different from collected soil carbon (data). Error bars represent standard errors.

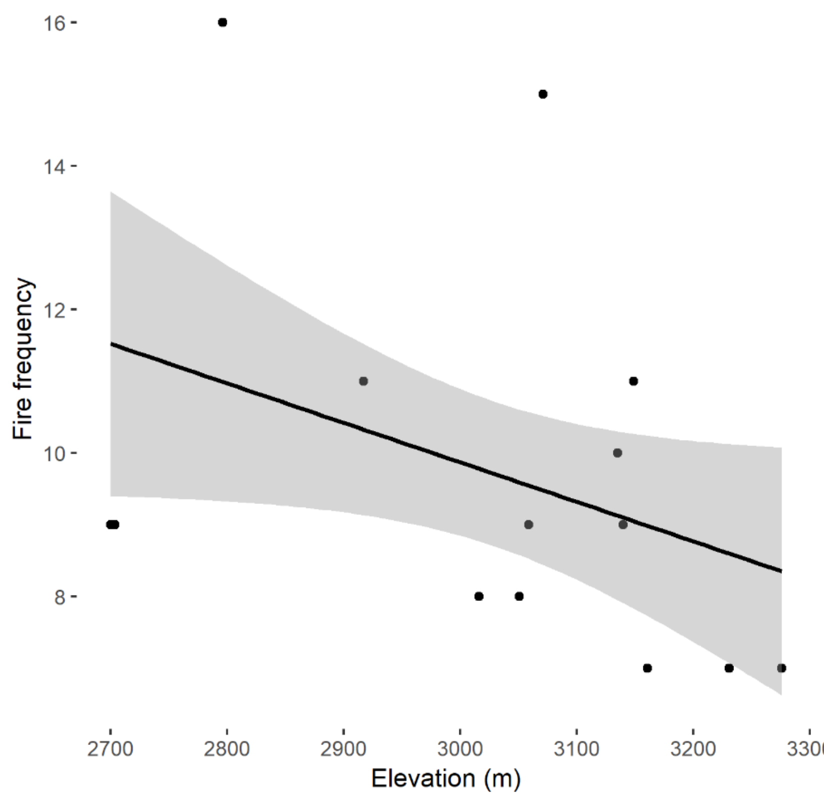


Figure S4. Fire frequency (number of fires over the length of the simulation period) by elevation (m). r^2=0.1325, p= 0.20.

Table S1. Number of fires that were prescribed in both the paleo-fire scenario and high-fire scenario for each model simulation.

Lake	Paleo Fire Frequency	High Fire Frequency
Eileen	10	20
Seven	7	14
Gold Creek	11	22
Hidden	9	18
Beaver	7	14
Tiago	9	18
Whale	9	18
Summit	11	22
Round	15	30
Chickaree	16	32
Odessa	8	16
Lonepine	8	16
Thunder	7	14
Sandbeach	9	18

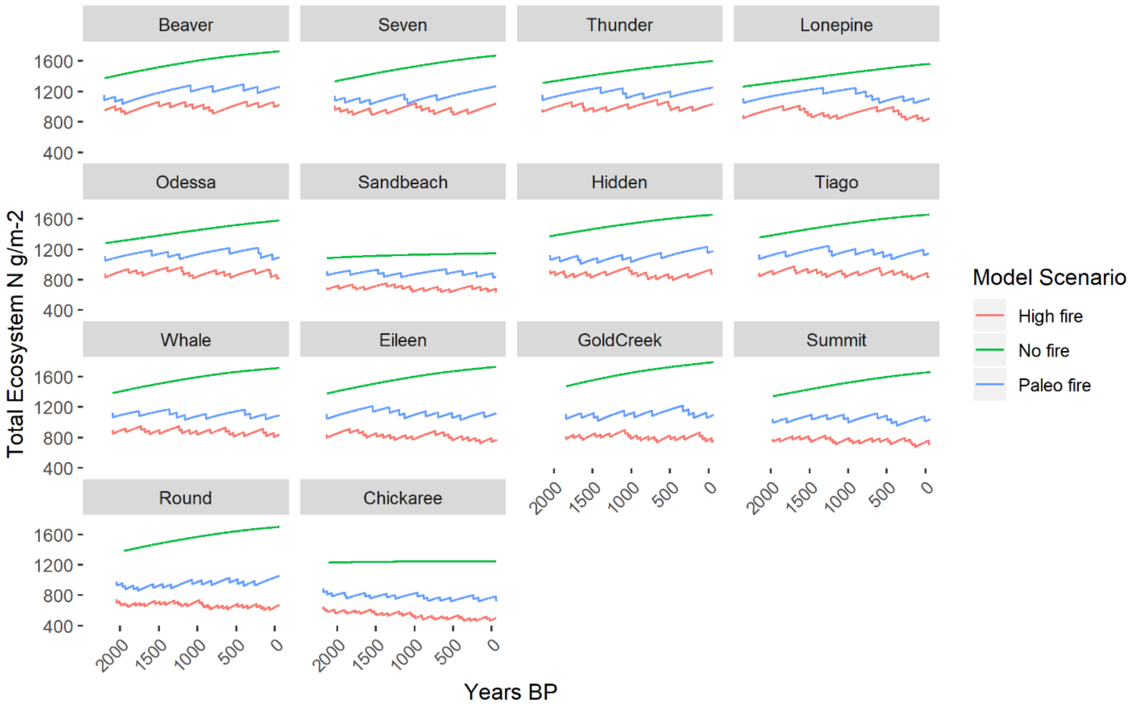


Figure S5. Total ecosystem nitrogen over the simulation length for each scenario and each study site.

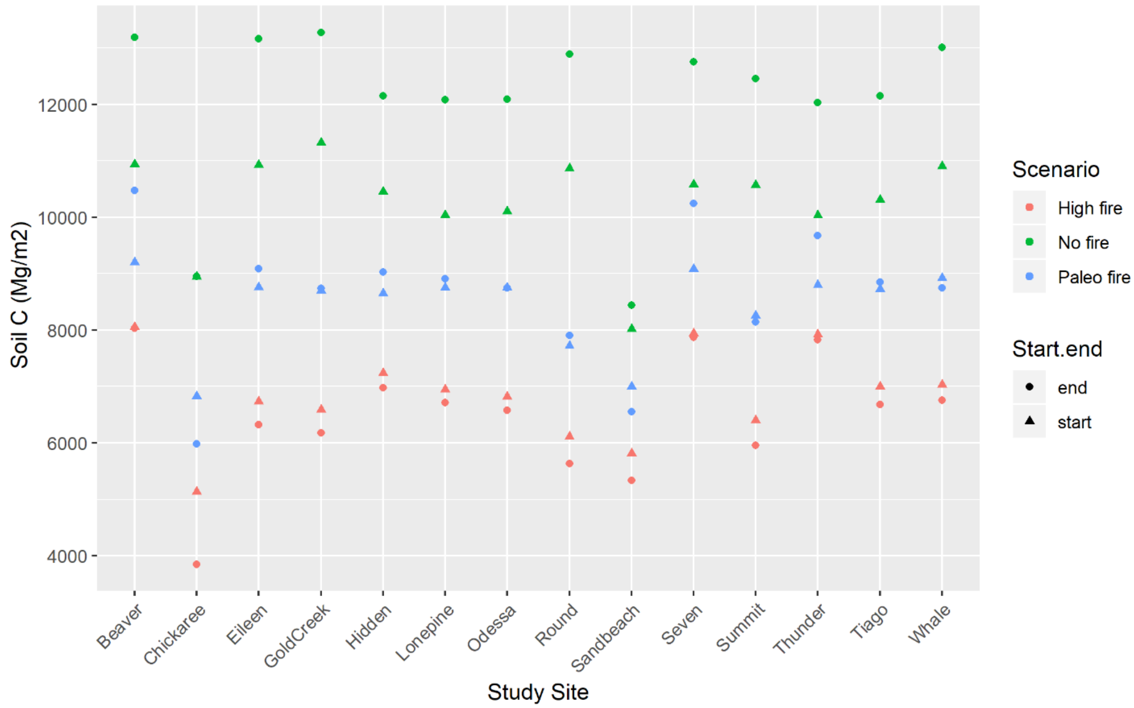


Figure S6. Difference between start and end soil C values for each study location and each simulation scenario.

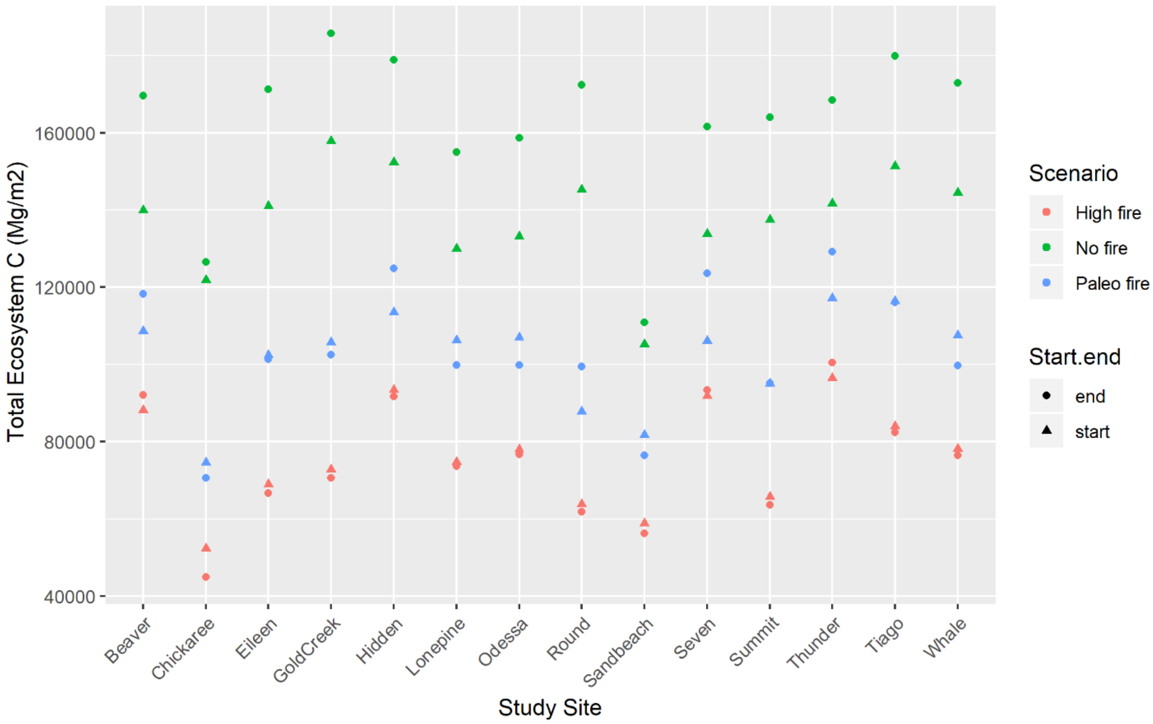


Figure S7. Difference between start and end total ecosystem C values for each study location and each simulation scenario.

Table S2. Field collection study sites.

Lake	Forest Type	Lat/Long	Samples Collected	Modeled in Study?
Chickaree	Lodgepole	40.334, −105.840	Soil, conifer foliage	Yes
Gold Creek	Spruce-fir	40.782, −106.678	Soil, conifer foliage	Yes
Himnan	Spruce-fir	40.771, −106.827	Soil, conifer foliage	No
Summit	Upper treeline spruce-fir	40.545, −106.682	Soil, conifer foliage	Yes

Chapter 2: Forest carbon emission sources are not equal: putting fire, harvest, and fossil fuel emissions in context

In Revision at *Frontiers in Forests and Global Change* as:

Bartowitz, K. J., Walsh, E.S., Stenzel, J.E., Kolden, C.A., & Hudiburg, T. W. Forest carbon emissions sources are not equal: putting fire, harvest, and fossil fuel emissions in context.

Abstract

Climate change has intensified the scale of global wildfire impacts in recent decades. In order to reduce fire impacts, management policies are being proposed in the western United States to lower fire risk that focus on harvesting trees, including large-diameter trees. Many policies already do not include diameter limits and some recent policies have proposed diameter increases in fuel reduction strategies. While the primary goal is fire risk reduction, these policies have been interpreted as strategies that can be used to save trees from being killed by fire, thus preventing carbon emissions and feedbacks to climate warming. This interpretation has already resulted in cutting down trees that likely would have survived fire, resulting in forest carbon losses that are greater than if a wildfire had occurred. To help policymakers and managers avoid these unintended carbon consequences and to present carbon emission sources in the same context, we calculate western US forest fire carbon emissions and compare them with harvest and fossil fuel emissions over the same timeframe. We find that forest fire carbon emissions are on average only 6% of anthropogenic fossil fuel emissions (FFE) over the past decade. While wildfire occurrence and area burned have increased over the last three decades, per area fire emissions for extreme fire events are relatively constant. In contrast, harvest of mature trees releases a higher density of carbon emissions (e.g., per unit area) relative to wildfire (150-800%) because harvest causes a higher

rate of tree mortality than wildfire. Our results show that increasing harvest of mature trees to save them from fire increases emissions rather than preventing them. Shown in context, our results demonstrate that reducing FFEs will do more for climate mitigation potential (and subsequent reduction of fire) than increasing extractive harvest to prevent fire emissions. On public lands, management aimed at less-intensive fuels reduction (such as removal of 'ladder' fuels, i.e., shrubs and small-diameter trees) will help to balance reducing catastrophic fire and leave live mature trees on the landscape to continue carbon uptake.

Introduction

Climate change has intensified and increased the scale of global wildfire impacts in recent decades (Bowman et al., 2020). The western US 2020 fire season exemplified intensifying fire impacts (Higuera and Abatzoglou, 2020), including high loss of life and property, and the record area burned in the last century in California, Oregon, and Colorado (Higuera and Abatzoglou, 2020). Historically, similar catastrophic wildfires events (i.e., the 1910 Big Burn) instigated development of management policies to prevent and contain wildfire, including a century of fire suppression. In the western United States, climate change is now amplifying the negative effects of these management practices, resulting in unprecedented catastrophic wildfire outcomes (Parks and Abatzoglou, 2020).

Forests provide many ecosystem services such as wildlife habitat, hydrologic benefits, recreation opportunities, and wood harvest (Lawler et al., 2014), and also serve as a critical “natural climate solution”; they act as extensive and persistent carbon sinks that sequester large amounts of carbon from the atmosphere (Turner et al., 2011; Fargione et al., 2018). Increases in climate change-driven wildfire events (Westerling et al., 2006) have led to proposals to increase extractive forest harvest (i.e., the removal of large, mature trees, including altering policy to increase diameter limits to remove even larger trees; Table 1) in areas at high-risk of wildfire to decrease fire risk (Figure 1; Executive Order, 2018a; Infrastructure Investment and Jobs Act, 2021). Public opinion and policies have been shaped by the misconception that harvest can reduce fire risk (or save other trees), or that harvest of a singular tree can save that tree from “burning down” (Table 2). These beliefs are widespread (Table 2), but their impact on policy and subsequent impact on on-the-ground harvest has not been quantified. While prescribed fire has been shown to decrease fire risk (Kolden, 2019) and increase carbon storage (Wiedinmyer and Hurteau, 2010), removal of biomass through large-diameter tree thinning or logging produces mixed outcomes for fire risk mitigation and forest resilience (Sohn et al., 2016) and reduces forest carbon storage and sequestration for decades to centuries (Campbell et al., 2012; Bartowitz et al., 2019; Stenzel et al., 2021). The misconception that trees need to be saved from wildfire through harvest (Zinke, 2018; Infrastructure Investment and Jobs Act, 2021; Table 2) may lead to unintended consequences through increased logging. These consequences include increased fire risk, a decreased forest carbon sink, decreased forest resiliency, and loss of the forest as a natural climate solution (Hudiburg et al., 2013; Law et al., 2018; Zald and Dunn, 2018; Stephens et al., 2020).

Although high intensity fire combusts less than 5% of mature, live tree biomass (Knorr et al., 2016), discussions of fire policy and forest management have framed tree biomass combustion as an undesirable outcome requiring mitigation through extractive forest management (i.e., harvest of mature trees for timber sales; (Mater, 2017; Zinke, 2018; Senate Bill 762, 2021; Newhouse, 2021). Increasing i.e., extractive forest management (Table 1), to ‘lock’ carbon into man-made structures, to increase forest productivity (CORRIM, 2020), or reduce fire risk ignores the volume of forest fire emissions relative to the direct emissions of such strategies (Hudiburg et al., 2019; Stenzel et al., 2019). Previous studies have shown that timber harvest directly kills more trees than forest fire in the western US (Berner et al., 2017), but it remains unclear how much fire and harvest are contributing to regional total carbon emissions in the western US, especially in the context of how these emissions compare with anthropogenic FFE (Hudiburg et al., 2019; Stenzel et al., 2019).

Here, we calculate forest fire emissions (average for the last decade; large historical events, and the record 2020 fire season) and compare those to 1) average and hypothetical timber harvest emissions, and 2) average decadal FFE. Our comparisons clarify the relative contributions of extractive forest management, fire, and fossil fuels to atmospheric carbon dioxide concentrations and help provide clarity for future management scenarios intended to reduce carbon emissions and/or increase carbon uptake and the scientific observations that show the opposite occurs. We further show how misrepresentation of fire and management impacts on forest carbon cycling leads to discussions and policies that overestimates benefits to carbon stocks and sequestration, or downplays carbon consequences (Figure 1). Finally, we discuss how policy and management based on carbon cycle science and observations could be used to both reduce fire risk and to increase and maintain carbon storage.

Materials and Methods

Study area: Forest fires across the western US

We calculated carbon emissions from the forest fires in the western US (Figure 1) between 1984-2020 and the largest fire in the continental US, the 1910 Big Burn. Here, we group the “western US” as the 11 states in the contiguous US West (i.e., Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming). While there were other extreme forest fires in the 20th century (e.g., 1902 Yacoult Burn in Washington, 1933 Tillamook Burn), historic records of forest attributes were not available for analysis.

Extreme fires have continued to occur in recent decades (Figure 2). Availability of high-resolution fire perimeter and burn severity data allows for analysis of fires since 1984 (Eidenshink et al., 2007) through 2020. All wildfires >526 ha (1000 acres) with >50% forest area within the burn perimeter were included in this analysis. In addition, we selected large, notable forest fires (or complexes of individual fires; referred to as "extreme" fires throughout the manuscript) that occurred between 1984-2020. Fires were selected based on how notable they were at the time for size, duration, volatile fire behavior and legacy of impact in the subsequent years. Wildfires included in the "extreme fires" list (Table 1) were chosen from the created emissions database based on high area burned (i.e., > 40,000 ha), and overall significance of fire event (i.e., most were record events in some way such as: highest area burned in that state or human impacts).

Emissions have not been previously calculated for the Big Burn. We have calculated an estimate from the Big Burn not only because it is the largest known fire to have occurred in the continental US, but also to serve as a baseline or reference for the range of emissions possible in the absence of fire suppression. While the Big Burn emissions estimate is calculated differently from modern fires due to lack of forest data from that time, the comparison between modern fire emissions and the Big Burn is still useful and has been completed with the best possible methodology given data availability. The 1910 Big Burn encompassed an area throughout Washington, Montana, and Idaho (Figure 2). We calculated fire-induced carbon emissions of the Big Burn using historical accounts and records (Koch, 1942). The fire perimeters used in this study were a cross-reference between Koch's account and the 1910 Fire perimeters (USFS, 1978; Gibson, 2005).

Forest fire emissions calculations

Direct carbon emissions for contemporary forest fires (1984-2020) were calculated using, fire severity and area burned from the Monitoring Trends in Burn Severity database (MTBS) (Eidenshink et al., 2007) for forest fires between 1984-2019, and Burned Area Emergency Response (BAER; Parsons, 2003) and National Interagency Fire Coordination (Center, 2020) data products for 2020 fires. Carbon emissions for the 1910 Big Burn were calculated using area burned from the Northern Rockies Fire atlas for the Big Burn (Gibson, 2005). All carbon stock calculations were from forest type and ecoregion-specific carbon data (Figure S1; Buotte et al., 2019; Stenzel et al., 2019), and severity-specific combustion factors (Table S1; Stenzel et al., 2019). Only fires that burned >526 ha and in 50% or greater forested area within the burn perimeter (Ruefenacht et al., 2008) were used in this analysis. Aboveground carbon stocks were calculated for each forest fire area based on average carbon stocks for the forest type and ecoregion and area of the specific forest type within the burn perimeter (Table S1). Aboveground carbon stocks were multiplied by the appropriate combustion factor for the fire severity value of that forested area to obtain carbon losses (Table S1). Fires between 1984-2019 were calculated using MTBS severity classes. Smaller forest fires in 2020 were calculated using an average combustion factor. Big Burn carbon emissions were calculated using a range for the moderate-severe combustion factor which gives us a range (uncertainty) of emissions for this fire. Extreme 2020 forest fire emissions were calculated using BAER severity classes (which are precursors to MTBS severity classes). While we used contemporary forest structure data to calculate emissions from the Big Burn, our range of carbon emissions (Table 4) from this fire are robust because we used stem tree biomass and demographic data from pre-1910 timber cruise inventories (Koch, 1942) to identify FIA plots of similar structure (diameter and heights) and age classes to the 1910 inventory.

We calculated mean annual forest fire emissions for the western US and each western US state based on the 2009-2018 decade, to best represent the observed trends toward increased area burned under climate change (Abatzoglou and Williams, 2016). These calculations were completed using MTBS (Eidenshink et al., 2007) perimeter and severity data, carbon stock data, and combustion factors. All fire carbon losses were converted to Tg CO_2e (i.e., tera-grams CO_2 equivalent) for comparison with fossil fuel emissions. To normalize emissions on a per area basis, we calculated megagrams of carbon lost per hectare burned.

To calculate uncertainties for contemporary forest fire emissions, we used a propagation of error approach. We combined uncertainty estimates of each emissions calculation component to calculate total uncertainty for each individual extreme fire event (Table 4). We used the Combining Uncertainties Propagation of Error estimates from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Equation 1; IPCC Good Practice Guidance for LULUCF, 2006).

Equation 1: Combining Uncertainties (individual associated uncertainties)

$$U_{total} = \frac{\sqrt{(U_1 * x_1)^2 + (U_2 * x_2)^2}}{|x_1 + x_2|}$$

Where U_{total}= the percentage uncertainty in the sum of the quantities (half the 95 percent confidence interval divided by the total (i.e., mean and expressed as a percentage).

x_i and U_i = the uncertain quantities and the percentage uncertainties associated with them. x_i refers to the specific fire emission calculation. U_1 refers to the uncertainty in biomass calculations (0.05) and U_2 refers to remote sensing uncertainty in area burned calculations (0.10).

Calculations and spatial analyses were conducted using R (R Core Team, 2017) and ESRI software (ESRI, 2020).

Timber harvest and wood product emissions: Hypothetical harvest carbon losses

Hypothetical harvest carbon losses were calculated for all states for burned areas between 2009-2019; these are the exact burned areas and pre-fire carbon stocks used to calculate forest fire emissions for this study. This hypothetical calculation allows us to directly compare fire carbon losses to harvest carbon losses on a per area basis. Here, we calculated three scenarios for standing tree carbon (both live trees and snags): 30% harvest, 50% harvest, and 100% harvest. Both 30% and 50% harvests are meant to represent different levels of thinning (thinning-from-below and commercial, respectively), while 100% harvest is akin to a clear-cut harvest (Table 1). For these scenarios, the fraction (30%, 50%, or 100%) of aboveground carbon for standing live and dead trees was calculated and counted as carbon loss, and then converted to a per area basis. For the hypothetical thinning scenarios we did not include carbon stored in wood products because very little to no long-term wood products would be created from the smaller-diameter trees removed from these types of thinning. These smaller-diameter trees will most likely be used in short-term wood products such as paper (Hudiburg et al., 2019). The hypothetical clear-cut used a static 60% emission from aboveground tree carbon stocks, with 40% remaining in long-term wood products pools. To normalize harvest carbon losses on a per area basis, we calculated megagrams of carbon lost per hectare harvested.

Timber harvest and wood product emissions: Actual timber harvest carbon losses

Actual timber harvest calculations were aggregated from publicly-available state and federal historical harvest sources (Hudiburg et al., 2019), including privately-owned lands. Detailed methodology can be found in Hudiburg et al. 2019. We calculated a mean annual harvest loss for the most recent available harvest data for each state (2007-2016) as well as an annual average for the entire western US. Reported harvest volumes (merchantable) were converted to grams carbon using board feet to cubic volume estimates from Keegan (Keegan et al., 2010). Our calculations include the carbon stored (and released from at end of life) in wood products for the years of this analysis. Wood was assumed to enter short-term (1 to 10 years before emissions return to the atmosphere; includes wood waste at the mills) and long-term (50-year half-life) product pools at rates of 60% and 40%, respectively (Heath et al., 2010; Hudiburg et al., 2019). All timber harvest carbon losses were converted to Tg CO_2e for comparison with fossil fuel emissions.

Fossil fuel emissions

Carbon emissions from forest fires and fossil fuel emissions were normalized on a state-by-state basis by normalizing both average fossil fuel emissions (2009-2018) and record year fire emissions (1984-2020) with average fire emissions (2009-2018). A factor of both average fossil fuel emissions and record year fire emissions over the average fire emissions was calculated for each state.

Results

Forest fire carbon emissions

Carbon emissions from 1984-2020 wildfire events varied considerably by fire severity (Figure S1), forest type (e.g.,, varied carbon density), and size (Figure 2). As forest fire carbon emissions are a product of forest type (pre-fire aboveground carbon density per area, Figure 3) and fire severity (Table 4), it is notable that Colorado fires generally exhibit higher emissions per unit area (27.60 Mg C ha^{-1}) compared to other 2020 fire events in Oregon and California, although the 2020 Creek Fire in California had the highest emissions per unit area for a single contemporary fire (Table 4). This highlights how severely Colorado wildfires have burned in recent decades, given their lower pre-fire carbon density. By contrast, Oregon forests have much higher pre-fire carbon density and slightly lower area-normalized emissions compared to other western fires because they burned, on average, at a lower severity (Figure 3). When normalized by area burned to control for size, there is notable variation amongst the contemporary extreme fires in emissions per hectare (Table 4). For example, the 2020 Creek Fire in California had the highest emissions per hectare (29.7 Mg C ha^{-1}), and fires in Colorado all exceed the Idaho, Montana, and Wyoming fires, and many in the carbon-dense forests of Oregon when normalized by area. In addition, >90% of the burn area of extreme forest fires in 2020 were in low-to-moderate severity classes (Figure S1)

Harvest carbon losses

Total average annual western US total harvest emissions were lower than total average forest fire emissions (Table 4), however, actual harvest area is much lower than area burned (Berner et al., 2017). Actual harvest carbon losses vary greatly by state, with carbon-dense Oregon and Washington having the highest biomass harvest removals (Table 4). However, on a per unit area basis, hypothetical 100% harvest is 2-8 times greater than fire for the same perimeters across the entire region (Figure 4). We calculated hypothetical harvest carbon losses for the exact burn areas in each state to compare per area harvest losses. We found that for all states a 50-100% harvest would have led to greater carbon losses than fire for those burned areas, and even a 30% harvest led to greater carbon losses than fire for all but four of the western US states. Hypothetical harvest carbon losses continue to outpace fire carbon losses on a per unit area basis for most scenarios (Figure 4).

Anthropogenic fossil fuel emissions

Anthropogenic fossil fuel emissions (AFFE) for each western US state and for the total western US substantially exceed forest fire carbon emissions (mean annual and 2020), and average actual timber harvest (Figure 5, Table 4). Mean annual AFFE in the western US were over 15x higher than mean annual forest fire emissions and mean annual AFFE were 420% higher than forest fire emissions from the 2020 record fires across the west (Figure 5). Emissions vary widely by state, primarily due to population size (i.e., population and fossil fuel emissions are positively correlated) and large-scale, high-emissions industries within the state. Total western US 2020 fire emissions were higher than the mean annual fire emissions (2009-2018), driven by large fire events in California, Oregon, and Colorado (Table 4).

California, Oregon, Colorado, and New Mexico all had record-high forest fire emissions in 2020.

Discussion

Forest fire, harvest, and fossils fuels: putting emissions in context

Public perception and existing overestimates of forest mortality and carbon emissions from wildfire feeds into the misconception that wildfire kills all live forest cover and combusts all forest carbon (Wiedinmyer and Neff, 2007; Mater, 2017; Zinke, 2018). The reality of actual fire emissions calculated from mixed-severity combustion rather than overestimates calculated from the false high-severity narrative highlights the need to disentangle ecological impacts of wildfire from societal impacts (i.e., loss of lives and houses). This will help to ensure that risk-reduction solutions can decrease wildfire disasters while still maintaining ecosystem services, such as live tree carbon uptake and wildlife habitat (Kolden, 2020).

As wildfire policy discussions increasingly include extractive forest harvest to mitigate forest fires (Executive Order, 2018b; Senate Bill 762, 2021; Newhouse, 2021), a comparison of emissions from forest fire, timber harvest, and fossil fuels provides a more complete understanding of the relative contributions of emissions sources to anthropogenic climate change. Despite increasing area burned trends across the western US (Parks and Abatzoglou, 2020), fossil fuel emissions still greatly outpace forest fire emissions in the last decade, including 2020. Fossil fuel emissions are also significantly higher than intensive and large-scale land management operations like timber harvest in many US states (i.e., California).

Policy implications and ways forward

Much of US fire management and policy has been shaped by specific, previously unprecedented wildfire events. The Big Burn of 1910 was the first massive fire event for the fledgling US Forest Service (Koch, 1942), and is still the largest wildfire complex that has occurred in the contiguous US. Fire suppression as the main form of fire control persisted until the late 20th century, when ecological restoration efforts began seeking to reduce hazardous fuels and increase ecologically beneficial fire effects (Parsons, D.J., D.M. Graber, J.K. Agee, 1986). However, these efforts have not yet altered the fire suppression culture instilled by 1910 (Stephens and Ruth, 2005; Kolden, 2019; McWethy et al., 2019).

Like past extreme fire events, the 2020 and 2021 fire seasons have accelerated fire policy and forest management discussions at all levels of government – federal, state, and local – including recent bills introduced in the US Senate (S.4625, S.4331). Many new policy discussions on fire and forest management are being based upon the misconception that harvest will protect forests from mortality and carbon loss (Executive Order, 2018b; Infrastructure Investment and Jobs Act, 2021; Zinke, 2018; Newhouse, 2021), and decrease fire risk (Forest Climate Action Team, 2018) (Figure 1) despite substantial uncertainty over long-term impacts to forest climate resilience (i.e., forest treatments may decrease forest resilience in the era of climate change). Our results and the majority of full-carbon accounting studies conclude that any type of harvest (logging or commercial thinning) decreases forest carbon storage (Law et al., 2013), and this research shows harvest emits more carbon per unit area than fire at all scales (Figure 5).

To mitigate climate change, it is key we understand exactly where emissions are originating. While increased intensity and size of fires are increasing overall fire emissions, these emissions are still substantially less than fossil fuel emissions. This is true even in record forest fire years (Figure 5). While the 2020 fire season was unprecedented in many ways (record forest area burned in California, Oregon, and Colorado; societal devastation including fatalities, thousands of homes consumed, dramatic evacuations, and regional hazardous air quality events), ecologically, most of the forested area burned in extreme fires was in a low-to-moderate severity class (>90%, Figure S1). Moreover, while there is assumed high tree mortality in these forest fire perimeters, many of these burns were mixed-severity fires (Figure S1, 3) meaning many live trees will persist across most of the low-to-moderate severity burned areas. Locations with high-harvest rates and carbon-dense forests, such as the Pacific Northwest US, see higher carbon losses from harvest than fire compared to areas in the Southwest US with low harvest rates and carbon-sparse forests (e.g., Oregon versus Arizona). Forest management needs to be specific to forest type and region; old-growth and wet forests in the Northwest are best left preserved while dry, fire-prone forests or areas in the Wildland Urban Interface benefit from fire risk-reduction strategies like small-diameter thinning and prescribed fires (Law et al., 2018; Case et al., 2021). Inclusion of specific diameter limits in policy for public lands could help prevent large-diameter tree removal and subsequent unintended consequences.

Forest management strategies that are site-specific and balance the immediate protection of life and property with long-term preservation of existing and potential carbon stocks in forests are critical to mitigating the negative impacts of climate change. The most effective forest management strategy to protect forest carbon stocks on public lands is to preserve forests through decreased harvest and thinning, lengthened harvest rotations, increased proportion of long-term wood products, reduced harvest and mill waste, and working towards afforestation and reforestation (Law et al., 2018; Buotte et al., 2020; Hudiburg et al., 2013; Figure 1). Prescribed burns reduce fire risk while minimizing carbon losses and amplify tree growth and carbon sequestration in large-diameter trees in fire-adapted forests (Hurteau and North, 2009). In western US forests, 33 to 46% of aboveground live biomass is stored in the large diameter trees (> 60cm; Lutz et al., 2018; Mildrexler et al., 2020). Carbon-smart treatments on public lands need to be specific about diameter limits to avoid large-diameter tree removal.

Here, we have shown that fossil fuel emissions for the western US are 7 times greater than emissions associated with timber harvest and fire (Figure 5, Table 4). As more forest-fire policy and management plans are expanded, written, and discussed following extreme fires of the recent decades, and especially the extreme forest fires of 2020 (DNR, 2020), it is crucial that these policy changes focus on the largest driving factor of these fires – anthropogenic climate change. In practice, large-scale extractive forest management efforts will hamper climate mitigation and may be futile for decreasing fire risk. To be most effective, policy will need to focus on fire-wise adaptations for homes and property and disentangle ecologically-good fire from destructive fires (Kolden, 2020). Protecting forests with ecologically sound principles, rather than increasing extractive management, may be the best scenario for the mitigation of climate change (Law et al., 2018), and protecting humans, biodiversity, and forests (Walsh et al., 2019; Buotte et al., 2020; Law et al., 2021). The continued escalation of fires throughout the 21st century is evidence of climate change-mediated intensification of fire regimes in the US (Williams et al., 2019). Fire catastrophes will continue to occur and worsen if we do not focus on decreasing fossil fuel emissions, the primary driver of climate change (IPCC, 2018).

Figures

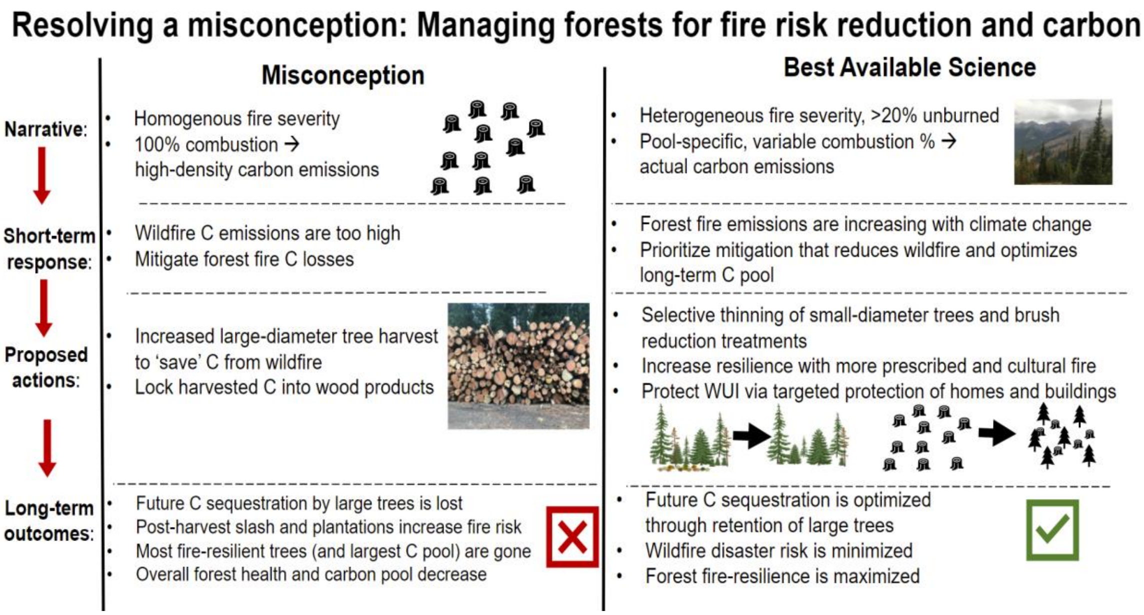
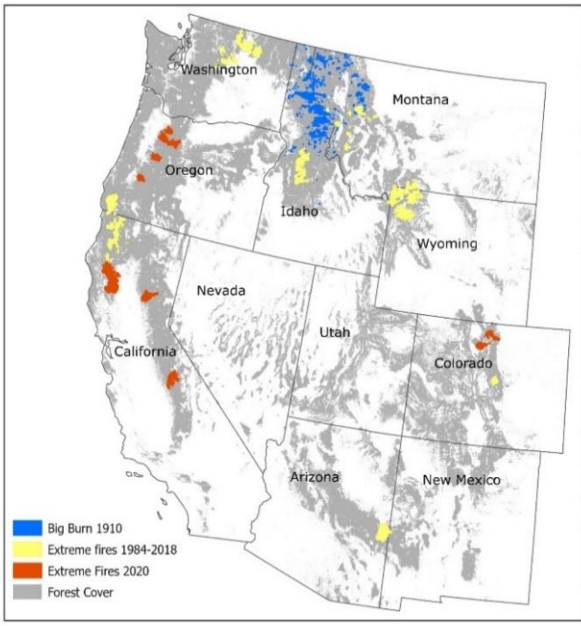


Figure 1. Conceptual figure describing the misconception about extractive forest management (Column 1) and how it can lead to unintended and unwanted consequences with forest resilience and the forest carbon sink. Column 2 describes how we can correct that misconception and develop policies that enhance forest resilience and the forest carbon sink.



Fire	Year	Area burned (ha)	State(s)
The Big Burn	1910	1,257,690	ID, MT, WA
Siege of '87	1987	151,339	CA
Yellowstone Fires	1988	672,509	WY, MT
Big Bar	1999	57,158	CA
Biscuit	2002	200,444	OR, CA
Hayman	2002	52,373	CO
Tripod	2006	70,753	WA
Central Idaho	2007	298,821	ID
Klamath Theater	2008	86,795	CA
Wallow	2011	228,106	AZ
August	2020	417,891	CA
Creek	2020	153,700	CA
North	2020	126,220	CA
Oregon	2020	340,702	OR
Colorado	2020	153,294	CO

Figure 2. Extreme forest wildfires in the western US. a) Perimeters of forest fires in 2020, a selection of extreme forest fire events 1984-2018, and of the 1910 Big Burn fires. b) Fire statistics of the 1910 Big Burn and contemporary fires (1984 – 2020) within the Western United States.

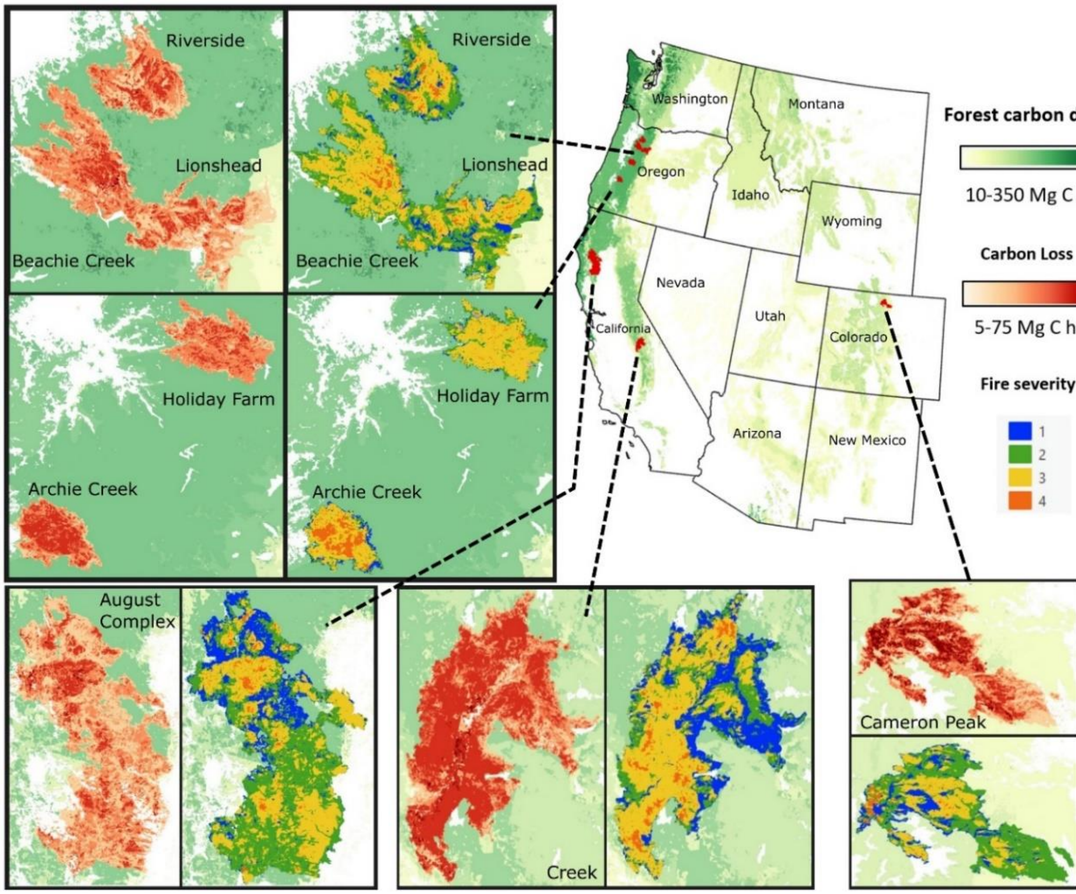


Figure 3. Fire perimeters and forest carbon density losses (Mg C ha^{-1}) from 2020 extreme, large forest fires in CA, CO, and OR (>100,000 acres). Green background indicates aboveground carbon forest layer, where darker green forest cover denotes higher density of aboveground carbon. Detailed maps display both fire severity (multicolored fire area), and per area carbon losses (red fire area).

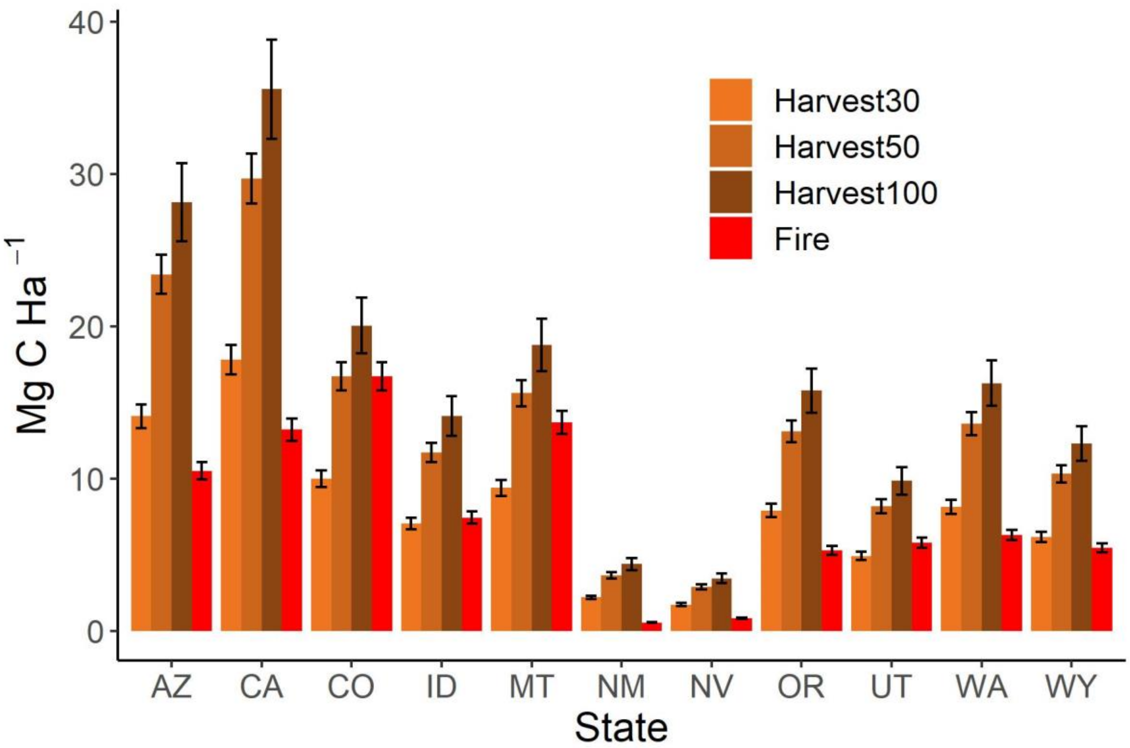


Figure 4. Comparison of per area (Mg C ha $^{-1}$) hypothetical harvest scenario carbon losses to actual fire emissions. Harvest scenarios were calculated for the exact burn area in these states for 2009-2018. Harvest scenarios are based on 30%, 50%, and 100% aboveground tree removal rates. Here, a 30% is showing a thin-from-below, 50% harvest is akin to a commercial thin, while 100% would be representative of a clear-cut removal. Fire emissions are based on the fire perimeters of forest fires used in this study. Error bars represent standard error.

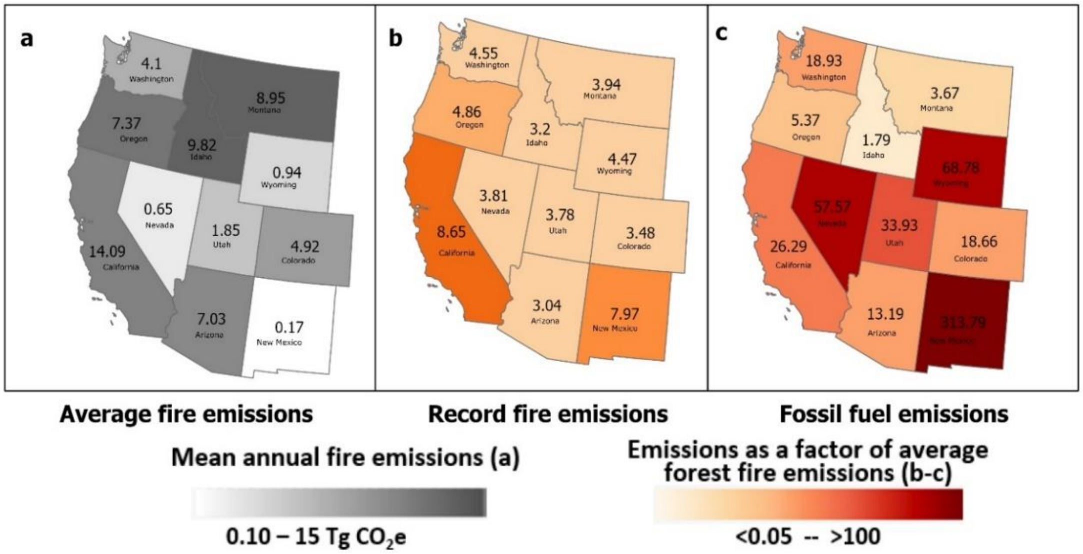


Figure 5. Fossil fuel and record-year forest fire emissions as a factor of mean annual forest fire emissions for the baseline decade 2009-2018. This comparison shows (a) mean annual fire emissions (Tg CO_2e) calculated per state for a baseline 10-year (2009-2018) period, and factors from mean annual forest fire emissions (i.e., the number of times higher, or the proportion of those emissions relative to mean annual forest fire emissions) for (b) record-year forest fire year emissions (i.e., the year with the highest forest fire emissions for that state, Table 4), and (c) mean annual fossil fuel emissions.

Tables

Table 1. Common management scenario types in western US forests. Tree removal scenarios (thins and clear-cut) were used in the hypothetical harvest carbon loss calculations (Figure 4). Extractive management (i.e., if there is also a financial sale from the management rather than just for restoration or fuels reduction) is noted for each scenario.

Management scenario	**Description**	**Calculation scenario (Fig. 4)**	**Extractive management?**
Thin-from-below	Removal of understory brush and small-diameter trees. No tree sales.	30% harvest	No
Commercial Thin	Removal of understory brush, small-diameter trees, and some larger, mature trees for sale.	50% harvest	Yes
Clear-cut Removal	Removal of all trees (small and mature) for sale.	100% harvest	Yes
Prescribed Burn	Intentionally set fire to remove ground fuels. Often coupled with a restoration or commercial thin.	Not included in calculations	No

Table 2. Examples of recent public opinions surrounding the logging-forest-carbon misconceptions and how they lead to policy that increases harvest.

Source	Year	Author	Quote or summary	Description
Public	2020	Logging and grazing organizations (Radke, 2020)	"Log it, graze it, or watch it burn it"	Logging and grazing orgs believe logging and grazing will solve the fire problem
Public	2020	Consortium for Research on Renewable Industrial Materials (CORRIM, 2020)	"Sustainably harvesting forest carbon not only provides significant opportunities for carbon storage"	Logging industry promotion trying to show "reducing carbon emissions by using wood products"
Public	2018	Former US Cabinet Member Ryan Zinke (Zinke, 2018)	"When an entire forest burns to the ground"	Advocates for logging to prevent wildfires, boost the economy, and to save lives.
Public	2017	Catherine Mater (Mater, 2017)	"Half of those emissions are due to tree mortality"	Misconception that tree mortality equals direct emissions
Policy	2021	US Government - Infrastructure Investment and Jobs Act (Infrastructure Investment and Jobs Act, 2021)	Significant increase in project funds to increase logging and commercial thinning on public lands for fire risk reduction	$3.3 billion allocated to hazard fuels reduction with no diameter limits set. 12 million ha opened to logging on public lands.
Policy	2020	US Government - Twisp River Restoration Project(USFS, 2020)	Increase diameter limits on trees harvest to cut down larger trees for fire risk reduction and restoration	>30,000 ha forest management project in fire-prone forest in Washington state

Table 3. Carbon emissions from 1910 Big Burn and extreme contemporary (1984-2020) forest fires in the western United States.

Complex	**Year**	**Area burned (ha)**	**Tg C**	**Mg C ha^{-1}**	**Tg CO2e**
Big Burn	1910	966,564-1,257,690*	29.79-49.87**	23.69-39.65**	94.60-158.51**
Siege of '87	1987	151,339	3.58±0.20	23.70±1.32	13.10±0.73
Yellowstone	1988	672,509	16.3±0.91	24.30±1.36	59.90±3.35
Big Bar	1999	57,158	1.40±0.08	24.60±1.38	5.10±0.29
Biscuit	2002	200,444	4.40±0.25	22.0±1.23	16.10±0.90
Hayman	2002	52,373	1.53±0.09	29.20±1.63	5.60±0.31
Tripod	2006	70,753	1.31±0.07	18.60±1.04	4.80±0.27
Central Idaho	2007	298,821	5.96±0.33	20.0±1.12	21.90±1.22
Klamath Theater	2008	86,795	2.16±0.12	25.0±1.40	7.90±0.44
Wallow	2011	228,106	3.39±0.19	14.90±0.83	12.40±0.69
August	2020	417,891	9.02±0.50	24.60±1.38	33.10±1.85
Creek***	2020	153,700	4.56±0.25	29.70±1.66	16.70±0.93
North	2020	126,220	2.35±0.13	18.60±1.04	8.60±0.48
Oregon****	2020	340,702	8.18±0.46	24.0±1.34	30.0±1.68
Colorado****	2020	153,294	4.23±0.24	27.60±1.54	16.90±0.94

* The area estimates are from (Koch, 1942) and (Gibson, 2005).

** The emissions from Big Burn were calculated using present day USFS Forest Inventory and Analysis data. Here we provide a range of carbon emissions values, rather than uncertainty ranges, because we use a range of combustion factors as we do not have detailed severity data.

*** Prior to the 2020 Creek Fire, this forest had a proportion killed by the 2012-2017 drought and was subsequently salvaged logged. Our emissions calculation is likely an overestimate due to the large amount of biomass already removed from salvage logging, and slash left behind from salvage logging driving higher fire severity.

**** Oregon and Colorado forest fire area and emissions are aggregated for the 2020 extreme forest fires.

Table 4. Average fossil fuel emissions, forest fire emissions, and harvest emissions, 2020 fire emissions, and record year fire emissions (2008-2020) for all western US states and for the entire western US region.

State	10-yr average fossil fuel emissions ($TgCO_{2e}$)	10-yr average forest fire emissions ($TgCO_{2e}$)	10-yr average harvest emissions ($TgCO_{2e}$)	2020 forest fire emissions ($TgCO_{2e}$)	Record year forest fire emissions ($TgCO_{2e}$)	Record Year
Arizona	92.76±1.57	7.02±0.79	0.41±0.07	8.28±0.93	21.34±2.39	2011
California	370.71±4.98	14.09±1.58	7.38±1.27	121.92±13.63	121.92±13.63	2020
Colorado	91.84±1.04	4.92±0.55	0.36±0.06	33.35±3.73	33.35±1.91	2020
Idaho	17.66±0.32	9.81±1.09	5.03±0.86	5.06±0.56	31.37±3.51	2012
Montana	32.86±0.71	8.95±1.00	2.03±0.35	2.20±0.25	35.30±3.95	2017
Nevada	37.24±1.46	0.64±0.07	0.03±0.01	0.59±0.07	2.46±0.28	2018
New Mexico	52.68±1.06	0.16±0.02	0.17±0.03	1.33±0.15	1.33±0.15	2020
Oregon	39.58±0.60	7.36±0.82	19.38±3.33	35.78±4.00	35.78±4.00	2020
Utah	63.01±0.89	1.85±0.21	0.14±0.03	3.21±0.36	7.01±0.78	2018
Washington	77.70±1.21	4.10±0.45	14.72±2.53	2.11±0.24	18.68±2.09	2015
Wyoming	64.91±0.60	0.94±0.01	0.18±0.03	10.25±1.15	10.25±1.15	2020
Total WUS	941.00±10.74	59.95±6.70	49.88±8.56	224.09±25.05	224.09±25.05	2020

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Supporting Information

Table S1. The combustion coefficients all for carbon pools, used to estimate direct fire carbon emissions from contemporary fires based on fire severity.

Severity Code	Foliage	Live-wood	FWD	CWD	Litter	Snag	Duff	Shrub
4	0.69	0.05	0.95	0.6	1	0.12	0.99	0.86
3	0.27	0.01	0.9	0.55	0.9	0.04	0.9	0.66
2	0.08	0	0.7	0.35	0.75	0.02	0.65	0.42
1	0.02	0	0.5	0.05	0.5	0.02	0.45	0

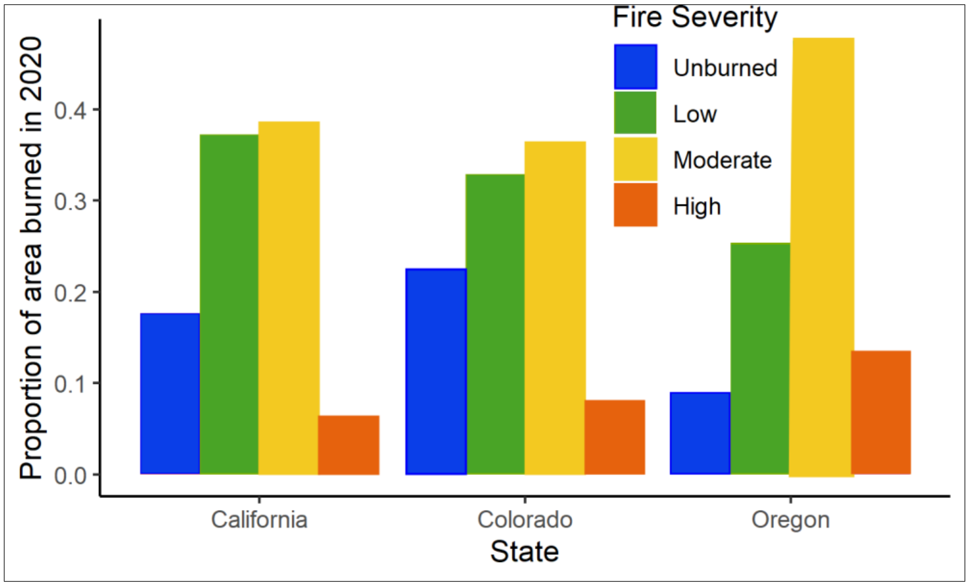

Figure S1: Proportion by state of 2020 forest fire area burned by severity class in California, Colorado, and Oregon.

Chapter 3: Playing with fire: Investigating the future of fire and carbon dynamics in Northern Rockies forests using CLM-FATES-SPITFIRE

Abstract

Climate change is intensifying fire regimes across the globe. Wildfires across western North America have been increasing in frequency and area burned over the past several decades – potentially leading to increased carbon emissions and decreased carbon uptake, loss of forest area, and other negative effects on ecosystem services and communities. Under continued climate change, fire regimes and forest recovery may differ from the past. The Northern Rocky Mountain forests (Northern Rockies) are unique in the western US – these forests have been relatively untouched by wildfire over the past 100 years. Since the 1910 Big Burn, many of the most productive Northern Rockies forests have experienced few and small-scale forest fires. Northern Rockies forests are wetter and more productive compared to other dry forests of the Inland West, including the adjacent forests of Central Idaho. Central Idaho forests are significantly drier and have had high fire occurrence in the past century. Despite the lack of wildfire in Northern Rockies forests over the last century, future fire occurrence and carbon dynamics in these forests under continued warming and drying are unclear.

Here, we use a state-of-the-art Earth System model (ESM; CLM-FATES) coupled to a prognostic fire model (SPITFIRE) to investigate the future of fire and carbon dynamics in Northern Rockies forests over the 21st century (2000-2080). Forest types were split into three plant functional types: warm-dry (*P. ponderosa,* 5% of modeled domain), wet (*P. menziesii, A. grandis,* 47% of modeled domain), and subalpine (*P. engelmannii, A. lasiocarpa,* 17% of modeled domain). These forest types vary by species composition,

carbon density, climate (temperature and precipitation), and historic fire return intervals (FRI). We calibrated the model using present-day biomass stock, fire occurrence, mortality, and NPP data, and validated output using linear regressions. The dry, *P. ponderosa* forests have a low FRI of 21-25 years, wet forests 71-80 years, and the subalpine forests 151-200 years. Average total aboveground carbon (AGC) for the Northern Rockies domain was lowest for warm-dry forests (82.51±52.87 Mg C ha^{-1}), followed by subalpine forest (137.74±38.88 Mg C ha^{-1}), with the wet forests having the highest carbon stocks (139.70±46.21 Mg C ha^{-1}). Future simulations (until 2080) forced with future climate data show an increase in wildfire from the modern record for the wet and cold forest types, while the warm-dry forest type continues to have a shorter mean fire return interval (15-25 years). Fire occurrence in the wet and cold forests is followed by immediate, subsequent decreases in forest carbon (up to 20% loss). However, post-fire recovery of forest carbon stocks occurs for all forest types for the simulation range, with complete AGC recovery seen in as little as 10-20 years following some of the disturbances.

Introduction

Western US forests provide critical ecosystem services such as wood products, climate regulation, carbon storage and sequestration, wildlife habitat, and erosion control (Lawler et al., 2014), but also experience widespread disturbance such as drought, insect outbreaks, wildfire, and anthropogenic land management (Law et al., 2018; Seidl et al., 2016). Western forests are also facing extensive climatic changes that are amplifying drought, insect outbreaks, and wildfire (Berner et al., 2017; Higuera & Abatzoglou, 2020; Westerling et al., 2006; Williams et al., 2020). As climate change continues to intensify, these forest disturbances are occurring more often and are becoming more widespread (Bowman, David;

Kolden, Crystal A.; Abatzoglou, John T.; Johnston, Fay H.; van der Werf, Guido R.; Flannigan, 2020; Law & Waring, 2015; Seidl et al., 2014). The interactive effects of climate change, land use, and disturbance regimes influence the sustainability of forest growth and stability, and subsequently, forest cover and ecosystem services (Lawler et al., 2014; Stevens-Rumann et al., 2018). There is a need to better understand and accurately predict the nature and severity of the impacts of climate change and disturbances to guide forest management and policy decisions aimed at sustaining forest ecosystem resilience and carbon stocks. Due to unknown impacts of novel, climate change driven disturbance regimes such as increasing fire events and size (Berner et al., 2017; Bowman, David; Kolden, Crystal A.; Abatzoglou, John T.; Johnston, Fay H.; van der Werf, Guido R.; Flannigan, 2020; Westerling et al., 2006), resilience of the forest carbon sink is unclear.

In the 21st century, the intensification of fire activity in the western US has caused an increase in fire occurrence and area burned (Abatzoglou et al., 2021; Halofsky et al., 2020; Williams et al., 2019). This intensification is increasing uncertainty surrounding forest resilience and future successional trajectories (Anderson-Teixeira et al., 2013; Buotte et al., 2019a; Harvey et al., 2016a). Forest resilience (i.e., the ability of forests to recover following a disturbance to the original forest type) depends on favorable post-fire conditions including sufficient precipitation, normal temperatures, and seed sources (Stevens-Rumann & Morgan, 2019). Post-fire recovery depends on many factors, such as pre- and post-fire climate, and burn extent and severity (Hansen et al., 2018; Harvey et al., 2016b). Failure of post-fire recovery due to intensification of fire regimes and unfavorable climatic changes may lead to phase-shifts of forests to non-forest land cover types (Coop et al., 2020). Loss of forest cover could lead to declines in forest ecosystem services, such as wood products, erosion control, wildlife habitat, watershed services, recreation, and carbon storage and sequestration (Law et al., 2018; Lawler et al., 2014). Increases in fire occurrence over decades to centuries may also lead to overall declines in total ecosystem carbon (Bartowitz et al., 2019). Uncertainty associated with post-fire forest successional trajectories (Gill et al., 2017; Seidl et al., 2014) makes recovery of these systems difficult to predict, compounding the difficulty of using management tools effectively and efficiently (Schoennagel et al., 2004).

The Northern Rocky Mountain forests (Northern Rockies, Figure 1) of Idaho and Montana are unique in the western US – these forests have been relatively low amounts of wildfire over the past century (E.S. Walsh & Hudiburg, 2021). This is especially true for the northern part of the region (i.e., the Idaho panhandle)(Higuera et al., 2015), which is known by local managers as “asbestos forests”. Since the 1910 Big Burn (Koch, 1942), Northern Rockies forests have experienced few and relatively small-scale forest fires (Eidenshink et al., 2007). Northern Rockies forests have higher precipitation and are more productive compared to other dry forests of the Inland Northwest, including the adjacent forests of Central Idaho. Central Idaho forests are significantly drier and warmer and have had high fire occurrence in the past century. Despite the lack of wildfire in Northern Rockies forests over the last century, future fire occurrence and carbon dynamics in these forests under continued warming and drying are unclear. This region is underrepresented carbon cycle science studies; there have been relatively few experimental (Jeffrey E Stenzel, 2021) and mechanistic modeling studies completed for this region (Buotte et al., 2019b; Eric S. Walsh & Hudiburg, 2021). Western US simulations have shown Northern Rockies forest may be less vulnerable to drought and wildfire than other forests across the west (Buotte et al., 2019b), and protection of these forests will have significant carbon sequestration and biodiversity co-benefits (Buotte et al., 2020; Law et al., 2021). It's still unclear how future fire and climate change will impact this understudied, but potentially very important from a climate and biodiversity perspective, forested region in the future.

ESMs are necessary to answer climate impact questions on forested ecosystems comes closer each year. The Community Land Model (CLM) is the land model component of Community Earth System Model – a state-of-the-art ESM that unlike many other forest ecosystem models regularly used to answer forest dynamic questions in the western US (Creutzburg et al., 2017; Kim et al., 2018; E.S. Walsh & Hudiburg, 2021), is almost completely mechanistic (Lawrence et al., 2019). CLM has recently been coupled with the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) (Buotte et al., 2021; Rosie A. Fisher et al., 2018). FATES is a cutting-edge dynamic global vegetation model (DGVM) that allows for structural modeling of forests, rather than the common "big leaf" modeling approach (R. A. Fisher et al., 2015). Providing an avenue for simulating forest structure and age classes within the model allows for more accurate representation of forest function and forest carbon cycling, including carbon pool shifts, plant functional types, competition, and more precise fire modeling. With the inclusion of forest structure in the model, FATES now allows for forest modeling that is relevant to on-the-ground forest disturbances and forest management than ever before. In addition to the FATES module, CLM is also coupled to a state-of-the-art prognostic fire model, SPITFIRE. SPITFIRE improvements from previous CLM fire modules by incorporating stand structure (from FATES, plant functional types (PFTs), fuel load, and fuel class sizes into fire spread (Kirsten Thonicke et al., 2010). The fires that occur in a CLM-FATES-SPITFIRE simulation feed back into FATES. The modeling improvements from FATES (i.e., detailed forest structure and age cohorts) and SPITFIRE (variable fire rate of spread, fire feedbacks to FATES, PFT composition, vegetation dynamics, carbon pools, fuel size classes) allow for exploration of the future of fire and forest dynamics in the Northern Rockies forests.

Here, for the first time, we have parameterized and evaluated CLM-FATES-SPITFIRE to the Northern Rockies forests. Forested area in the modeled domain was split into three plant functional types (PFT) that describe the dominant forests (and climate types) of the region: warm-dry (*P. ponderosa*), wet (*P. menziesii*, *A. grandis*), and subalpine (*P. engelmannii*, *A. lasiocarpa*). This study 1) evaluates FATES-SPITFIRE performance in the under-modeled Northern Rockies forests and 2) examines how fire regimes may shift over the 21st century with continued climate change in this region, and 3) examines regional 21st century carbon dynamics and storage.

Materials and Methods

Study region

The study region focuses on the Northern Rockies forests of Idaho and Montana (Figure 1, Table 1). The modeled domain is 10,372,542 ha which includes the entire Idaho panhandle and parts of northwestern Montana. Forest types range from low elevation dry, *Pinus ponderosa* forests with short fire return intervals, to wetter low-to-mid elevation mixed conifer forests (*Abies grandis* and *Pseudotsuga menziesii*), to wetter and colder subalpine forests (dominated by *Picea engelmannii* and *Abies lasiocarpa*), (Figure 2, Figure 3). While there are several other forest types throughout the domain, these are the three dominant forest types (>90% of forested area in domain) and PFTs in this study will be limited to these forest types to simplify parameterizations.

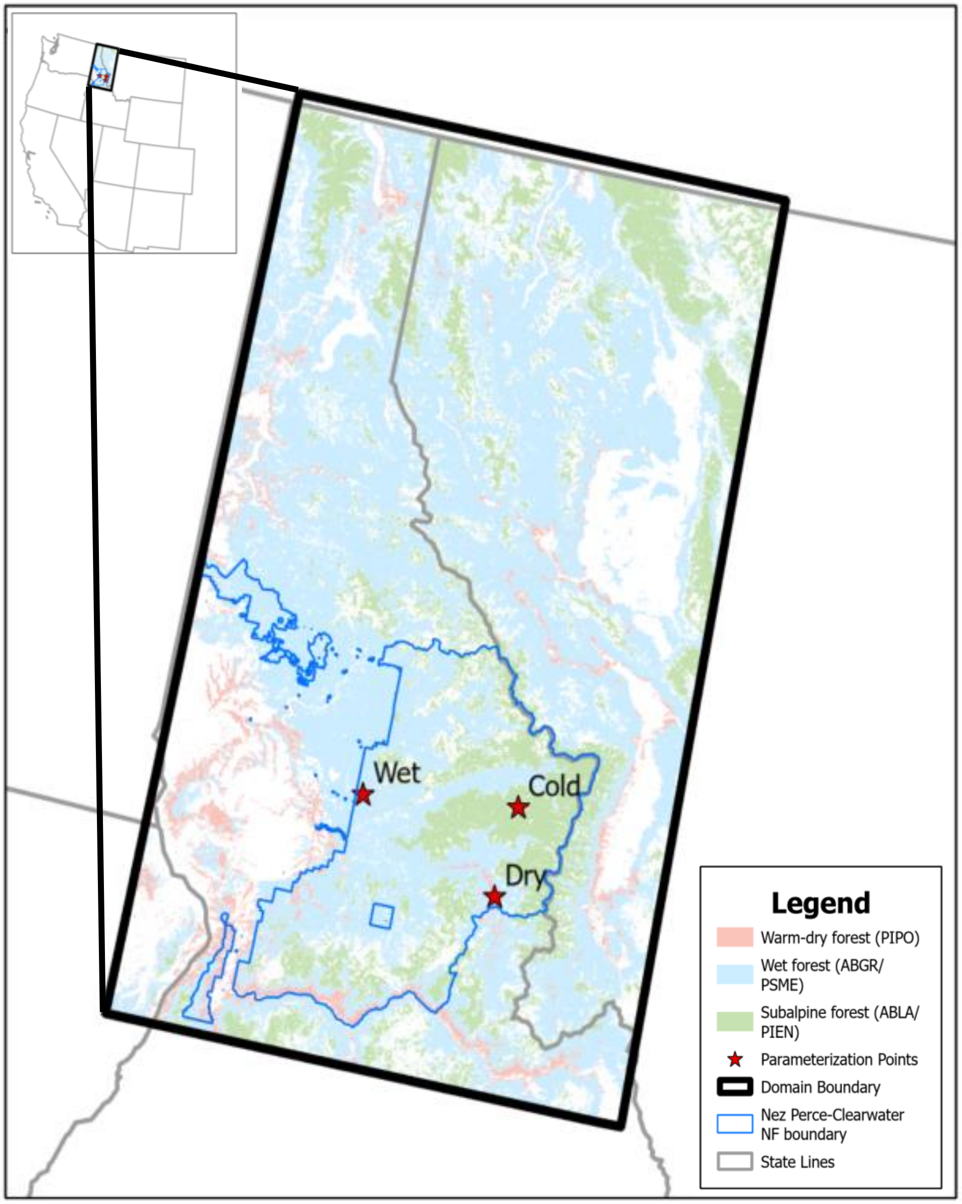

Figure 1. Northern Rockies domain (thick black outline). Labeled, red points denote parameterization points of each modeled PFT (i.e., wet, subalpine, warm-dry). Background colors show extent of each PFT, no color (white) implies no forest cover for that area. Blue outline represents boundary of the Nez Perce-Clearwater National Forest.

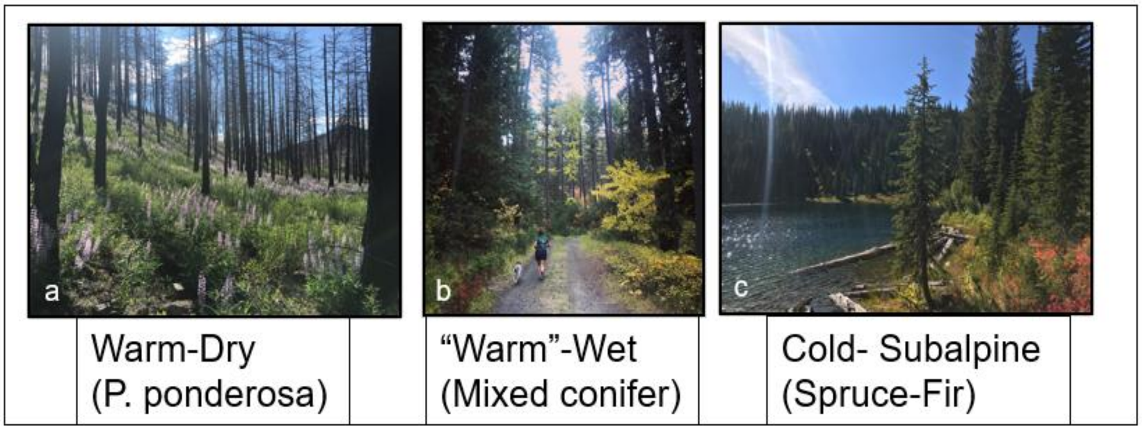

Figure 2. Examples of the three dominant forest types modeled in this study. a) Ponderosa pine forest (post-fire), b) wet, mixed conifer forest (Douglas-fir and grand fir), and c) subalpine, cold forest (Engelmann spruce and subalpine fir).

Parameterization point site selection was completed by aggregating 30-year climatic data (mean annual temperature and mean annual precipitation) (Abatzoglou et al., 2018) for each pixel throughout the domain (Figure 3).

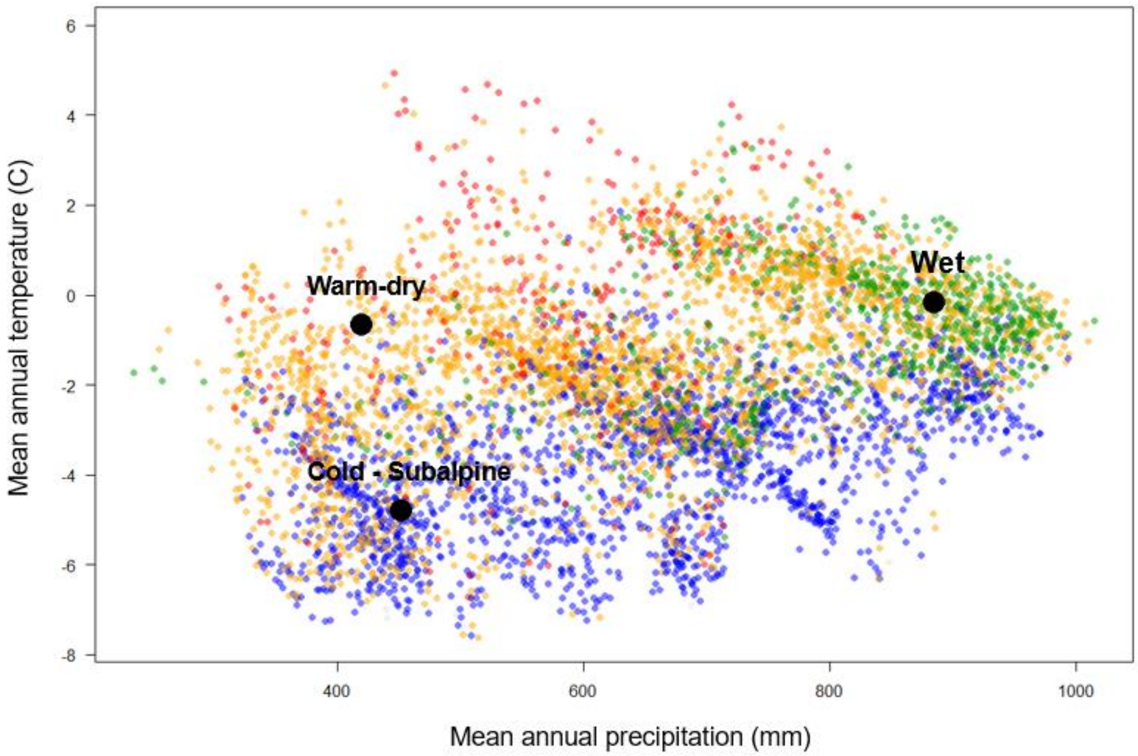

Figure 3. Average annual temperature and precipitation for all pixel points within the domain. Black points are the parameterization points. Yellow denotes warm-dry, blue subalpine, green wet forests.

Table 1. Forest plant functional types used in modeling domain.

Forest/PFT	**Dominant species**	**Parameterization points**	**Historic climate description (domain wide)**	**Fire Regime (domain wide)**
Warm/dry	*P. ponderosa* (PIPO)	46.02, -114.81	MAP: 410 mm MAT: 0 C	21-25 years
Wet	*P. menziesii* (PSME), *Abies grandis* (ABGR)	46.31,-115.72	MAP: 900 mm MAT: -1 C	71-80 years
Cold/Subalpine	*P. engelmannii* (PIEN), *A. lasiocarpa* (ABLA)	46.39, -114.76	MAP: 450 mm MAT: -5 C	151-200 years

Parameterization points chosen were limited to within the boundaries of the Nez Perce Clearwater National Forest (Figure 1) in northcentral Idaho, as management plans written for this administrative unit will be used in future simulations of the domain. These plans include management strategies to alter tree species composition throughout the national forest based on perceived resilience of different species. In addition, the southernmost part of the Northern Rockies domain has experienced the most fire within the study domain, making it the best location to begin parameterizing SPITFIRE (Figure S6).

Model description

The Community Land Model (CLM) simulates biogeochemical cycles (Lawrence et al., 2019) and is coupled with the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) to simulate age and height classes (forest structure) (Buotte et al., 2021; Rosie A.

Fisher et al., 2018; Koven et al., 2019). CLM-FATES uses a state-of-the-art prognostic fire model (SPITFIRE, (K. Thonicke et al., 2010)) to simulate wildfire. Point-scale simulations allow site-specific analysis in a diagnostic, calibration environment to evaluate forest dynamics that can be compared with observations, followed by future regional-scale runs. Future simulations using regional-scale fire and vegetation were run prognostically to allow for future predictions of forest dynamics and disturbance interactions and evaluate how forests react to novel fire regimes and climate.

CLM requires climatic inputs at a 3-hourly, 4km scale include air temperature, humidity, precipitation, solar radiation, and windspeed. Climatic inputs for these simulations were generated from the MIROC5 General Circulation Model for both historical (1979-2005) and future experiments in the RCP 8.5 concentration pathway (2006-2080, (Taylor et al., 2012)). These inputs were downscaled as descripted in Taylor et al. 2012. CLM also uses surface datasets as required inputs which include land cover types (e.g., vegetation, lake, glacier, crop, or urban), slope, soil depth, soil depth, soil texture, soil color, and elevation. The surface dataset used in this study was acquired from Buotte et al. 2021.

The Functionally Assembled Terrestrial Ecosystem Simulator (FATES) is a dynamic global vegetation model that has been recently coupled to CLM (Figure S1 and S2). FATES is designed to represent forest structure through age classes (time since disturbance) and height classification through forest stand cohorts (Figure S2). This is an improvement over the CLM big leaf model, which used a PFT-based tiling scheme where all modeled trees within a PFT are the same age and height (Figure S2 and S3), rather than a time-since-disturbance tiling scheme (Figure S4). Although, the change from the big-leaf organization to time-since-disturbance cohorts greatly increases the computational power and the amount of time needed to run CLM-FATES, as each disturbance creates a new patch, sub-grid cell heterogeneity is allowed for different aged and height cohorts (Figure S3). Sub-grid cell heterogeneity allows for height structured vegetation, age classes, heterogeneity in light availability (including competition for light), dynamic recovery after fire (or other disturbances), and arbitrary PFT definitions (Team, 2019). Another benefit of FATES is that plant success or mortality is not driven by set climate envelopes. Rather, plant success or mortality is based on mechanisms rather than climate tolerances, which is important for climate change studies. There are many additional input parameters (>200) used in the FATES module that impact both fire dynamics (and feedback to the SPITFIRE fire module), and plant physiology. The base PFT used in this study was a *Pinus*-PFT from a parameter assessment project obtained from Buotte et al. 2021 and Stenzel 2021 (Table S1). Specific parameters changed from this base PFT for the warm-dry, wet, and subalpine PFTs used in this study can also be found in Table S1.

We used the CLM-FATES-SPITFIRE configuration for the simulations in this study (Figure S5). SPITFIRE is a process-based, rate-of-spread fire model (Drüke et al., 2019; G. Lasslop et al., 2014; K. Thonicke et al., 2010). SPITFIRE allows for variable fire intensity and fuel combustion is separated by PFTs. Tree mortality from ground fires is via crown scorching and cambial damage. Flame height determines crown scorch. Trees with thicker bark have greater fire survival rates. Combustion completeness is a dynamic process which depends on fire characteristics (fire intensity, flame height), fuel class moisture content. Combustion is PFT and fuel-type specific. The SPITFIRE prognostic module is a vast improvement over the CLM 4.5 fire module (Lawrence et al., 2019; Li et al., 2014) (the predecessor fire module for any CLM fire modeling). Coupling a fire module to SPITFIRE allows for fire to interact with forests in an age and size class manner. This is a crucial improvement as fire can now be represented more realistically: fires can burn solely in the understory (an example of low-severity fire that may happen in the warm-dry PFT of our modeling experiments) or in the understory and overstory (a high-severity fire). In addition, coupling SPITFIRE to FATES allows the user to track fire impacts across cohorts and see impacts on different age-PFT-height class stands, compared to fire area-average methodology used in previous fire models (Figure S5).

Model parameterization and validation

National databases were synthesized for baseline parameterization and validation data for CLM-FATES, along with foliage samples from the region(J. E. Stenzel et al., 2021) , values from literature (Berner & Law, 2016; J. E. Stenzel et al., 2021), and national databases (Table 2). CLM-FATES was parameterized with dynamic mortality rates, biological nitrogen fixation, physiological traits (e.g., foliar C:N, specific leaf area), and tree allometry. There are many additional input parameters (>200) used in the FATES module that impact both fire dynamics (and feedback to the SPITFIRE fire module), and plant physiology. The base PFT used in this study was a *Pinus*-PFT from a parameter assessment project obtained from Buotte et al. 2021. Specific FATES parameters changed from this base PFT for the warm-dry, wet, and subalpine PFTs used in this study can be found in Table S1. Descriptions of specific SPITFIRE parameters changed from this base PFT for the warm-dry, wet, and subalpine PFTs used in this study can be found in Table S1, and values swapped can be found in Table S2. Site parameterization was completed with observations from observations and remotely sensed data from national databases (Table 2.) These include live and dead carbon stocks, net primary productivity, fire occurrence, and fire area burned.

Table 2. Data sources used for parameterization and validation

Data type	Data source	Description
Live and dead biomass stocks	USFS Forest Inventory and Analysis (Shaw et al., 2005)	Continuous tree inventory plots across the US
Net primary productivity	MODIS (Hicke et al., 2007), Stenzel et al. 2021	Remotely sensed NPP data; observation based NPP data
Mean fire return interval	Landfire	Average period between fires under presumed historical fire regime
Area burned, fire occurrence, mean fire return interval	Monitoring Trends in Burn Severity (Eidenshink et al., 2007; Rollins et al., 2007)	Remotely sensed burn area

Model experiments

Model experiments focused on evaluating the impacts of SPITFIRE based on two FATES structural variables (Bark Thickness and Crown Depth, Table 3), and the subsequent impacts on carbon dynamics and wildfire. Model sensitivity was specifically focused on fire, for both FATES and SPITFIRE specific variables. PFT-specific parameterization values can be found in Tables S1 and S2. Several SPITFIRE and FATES parameters were tested to parameterize fire.

Model experiments included two types of exploration: 1) model sensitivity for fire using specific SPITFIRE variables of importance (Table 3), and 2) simulation of future fire and carbon dynamics across the three tested PFTs. Model sensitivity tests were run at all PFTs and included simulations with default SPITFIRE parameters and simulations where the

SPITFIRE module was turned off (“No Fire”). All model scenarios were run with the SPITFIRE module on and off to test how fire impacts the forest dynamics across time (Table 4, Table S3). Model experiments included altering two forest structure parameters for each PFT to see how they would impact fire over the 100-year simulations. The parameters altered were bark thickness (Pausas, 2015) and crown depth (Tang et al., 1999). The two model experiments (bark thickness and crown depth) were run with Buotte et al. 2021 SPITFIRE parameters rather than default to ensure a realistic amount of fire would occur (Table S3).

Table 3. SPITFIRE Variables of importance tested for model sensitivity (Buotte et al., 2021).

SPITFIRE Parameters of importance	**Long name**	**Description**
Drying ratio	fates_fire_drying_ratio	Fire drying ratio for fuel moisture
Cloud-to-ground	fates_fire_Cg_strikes	Fraction of c-g lightning strikes
Bark thickness (scaler)	fates_fire_bark_scaler	Scaler to calculate bark thickness from DBH
Crown Depth (scaler)	fates_fire_crown_depth_frac	Scaler to calculate depth of crown in meters = fates_fire_crowth_depth_frac * height

Table 4. Model simulations for future fire across forest types in the Northern Rockies domain.

#	**Model Simulations**	**PFT**	**Years**	**SPITFIRE**	**Future Climate**	**Type**
1	SPITFIRE-warm-dry (default)	Warm-dry	100	On	MIROC5	Sensitivity
2	SPITFIRE-warm-dry (Bark Thickness)	Warm-dry	100	On	MIROC5	Experiment
3	SPITFIRE-warm-dry (Crown Depth)	Warm-dry	100	On	MIROC5	Experiment
4	No fire – warm-dry	Warm-dry	100	Off	MIROC5	Sensitivity
5	SPITFIRE – wet (default)	Wet	100	On	MIROC5	Sensitivity
6	SPITFIRE – wet (Bark Thickness)	Wet	100	On	MIROC5	Experiment
7	SPITFIRE – wet (Crown Depth)	Wet	100	On	MIROC5	Experiment
8	No fire – wet	Wet	100	Off	MIROC5	Sensitivity
9	SPITFIRE – subalpine (default)	Cold/Subalpine	100	On	MIROC5	Sensitivity
10	SPITFIRE – subalpine (Bark Thickness)	Cold/Subalpine	100	On	MIROC5	Experiment
11	SPITFIRE – subalpine (Crown Depth)	Cold/Subalpine	100	On	MIROC5	Experiment
12	No fire – subalpine	Cold/Subalpine	100	Off	MIROC5	Sensitivity

Model evaluation

Model sensitivity tests focused on getting SPITFIRE to produce wildfire results because default SPITFIRE parameterizations showed very little fire activity at the Northern Rockies sites. Model sensitivity was specifically focused on fire, for both FATES and SPITFIRE specific variables. PFT-specific parameterization values can be found in Tables S1 and S2. Several SPITFIRE and FATES parameters were tested to parameterize fire. All simulations were from a cold-start, they were not pre-initialized with stand conditions. Model spin-up (equivalent to NPP reaching equilibrium) took approximately 20-30 years for all simulations. Simulations begin in 1980, to allow for several years of spin-up of the forest stands before future years are simulated.

Model output was evaluated against independent observations from databases, literature, and field data for net primary productivity, aboveground biomass, and mean fire return intervals (Table 5). To validate model performance, outputs were compared with data from plots and sites not used in development or calibration (Table 5). Fire occurrence was validated with LANDFIRE (Rollins et al., 2007) and MTBS data (Eidenshink et al., 2007) (Figure S6).

Results

Model sensitivity and evaluation

With default SPITFIRE parameters run for each of the 3 PFTs, we found the Cold PFT had the highest NPP, total live biomass, and fine root biomass, followed by warm-dry and wet PFTs (Figure 4) Total fuel consumed over the course of the simulation was highest in the Warm-dry PFT, followed by Wet and Cold PFTs (Figure 4).

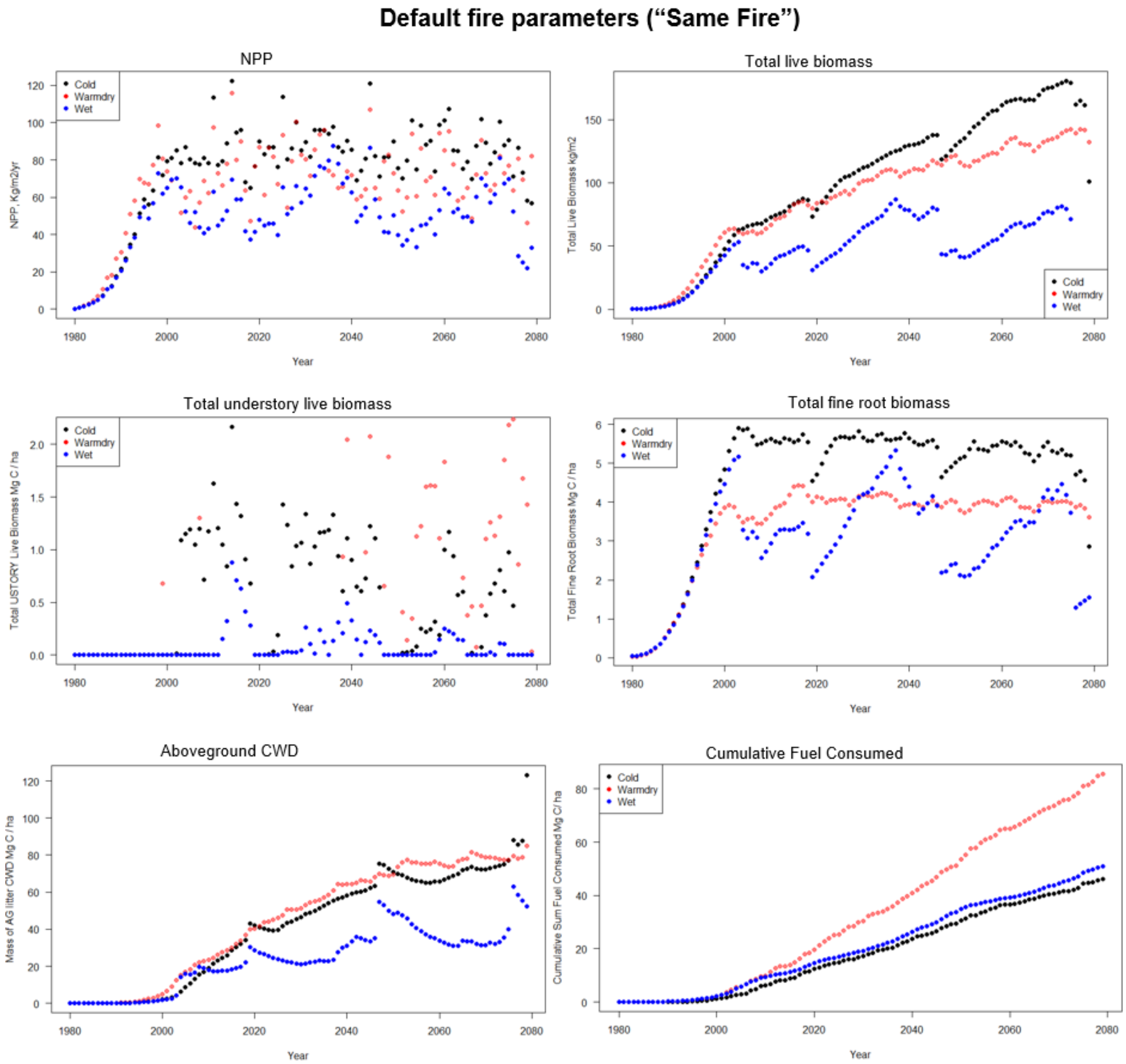

Figure 4. Carbon and fire output variables over the course of the 100-year simulation (1980-2080) for simulations run with the same fire parameters for each PFT (Warm-dry, Wet, Cold).

With the SPITFIRE module turned off ("No Fire") run for each of the three PFTs, we found the Cold PFT simulation had the highest NPP, total live biomass, total aboveground coarse woody debris, and total fine root biomass, followed by warm-dry and wet (Figure 5). Total fuel consumed over the course of the simulation was highest in the Warm-dry PFT, followed by the Wet and Cold PFTs (Figure 5).

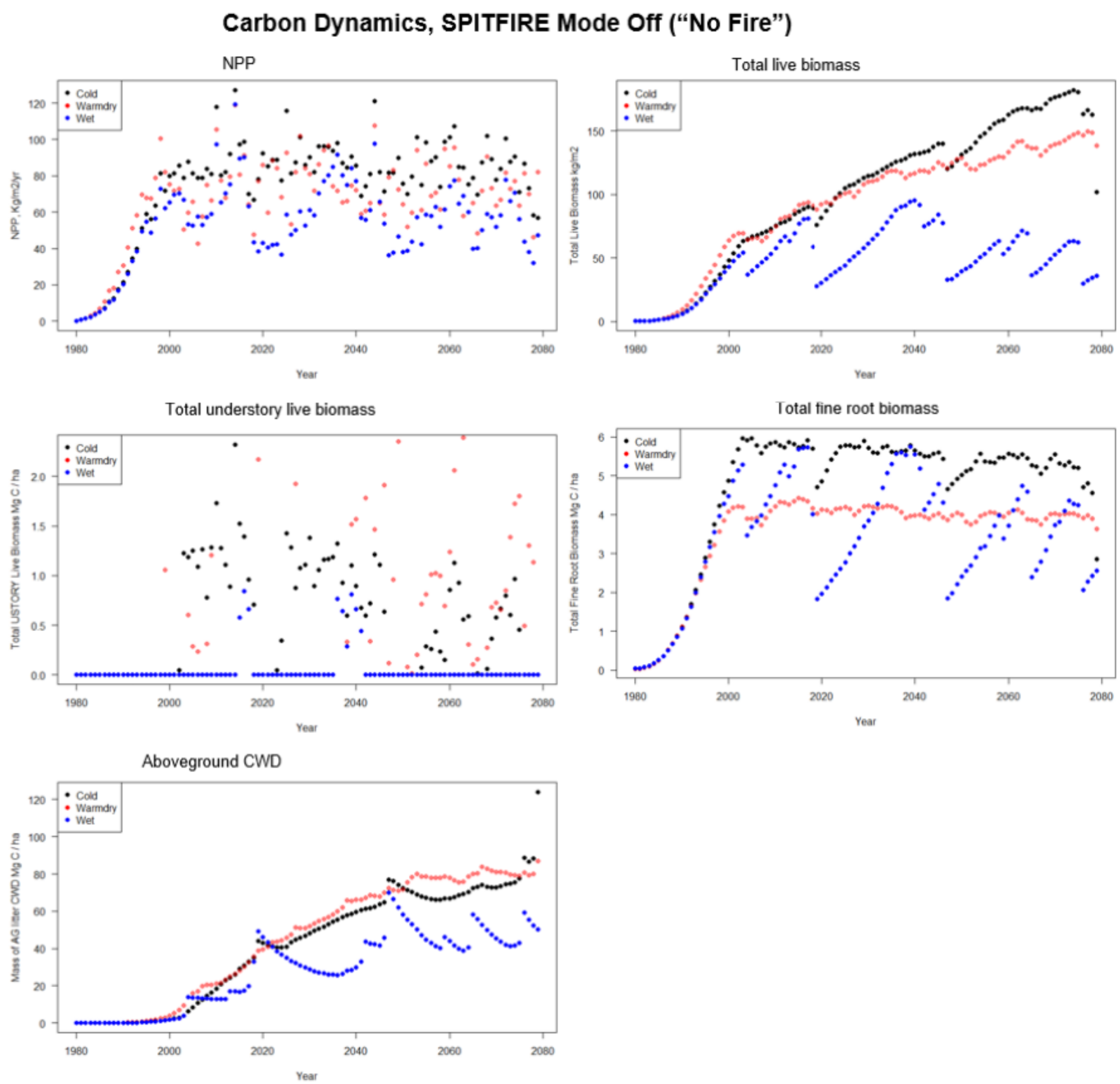

Figure 5. Carbon and fire output variables over the course of the 100-year simulation (1980-2080) for simulations run with the SPITFIRE module turned off (“No Fire” for each PFT (Warm-dry, Wet, Cold).

Because default fire parameters did not produce much of a fire effect, as shown by similarities in carbon dynamics from “default fire” and “no fire” simulations (Figures 9, 10). SPITFIRE was then further parameterized to develop PFT-specific fire effects (see Model Experiments).

Table 5. Model evaluation for biomass (Wilson et al., 2013), fire (Eidenshink et al., 2007), and NPP (Hicke et al., 2007; J. E. Stenzel et al., 2021) outputs.

Output variable	**PFT**	**Model output**	**Validation output**
Biomass: Mg C ha^{-1}			
	Warm-dry	58.02 ±4.54	82.51±52.87
	Wet	116.15±2.49	139.70±46.21
	Cold	115.38±5.61	137.74±38.88
Fire: MFRI (years)			
	Warm-dry	11.82	21-25
	Wet	45.50	71-80
	Cold	119.05	151-200
NPP: Kg C m^{-2}			
	Warm-dry	66.35±24.52	79.5
	Wet	53.51±22.96	135.45
	Cold	74.69±28.44	120.25

Model experiments

The simulated future of fire in these forest types is impacted by bark thickness and crown depth. In these simulations, fire is driven by differences in bark thickness and crown depth (forest structure), climatic differences in sites, and forest type differences in parameterization (Table S2).

When bark thickness is adjusted based on species types of the PFT (Table S2), we found successful ignitions are higher overall in the Warm-dry PFT, followed by the Cold and Wet PFTs (Figure 6). Cumulative carbon loss followed the same pattern, while fuels consumed had a tighter pattern with less differences between the PFTs (Figure 6).

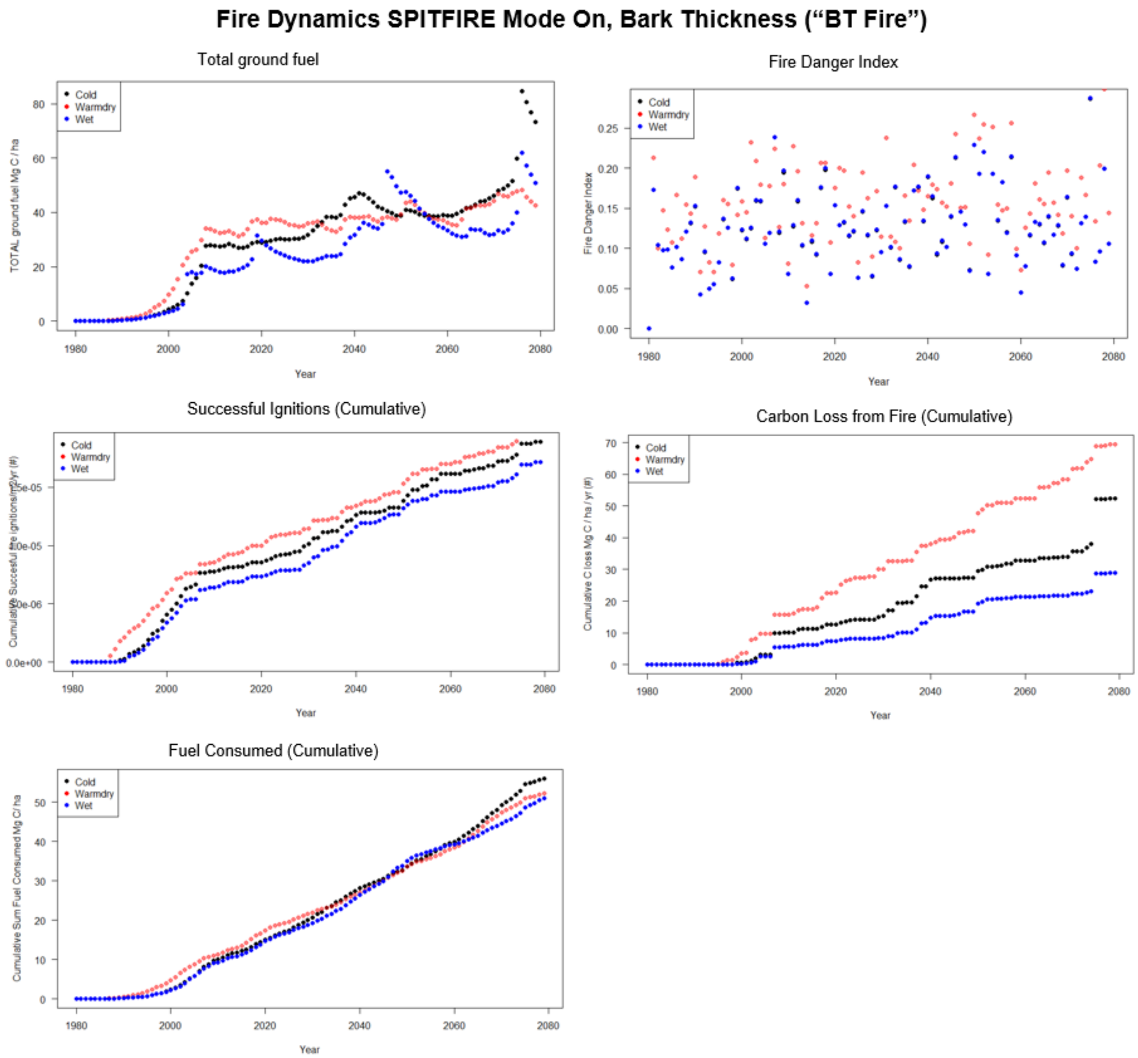

Figure 6. Fire dynamics over the 100-year simulation for each PFT, for the Bark Thickness experiment ("BT Fire").

When crown depth is adjusted based on species types of the PFT (Table S2), we found successful ignitions are higher overall in the Warm-dry PFT, followed by the Wet PFT, with very few ignitions for the Cold PFT (Figure 7). Cumulative carbon loss followed the same pattern, while fuels consumed had a tighter pattern with less differences between the PFTs, except for the Cold PFT (Figure 7).

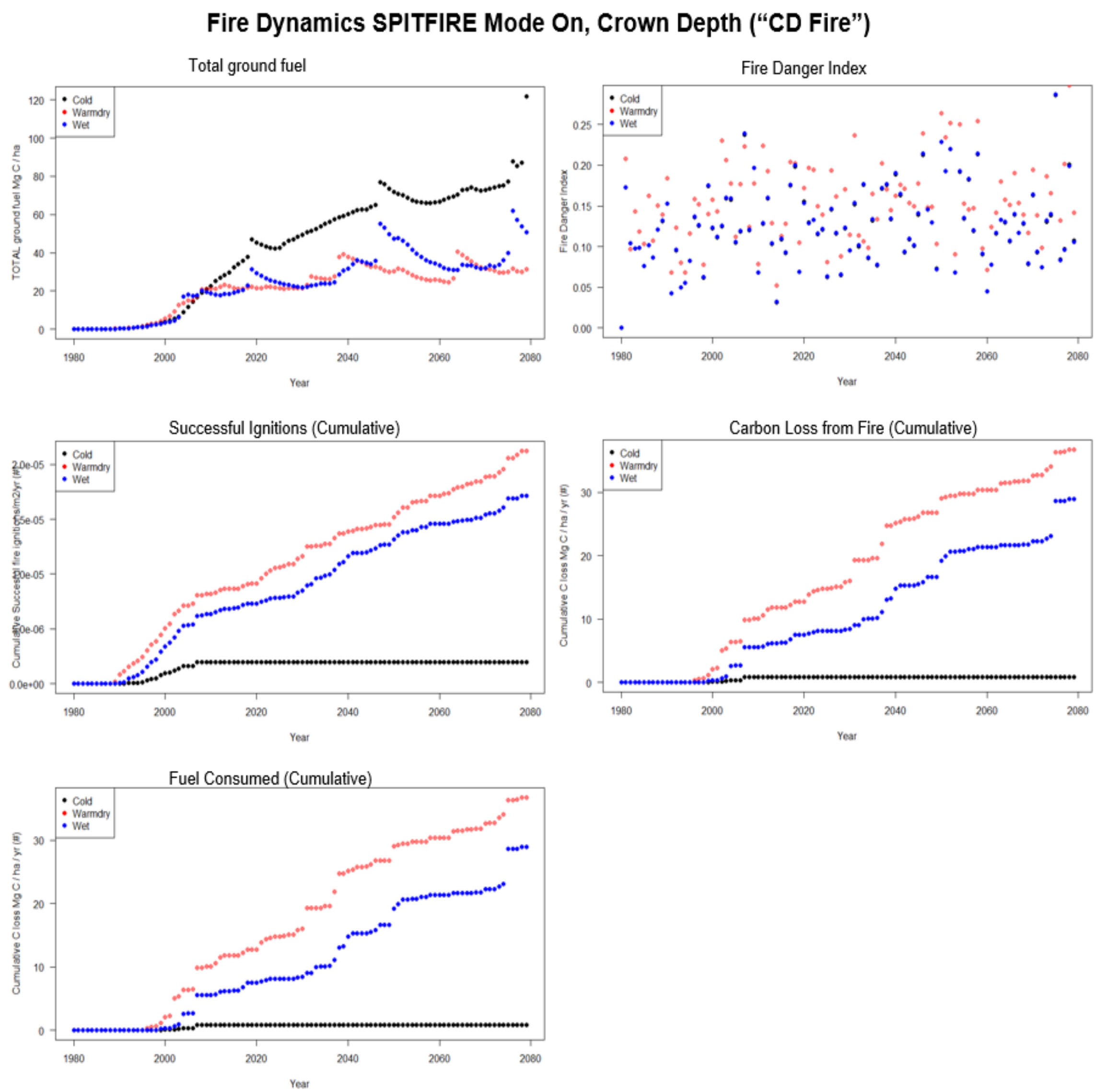

Figure 7. Fire dynamics over the 100-year simulation for each PFT, for the Crown Depth experiment ("CD Fire").

When bark thickness is adjusted based on species types of the PFT (Table S2), we found total live biomass, NPP, and fine root biomass were are higher overall in the Cold PFT, followed by the Warm-dry and Wet PFTs (Figure 8). Total understory biomass did not follow the same pattern and was relatively varied across the simulation for the Cold and Warm-dry PFTs, with much less understory development throughout the simulation for the Wet PFT (Figure 8).

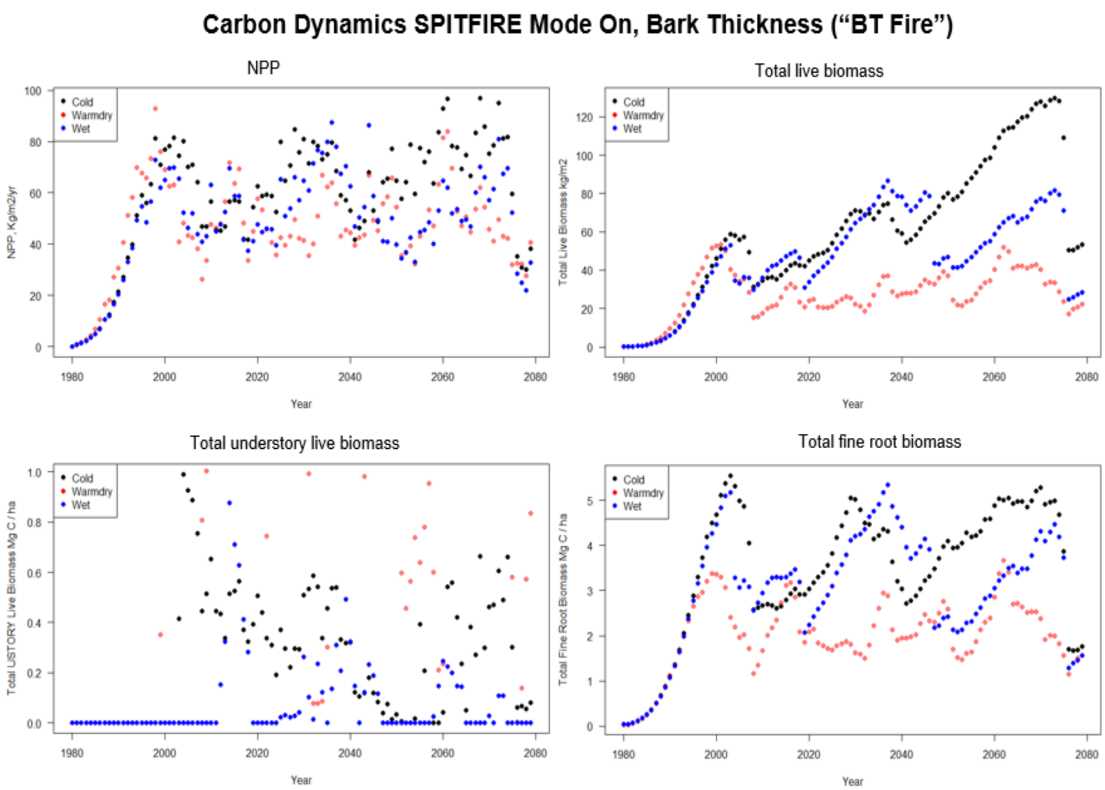

Figure 8. Carbon dynamics over the 100-year simulation for each PFT, for the Bark Thickness experiment ("BT Fire").

When crown depth is adjusted based on species types of the PFT (Table SX), we found total live biomass and NPP were higher overall in the Cold PFT, followed by the Warm-dry and Wet PFTs (Figure 9). Fine root biomass was more consistent for all three PFT types. Total understory biomass did not follow the same pattern, with the Cold PFT having the highest understory live biomass, followed by the Wet PFT and Warm-dry PFT (Figure 9).

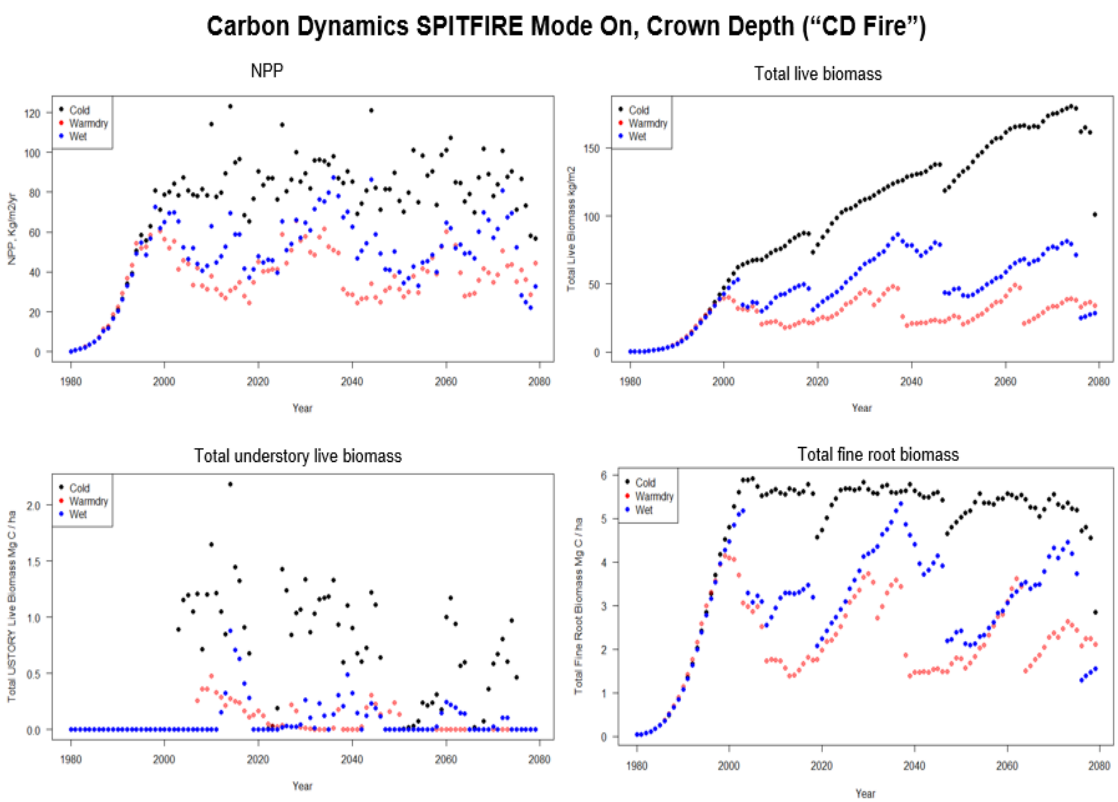

Figure 9. Carbon dynamics over the 100-year simulation for each PFT, for the Crown Depth experiment ("CD Fire").

Discussion

There is critical need to understand forest resilience to intensifying fire regimes (Johnstone et al., 2016). Here, we use CLM-FATES-SPITFIRE to investigate the future of fire and forest dynamics in Northern Rockies forests over the 21st (2000-2080). We calibrated the model using present-day biomass stock, fire occurrence, mortality, and NPP data. Future simulations (until 2080) forced with future climate data show an increase in wildfire ignitions and fuel consumed, especially for the warm-dry PFT which is where we would expect the most fire activity. The comparisons show fire increases from the modern record for Wet and Cold forest types, while the Warm-dry forest type continues to have a shorter mean fire return interval (20-40 years). Fire increase for wet and cold forests is followed by immediate, subsequent decreases in forest carbon (up to 20% losses). However, post-fire recovery of forest carbon stocks occurs for all forest types for the simulation range, with complete AGC recovery seen in as little 10-20 years following some of the disturbances.

Running FATES without SPITFIRE compared with simulations run with default SPITFIRE parameters show limited differences in carbon dynamics. Here, climate and land surface variables are driving the differences seen in carbon dynamics and fire dynamics. These results vary from other studies showing carbon dynamics are significant impacted by fire frequency and timing (Bartowitz et al., 2019; Hudiburg et al., 2017; Kelly et al., 2015). However, these results may be a relic of the default SPITFIRE parameterization used for this sensitivity test. Default SPITFIRE parameters lead to limited fire occurrence – drying ratio and lightning strike scale (Table S2 and (Buotte et al., 2021)) needed to be altered in order to have more realistic fire effects (as shown in the crown depth and bark thickness experiments, discussed below).

Altering bark thickness and crown depth did lead to some PFT-specific differences in fire dynamics and impacts on forest carbon. Patterns were similar for successful ignitions and carbon loss, with differences between the PFTs exaggerated more in the crown depth simulations, i.e., there were bigger differences in ignitions and carbon loss for crown depth simulations than for bark thickness simulations. One thing to note is that for the Cold PFT, crown depth seems cause fires to stop occurring early in the simulation. This is surprising as fires did occur later in the simulation in the Cold PFT for the bark thickness simulation. This may be because crown depth (horizontally) was set too low for the cold PFT (crown depth was lowest for the Cold PFT, followed by the Wet PFT, with the Warm-dry PFT having the largest crown depth, Table S2), which may have impacted fire spread. The Cold PFT had the lowest crown depth, which may have led to starvation and subsequent impacts on fire dynamics.

Despite having very little fire occur, the Cold PFT for the crown depth experiment still had the highest total biomass of the three PFTs, which may be due to the fact that the cold forest was not losing carbon to fire (Bartowitz et al., 2019). Successful ignitions were the highest in the warm-dry forest, which follows modern patterns where warm-dry forests have high fire return intervals (Rollins et al., 2007). Carbon loss from fire was higher for the warm-dry and wet forests in the bark thickness simulation than in the crown depth simulation, showing that altering crown depth led to lower losses of carbon from fire. The simulated future of carbon dynamics in these forest types is impacted by bark thickness and crown depth. In these simulations, carbon dynamics are driven by differences in bark thickness and crown depth (forest structure), climatic differences in sites, and forest type differences in parameterization (Table S1).

Future simulations also showed PFT-specific differences in carbon dynamics. Despite immediate losses of total aboveground biomass following fire events, in nearly every fire simulation there is a recovery of carbon stocks in the following decades. This follows other modeling and observational studies of post-fire carbon dynamics (Dunnette et al., 2014; Harris et al., 2019; Hudiburg et al., 2017; Meigs et al., 2009; Smithwick et al., 2009). Understory live biomass is highly impacted by fire, in many of the fire simulations it is completely depleted, but recharges quickly. Total live biomass in the bark thickness experiment was highest for the cold PFT starting at mid-century and going towards the end of the simulation (2080). This may be because the cold, subalpine forests may see an increase in the growing season with climate change towards the end of the century, including warmer spring and fall seasons allowing for increased growth for this forest type. In contrast, the warm-dry PFT sees less recovery of carbon stocks after fire events compared to the other PFT types, which may be due to the increase in fire and less favorable growing conditions in lower elevation forests (including hotter and drier growing seasons). While *P. ponderosa* is a very resilient tree species (Restaino et al., 2019; Savage & Mast, 2005; J. E. Stenzel et al., 2021) and is able to survive seasonal drought by going dormant, an increase in the duration of seasonal drought coupled with even hotter temperatures may lead to less overall growth in this forest type in the future (Skov et al., 2004).

There are several limitations to this study. We only simulated three PFTs, which are based on three forest types (although these three forest types make up >90% of the forested area of the domain). Most DGVM models use low-resolution PFTs to simply the model and the PFTs we use are more resolute than what is used in many DGVM simulations (Buotte et al., 2019a). One of the highlights of FATES is the perfect plasticity approach to capture canopy spread and fill (Team, 2019), however, we did not use this function because it was causing carbon starvation and high tree mortality as a relic of how the PPA is coded in the model (not mechanistic forest dynamics). The FATES community is not yet using the dynamic spread function. There are also many difficulties with spread when the FATES harvest/management module is on, so we did not use harvest scenarios in this study (canopy spread does not work post-harvest). Finally, competition between trees and non-tree species is challenging to incorporate in FATES, and is still in the beginning phases for the FATES community. We did not incorporate a non-tree understory in our simulations, but this will be important to incorporate once competition between PFT types (i.e., forest, shrubland, grassland) is resolved.

Future research focusing on modeling the fire and carbon dynamics in the Northern Rockies region can now be accomplished because of this study. This is important because a range of forest-fire-carbon scenarios can now be run for the Northern Rockies region with a state-of-the-art ESM and prognostic fire model. Prescribed fire has never been attempted with CLM-FATES-SPITFIRE; in simulated prescribed fire scenarios, a prescribed fire SPITFIRE parameterization would need to be developed to explore scenarios with this type of management strategy. Alternatively, a modified harvest module parameterization could be used to create a prescribed fire scenario. As prescribed fire becomes a more popular treatment method (Schoennagel et al., 2017) due to studies showing how effective it is for returning fire to the land (Kolden, 2019), that will have more funding availability, being able to use a mechanistic DGVM (Buotte et al., 2021; Koven et al., 2019) with a state-of-the-art fire mechanism (Gitta Lasslop et al., 2014; K. Thonicke et al., 2010) will be crucial to understand long and short-term impacts of this management strategy.

The future of fire and carbon dynamics is understudied in Northern Rockies forests. For the first time, we have parameterized a state-of-the-art dynamic global vegetation model (FATES) coupled with a mechanistic fire model (SPITFIRE) in an important, forested region. Prior to this effort, this model has only been used to simulate a handful of locations on the planet (Buotte et al., 2021; Huang et al., 2020; Koven et al., 2019) – the Northern Rockies (Figure 1) is only the second temperate forest location where CLM-FATES has been run (Buotte et al., 2021; Jeffrey E Stenzel, 2021). The Northern Rockies are a unique forested region in the inland west – they are wetter and more productive than neighboring northern inland forests and much more productive than forests in the southern inland part of the country. In addition, they have had limited fire occurrence in the last several decades compared to other inland forests. Despite how unique these forests are, and their importance in acting as a natural climate solution due to their carbon-dense nature, it's unclear how future climate change will impact both carbon dynamics and wildfire occurrence in the region. Parameterizing the most common forest types and SPITFIRE to this region is a tremendous first step towards understanding future fire and carbon dynamics in the region and opens the door to many other explorations regarding forest management.

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Supporting Information

Table S1. FATES parameters used for PFT-specific parameterization (Buotte et al. 2021, Stenzel 2021).

Fates Parameter	PFT	Value
fates_leaf_long	WET & COLD	7
fates_smpsc	WET & COLD	250000
fates_leaf_stomatal_slope_medlyn	WET & COLD	2.3
fates_leaf_vcmax25top	WET & COLD	45
fates_mort_freezetol	WET & COLD	-55
fates_alloc_storage_cushion	WET & COLD	1.2
fates_mort_scalar_cstarvation	WET & COLD	0.6
fates_recruit_initd	WET & COLD	0.1
fates_allom_d2h1	WET & COLD	0.64
fates_allom_d2h2	WET & COLD	0.37
fates_recruit_hgt_min	WET & COLD	1.3
fates_allom_d2ca_coefficient_max	WET & COLD	0.23
fates_allom_d2ca_coefficient_min	WET & COLD	0.23
fates_leaf_slatop	WET & COLD	0.0087
fates_leaf_slamax	WET & COLD	0.009
fates_allom_d2bl1	WET & COLD	0.35
fates_allom_d2bl2	WET & COLD	1.4
fates_allom_d2bl3	WET & COLD	0.85

fates_allom_agb1	WET & COLD	0.06896
fates_allom_agb2	WET & COLD	0.572
fates_allom_agb3	WET & COLD	1.94
fates_allom_agb4	WET & COLD	0.931
fates_allom_l2fr	WET & COLD	1
fates_allom_agb_frac	WET & COLD	0.7
fates_mort_bmort	WET & COLD	0.0025
fates_fnrt_prof_a	WET & COLD	5
fates_fnrt_prof_b	WET & COLD	4
fates_wood_density	WET & COLD	0.35
fates_seed_alloc	WET & COLD	0
fates_seed_alloc_mature	WET & COLD	0.05
fates_seed_dbh_repro_threshold	WET & COLD	15
fates_fire_bark_scaler	WET & COLD	0.07
fates_prt_nitr_stoich_p1	WET & COLD	0.017
fates_allom_dbh_maxheight	WET & COLD	90
fates_comp_excln	WET & COLD	3
fates_mort_cstarvetol	WARM-DRY	0.5
fates_leaf_long	WARM-DRY	4
fates_smpsc	WARM-DRY	-250000
fates_leaf_stomatal_slope_medlyn	WARM-DRY	2.3
fates_leaf_vcmax25top	WARM-DRY	63
fates_mort_freezetol	WARM-DRY	-55

fates_alloc_storage_cushion	WARM-DRY	1.2
fates_mort_scalar_cstarvation	WARM-DRY	0.6
fates_recruit_initd	WARM-DRY	0.1
fates_allom_d2h1	WARM-DRY	0.64
fates_allom_d2h2	WARM-DRY	0.37
fates_recruit_hgt_min	WARM-DRY	1.3
fates_allom_d2ca_coefficient_max	WARM-DRY	0.23
fates_allom_d2ca_coefficient_min	WARM-DRY	0.23
fates_leaf_slatop	WARM-DRY	0.0069
fates_leaf_slamax	WARM-DRY	0.0072
fates_allom_d2bl1	WARM-DRY	0.2
fates_allom_d2bl2	WARM-DRY	1.4
fates_allom_d2bl3	WARM-DRY	0.85
fates_allom_agb1	WARM-DRY	0.06896
fates_allom_agb2	WARM-DRY	0.572
fates_allom_agb3	WARM-DRY	1.94
fates_allom_agb4	WARM-DRY	0.931
fates_allom_l2fr	WARM-DRY	1
fates_allom_agb_frac	WARM-DRY	0.7
fates_mort_bmort	WARM-DRY	0.0025
fates_fnrt_prof_a	WARM-DRY	5
fates_fnrt_prof_b	WARM-DRY	4
fates_wood_density	WARM-DRY	0.38

fates_seed_alloc	WARM-DRY	0
fates_seed_alloc_mature	WARM-DRY	0.05
fates_seed_dbh_repro_threshold	WARM-DRY	15
fates_fire_bark_scaler	WARM-DRY	0.07
fates_prt_nitr_stoich_p1	WARM-DRY	0.022
fates_allom_dbh_maxheight	WARM-DRY	90
fates_comp_excln	WARM-DRY	3

Table S2. FATES-SPITFIRE parameters swapped from default values (Buotte et al. 2021).

FATES-SPITFIRE Parameter	**PFT**	**Value**
fates_fire_cg_strikes	WET	0.5
fates_fire_drying_ratio	WET	13000
fates_fire_bark_scaler	WET	0.12
fates_fire_crown_depth_frac	WET	0.5
fates_fire_cg_strikes	WARM-DRY	0.5
fates_fire_drying_ratio	WARM-DRY	13000
fates_fire_bark_scaler	WARM-DRY	0.15
fates_fire_crown_depth_frac	WARM-DRY	0.7
fates_fire_cg_strikes	SUBALPINE	0.5
fates_fire_drying_ratio	SUBALPINE	13000
fates_fire_bark_scaler	SUBALPINE	0.08
fates_fire_crown_depth_frac	SUBALPINE	0.3

Table S3. Selection of simulation runs completed to test default fire (drying ratio, cloud-to-ground strikes), no fire, bark thickness, and crown depth impacts on carbon dynamics and fire dynamics.

Run name	Simulation testing	Length
fire_fut_pipo	Default Fire	71
fire_fut_wet	Default Fire	71
fut_cold	Default Fire	71
_fire_fut_pipo	Default Fire	50
_fire_fut_wet	Default Fire	50
_dryratio_fut_cold	Default Fire	50
pipo_fire_fut	Default Fire	100
wet_fire_fut	Default Fire	100
sub_cold_fire_fut	Default Fire	100
19jan2022_fire_fut	Drying ratio	71
26jan2021_fire_fut	Drying ratio	50
26jan_dryratio_fut	Drying ratio	50
pipo_NO_FIRE	No fire	100
abgr_wet_NO_FIRE	No fire	100
sub_cold_NO_FIRE	No Fire	100
cg_1	Crown-ground strikes	70
cg_1_sf2	Crown-ground strikes	70
cg_dr_sf2	Crown-ground strikes	70
cg2	Crown-ground strikes	100
pipo_cg2	Crown-ground strikes	119
abgr_wet_cg2	Crown-ground strikes	119
abgr_sub_cg2	Crown-ground strikes	119
pipo_cg2_BT	Bark Thickness	119
abgr_wet_cg2_BT	Bark Thickness	119
sub_cold_cg2_BT	Bark Thickness	119
pipo_cg2_BT	Bark Thickness	100
abgr_wet_cg2_BT	Bark Thickness	100
sub_cold_cg2_BT	Bark Thickness	100
pipo_cg2_BT	Bark Thickness	100
abgr_wet_cg2_BT	Bark Thickness	100

sub_cold_cg2_BT	Bark Thickness	100
pipo_cg2_BT	Bark Thickness	100
abgr_wet_cg2_BT	Bark Thickness	100
sub_cold_cg2_BT	Bark Thickness	100
pipo_cg2_CD	Crown Depth	119
abgr_wet_cg2_CD	Crown Depth	119
sub_cold_cg2_CD	Crown Depth	119
pipo_cg2_CD	Crown Depth	100
abgr_wet_cg2_CD	Crown Depth	100
sub_cold_cg2_CD	Crown Depth	100
pipo_cg2_CD	Crown Depth	100
abgr_wet_cg2_CD	Crown Depth	100
sub_cold_cg2_CD	Crown Depth	100
pipo_cg2_CD	Crown Depth	100
abgr_wet_cg2_CD	Crown Depth	100
sub_cold_cg2_CD	Crown Depth	100

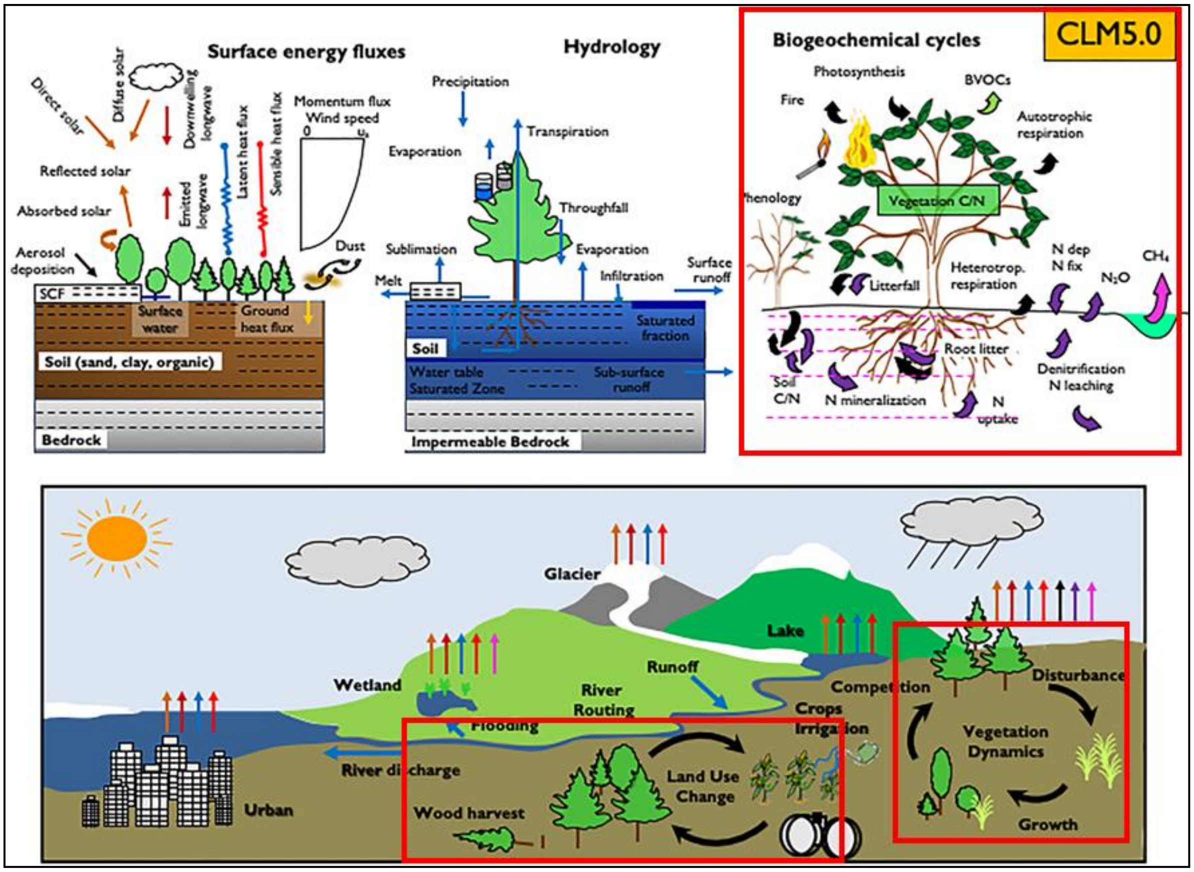

Figure S1. Conceptual figure of all modules of the Community Land Model, adapted from NCAR. Red boxes indicate processes of importance for this study: biogeochemical cycling (carbon), vegetation dynamics, and land use change. Figure adapted from CLM documentation and NCAR (Lawrence et al., 2019; Team, 2019).

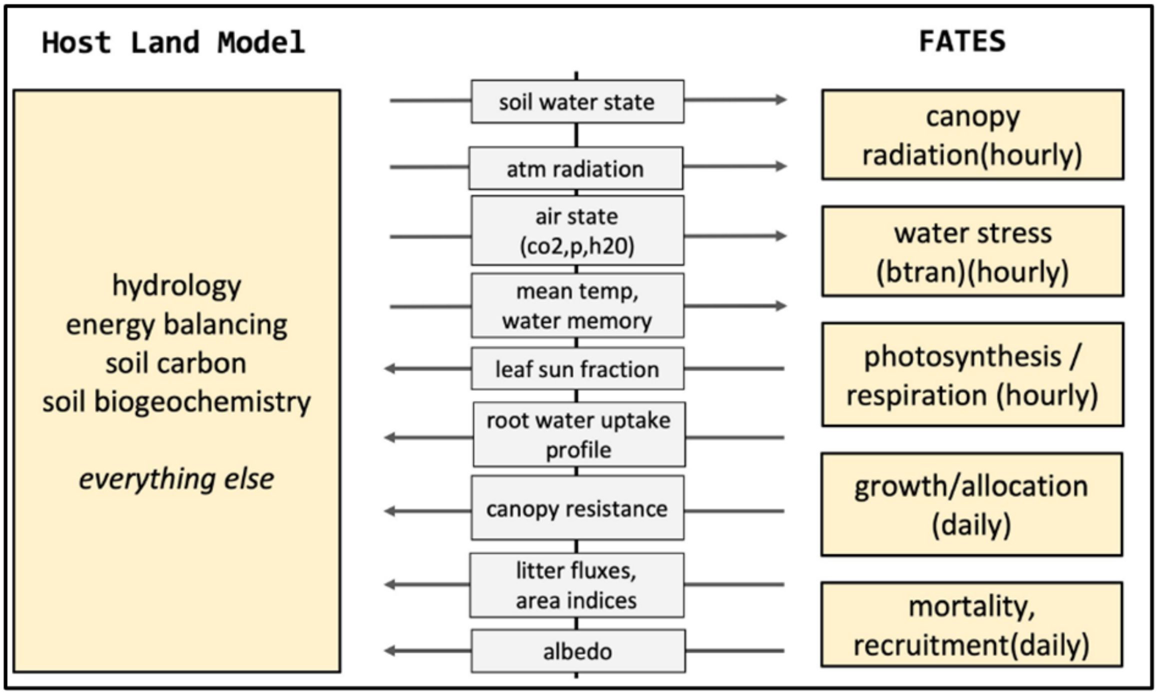

Figure S2. Connections between the Host Land Model (HLM, e.g., CLM) and FATES. The HLM runs hydrology, energy balance, soil carbon, soil biogeochemistry, while FATES runs canopy radiation, water stress, photosynthesis and respiration, growth and allocation, and mortality and recruitment. Figure adapted from FATES documentation and NCAR (Team, 2019).

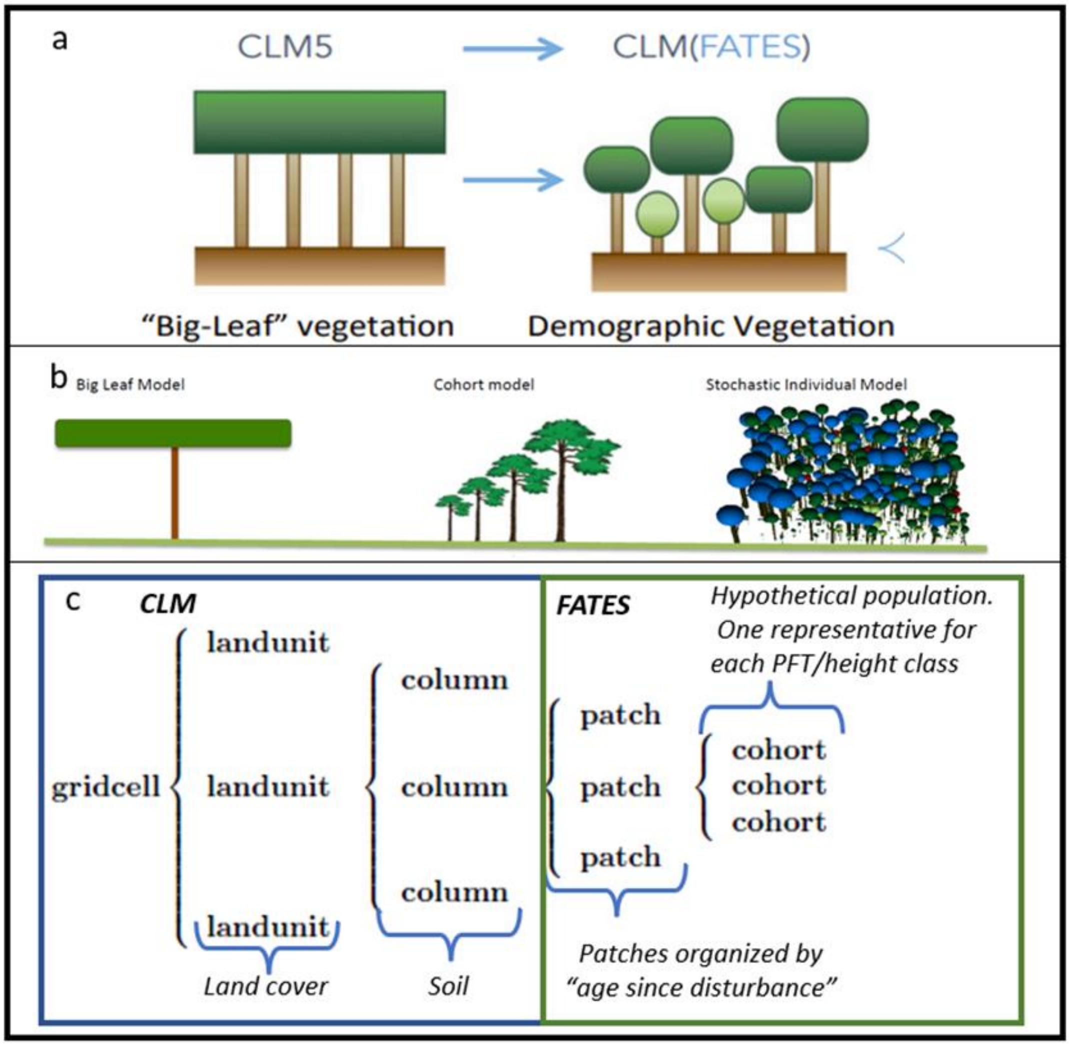

Figure S3. Conceptual model showing organization differences between CLM and CLM coupled with FATES. a) Complexity comparison between a Big Leaf Model (e.g., CLM), Cohort Model (e.g., FATES), and Individual Based Model (e.g., LPJ, Landis). b) Organizational structure of CLM with the FATES module. In CLM, columns would be directly broken down into PFT components (not shown), while in FATES columns are broken down into patches (age since disturbance) and cohorts (PFT and heigh classes), which allows for forest age and structure differences within a grid cell. Figure adapted from NCAR and FATES Documentation (Team, 2019).

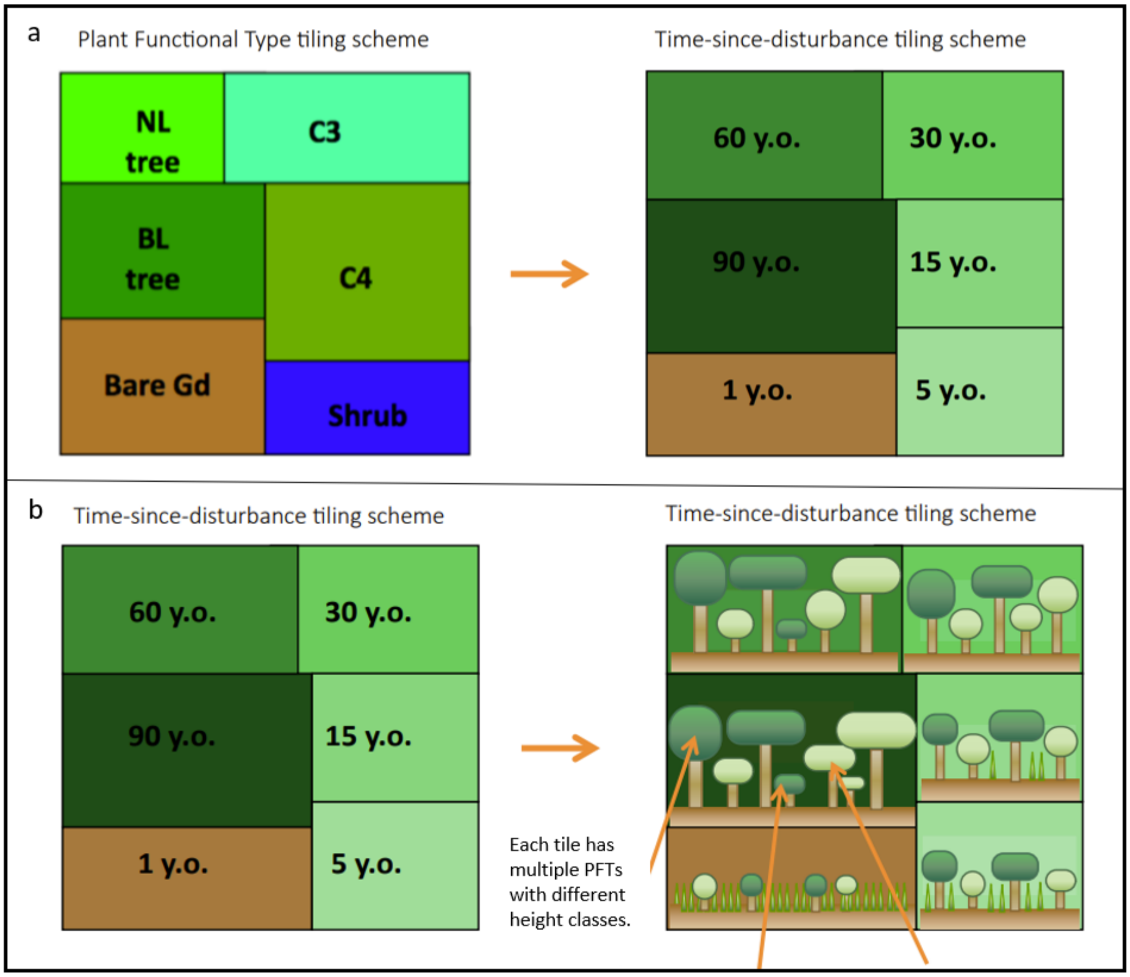

Figure S4. Tiling scheme used in CLM 5.0 and CLM-FATES. a) CLM 5.0 uses a plant functional type tiling scheme (left), FATES has moved to a time-since-disturbance (TSD) tiling scheme (right). b) Description of the time-since-disturbance tiling organization. Each TSD tile is made up of one or more PFTs, which can have multiple height classes. Figure adapted from FATES documentation and NCAR (Team, 2019).

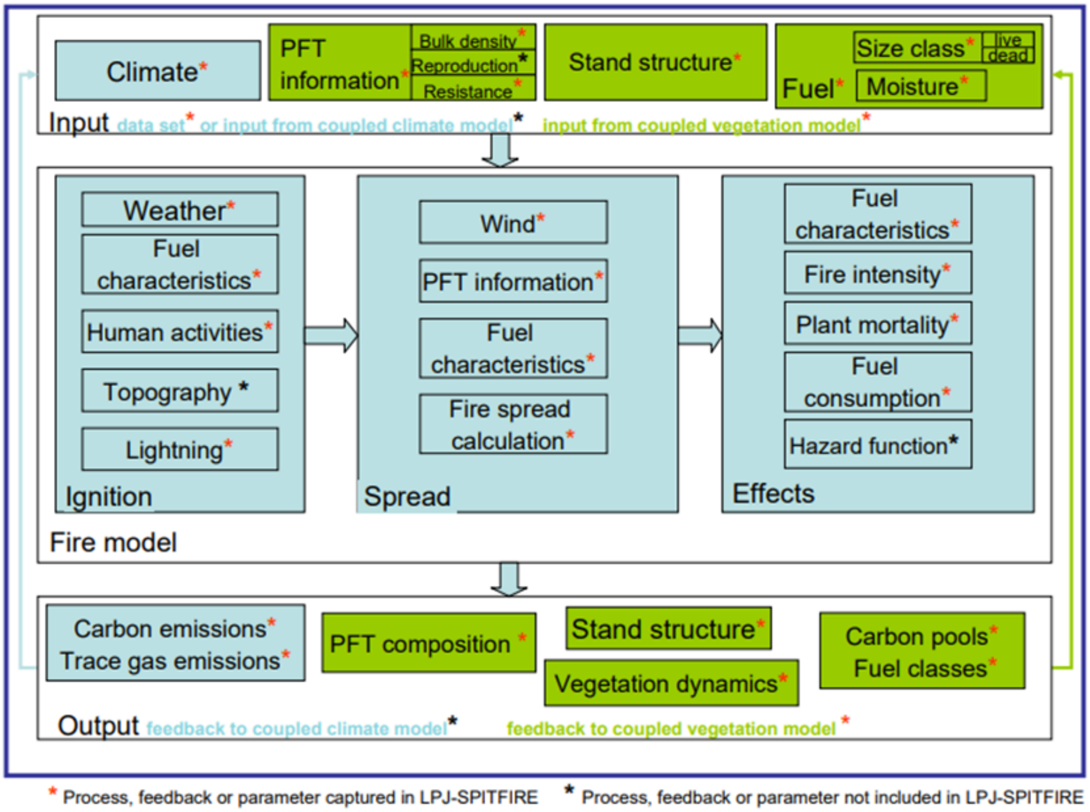

Figure S5. Conceptual figure showing SPITFIRE processes and integration to CLM-FATES processes. Figure adapted from Thonicke et al. 2010 (Kirsten Thonicke et al., 2010)

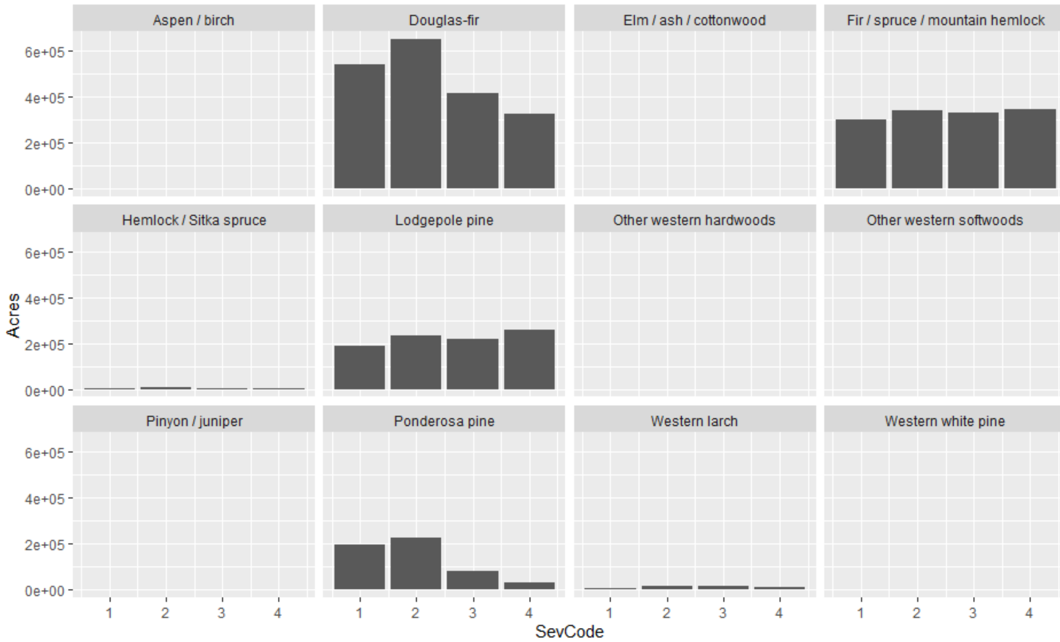

Figure S6. Acres burned by severity class (1-4, unburned to high severity) within the study domain (1984-2018) (Eidenshink et al., 2007).