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Incorporating Disturbance in Forest Carbon Modeling: A Review of Available Models for Pacific Northwest Forests

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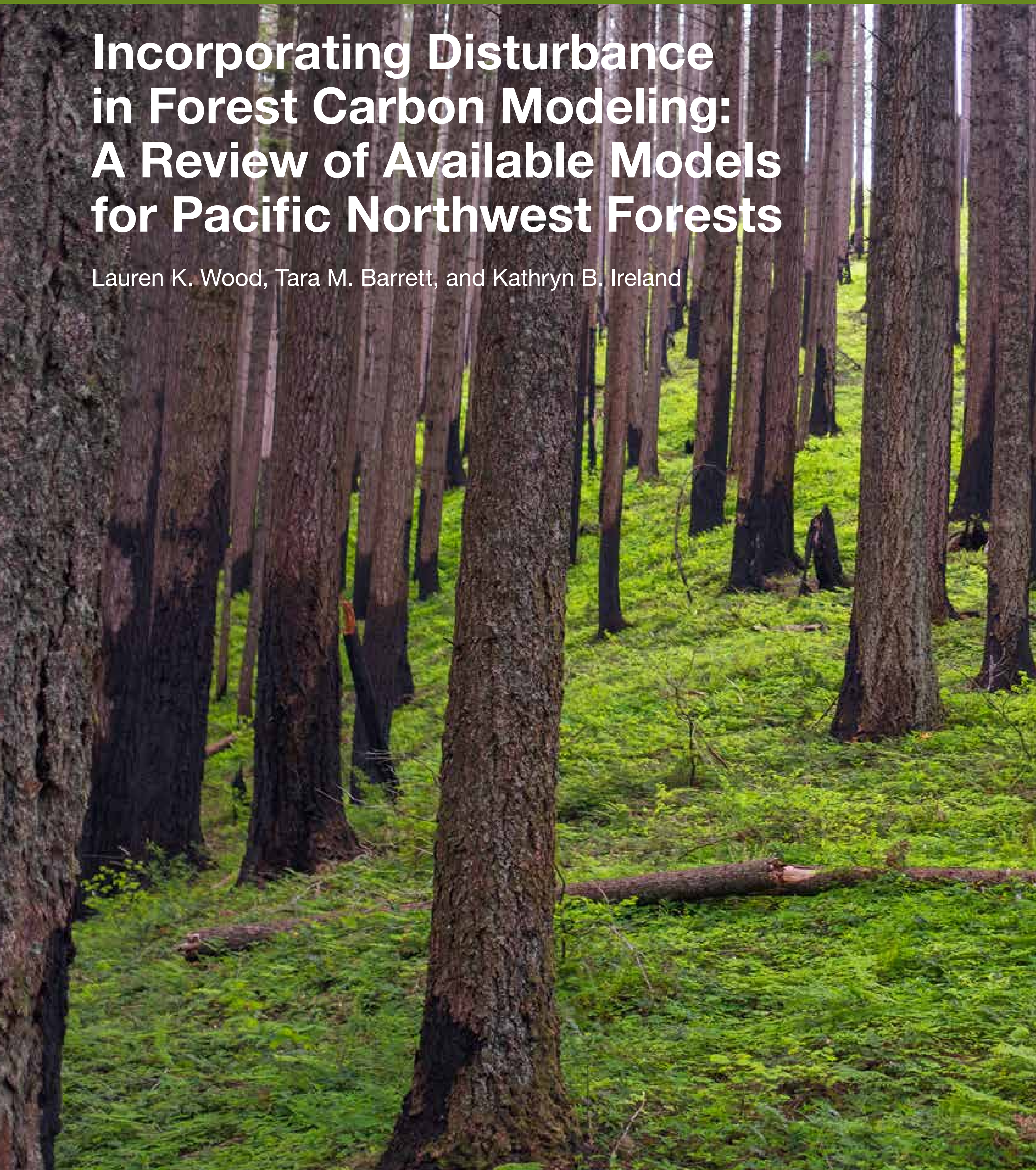

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Cover photo: A forest recovering from wildfire in the Columbia River Gorge, Oregon. Photo by aquamarine4; stock.adobe.com.

Abstract

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Storing carbon in forests is one approach often proposed to help reduce atmospheric carbon dioxide, one of the greenhouse gases contributing to climate change. Land managers can use models to better understand how much carbon is stored in forests, and how forest carbon changes in response to forest growth, mortality, management, and disturbance. Knowing which model to choose based on land management goals can be a challenge. This report describes 15 forest carbon models that are applicable to Washington, Oregon, and California, with a focus on how each model incorporates disturbance and harvest.

KEYWORDS:

Carbon

Disturbance

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Models

Contents

Introduction

Forests are a vital part of climate change mitigation. Anthropogenic carbon dioxide (CO_2) emissions and climate change have driven new management goals to increase forest carbon storage (carbon stocks) and sequestration through photosynthesis and carbon storage in wood and soils (Edenhofer et al. 2014, Goodale et al. 2002). An array of models that can account for forest carbon stocks and changes are used to project tree growth, tree species survival, timber production, and the most efficient location for wood processing plants, among other things. Changing climate conditions are expected to alter disturbance regimes, highlighting the importance of projecting changes to forest carbon dynamics. Projecting forest carbon dynamics also requires predicting changes to forest structure, such as density, height, patch size, connectivity, and woody debris. These forest structure and carbon projections also connect with many management objectives under novel climate and disturbance scenarios (Bugmann and Seidl 2022, Seidl et al. 2016).

Different forest carbon models are used to answer different questions depending on the organization and the forest management goals. Many models are used to inform public policy (i.e., how to sequester carbon statewide) to meet criteria for forest carbon assimilation federally and to calculate the magnitude of carbon offsets in participating states (Case et al. 2021, Janowiak et al. 2017, Kurz and Apps 2006, Maness 2009, Prisley and Mortimer 2004). The California carbon offset program is one example of a state-run carbon offset program. It is designed to allow companies or individuals to earn credits through projects that store or absorb more carbon than would be emitted through industry or individual activities. Although the use of forest carbon offset projects has the potential to slow the rate of atmospheric CO_2 increase (Edenhofer et al. 2014), the longevity and success of offset projects may depend on verification procedures (Moura Costa et al. 2000) and whether difficulties in creating and regulating carbon markets can be overcome (Lovell 2010). Specifically, voluntary carbon offset markets have undergone previous updates to regulations, as noted in the United Kingdom by Lovell (2010), to also account for additionality, verification, project types, and sustainable development. Recent studies have called for a better understanding and inclusion of permanence in carbon offsets to account for changes in forest disturbance frequency (Badgley et al. 2022).

Many modeling efforts to calculate carbon offset credits do not effectively account for the effects of disturbance, often underestimating the chance of reversal (van Kooten et al. 2019) and excluding carbon effects that can occur following disturbance. For example, fire immediately releases some of the carbon from the living and dead pools of the forest into the atmosphere and releases more over time as dead wood decays. However, low- and mixed-severity fires can also lead to growth releases in surviving trees and a shift to carbon storage in larger, more fire-resistant trees (Hurteau and Brooks 2011, North and Hurteau 2011).

Modeling efforts tend to include fire more often than other disturbance types because it is well-studied and the resulting carbon consequences are better understood. In contrast, the effects of other disturbances on forest carbon dynamics, such as wind, insect infestation, disease, and freezing are less studied and thus hard to incorporate into models. Previous work investigating the carbon offset projects in California concluded that the model projections fail to account for the increasing severity and frequency of fire, insects, and pathogens, resulting in carbon storage that could be more temporary than the offset credits guarantee (Badgley et al. 2022).

This report is an assessment of currently available forest carbon models, how they incorporate disturbance, and areas for improvement. It was designed to inform planners, land managers, private foresters, and other partners who engage with forest management and planning for a changing climate. Individual chapters focus on model summaries, what is known about disturbances, and areas of improvement for the models.

Model Summaries

There are many different forest models with varying objectives, modeling approaches, and appropriate questions or spatial scales to which they can be applied. Broadly, the model types include gap models, biophysical process models, empirical growth and yield models, and state and transition models (see glossary). Gap models, also known as models of forest dynamics (Bugmann 2001, Bugmann and Seidl 2022), are built on the changes in a gap formed when a tree falls in the forest; these models are often used to address smaller forested areas. This modeling approach allows for simulation of fine resolution forest dynamics and associated processes. Biophysical process models scale up plant and ecosystem processes, such as photosynthesis and respiration; these models are usually applied to regional to continental scales (Perry and Enright 2006). Empirical growth and yield models were created to predict tree growth and timber harvest yield of forests but have been expanded to include other management goals (Ashraf et al. 2013, Shifley et al. 2017). State and transition models typically work on a landscape scale and represent different ecosystem states and thresholds that, when crossed, lead to changed states; for example, a transition from a ponderosa pine-dominated forest to a grass- and shrub-dominated community (Bestelmeyer et al. 2017). This report focuses on models that include natural disturbances and allow for management decisions within the user's control; it does not address models designed to forecast national or global economic trends.

Our subset of models was chosen from the pool of all forest models because each model (1) is applicable to California, Oregon, and Washington; (2) incorporates carbon in some way, whether by design or as a later extension to the original model; (3) can include one or more aspects of disturbance; (4) is suited to regional, bioregional, or finer spatial scales of the aforementioned Pacific states; and (5) is applicable where policy or management decisions at the modeled scales are within control of the user. We define "disturbance" to include direct and intentional modifications of anthropogenic origin, such as silviculture and prescribed fire; indirect and unintentional modifications, such as climate change outcomes (increased CO_2, higher temperatures); and natural disturbances in the form of wildfire, drought, weather, insects, and disease. These disturbance types are not necessarily independent; for example, elevated temperatures may beget drought and increase risks of insect damage.

MC2 Model

MC2 is a dynamic global vegetation model that uses biophysical processes of plant functional types (PFTs) (see glossary) rather than species to model vegetation composition, productivity, and ultimately the carbon stores of forests (Bachelet et al. 2015, Kim et al. 2018b). MC2 was developed to simulate the effects of future climate on vegetation composition using ecosystem processes and fluxes in relation to past climate scenarios and future climate projections. This model can be run on a regional to global scale, with corresponding cell resolution varying from fine to coarse (e.g., 1–50 km) as spatial extent increases. Vegetation is modeled as a single plant functional type in each cell. Carbon assimilation is determined through net primary production (photosynthesis minus plant respiration) and heterotrophic respiration on a monthly timestep. Belowground carbon dynamics are simulated in this model using soil decomposition rates for eight soil organic matter pools, soil nutrient loss via volatilization and leaching, and nitrogen deposition and fertilizer inputs. It includes several soil layers throughout the observed soil depth to improve the model performance (Kim et al. 2018b, Peterman et al. 2014).

The ways in which disturbance can be applied in this model are limited. Silvicultural practices included in MC2 are aboveground harvest with or without woody debris removal, fire suppression, and grazing (Rogers et al. 2011). Climate change can be incorporated mechanistically by investigating net carbon sequestration under temperature extremes, or by coupling the inputs of the model with climate projections from general circulation models (Bachelet et al. 2001, 2015; Golub et al. 2022; Kim et al. 2017, 2018a). MC2 can also incorporate CO_2 fertilization effects wherein increased atmospheric carbon increases CO_2 available for plants to fix during photosynthesis (Sheehan et al. 2019).

This model uses fuel loads and moisture thresholds to determine wildfire occurrence, which is the main disturbance simulated by this model. Fire ignition is not limited by ignition source (e.g., lightning or human ignitions), which it assumes to always be present. Rather, fire ignitions occur when fuel loads, time since last burn, and climatic conditions meet predefined thresholds (Lenihan et al. 2008). Fire does not spread among cells and is limited to one occurrence per grid cell per year (Kim et al. 2018b, Lenihan et al. 2008). Fire is applied to PFTs and the extent and severity are sensitive to fuel load, fuel characteristics (e.g., fuel moisture), and vegetation structure (Bachelet et al. 2001, Boisramé et al. 2022, Rabin et al. 2016).

Biome-Biogeochemical Cycle Model

Biome-Biogeochemical Cycle (Biome-BGC) is a biophysical process model that models both carbon assimilation rates and carbon storage based on PFTs. It was originally developed to investigate regional to global interactions of climate, biogeochemical cycles, and disturbance. Like MC2, Biome-BGC is considered a “big-leaf” model, meaning vegetation is simulated as one PFT per grid cell. Biome-BGC uses a daily timestep for meteorological and physiological input; typically, a 1-km^2 grid cell for spatial resolution; and a modeled area that usually ranges from regional to global. Biome-BGC includes belowground aspects of carbon, including soil carbon and nitrogen pools, fine root carbon and nitrogen, and soil organic matter (Hidy et al. 2016, Kang et al. 2014, Law et al. 2003, Thornton 1998).

Climate change, increased CO_2 concentration in the atmosphere, and nitrogen deposition are applied to the model through the application of a daily meteorological timestep. Biome-BGC can be coupled with other models to project climate change scenarios (Hlásny et al. 2014). Intentional human disturbance is represented via harvest, partial harvest, thinning, and slash burns (Hidy et al. 2016, Law et al. 2001, Thornton et al. 2002). Partial harvest is modeled as a proportion of the live tree pool that is felled then removed or routed to the dead wood pool; this is limited to even-age, single-species stands (Thornton et al. 2002, Turner et al. 2015). Thinning was later added, creating another path between live and dead carbon pools, and it can be applied to the original PFTs of Biome-BGC (Hidy et al. 2016).

Additional disturbances included in this model are wildfire of varying severities, general plant mortality and succession, and drought-induced senescence. Other disturbances, such as disease and insect infestation, can be added as a proportional mortality (Hidy et al. 2016; Turner et al. 2015, 2016). Fire can be relatively simplistically and probabilistically applied on an annual basis as a fraction of plant pools susceptible to fire. This method of fire modeling does not include spread among cells, nor does it use fuel moisture as a measure of fire likelihood or severity. Other disturbances are modeled relatively simply using the "whole-plant mortality fraction" that returns the carbon to the soil carbon pool (Thornton et al. 2005).

Community Land Model

The original objective of the Community Land Model (CLM) was to model how terrestrial systems influence and are influenced by climate using physical (i.e., climate), chemical (i.e., carbon and nitrogen cycling), and biological interactions. CLM is a biophysical process-based model that runs on PFTs and is capable of modeling heat fluxes, solar radiation, heterogeneous land types, soil hydrology, soil and litter decomposition, plant mortality, and land cover. The physiological variables of each PFT are sensitive to nitrogen and CO_2 enrichment (Fisher et al. 2019, Sakaguchi et al. 2016). Typical spatial resolution of CLM is 0.05 × 0.05° latitude and longitude (~6 × 6 km), although resolution can be user-defined, with smaller PFT patches making up the plant cover within the ~6 × 6 km cell. This model runs on 30-minute timestep weather and physiological inputs. CLM accounts for belowground biomass by modeling fine and coarse roots (Bonan et al. 2011, Duarte et al. 2017, Hudiburg et al. 2013).

Disturbance—wildfire, harvest, and mortality—can be modeled in updated CLM using Functionally Assembled Terrestrial Ecosystem Simulator (FATES), an extension used to better include the ecological complexities of forest landscapes (Koven et al. 2020). Management practices modeled in CLM are implemented through FATES by focusing on harvest, logging practices, and logging-related disturbance and mortality, such as roads, heavy machinery, and collateral mortality (Huang et al. 2020, Lawrence et al. 2019). Wildfire and drought are the only other disturbances included in CLM. Fire is incorporated into CLM as a disturbance using lightning or anthropogenic ignition and suppression, clearing for agriculture, and peat fires (Buotte et al. 2021, Lawrence et al. 2019). The SPITFIRE module in the FATES extension allows for more complex fire modeling. Fire establishment and spread are dependent on fuel availability, fuel moisture, and suppression level. Fire spread is dictated by wind speed, PFTs, fuel moisture, and suppression efforts (Law and Waring 2015, Lawrence et al. 2019). With FATES, intensity, duration, area, crown damage, and cambial damage can all be modeled (Thonicke et al. 2010). Belowground fire effects are limited to soil litter; the proportion of soil litter burned is equivalent to the proportion of aboveground vegetation burned (Oleson et al. 2010).

Water stress in forests can be modeled using the Plant Hydraulic module in FATES (FATES-Hydro) and is determined by the point at which 50 percent of the leaf stomata close (Fang et al. 2022, Xu et al. 2023). Drought-induced mortality can be modeled with CLM by establishing a threshold for hydraulic failure (when hydraulic tension in the plant can induce embolism, i.e., disruptions in continuity of the water stream transported within the xylem) and carbon starvation (the depletion of carbon stores associated with decreased photosynthesis, potentially in response to stomatal closure). Using a threshold of carbon starvation, the duration of hydraulic failure is more predictive of mortality than the individual occurrence of drought (McDowell et al. 2013).

Ecosystem Demography Model

Ecosystem Demography (ED2) is a dynamic global vegetation model that includes microenvironments and heterogeneity associated with individual tree and PFT dynamics (Longo et al. 2019, Medvigy et al. 2009). It is designed to model plant community dynamics and accompanying terrestrial carbon, water, and nitrogen fluxes with a focus on improved projection of plant-level responses to future climate scenarios (Longo et al. 2019, Medvigy et al. 2019). ED2 was the first land surface model to use a cohort-based approach to represent canopy diversity and heterogeneity. Cohorts are trees that are often grouped together because they commonly co-occur and are represented by one category (see glossary). In ED2, cohorts are collections of plants grouped together based on their size and PFT designation, and can include the disturbance history of their location. The model runs on a sub-hourly timescale, and model simulations are typically run on a climatological grid at spatial resolutions ranging from 1 to ~100 km (1 × 1° latitude and longitude). Areas modeled are landscape to continental scales. Within the climatological grid cells, finer resolution heterogeneity in soil properties, or differences in successional age and disturbance history can be represented as sub-grid cells. Sub-grid cells vary dynamically and can be either spatially implicit (e.g., Levine et al. 2016, Zhang et al. 2015), or represent specific spatial locations (e.g., Antonarakis et al. 2022, Medvigy et al. 2009).

The ED2 model accommodates management applications, including silvicultural practices (i.e., thinning, clearcutting), and a simplistic representation of prescribed fire. Plant and soil processes are sensitive to climate input and can be modeled to reflect changing CO_2 concentration, temperature, and precipitation regimes associated with climate change (Albani et al. 2006, Antonarakis et al. 2022, Levine et al. 2016, Zhang et al. 2015). ED2 also includes tree fall, windthrow, wildfire, and hurricanes (Longo et al. 2019, Zhang et al. 2022). The rates at which trees fall and transition to coarse woody debris is probabilistically determined by stand age. Fire ignition is controlled by soil moisture. Mortality resulting from fire events is assumed to be 100 percent, although recent modifications allow for more complex representation; this includes ignitions that are linked to lightning frequency and burn areas influenced by proximity to human settlements to account for fragmentation effects. The effects of drought stress can be represented either through decreasing the rate of stomatal conductance proportional to soil water availability (Longo et al. 2019), or a mechanistic representation of plant hydraulics (Xu et al. 2016). In both approaches, plant photosynthesis and stomatal conductance are directly coupled to soil moisture status (Longo 2014, Longo et al. 2018).

LANDIS-II Forest Landscape Model

LANDIS-II is a forest landscape model that was originally designed to model disturbance and succession across large landscapes. It is open source and modular, with multiple extensions that range from simple stochastic (e.g., randomly assigned or random onset of a disturbance) (see glossary) models to more complicated data-driven extensions. The primary processes modeled by LANDIS-II are successional processes and biogeochemical processes associated with seed dispersal, carbon flux, forest management, and climate change. This model uses a variable timestep for input, which depends on the extensions applied, and the timestep of the output is user defined. LANDIS-II is often used to model on the landscape scale and spatial resolution is also user defined based on a cell, which is a flexible size. Most LANDIS-II extensions focus on aboveground factors—aboveground living and dead biomass, aboveground mortality, and net primary productivity. However, the Net Ecosystem Carbon and Nitrogen (NECN) extension and DGS (DAMM-MCNiP [a soil carbon model], GIPL [a permafrost model] and SHAW [a hydrologic model]) extensions simulate soil carbon and nitrogen cycling and belowground productivity, such as fine and coarse roots, as a proportion of aboveground productivity (Gustafson et al. 2000, Scheller et al. 2011). The Forest Carbon Succession extension (ForCS) allows tracking of carbon dynamics in multispecies and multiage cohorts and can include disturbance and climate change (Dymond et al. 2015, Landry et al. 2021, Ling et al. 2020).

Forest management practices are coded into LANDIS-II and range from short rotation clearcutting to limited thinning (Creutzburg et al. 2017, Dymond et al. 2015). Extensions include additional practices such as fuels management and land-use change (Thompson et al. 2016). Carbon emissions from prescribed burns are modeled via the Social-Climate Related Pyrogenic Processes and their Landscape Effects (SCRPPLE) fire extension (Scheller et al. 2011). Climate change can be projected in LANDIS-II using the Climate Library (Lucash and Scheller 2021). This extension allows the user to either keep the mean temperature and total precipitation the same for each year of the model, input projected monthly mean temperature and sum precipitation, or randomly select the climate for each year of the simulation (Lucash and Scheller 2021). Drought can be modeled using the climate inputs—daily or monthly temperature and precipitation from climate projections can be input to simulate standard precipitation and evapotranspiration index (SPEI) and, thus, drought (Creutzburg et al. 2017). The drought extension (DGS) calculates soil moisture, thereby simulating water limitation (Lucash et al. 2023).

Disturbance was incorporated into LANDIS-II forecasting by design, particularly wildfire disturbance (Cassell et al. 2019, Maxwell et al. 2022, Sturtevant et al. 2009). In base LANDIS-II fire modeling, fire ignition is probabilistic, and spread is dictated by wind direction and speed, temperature, relative humidity, and rain; fire severity is modeled mechanistically based on wind, fuel, and time since last fire (Mladenoff 2004). There are many additional fire extensions, however, that can model wildfire, anthropogenic ignition, and prescribed burns, allowing the user to investigate the effect of prescribed fire on wildfire risk (Scheller et al. 2019). LANDIS-II has additional extensions to incorporate browsing on leaves by ungulates (De Jager et al. 2017), wind (Gustafson et al. 2018, Mladenoff and Baker 1999), insects (Sturtevant et al. 2004), and diseases (Tonini et al. 2018). Insect pests are implemented using the Biological Disturbance Agent (BDA) extension, where the probability of disturbance is determined by the density of the preferred host of the BDA (Foster 2011, Sturtevant et al. 2004). Insect disturbance is often compounded by drought effects, increasing both likelihood of and vulnerability to insect pests (Canelles et al. 2021, Sangüesa-Barreda et al. 2015, Temperli et al. 2015), but the LANDIS-II extension that accounts for that synergistic interaction has not yet been released. Pathogens and diseases are applied through the Epidemiological Disturbance Agent (EDA) extension (Tonini et al. 2018)—probabilistic transmission is based on land type, recent disturbances, forest species, and age susceptibility. Spread is weather dependent. The mechanism of infection is relatively simplified: infected cells are immediately infectious, and infection is either present or absent.

Carbon Budget Model of the Canadian Forest Sector

The Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) is a forest ecosystem carbon stock and change model that is driven by growth and yield curves. CBM-CFS3 can model past and future carbon fluxes, employing a user-defined climate projection, growth and yield, harvest, land-use change, natural and anthropogenic disturbance event, and decomposition data (Kurz et al. 2009, 2013; Pilli et al. 2016; Stinson et al. 2011). The main objective for developing CBM-CFS3 was to provide a carbon accounting tool for Natural Resources Canada's Canadian Forest Service to meet the Canadian greenhouse gas emissions and removals reporting requirements under the United Nations Framework Convention on Climate Change. The model needed to have the capacity to quantify carbon stocks and carbon stock changes in response to management practices and natural disturbances on forested land. CBM-CFS3 has been used for annual greenhouse gas reporting for Canada's forest sector since 2006 (Blondel et al. 2024). CBM-CFS3 is a stand- and landscape-level model that reports in annual timesteps. It models aboveground and belowground biomass and dead organic matter carbon stocks, including litter and soil organic carbon. Initial soil carbon stocks are calculated based on historic management, disturbance, growth, and species cover, and are dynamic over a model simulation.

CBM-CFS3 was designed to include anthropogenic disturbances from the outset to ensure that annual carbon fluxes could be determined under different silvicultural applications and harvesting regimes, such as thinning, partial harvest, clearcut, deforestation due to land-use change, or afforestation (Stinson et al. 2011). The ability to account for other disturbances, such as wildfire and insects is also available in CBM-CFS3. Wildfire, as well as any other disturbance in the CBM-CFS3, can be modeled with stand eligibility and area constraints. A wide variety of Canada-specific insect disturbances are available in CBM-CFS3, and some, including bark beetles and defoliating insects (i.e., mountain pine beetle, spruce beetle, forest tent caterpillar, spruce budworm, and large aspen tortrix) could be applied for use with potential modifications in projects in Washington, Oregon, and California. Since initial public release of the model in 2005, there have been ongoing improvements made to the model's list of disturbance types and options, volume-to-biomass conversion, and soil decay parameters. CBM-CFS3 users also have the option to modify any existing disturbance types in the model or insert new ones if the carbon transfer dynamics of said disturbances are known or can be determined. Any disturbance during a CBM-CFS3 simulation follows the user-defined criteria for stand eligibility, target (area, merchantable carbon, or proportion of area of all eligible stands), amount to be disturbed, and post-disturbance stand dynamics (Kull et al. 2019). While changes in CBM-CFS3 simulation climate data will only directly affect decay and dead organic matter carbon pools, it is possible for the user to model a project in a way that implements empirical adjustment in response to anticipated changes in climate data (Kull et al. 2019).

A spatially explicit version of the CBM-CFS3 called the Generic Carbon Budget Model (GCBM) is also available from the Canadian Forest Service. It uses the same representation of carbon dynamics as the CBM-CFS3 but can simulate very large areas that are >50 000 000 ha at user-defined spatial resolutions (Metsaranta et al. 2023, Smyth et al. 2020). Both CBM-CFS3 and GCBM are supported by the Canadian Forest Service via documentation and user training.

Forest Vegetation Simulator

Forest Vegetation Simulator (FVS) was originally designed for experimentation via simulation of forest vegetation changes in response to management actions (treatments), succession, and disturbance. FVS is an individual-tree, semi-distance independent growth and yield model and is the standard model in this category used by the U.S. Department of Agriculture Forest Service. Specific geographic variants of the model relevant to the west coast are Alaska, Pacific Northwest, west-side Cascades, east Cascades, Inland Empire, Blue Mountains, south-central Oregon and northeast California, inland California and southern Cascades, Klamath Mountains, western Sierra Nevada, and Central Rockies. Stands are the basic unit of management in FVS, and projections are dependent on interactions among the trees in the stand, however, the user interface easily allows for thousands of stands to be run at a time to provide summarized data at the stand, landscape, or regional level (Crookston and Dixon 2005). FVS accounts for carbon dynamics via the Fire and Fuels Extension (FFE) (Rebain 2010), which tracks the biomass of live and dead standing trees, dead downwood, duff and litter, herb and shrub components, and live and dead coarse roots, and the carbon that is removed from the stand via management (i.e., harvest) or released to the atmosphere by fire.

The FVS model incorporates disturbance in multiple ways. Intentional human disturbance through forest management practices (e.g., thinning, pruning, prescribed fire, fuels treatment) can be applied at the tree, plot, or stand level, allowing users to simulate both common and user-defined management actions. Fire, treatments of surface fuels, and carbon dynamics are modeled using the FFE (see below). The model includes climate change to influence mortality, growth rates, and species genetic interactions (Crookston et al. 2010). The process uses viability scores, which are individual tree climate scores that measure the likelihood that the climate at a given location and point in time is consistent with the climate recorded for the contemporary distribution of the species. The viability scores are based on climate predictions generated from downscaling general circulation models and scenarios from the Intergovernmental Panel on Climate Change's third and fifth assessments (Crookston 2014). The FVS climate extension (Climate-FVS) modifies, rather than replaces, the base components of the growth and yield model. In the climate model, the empirical growth rates are modified by genetic components, climate effects on site index, and species viability scores, while mortality and regeneration are primarily modified by species viability scores.

Additional disturbances, such as wildfire, insect and pathogens, and wind, can be incorporated into FVS simulations through user-defined mortality modifiers. FFE addresses fire mechanistically using surface fuel models, user-provided parameters for fuel moisture and wind speed, and stand conditions (slope and stand structure) to predict the intensity of surface fire based on surface flame length. This, combined with the canopy fuels, provides the basis for predicting occurrence of torching (whether the crown would catch on fire) or active crown fire (spread of fire from crown to crown). Based on the fire intensity calculated, FFE reports two indicators of fire behavior: flame length and fire type (surface, passive, conditional, or active). Torching index (wind speed needed for torching to occur) and crowning index (wind speed needed to sustain an active crown fire) are also reported as crown fire hazard indices (Rebain 2010, Reinhardt and Crookston 2003). Fire mortality is derived from scorch height, crown length, diameter, and species; some species have traits (e.g., thicker bark) that are more adapted to survive fires than others (Reinhardt and Crookston 2003).

Insect and pathogen models are available in some variants of FVS. Dwarf mistletoe infection can be applied to any western geographical variant, while western root disease models are applicable in a subset of western variants (Dixon 2022). Douglas-fir beetle, white pine blister rust, lodgepole mountain pine beetle, and west-wide pine beetle extensions have been created but not updated with the base FVS model, so they are not currently available. When available, these extensions use probabilistic infestation for susceptible stands but do not include infestation events in neighboring stands as part of the probability; these extensions cause automatic mortality in all the infested trees. The Douglas-fir beetle model extension includes effects from windthrow as a condition threshold within a stand as well as probability of infestation based on species and age class (Dixon 2022).

Bioregional Inventory Originated Simulation Under Management

The Bioregional Inventory Originated Simulation Under Management (BioSum) model simulates biophysical and economic outcomes of multiple alternative silvicultural trajectories on a statistically representative, spatially balanced sample of stand-level inventory data from the Forest Inventory and Analysis (FIA) database. BioSum can help evaluate landscape-scale effectiveness of broad management goals, including restoration, forest resilience to fire, merchantable and non-merchantable wood production, and wood-utilization facility prospects (Cabiyo et al. 2021, Loreno et al. 2015). Biophysical simulation is accomplished primarily via the individual tree-level FVS model and FFE extension, enabling granular analysis of in-forest and harvested wood by species, size, fire-effect characterization (fuel treatment and wildfire), and associated carbon dynamics. Although outcomes can be tracked at the tree level, the fundamental analysis unit is a forested FIA "condition" (full or partial plot represented as a stand in FVS), which is linked to on-the-ground measurements of vegetation on up to ~0.4 ha, which represents >2400 ha of landscape. Results can be statistically "expanded" based on that representation. BioSum relies on data from the FIA database, which is updated annually; FVS projections can be any length, but are typically either 5 or 10 years, with up to four cycles projectable within the BioSum framework. BioSum does not include soil carbon stocks but can be used to account for belowground tree carbon. BioSum can be applied to forests within all FVS variant regions.

Because BioSum uses FVS outputs, different management scenarios that can be modeled in FVS (see above) can be applied to the BioSum model (Barbour et al. 2008, Jain et al. 2020). BioSum can ingest any FVS output table, including those from the FFE extensions, allowing the user to apply fire in the same way. Thinning and pruning are applied through the base FVS model and can be fine-tuned to include only certain species, species groups, or size classes; in this way, the user can define forest management goals with certain basal areas, densities, or species as targets. Fire treatments can be applied in the FFE extension in FVS wherein the user can model prescribed burns, pile burns, or wildfires mechanistically using fuel load type, moisture, and site condition (slope, aspect, elevation, habitat type, location, stand index, and stand density). Pests and diseases in the form of dwarf mistletoe, Douglas-fir beetle, lodgepole mountain pine beetle, white pine blister rust, and general insect defoliation can be added into BioSum via prescriptions in FVS, although that has not been a focus of applications to date and the FVS base model is in the process of being updated to characterize these effects (Fried et al. 2017; Potts et al., n.d.). Live tree carbon stocks in the forest and in harvested trees are tracked in BioSum for each timestep and calculated via FIA equations at tree level, enhancing the granularity of carbon representation relative to that which is available in tables produced by FVS-FFE.

Vegetation Dynamics Development Tool

Vegetation Dynamics Development Tool (VDDT) is a state and transition model that was originally created to provide a framework for specifically investigating disturbances and how they change the vegetation type and structure. This is a landscape model that simulates landscape change. State and transition models use conditions/successional stages of vegetation types and vegetation structure, coupled with the probability of transitioning to a different state through succession or disturbances. VDDT runs on a stand spatial scale and an annual temporal scale, incorporating user-defined vegetation categories and user-defined transition rules. The model is usually applied to a predefined scale from landscape to ecoregion, state, or region. State and transition models run on the theoretical assumption that there are multiple stable states of an ecosystem that are differentiated by thresholds (Stringham et al. 2003). Vegetation biomass, and thus carbon stocks, can be estimated by combining VDDT with regression models derived from forest inventory data and potential vegetation combinations, similar to cohorts (Spies et al. 2017).

The application of disturbance in VDDT is extensive—the model can include both silvicultural forest management disturbances and natural disturbances. Direct silvicultural disturbances that can be applied to a stand include clearcutting, prescribed burns, thinning, partial cuts, overstory removal, sanitation cuts, and group and individual cuts (Hemstrom et al. 2007). Climate change events and trends (i.e., warming) can be included as a user-modified time series file with Monte Carlo multipliers that allow for normal, high, and severe years for cyclical weather events, diseases, or insect disturbances. Many additional disturbances can be included: bark beetles, blister rusts, dwarf mistletoe, root diseases, pine beetles, wooly adelgid, drought, wildfire of different severities, exotic plant invasion, leaf diseases, and herbivores (Spies et al. 2017). These disturbances are modeled in VDDT probabilistically. Fire, insects, wind, and drought can be addressed by probability of disturbance occurring (0–1) and proportion, with higher probability and proportion increasing the likelihood of a state transition.

A spatially explicit version of VDDT called the Tool for Exploratory Landscape Scenario Analyses is also available from ESSA (Environmental and Social Systems Analysts) Technologies Ltd.—it models between 2000 and 360 000 ha, with thousands of user-defined polygons. The spatial aspect requires user-defined information about the size-class distribution of the various disturbance types (Klenner et al. 2000, Kurz et al. 1999).

Forest Carbon Management Framework/Integrated Terrestrial Ecosystem Carbon

The Forest Carbon Management Framework (ForCaMF) and Integrated Terrestrial Ecosystem Carbon (InTEC) are two models that were applied jointly to national forest units. Together, they constitute a carbon accounting system that was originally developed to assess carbon stocks on forested land and how stocks respond to different disturbances and aging. The ForCaMF model uses FIA data and post-1990 disturbances from FVS to model non-soil carbon. The InTEC model uses biophysical processes and atmospheric data to estimate effects of disturbance and nondisturbance (climate variables) on forest carbon assimilation rates and pools, calibrated using FIA net primary productivity curves (Chen et al. 2000, Dugan et al. 2017, Raymond et al. 2015). This model uses 30- × 30-m cells and runs on a decadal timescale resolution but is often used to model national forests or groups of national forests in the United States (Birdsey et al. 2019). Combined, ForCaMF and InTEC have the ability to include error spatially (Healey et al. 2014, Zhao et al. 2018), which can better provide realistic estimates, but does not project into the future. ForCaMF/InTEC does include some belowground carbon: soil organic carbon (up to 1-m deep), fine roots, tree litter, and small woody debris (Birdsey et al. 2019). Simply put, FIA data are used to estimate carbon stocks over time: ForCaMF is used to identify the role of disturbance since 1990 on carbon stocks, and InTEC is used to put those effects into a process and climatic context.

Forest management practices are included in ForCaMF/InTEC—harvest, thinning, grazing, and prescribed burns that are derived from FVS models are all applicable within the model (Healey et al. 2014). As elaborated under the FVS description above, management practices are applied to the stands probabilistically; the user can control thinning and pruning practices for stand density, height, basal area, or species cover goals. The carbon dynamics are averaged regionally in ForCaMF (Birdsey et al. 2019). Wildfire is modeled using ForCaMF, specifically using the FVS-FFE module. With ForCaMF, the fire model is focused on the historical instance of fire and empirically applies carbon lost based on an average of tree communities (Birdsey et al. 2019). Forest carbon response to climate variables—temperature, wind, drought, CO_2, and nitrogen deposition—is done in InTEC (Birdsey et al. 2019). InTEC uses a combination of empirical and mechanistic processes to understand change in carbon stocks with increased climate variability and atmospheric gas concentrations. InTEC also incorporates historical disturbances by using stand age in 1990 as an indicator of time since disturbance and then incorporating remotely sensed disturbances from current years; a proportion of carbon from each natural forest disturbance transfers to the atmosphere and an additional proportion gets shifted to dead carbon pools (Zhang et al. 2012).

Land Use and Resource Allocation Model

Land Use and Resource Allocation (LURA) is a model that was designed to understand macroeconomic conditions and their effects on localized forest management and biomass (Latta et al. 2018, Wade et al. 2019). It was created to provide a contemporary version of the Forest and Agricultural Sector Optimization Model (Wade et al. 2022), which is one of three forest carbon models used by the United States in its required reporting under the United Nations Framework Convention on Climate Change. LURA is a dynamic spatial equilibrium model of the U.S. forest sector that balances supply and demand annually across the 164,723 FIA forested condition classes and 3,365 forest products processing facilities (Visser et al. 2022). In doing so, it represents the decision of where the disturbance of forest harvest (clearcutting or thinning) occurs on the landscape and the resulting forest carbon consequences. LURA moves the forest resource base through time using empirically derived yield curves specific to 36 ecoprovinces, seven FIA site classes, and 14 forest types; it moves demand through time using projections of gross domestic product, housing starts, bioenergy, and diesel prices. The two primary disturbances modeled in LURA are harvest decision and wildfire.

The harvest decision in LURA is determined by a price-sensitive demand disaggregated to the individual mill level and an opportunity cost that recognizes the foregone income associated with harvest plot values increasing beyond their 5-percent discount rate. The linkage between forest plots and mills, using a network of roads, allows competition between local facilities, and supply chain interactions of byproducts also enter the harvest disturbance decision within the model (Pokharel and Latta 2020). It is for this reason that it has been used to evaluate the forest carbon dynamics of additional harvest disturbances associated with new facilities for pellets (Visser et al. 2022), biofuels (Martinkus et al. 2017), and bioelectricity (Xu et al. 2021).

Wildfire is the only natural disturbance included in LURA. For fire disturbance, older LURA iterations assume that forested plots that burned in each county were equivalent to the proportion of 2004–2014 fire frequency and 50 percent of the area that burned resulted in a total loss of all forest species (Latta et al. 2018). The current version of LURA uses a two-phase fire model based on Pokharel et al. (2023). The fire risk equation uses a climate projection to calculate a spatially explicit fire probability. A second equation then brings in per-acre (0.4 ha) biomass to determine the fire-related mortality proportion of the plot. The model then allows user-defined combustion rates to determine the carbon emissions from fire. The fire risk component of the model can function in either a deterministic or stochastic mode. In deterministic mode, a small area of each plot, resembling a fire risk map, is burnt. Alternatively, in stochastic mode, a random number is drawn to determine if the entire plot burns, resulting in a landscape disturbance pattern that resembles an individual year's fire occurrence map.

Regional Hydro-Ecological Simulation System

The Regional Hydro-Ecological Simulation System (RHESSys) is a biophysical process model that was created to focus on interactions among spatially distributed hydrological processes, including lateral redistribution, and ecosystem biogeochemical cycling, including plant growth. Most studies that employed RHESSys shortly after its release in 1993 focused on hydrology and climate change (Kim et al. 2018b), but recent applications have shifted toward land management (e.g., Chen et al. 2020), fire modeling (Hanan et al. 2021, Kennedy et al. 2021), and urban ecohydrology applications (Shields and Tague 2015). This model generally uses a daily climate timestep, but the frequency may be increased to hourly to model storm events when hourly precipitation data are available. Vegetation, litter, and soil carbon and nitrogen cycling processes are modeled on a daily timestep. Vegetation carbon allocation generally occurs annually during spring leaf-out, using either fixed or variable phenology (Bart et al. 2017). RHESSys is often applied to watershed basins with an area of about 100 km^2, and the model can include carbon pools associated with soil and litter (Chen et al. 2020, Hanan et al. 2018, Hwang et al. 2008, Tague and Band 2004). One strength of RHESSys is the ability to model lateral redistribution of water that facilitates modeling both upland and riparian processes (e.g., Graup et al. 2022, Tague and Peng 2013). More recently, RHESSys' spatial structure has also been extended to allow fine-scale processes within forest stands to be modeled, including structural (e.g., forest gaps) (Burke et al. 2021) and compositional heterogeneity (interaction among species) (Rog et al. 2021). This heterogeneity is represented as semi-spatial units that exchange water and nutrients but are embedded in larger spatially explicit units within watersheds.

Externally driven disturbances, such as forest thinning, can be applied to RHESSys using the temporal event control input file, which updates carbon and nutrient stores based on user inputs. Silvicultural treatments applicable in RHESSys include harvest and thinning, although any temporal event control can be created to change any state variable on the landscape (Saksa et al. 2017, Tsamir et al. 2019). The ability to explicitly represent forest gaps, as well as overstory and understory interactions, allows the RHESSys model to capture thinning effects on hydrologic and carbon cycling processes.

Additional disturbances, including wildfire and drought mortality, have been fully coupled to the RHESSys hydrology and ecosystem biogeochemical cycling model. This means they are not externally driven, although temporal event control can also be used to initiate these disturbances, as well as insect effects. RHESSys-WMFire is based on WMFire (Kennedy et al. 2017) combined with a fire effects model (Bart et al. 2020). Using WMFire, RHESSys initiates ignitions with an empirical Poisson distribution, the location is stochastic, and the area burned is spatially aggregated using seasonality and individual fire area (Bart et al. 2020, Kennedy et al. 2017). Whether ignition starts a fire is based mechanistically on fuel load and fuel moisture. Potential fire spread to adjacent pixels is based on the probability of combustion given the fuel moisture, fuel load, ground slope, and wind (Bart et al. 2020). Fire intensity and severity (e.g., vegetation losses) are also based on fuel load, moisture, slope, and wind; however, it uses canopy threshold within RHESSys to identify canopy layer mortality and indicate how much carbon transfers to the atmosphere via combustion or moves to a surface carbon stock (Bart et al. 2020). Overstory and understory relationships are considered within the fire effects model and thus account for the effects that ladder fuels thinning has on fire severity (Bart et al. 2020).

Drought is modeled in the RHESSys carbon sub-model through complex interactions among plant physiological processes, soil hydrological processes, plant morphology (leaf area index), and nonstructural carbohydrate allocation within the vegetation (Tague et al. 2013). Using mechanistically modeled water use for plant physiology and morphology, coupled with water availability, leaf area index decreases during times of water stress. Once leaf area decreases below a defined threshold (relative to total aboveground carbon), the plant will utilize nonstructural carbohydrate reserves to support respiration and fine root growth. An increase in mortality risk is modeled when nonstructural carbohydrate reserves approach user-defined thresholds as a result of the assumption that low nonstructural carbohydrate reserves prevent the plant from recovering from other complex physiological occurrences associated with drought, such as cavitation, hydraulic failure, or defense mechanisms (Tague et al. 2013).

LANDCARB

LANDCARB is a gap model that uses biophysical processes and was designed to analyze landscape carbon accumulation; it incorporates stands with mixed ages and species, building on a previous model called STANDCARB (Cohen et al. 1996, Harmon et al. 1990). Vegetation is input on an annual timestep, while climate and factors influenced by climate are used on a monthly timescale. The model can incorporate multiple horizontal layers of vegetation (herbaceous, shrubs, understory, overstory) and the carbon pool includes fine roots and coarse roots as belowground biomass (Harmon et al. 1996). LANDCARB incorporates soil carbon with detritus, woody debris, decomposition, and carbon transfer between aboveground biomass and soil.

LANDCARB can address many different disturbances. Forest management practices are in the form of harvest, clearcut, thinning, branch and root pruning, and prescribed burns (Harmon and Domingo 2001). In STANDCARB 2.0, prescribed fire and wildfire can be probabilistically controlled through the "burnkill" function by which the user can establish the percentage of above- and belowground survival postfire (Harmon and

Domingo 2001). In a later LANDCARB implementation, fire severity can be modeled using fuel type and load, where fuel loads are divided into classes (light, medium, high, and max) and higher fuel loads result in correspondingly higher severity fires (Mitchell et al. 2012). Other natural disturbances include mortality from succession, light competition, and trees aging out (Harmon and Domingo 2001). Temperature, soil moisture, transpiration, and water potential can be input from climate models to correlate to climate change variables such as drought and temperature limitations (Harmon et al. 1996).

Carbon Assimilation in the Biosphere

Carbon Assimilation in the Biosphere (CARAIB) is a process-based dynamic global vegetation model that was created to examine the role of vegetation in the global climate cycle in the past and present by modeling carbon and water fluxes (Laurent et al. 2008). Like Biome-BGC, CARAIB is a "big-leaf" model that simulates photosynthesis as one PFT per grid cell, effectively representing the whole cell as one leaf. However, unlike Biome-BGC, each cell is divided into two big leaves—sun leaves and shade leaves—which have different rates of light capture on sunny days and the same rate of light capture on shady days (Otto et al. 2002, Reyer et al. 2017, Warnant et al. 1994). This model uses a 0.5 × 0.5° latitude and longitude spatial resolution; however, because this is intended to model within the global carbon budget, it is usually used to model continental to global carbon. Temporal resolution is annual for woody species (shrubs and trees), monthly for herbaceous species, daily for carbon and water reservoirs, and in 2-hour timesteps for photosynthesis and plant respiration.

Disturbances modeled by CARAIB include drought, natural senescence, and cold temperatures, but silvicultural management practices, human-caused fire, storms, and insects are not included (Minet et al. 2013). Climate change is incorporated into the model using carbon effects, soil moisture, and low temperatures. Drought is modeled mechanistically through soil moisture—which ranges from the wilting point to saturation—and high temperatures leading to hydric stress (Minet et al. 2013). Species have assigned soil moisture values that indicate a drought-mortality threshold, though in its current state, CARAIB likely overestimates drought mortality (Dury et al. 2011). Wildfire is also included probabilistically in CARAIB, allowing for more user control based on burnable PFT classes, fuel, fuel moisture, and presence of lightning to ignite fires (Dury et al. 2011). Ignition is mechanistically modeled using lighting flash data; success of ignition is modeled using soil moisture and fuel availability. Soil moisture and windspeed mechanistically dictate spread of the fire.

Lund-Potsdam-Jena General Ecosystem Simulator

Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) is a biophysical process model that was originally designed to use both atmospheric and ecosystem data to evaluate structural, compositional, and functional properties of ecosystems on a large scale. This model uses eight woody PFTs that use annual timesteps for vegetation cover types and monthly timesteps for biophysical processes and soil water dynamics (Sitch et al. 2003, Smith et al. 2001). The spatial resolution of LPJ-GUESS is 0.5 × 0.5° latitude and longitude and it is usually employed to model on a regional to global scale. It has recently been parameterized to better simulate Western U.S. tree species (Emmett et al. 2021). Belowground carbon is included through soil litter and organic matter turnover (Luo et al. 2016).

The LPJ-GUESS model does not include silvicultural practices as a disturbance. Climate change is included with climate projections in the GetClim section of the model setup and can be used to input changes in mean or variability of temperature, CO_2, and precipitation. The main disturbance included in the LPJ-GUESS framework is wildfire. Biomass mortality and emissions from wildfire are empirically calculated from the climatic conditions and accumulated litter fuel. LPJ-GUESS can be coupled with other fire modules (e.g., LmfireCF) to have more control over surface and crown fire characteristics (Emmett et al. 2021). Additional disturbances can be included in cohort mode stochastically as exogenous patch disturbances where the user specifies the average annual return interval.

Interaction Between Disturbance and Forest Carbon Dynamics

Forest disturbances can lead to direct, short-term emissions (i.e., combustion of live and dead carbon pools) and shifts in carbon pools (live biomass transferred to snags or coarse woody debris) with variable residence times (fig. 1) (Williams et al. 2016). In general, forest disturbances lead to an initial decrease in forest carbon assimilation immediately after disturbance, sometimes followed by recovery and potentially a transition to a carbon sink as the forest regrows (McKinley et al. 2011, Williams et al. 2016). Different disturbance types (i.e., harvest, fire, drought, insects, pathogens) vary as to the timing and magnitude of their effects on forest carbon stocks (figs. 2–3) (Williams et al. 2016). This section reviews what is known about the effects of the major disturbance types on forest carbon stocks based on both empirical research and modeling.

With climate change, disturbances that are not intentional management actions (e.g., wildfire, drought, insect infestation) are increasing in frequency and severity, which can have major effects on the composition and structure of forests (Cannon et al. 2017, Overpeck et al. 1990, Pan et al. 2011). Specifically, the Pacific Northwest has experienced increased fire and insect disturbance since the 1980s (Masek et al. 2013). Past management practices also interact with climate change and disturbances to alter forest composition, function, carbon storage, and carbon sequestration (Brewer 2016, Nemens et al. 2018, Seidl et al. 2016, Whitlock et al. 2015). For example, warmer, drier summers and warmer winters associated with climate change have been shown to increase the risk of mortality and decreased carbon assimilation with both mountain pine beetle infestation and other

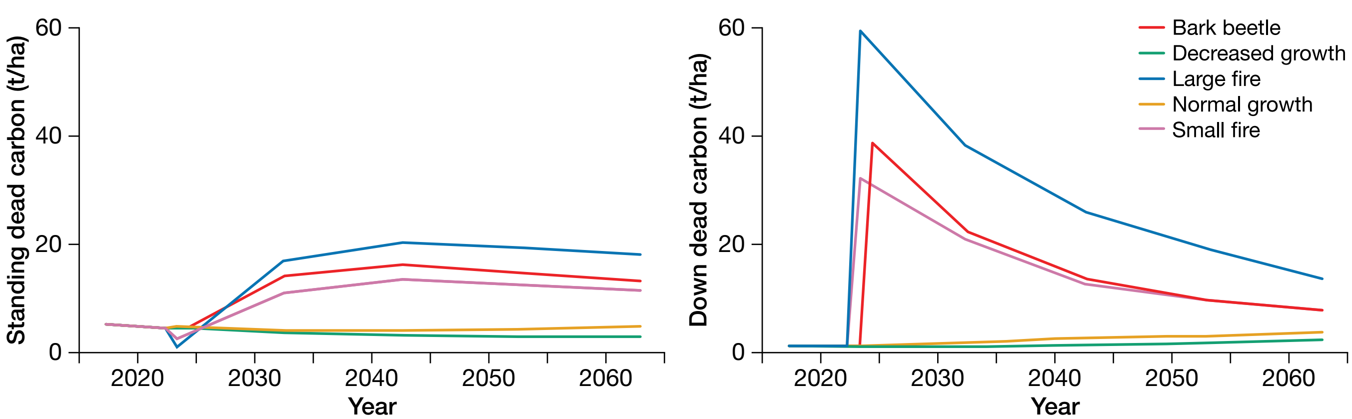


Figure 1—Standing and down dead carbon pools after four different types of disturbances over 50 years. The change in dead carbon pools after disturbance shows the carbon transfer from the standing and down dead pools to other pools.

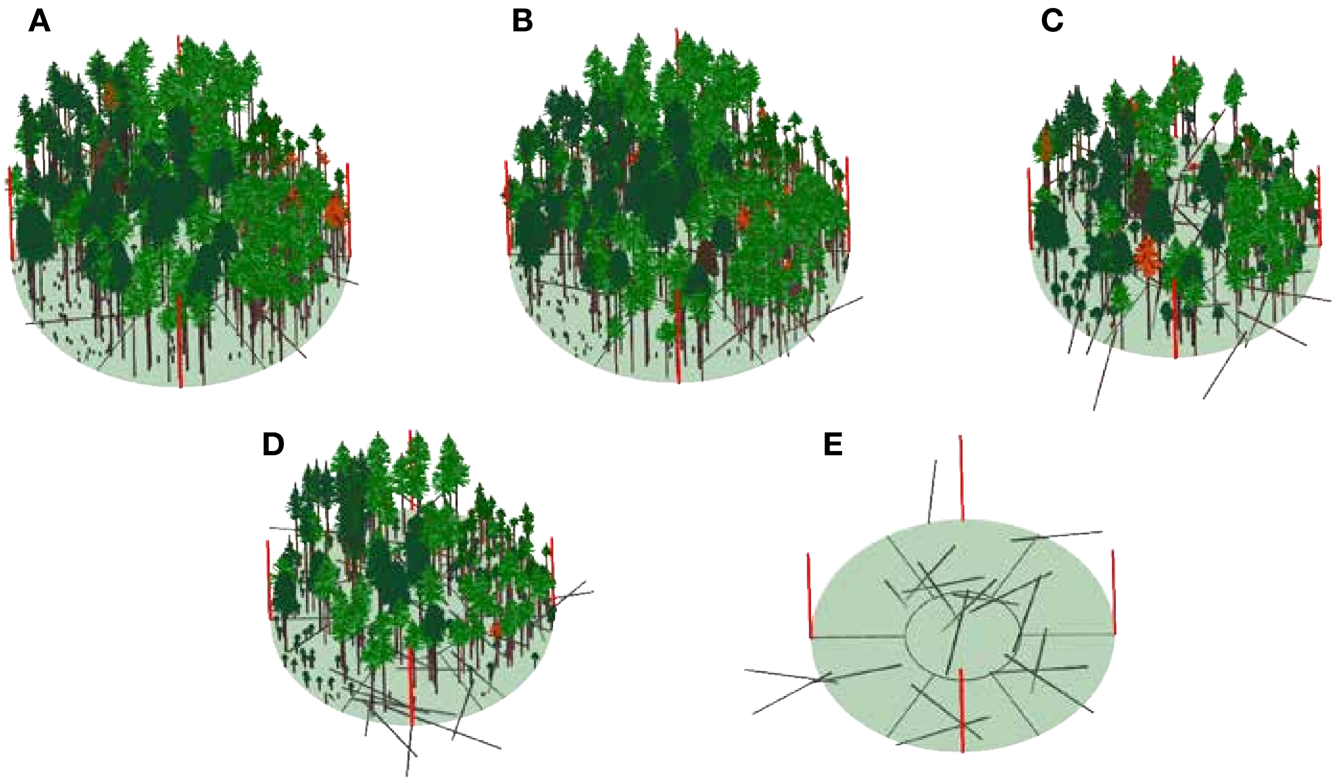


Figure 2—Forest Vegetation Simulator outputs for a Douglas-fir stand 50 years after (A) a normal growth year, (B) the onset of decreased growth, (C) a bark beetle outbreak, (D) a small fire, and (E) a large fire.

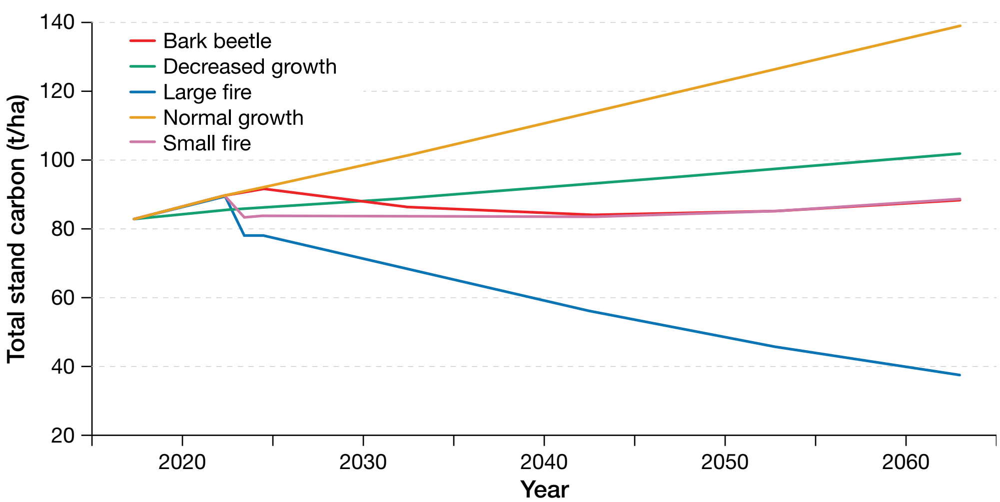


Figure 3—Total simulated aboveground carbon stocks after applying Forest Vegetation Simulator disturbances (none [normal growth], decreased growth, bark beetle, small fire, large fire). This is a simplified look at general disturbance types with no disturbance interactions or regeneration.

bark beetle species in pines and spruces (Flint et al. 2009). However, the long history of fire suppression has also contributed to the increased effect of many insects by allowing more trees to survive to maturity, leading to higher numbers of host trees (Flint et al. 2009). The frequency and severity of these disturbances have been increasing with climate change, with effects that persist long after infestations subside (Flint et al. 2009). Similarly, the comparatively limited application extent of prescribed fire and more than a century-long focus on fire suppression, coupled with drier and warmer summers, have increased the severity of wildfires seen in the Pacific Northwest today (Berkey et al. 2021, Parks and Abatzoglou 2020, Rogers et al. 2011, Whitlock et al. 2003, Wimberly and Liu 2014).

In the west coast states, climate change may alter carbon storage capacity of the forests, but a high degree of uncertainty remains as to where and to what degree forests may remain carbon sinks or convert to net carbon sources. For example, a review that focused on dynamic global vegetation models (e.g., LPJ-GUESS, MC2, CARAIB) found that many forest types throughout Washington, Oregon, and California are projected to remain as carbon sinks and provide carbon storage opportunities under more moderate projected climate scenarios (slight temperature increase, slight change in precipitation amount) (Case et al. 2021). With a more extreme climate scenario, including greater increase in temperatures and decreased summer precipitation, all forest types are projected to decrease in carbon storage capacity and growth (Case et al. 2021). However, several empirical studies based on FIA data have shown that over the early 2010s, private forested land often acted as more of a source than a sink throughout the Pacific Northwest, particularly corporate-owned land (Christensen et al. 2017, 2019, 2020). A study using InTEC found that rates of carbon assimilation are reduced more via disturbances (fire, insects) in the west than by non-disturbance factors (CO_2 concentration, nitrogen deposition, and temperature variability) (Zhang et al. 2012), although both factors decrease carbon assimilation capacity. Disturbances, such as wildfire and insects, will decrease carbon storage regardless of the severity, though greater increases in fire frequency and insect infestation will cause greater decreases in carbon storage and forest growth (Case et al. 2021).

Harvest is considered the disturbance with the greatest effect on forest area throughout the United States, followed by fire, windthrow, insects, and drought (Williams et al. 2016), all of which can have large influences on forest carbon stocks and assimilation. For example, a study on the western forests of Oregon and Washington, using LANDCARB, showed that decreasing timber harvest would increase carbon storage in the remaining forest (not including harvested wood products) by up to 5.1 teragrams of carbon (TgC) per year in Oregon and 2.66 TgC per year in Washington (Krankina et al. 2012), although increased fire frequency and extent due to climate change, coupled with higher density from decreased harvest, may effect forest carbon stocks (Halofsky et al. 2018). Carbon storage within the forest is decreased immediately after harvest, but the rates of carbon assimilation following harvest may increase through higher growth rates of residual trees and post-harvest regrowth (Williams et al. 2016). Harvest can also affect the soil organic carbon stocks and fluxes—harvest can decrease stocks by stopping leaf litter input and additional fine root turnover but can increase soil stocks as slash and debris left on site decompose (Clarke et al. 2015). The decrease in soil organic carbon stocks post-harvest is likely temporary due to biomass removal and intermixing of organic matter and mineral soil (Clarke et al. 2015). Autotrophic soil respiration is also affected—compaction from harvest equipment can decrease respiration, while warmer temperatures and higher soil moisture can increase respiration (Clarke et al. 2015). Specific influence of harvest on soil carbon stocks and fluxes is highly influenced by harvest methods, soil type, and tree species cover. Harvest, however, can result in increased growth of residual trees and retain carbon storage in harvested wood products for the life of the product (fig. 4). Previous work has shown that using wood products in place of carbon-intensive construction materials (e.g., metals, concrete) results in a net positive effect on greenhouse gases (Geng et al. 2017), and the same can be true of bioenergy produced from woody biomass feedstocks, depending on the profile of energy generation sources that the bioenergy is replacing.

Of all modeled disturbances, fire is the most studied. Fire is a complicated process with altered frequency, severity, and intensity due to a combination of climate change factors and a history of fire-suppression-focused management. Fires immediately release carbon to the atmosphere through combustion, a proportion of which comes from dead wood, foliage, and fine branches. Severity of the fire dictates how much carbon remains in live wood, dead wood, and soil post-fire. Where fire burns at low intensity, the effects are less severe, with carbon distributed among a mix of live trees, standing dead trees, and down wood. High-intensity fire produces high-severity outcomes and a greater proportion of pre-fire forest carbon stocks migrating to the atmosphere both immediately and over time (Hurteau and Brooks 2011). Land management policies resulting in long-term fire suppression have

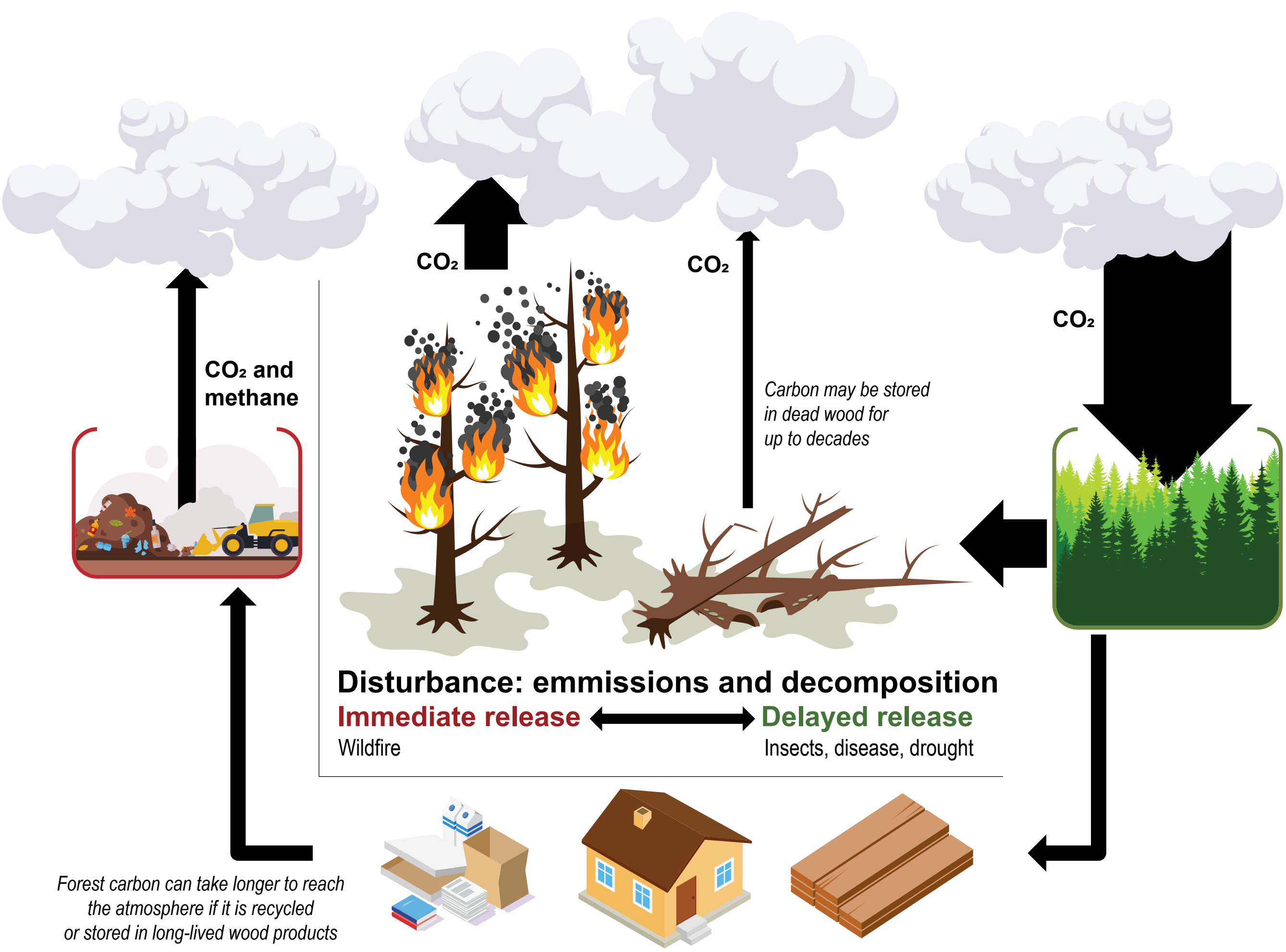


Figure 4—An overview of carbon transfer among the atmosphere, living and dead trees, and harvested wood products.

increased fuel loads and, with more unpredictable and severe weather, lead to wildfires that resist easy suppression (Berkey et al. 2021). Prescribed burns will reduce carbon stocks in the short term but can potentially decrease the risk of high-severity wildfire. Previous work found that prescribed burns only decrease the soil organic carbon stock on the soil surface, while wildfires can decrease soil carbon throughout surface organic and mineral horizons (Bormann et al. 2008, Nave et al. 2022). A study of public forests in the Northern Rockies that were managed with wildfire as an important and natural part of the ecosystem found that long-term planning for management that includes wildland fire can reduce the potential negative effects of wildfires (Berkey et al. 2021). Models also point to a similar trend, where suppression can temporarily increase forest carbon stocks but at the cost of increasing severity of potential future wildfires (Rogers et al. 2011, Whitlock et al. 2003, Wimberly and Liu 2014). Similar to harvest, individual tree growth rates following fire can be enhanced through decreased competition and reduced susceptibility to future fires (Hurteau and North 2010, Latham and Tappeiner 2002, North and Hurteau 2011).

Drought is a widely studied natural disturbance. Drought's effect on trees can include slowed growth, decreased carbon assimilation rates, or even halted carbon assimilation rates that lead to tree mortality and the transfer of carbon from a living pool to a dead pool (Anderegg et al. 2015, Arain et al. 2022, Martínez-Sancho et al. 2022). The susceptibility to drought-induced mortality in Pacific Northwest states is often dictated by topography and site history as well as species. Trees that live at higher elevations may be more sensitive to drought because they are adapted to greater water availability and lack drought-resilient characteristics compared to trees adapted to more arid climates. Trees in areas with high soil compaction (thus, lower soil moisture) and drier climates are more susceptible to drought stress and associated decrease in carbon assimilation rate than those situated in a valley with less compact soil (Cartwright et al. 2020). In Oregon and Washington, drought peaks during daylight hours in August in moist habitats but can be moderated by tissue rehydration overnight; drier habitats in Washington tend to be most vulnerable to drought in September (Mildrexler et al. 2016). Both wet and dry habitats have previously shown hydraulic redistribution, a phenomenon in which deep roots in combination with extremely dry surface soil move water from the deeper soil to the shallower soil (Brooks et al. 2002). Drought is also simulated effectively in some models, such as ED2, which has incorporated stomatal conductance susceptibility to soil moisture and vapor pressure deficit to show that periods of water stress decrease carbon assimilation in Washington forests (Jiang et al. 2019). On a biophysical scale, there are species-specific and ecotype-specific responses to drought and timing of rehydration to cope with drought stress and conserve water or to maintain photosynthesis (Du et al. 2015).

Other weather disturbances, such as wind and freeze events, are less often studied. Wind disturbances range from small-scale blowdown events to large-scale tornadoes, cyclones, or hurricanes. However, there are relatively few studies of wind-related forest damage and most focus on large-scale events, such as a single hurricane (Williams et al. 2016). Hurricanes are estimated to affect up to three times more forestland in the United States than forest fires (Dale et al. 2001, Williams et al. 2016), leading to potential loss in carbon assimilation and transfer of carbon between live and dead pools. Wind plays an important role in forest structure and community composition, and damage is influenced by elevation, slope, soil stability, and exposure to prevailing storm winds (Kramer et al. 2001, Momodu 2019, Sinton et al. 2000, Suvanto et al. 2019). Susceptibility to wind disturbance damage can also be dictated by species and age class; old-growth forests are more of a refuge from wind for several species than secondary growth forests (Canham et al. 2001). Freezing thresholds of different species are one of the predictors of species ranges and of timberline elevations, which influence carbon flux rates (Lafon 2016, Wardle 1993). Freezing frequency is woven into forest community composition and changes in freezing frequency can enhance or decrease the carbon assimilation rates of that plant community (Girardin et al. 2022). Experiments seeking to identify cold temperature thresholds for specific species are often performed on seedlings, saplings, and seeds because those are smaller and easier to freeze (Bigras and Margolis 1997, Hawkins et al. 2003, Ryyppö et al. 1998). The literature, then, can help predict freezing-induced mortality but mostly for younger trees, with limited information on more mature trees. Freezing can also change the carbon flux of belowground processes, particularly if recent precipitation allows for the soil to freeze (Groffman et al. 2006).

Insects and pathogens can reduce carbon flux and stocks. Cumulative effects of the 15 most damaging nonnative pests across the United States result in a loss of about 5.53 TgC per year because of mortality (Fei et al. 2019). Insect disturbances, even from native species such as mountain pine beetle and western spruce budworm, have negative effects on tree survival and interact with climatic variables (e.g., drought stress can increase tree mortality from insect infestation) (Meigs et al. 2015, Weed et al. 2013). Different types of insects, however, have different effects—defoliators tend to cause more temporary damage and reduction in carbon assimilation, while borers lead to higher mortality and a delayed recovery of pre-infestation net primary production (Flower and Gonzalez-Meler 2015, Hicke et al. 2012). Higher diversity stands, such as mixed deciduous forests in the Eastern United States, will have more scattered mortality and limited influence by pests, whereas less diverse stands, particularly those with a high proportion of insect host species, such as those present in the Western States, tend to have higher loss of net primary production and take longer to recover (Flower and Gonzalez-Meler 2015, Robert et al. 2020).

Empirically testing the effects of individual disturbance types on forest carbon dynamics lends itself to relatively straightforward experimental design. However, the influence of one disturbance on forest carbon can alter the vulnerability to and outcomes of other disturbances, and compounding effects quickly become difficult to control for experimentally. Interactions among fire, drought, and fuel management are especially common and strongly associated; therefore, they are often studied (Bartowitz et al. 2022, Burke et al. 2021, Earles et al. 2014). Managed forests, especially those thinned or harvested for fuel treatments to reduce severity of wildfires, tend to have an immediate decrease in carbon stock from managed biomass removal. However, these management actions may lead to lower carbon emissions in these forests during wildfire (North and Hurteau 2011), leading to an overall lower carbon cost through maintained live stocks and greater net carbon assimilation. Interactions of forest management practices (no management, harvest, and salvage logging) and insect disturbance effects on growth and carbon stocks have been previously identified using observational studies; however, those studies are limited to chance disturbance in comparatively similar areas with differing management histories (Davis et al. 2022). The dearth of empirical studies quantifying the interacting effects of multiple disturbances on forest carbon dynamics leaves a gap in the information required to capture these interactions in a predictive model.

As illustrated in this review, numerous forest carbon models are available that vary substantially in the types of disturbances and management represented and in the approaches to estimating the carbon outcomes of those disturbance and management events. Land managers face a difficult challenge when choosing a model to support their decisions concerning forest carbon management. A great place to start is to develop specific modeling objectives and to identify key ecological processes that relate to those objectives (Keane et al. 2019). Additional considerations include available computing resources, input data requirements and availability, access to analysts experienced with model operation, how well the spatial and temporal resolution and extent of a model match modeling objectives, and model documentation and accessibility (Keane et al. 2019). Decision trees can be useful tools in selecting the most appropriate model (e.g., fig. 5: A). Consideration of which kinds of disturbances are most important to accurately simulate and which carbon processes or pools (e.g., belowground carbon, soil carbon) must be included to meet management objectives may help focus attention on the models that are most appropriate. Matching spatial (e.g., landscape, regional, continental) extent and temporal resolution (e.g., daily, annual) to modeling objectives is also key.

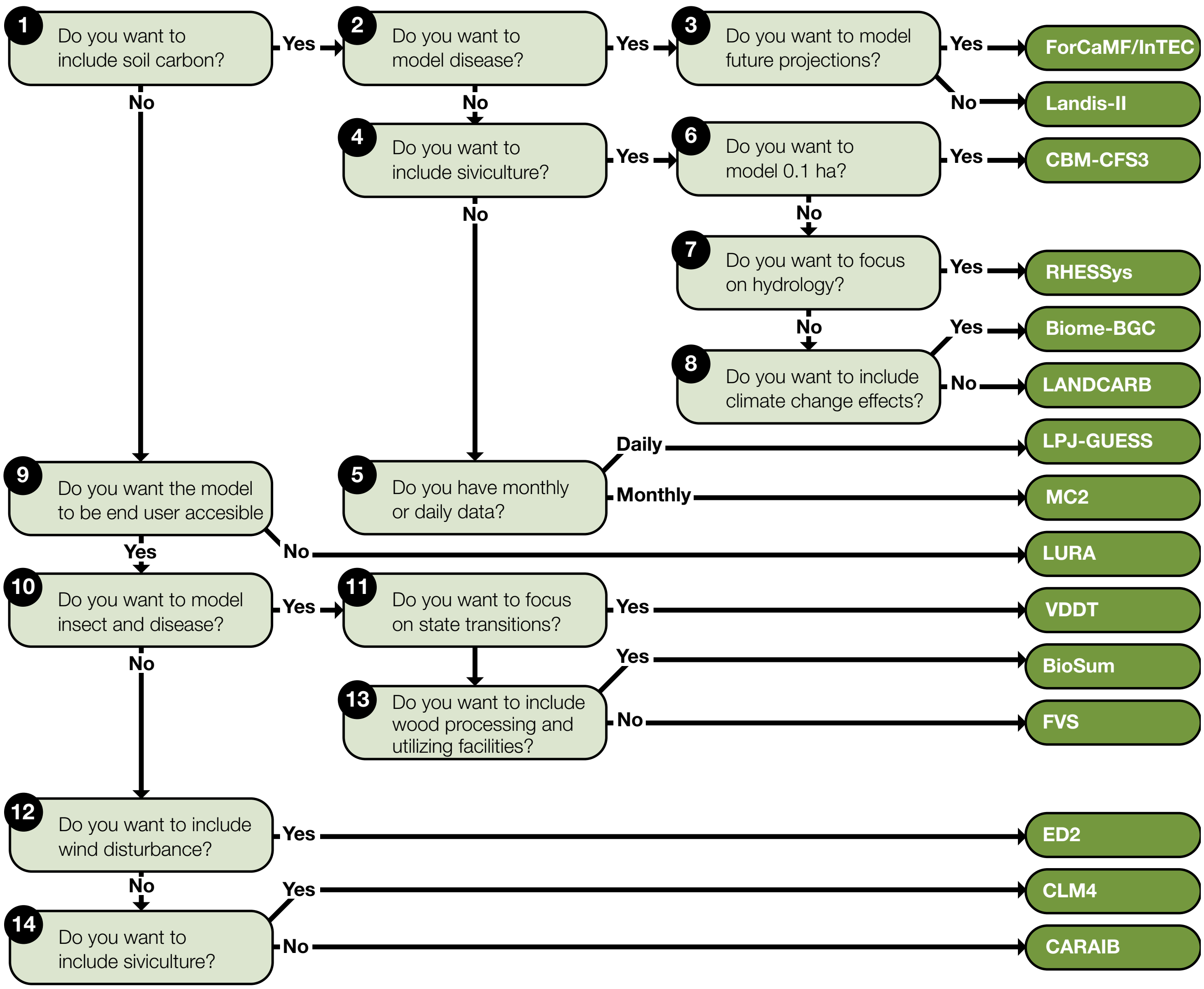
For example, consider a landowner whose land is adjacent to a natural forest that is affected by bark beetles. Suppose this landowner would like to harvest timber while taking advantage of carbon offset programs; the landowner could use the decision tree (fig. 5: A) to help select a candidate set of appropriate models. Each arrow on the decision tree represents a "yes" or "no" answer; they lead to the next questions to narrow down which model will be most helpful.

1. Question 1—No, they do not need to include soil carbon. The "no" arrow leads to question 9.
2. Question 9—Yes, they want the model to be accessible.
3. Question 10—Yes, they'd like to include insect and disease disturbance.

For questions 11 and 13, the landowner does not have a preference about state transition or wood processing and utilization facilities, but the decision tree has narrowed the modeling choices to VDDT, BioSum, and FVS. The landowner could then use table 1 to identify which among the VDDT, BioSum, and FVS models would work best for their forest management plans.

All models have their limitations, and no model is perfectly suited to any project. However, a structured evaluation of management objectives matched to model capabilities, while considering available resources such as expertise and data availability, can help determine the most useful model for addressing a specific situation. Disturbances of all types in Pacific Northwest forests will be changing in frequency and severity with climate change; projections that can help manage for resilient forests may be the key to limiting disturbance-induced carbon loss.

A



B

Includes siviculture

- Biome-BGC, CLM4, ED2, LANDIS-II, CBM-CFS3, FVS, BioSum, VDDT, ForCaMF/InTEC, LURA, RHESSys, LANDCARB

Includes insect infestation

- LANDIS-II, CBM-CFS3, FVS, BioSum, VDDT, ForCaMF/InTEC

Includes soil carbon

- MC2, Biome-BGC, LANDIS-II, CBM-CFS3, ForCaMF/InTEC, RHESSys, LANDCARB, LPJ-Guess

Includes drought

- CLM4, ED2, FVS, BioSum, VDDT, ForCaMF/InTEC, RHESSys, CARAIB

Figure 5—This decision tree (A) illustrates one example of how to select a model based on forest management objectives. The abbreviated table (B) illuminates which models include some of the major forest disturbances applicable to California, Oregon, and Washington. Fire is not included in this table because it is modeled to some degree in each model represented. Biome-BGC = Biome-Biogeochemical Cycle, BioSum = Bioregional Inventory Originated Simulation Under Management, CBM-CFS3 = Carbon Budget Model of the Canadian Forest Sector, CARAIB = Carbon Assimilation in the Biosphere, CLM4 = Community Land Model 4, ED2 = Ecosystem Demography Model, ForCaMF/InTEC = Forest Carbon Management Framework and Integrated Terrestrial Ecosystem Carbon, FVS = Forest Vegetation Simulator, LANDIS-II = LANDIS-II Forest Landscape Model, LPJ-GUESS = Lund-Potsdam-Jena General Ecosystem Simulator, LURA = Land Use and Resource Allocation Model, RHESSys = Regional Hydro-Ecological Simulation System, VDDT = Vegetation Dynamics Development Tool.

Table 1—Major disturbance, scale, and spatial and temporal resolution of models reviewed for carbon modeling in Pacific Northwest forests

Model	Fire	Insects	Disease	Drought	Wind	Silviculture	Climate change	Soil carbon	Typical scale modeled	Resolution	
										Spatial	Temporal
MC2	X						X	X	Regional to global	800 m × 800 m	Monthly
Biome-BGC	X					X	X	X	Regional to global	Stand	Daily
CLM4	X			X		X	X		Landscape	Patches in 6 × 6 km grid	Hourly
ED2	X			X	X	X	X		Landscape to continental	Individual tree	Hourly
LANDIS-II	X	X	X		X	X	X	X	Landscape	Stand	Annual
CBM-CFS3	X	X			X	X		X	Stand to landscape	0.1 ha	Annual
FVS	X	X	X	X	X	X	X		Stand to regional	Stand	Annual
BioSum	X	X	X	X	X	X	X		Landscape to regional	1 ha	Annual
VDDT	X	X	X	X	X	X	X		Ecoregions	Stand	Annual
ForCaMF/InTEC	X	X	X	X	X	X	X	X	National forests	30 m × 30 m	Annual
LURA	X					X			National	0.4 ha	Annual
RHESSys	X			X		X	X	X	5th field watersheds	Patches (m^2) in watersheds (km^2)	Daily
LANDCARB	X					X		X	Landscape	Stand	Annual
CARAIB	X			X			X		Continental to global	0.5° latitude × 0.5° longitude	Daily
LPJ-GUESS	X						X	X	Regional to global	0.5° latitude × 0.5° longitude	Daily

Biome-BGC = Biome-Biogeochemical Cycle, BioSum = Bioregional Inventory Originated Simulation Under Management, CBM-CFS3 = Carbon Budget Model of the Canadian Forest Sector, CARAIB = Carbon Assimilation in the Biosphere, CLM4 = Community Land Model 4, ED2 = Ecosystem Demography Model, ForCaMF/InTEC = Forest Carbon Management Framework and Integrated Terrestrial Ecosystem Carbon, FVS = Forest Vegetation Simulator, LANDIS-II = LANDIS-II Forest Landscape Model, LPJ-GUESS = Lund-Potsdam-Jena General Ecosystem Simulator, LURA = Land Use and Resource Allocation Model, RHESSys = Regional Hydro-Ecological Simulation System, VDDT = Vegetation Dynamics Development Tool.

Model Limitations

Models allow us to answer questions about climate and environmental scenarios that do not already exist and include far more disturbance regimes than we can feasibly test experimentally. Forest carbon models are great tools to help policymakers, planners, land managers, and other partners make decisions about how to reach their goals for storing carbon and maintaining biodiversity, timber production, and other ecosystem services. There are several ways, however, that use of these models could be improved, with the caveat that these models make projections that include some level of uncertainty.

As with any experimental design or mathematical model, there are tradeoffs between resolution and the size of the typical area tested or modeled. When models have very fine spatial resolution, they are used to model smaller areas (e.g., a small land parcel). Models that focus on a larger extent (e.g., national or global) will typically be based on coarser resolution data. If the spatial resolution is high and the area modeled is large, the time and amount of computing power needed to run the model will also be greater, limiting the accessibility of the model.

Aboveground carbon stocks and assimilation are largely the focus of many of these models (Merganičová et al. 2019). Belowground carbon dynamics are often hard to experimentally quantify because of the spatial and temporal variability. Disturbance effects on belowground carbon dynamics range from loss of soil carbon through wildfires to decreased microbial activity with increased compaction and erosion post-harvest (Grigal 2000, Nave et al. 2022). These carbon consequences are not always accounted for within the models and can introduce more uncertainty in forest carbon modeling. The models that do include belowground carbon do so in a few different ways: soil carbon stocks, coarse and fine-root biomass, and litter (Bonan et al. 2011, Duarte et al. 2017, Hidy et al. 2016, Hudiburg et al. 2013, Kim et al. 2018b, Kull et al. 2019, Oleson et al. 2010, Peterman et al. 2014, Sitch et al. 2003, Tague and Band 2004). When included, the influence of disturbance on belowground carbon stocks is often simplistically represented as a proportion of the aboveground carbon effects, although some models, such as LANDIS-II, can apply a percentage of removal based on disturbance severity (Lucash et al. 2023). The complexity and feedbacks of belowground carbon in these models varies—often the soil is considered in only one or two layers, and the response of soil carbon stocks to disturbance is limited to fire in many models, if disturbance is considered at all. Soil carbon stocks and emissions modeling can be improved by including data that address how microbial interactions and soil processes at different depths are altered under climate change scenarios (Case et al. 2021). For example, Lucash et al. (2023) employed an updated soil dynamics model that allowed for measurable soil carbon (and nitrogen) pools and included microbial physiology and more layers of soil, which increased data resolution.

At fine spatial scales, the different ways that models deal with connectivity among cells are important: many models that include belowground data use a bucket approach for belowground dynamics, which limits soil connectivity among cells, affecting whether soil nutrients, moisture, and root diseases can spread to vegetation in surrounding cells (Ferguson et al. 2003, Sanchez-Ruiz et al. 2018, Witcosky 1985). Many models are limited to just one layer of vegetation or soil characteristics, including carbon (Vetter et al. 2008), which can decrease time and computing-power needs. However, by assuming all foliage receives full sunlight, this single-layer approach decreases vertical spatial resolution and may misrepresent productivity of shaded trees.

Despite fire being frequently studied, many models represent fire very simply by imposing a proportion of area burned annually (e.g., Biome-BGC, VDDT, LURA, and LANDCARB) rather than a mechanistic modeling of fire ignition and spread. Modeling connectivity within the forest can substantially affect the modeled fire effects—the ability to model fire expansion and the risk of the surrounding area igniting can increase the accuracy of projected fire disturbance (Scheller et al. 2019). Increasing connectivity among spatial cells and increasing data accuracy through multiple soil horizons and vegetation canopy layers will likely give a more complete and complex projection of forest carbon dynamics but will also increase the training and computing needed to use the models.

Models are increasingly incorporating disturbance, though many of the models lean heavily toward harvest and fire as the main (or only) disturbances, while wind, insects, and drought are not consistently incorporated into the models. Disturbance is difficult to predict and, especially in the face of climate change, is increasingly complex with feedbacks from, and linkages to, other disturbances and management histories (Williams et al. 2016). For example, increased temperatures and altered precipitation regimes can lead to drought disturbance that, in turn, increases the incidence of insect disturbance (Canelles et al. 2021). The complex interactions between climate and instances of disturbance are often observationally or experimentally studied, providing data to inform or validate potential model updates, but it is difficult to get large enough sample sizes sufficient to generalize and apply across a wide variety of scenarios (Canelles et al. 2021, Dale et al. 2001, Flint et al. 2009). Moreover, when models are applied to understand future climate effects on forests it is because there are not analogous scenarios in the history of the landscape that can incorporate all the complex interactions. In this scenario, many disturbance effects on forest carbon dynamics are based on climate projection, compounding the uncertainty of modeled carbon predictions that are themselves based on modeled future climate scenarios (Liu et al. 2011, Whitlock et al. 2015). Disturbances can be predicted but the onset of many disturbances is stochastic (e.g., insect infestation), and thus predictability is limited (Hicke et al. 2012). Ongoing model improvements that include increased customization of applications of stochastic onset of disturbance as expectations change with climate change could lead to more robust land management plans.

Some models are more user-friendly than others. Many models have self-paced trainings, occasional instructor-led training sessions, or extensive user guides to help new users successfully complete model runs. Most of the models are open source and at the very least have available code to download and edit. A few models are more difficult to access because the program, model code, or input data are not publicly available. Additionally, similar to spatial resolution and model scale, there are tradeoffs between data resolution and computing power: higher input and output data resolution will increase the computing power requirements and the time it will take to run the model.

Conclusion

Disturbances are likely to affect carbon stocks in most forests and are important to incorporate into land management planning. However, uncertainties, knowledge gaps, and modeling limitations constrain our ability to integrate disturbances into management planning aimed at maintaining forest carbon stocks. Further research and model development is needed to better incorporate soil carbon dynamics as well as the carbon effects of lesser studied disturbances (i.e., insect and disease outbreaks, wind, drought, freezing events) into our carbon analysis and projection systems. Improvements in computing power may allow for more sophisticated modeling of spatial connectivity and thus disturbance spread in the future. Models are necessarily simplifications of reality, and no single model can include all the potential processes that could influence the effect of disturbance on forest carbon dynamics, although combining models (as with ForCaMF/InTEC) or working with several models that integrate with each other (as with FVS and BioSum) can give a more complete picture. There is also a need to improve potential applicability of models to a broader array of potential user groups.

However, models are increasingly important tools for understanding how disturbance and management may influence forest carbon stocks as climate change progresses and novel conditions arise that might not be reflected in past empirical studies. As our understanding of disturbance effects on forest carbon advances and computational power increases, forest carbon models and our ability to incorporate them in management planning are likely to improve.

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U.S. Equivalents

When you know:	Multiply by:	To find:
Meters (m)	3.28	Feet
Kilometers (km)	0.621	Miles
Hectares (ha)	2.47	Acres
Square kilometers (km^2)	0.386	Square miles
Teragrams (Tg)	1.102e + 6	Tons
Tonnes per hectare (t/ha)	0.446	Tons per acre

References

Albani, M.; Medvigy, D.; Hurtt, G.C.; Moorcroft, P.R. 2006. The contributions of land-use change, CO_2 fertilization, and climate variability to the Eastern US carbon sink: partitioning to the Eastern US carbon sink. Global Change Biology. 12(12): 2370–2390. https://doi.org/10.1111/j.1365-2486.2006.01254.x.

Anderegg, W.R.L.; Schwalm, C.; Biondi, F.; Camarero, J.J.; Koch, G.; Litvak, M.; Ogle, K.; Shaw, J.D.; Shevliakova, E.; Williams, A.P.; Wolf, A.; Ziaco, E.; Pacala, S. 2015. Pervasive drought legacies in forest ecosystems and their implications for carbon cycle models. Science. 349(6247): 528–532. https://doi.org/10.1126/science.aab1833.

Antonarakis, A.S.; Bogan, S.A.; Goulden, M.L.; Moorcroft, P.R. 2022. Impacts of the 2012–2015 Californian drought on carbon, water and energy fluxes in the Californian Sierras: results from an imaging spectrometry-constrained terrestrial biosphere model. Global Change Biology. 28(5): 1823–1852. https://doi.org/10.1111/gcb.15995.

Arain, M.A.; Xu, B.; Brodeur, J.J.; Khomik, M.; Peichl, M.; Beamesderfer, E.; Restrepo-Couple, N.; Thorne, R. 2022. Heat and drought impact on carbon exchange in an age-sequence of temperate pine forests. Ecological Processes. 11(1): 7. https://doi.org/10.1186/s13717-021-00349-7.

Ashraf, M.I.; Zhao, Z.; Bourque, C.P.-A.; MacLean, D.A.; Meng, F.-R. 2013. Integrating biophysical controls in forest growth and yield predictions with artificial intelligence technology. Canadian Journal of Forest Research. 43(12): 1162–1171. https://doi.org/10.1139/cjfr-2013-0090.

Bachelet, D.; Ferschweiler, K.; Sheehan, T.J.; Sleeter, B.M.; Zhu, Z. 2015. Projected carbon stocks in the conterminous USA with land use and variable fire regimes. Global Change Biology. 21(12): 4548–4560. https://doi.org/10.1111/gcb.13048.

Bachelet, D.; Neilson, R.P.; Lenihan, J.M.; Drapek, R.J. 2001. Climate change effects on vegetation distribution and carbon budget in the United States. Ecosystems. 4(3): 164–185. https://doi.org/10.1007/s10021-001-0002-7.

Badgley, G.; Chay, F.; Chegwidden, O.S.; Hamman, J.J.; Freeman, J.; Cullenward, D. 2022. California's forest carbon offsets buffer pool is severely undercapitalized. Frontiers in Forests and Global Change. 5: 930426. https://doi.org/10.3389/ffgc.2022.930426.

Barbour, R.J.; Fried, J.S.; Daugherty, P.J.; Christensen, G.; Fight, R. 2008. Potential biomass and logs from fire-hazard-reduction treatments in southwest Oregon and northern California. Forest Policy and Economics. 10(6): 400–407. https://doi.org/10.1016/j.forpol.2008.02.003.

Bart, R.R.; Kennedy, M.C.; Tague, C.L.; McKenzie, D. 2020. Integrating fire effects on vegetation carbon cycling within an ecohydrologic model. Ecological Modelling. 416: 108880. https://doi.org/10.1016/j.ecolmodel.2019.108880.

Bart, R.R.; Tague, C.L.; Dennison, P.E. 2017. Modeling annual grassland phenology along the central coast of California. Ecosphere. 8(7): e01875. https://doi.org/10.1002/ecs2.1875. (May 2, 2023).

Bartowitz, K.J.; Walsh, E.S.; Stenzel, J.E.; Kolden, C.A.; Hudiburg, T.W. 2022. Forest carbon emission sources are not equal: putting fire, harvest, and fossil fuel emissions in context. Frontiers in Forests and Global Change. 5: 867112. https://doi.org/10.3389/ffgc.2022.867112.

Berkey, J.K.; Miller, C.; Larson, A.J. 2021. A history of wilderness fire management in the Northern Rockies. RMRS-GTR-428. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 88 p. https://doi.org/10.2737/RMRS-GTR-428.

Bestelmeyer, B.T.; Ash, A.; Brown, J.R.; Densambuu, B.; Fernández-Giménez, M.; Johanson, J.; Levi, M.; Lopez, D.; Peinetti, R.; Rumpff, L.; Shaver, P. 2017. State and transition models: theory, applications, and challenges. In: Briske, D.D., ed. Rangeland Systems: Springer Series on Environmental Management. Springer Cham: Springer International Publishing: 303–345. https://doi.org/10.1007/978-3-319-46709-2_9. (November 7, 2022).

Bigras, F.J.; Margolis, H.A. 1997. Shoot and root sensitivity of containerized black spruce, white spruce and jack pine seedlings to late fall freezing. New Forests. 13: 29–49.

Birdsey, R.A.; Dugan, A.J.; Healey, S.P.; Dante-Wood, K.; Zhang, F.; Mo, G.; Chen, J.M.; Hernandez, A.J.; Raymond, C.L.; McCarter, J. 2019. Assessment of the influence of disturbance, management activities, and environmental factors on carbon stocks of U.S. national forests. RMRS-GTR-402. Ft. Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 131 p. https://doi.org/10.2737/RMRS-GTR-402.

Blondel, A.; Flemming, C.; Liang, C.; Libby, M.; MacDonald, D.; Samson, C.; Thiagarajan, A.; Dasné, S. 2024. Chapter 6: Land Use, Land-Use Change and Forestry. In: Government of Canada, Environment Canada, Greenhouse Gas Division; Environment and Climate Change Canada. National inventory report: greenhouse gas sources and sinks in Canada. Gatineau, PQ, Canada: Public Information Centre, Environment and Climate Change Canada.

Boisramé, G.F.S.; Brown, T.J.; Bachelet, D.M. 2022. Trends in Western USA fire fuels using historical data and modeling. Fire Ecology. 18(1): 8. https://doi.org/10.1186/s42408-022-00129-4.

Bonan, G.B.; Lawrence, P.J.; Oleson, K.W.; Levis, S.; Jung, M.; Reichstein, M.; Lawrence, D.M.; Swenson, S.C. 2011. Improving canopy processes in the Community Land Model version 4 (CLM4) using global flux fields empirically inferred from FLUXNET data. Journal of Geophysical Research. 116(G2): G02014. https://doi.org/10.1029/2010JG001593.

Bormann, B.T.; Homann, P.S.; Darbyshire, R.L.; Morrissette, B.A. 2008. Intense forest wildfire sharply reduces mineral soil C and N: the first direct evidence. Canadian Journal of Forest Research. 38(11): 2771–2783. https://doi.org/10.1139/X08-136.

Brewer, J.S. 2016. Natural canopy damage and the ecological restoration of fire-indicative groundcover vegetation in an oak-pine forest. Fire Ecology. 12(2): 105–126. https://doi.org/10.4996/fireecology.1202105.

Brooks, J.R.; Meinzer, F.C.; Coulombe, R.; Gregg, J. 2002. Hydraulic redistribution of soil water during summer drought in two contrasting Pacific Northwest coniferous forests. Tree Physiology. 22(15–16): 1107–1117. https://doi.org/10.1093/treephys/22.15-16.1107.

Bugmann, H. 2001. A review of forest gap models. Climatic Change. 51(3/4): 259–305. https://doi.org/10.1023/A:1012525626267.

Bugmann, H.; Seidl, R. 2022. The evolution, complexity and diversity of models of long-term forest dynamics. Journal of Ecology. 110(10): 2288–2307. https://doi.org/10.1111/1365-2745.13989.

Buotte, P.C.; Koven, C.D.; Xu, C.; Shuman, J.K.; Goulden, M.L.; Levis, S.; Katz, J.; Ding, J.; Ma, W.; Robbins, Z.; Kueppers, L.M. 2021. Capturing functional strategies and compositional dynamics in vegetation demographic models. Biogeosciences. 18(14): 4473–4490. https://doi.org/10.5194/bg-18-4473-2021.

Burke, W.D.; Tague, C.; Kennedy, M.C.; Moritz, M.A. 2021. Understanding how fuel treatments interact with climate and biophysical setting to affect fire, water, and forest health: a process-based modeling approach. Frontiers in Forests and Global Change. 3: 591162. https://doi.org/10.3389/ffgc.2020.591162.

Cabiyo, B.; Fried, J.S.; Collins, B.M.; Stewart, W.; Wong, J.; Sanchez, D.L. 2021. Innovative wood use can enable carbon-beneficial forest management in California. PNAS. 118(49): e2019073118. https://doi.org/10.1073/pnas.2019073118.

Canelles, Q.; Aquilué, N.; James, P.M.A.; Lawler, J.; Brotons, L. 2021. Global review on interactions between insect pests and other forest disturbances. Landscape Ecology. 36(4): 945–972. https://doi.org/10.1007/s10980-021-01209-7.

Canham, C.D.; Papaik, M.J.; Latty, E.F. 2001. Interspecific variation in susceptibility to windthrow as a function of tree size and storm severity for northern temperate tree species. Canadian Journal of Forest Research. 31(1): 1–10. https://doi.org/10.1139/x00-124.

Cannon, J.B.; Peterson, C.J.; O'Brien, J.J.; Brewer, J.S. 2017. A review and classification of interactions between forest disturbance from wind and fire. Forest Ecology and Management. 406: 381–390. https://doi.org/10.1016/j.foreco.2017.07.035.

Cartwright, J.M.; Littlefield, C.E.; Michalak, J.L.; Lawler, J.J.; Dobrowski, S.Z. 2020. Topographic, soil, and climate drivers of drought sensitivity in forests and shrublands of the Pacific Northwest, USA. Scientific Reports. 10(1): 18486. https://doi.org/10.1038/s41598-020-75273-5.

Case, M.J.; Johnson, B.G.; Bartowitz, K.J.; Hudiburg, T.W. 2021. Forests of the future: climate change impacts and implications for carbon storage in the Pacific Northwest, USA. Forest Ecology and Management. 482: 118886. https://doi.org/10.1016/j.foreco.2020.118886.

Cassell, B.A.; Scheller, R.M.; Lucash, M.S.; Hurteau, M.D.; Loudermilk, E.L. 2019. Widespread severe wildfires under climate change lead to increased forest homogeneity in dry mixed-conifer forests. Ecosphere. 10(11): e02934. https://doi.org/10.1002/ecs2.2934. (September 20, 2022).

Chen, W.; Chen, J.; Cihlar, J. 2000. An integrated terrestrial ecosystem carbon-budget model based on changes in disturbance, climate, and atmospheric chemistry. Ecological Modelling. 135(1): 55–79. https://doi.org/10.1016/S0304-3800(00)00371-9.

Chen, B.; Liu, Z.; He, C.; Peng, H.; Xia, P.; Nie, Y. 2020. The Regional Hydro-Ecological Simulation System for 30 years: a systematic review. Water. 12(10): 2878. https://doi.org/10.3390/w12102878.

Christensen, G.A.; Gray, A.N.; Kuegler, O.; Siemann, D. 2020. Washington Forest Ecosystem Carbon Inventory: 2002–2016. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station and Washington State Department of Natural Resources. PNW Agreement No. 18-C-CO-11261979-066. Olympia, WA: Washington State Department of Natural Resources. 234 p.

Christensen, G.A.; Gray, A.N.; Kuegler, O.; Tase, N.A.; Rosenberg, M. 2017. California Forest Ecosystem and Harvested Wood Product Carbon Inventory: 2006–2015. U.S. Department of Agriculture, Forest Service agreement no. 14-FI-11052021-220 and California Department of Forestry and Fire Protection agreement no. 7CA02025. Sacramento, CA: California Department of Forestry and Fire Protection and California Board of Forestry and Fire Protection. 390 p.

Christensen, G.A.; Gray, A.N.; Kuegler, O.; Yost, A.C. 2019. Oregon Forest Ecosystem Carbon Inventory: 2001–2016. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station and Oregon Department of Forestry. PNW Agreement No. 18-C-CO-11261979-019. Salem, OR: Oregon Department of Forestry. 347 p.

Clarke, N.; Gundersen, P.; Jönsson-Belyazid, U.; Kjønaas, O.J.; Persson, T.; Sigurdsson, B.D.; Stupak, I.; Vesterdal, L. 2015. Influence of different tree-harvesting intensities on forest soil carbon stocks in boreal and northern temperate forest ecosystems. Forest Ecology and Management. 351: 9–19. https://doi.org/10.1016/j.foreco.2015.04.034.

Cohen, W.B.; Harmon, M.E.; Wallin, D.O.; Fiorella, M. 1996. Two decades of carbon flux from forests of the Pacific Northwest: estimates from a new modeling strategy. BioScience. 46(11): 836–844. https://doi.org/10.2307/1312969.

Creutzburg, M.K.; Scheller, R.M.; Lucash, M.S.; LeDuc, S.D.; Johnson, M.G. 2017. Forest management scenarios in a changing climate: trade-offs between carbon, timber, and old forest. Ecological Applications. 27(2): 503–518. https://doi.org/10.1002/eap.1460.

Crookston, N.L. 2014. Climate-FVS Version 2: content, users guide, applications, and behavior. RMRS-GTR-319. Ft. Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 38 p. https://doi.org/10.2737/RMRS-GTR-319.

Crookston, N.L.; Dixon, G.E. 2005. The forest vegetation simulator: a review of its structure, content, and applications. Computers and Electronics in Agriculture. 49(1): 60–80. https://doi.org/10.1016/j.compag.2005.02.003.

Crookston, N.L.; Rehfeldt, G.E.; Dixon, G.E.; Weiskittel, A.R. 2010. Addressing climate change in the forest vegetation simulator to assess impacts on landscape forest dynamics. Forest Ecology and Management. 260(7): 1198–1211. https://doi.org/10.1016/j.foreco.2010.07.013.

Dale, V.H.; Joyce, L.A.; McNulty, S.; Neilson, R.P.; Ayres, M.P.; Flannigan, M.D.; Hanson, P.J.; Irland, L.C.; Lugo, A.E.; Peterson, C.J.; Simberloff, D.; Swanson, F.J.; Stocks, B.J.; Michael Wotton, B. 2001. Climate change and forest disturbances: climate change can affect forests by altering the frequency, intensity, duration, and timing of fire, drought, introduced species, insect and pathogen outbreaks, hurricanes, windstorms, ice storms, or landslides. BioScience. 51(9): 723 –734. https://doi.org/10.1641/0006-3568(2001)051[0723:CCAFD]2.0.CO;2.

Davis, T.S.; Meddens, A.J.H.; Stevens-Rumann, C.S.; Jansen, V.S.; Sibold, J.S.; Battaglia, M.A. 2022. Monitoring resistance and resilience using carbon trajectories: analysis of forest management–disturbance interactions. Ecological Applications. 32(8): e2704. https://doi.org/10.1002/eap.2704. (January 31, 2023).

De Jager, N.R.; Drohan, P.J.; Miranda, B.M.; Sturtevant, B.R.; Stout, S.L.; Royo, A.A.; Gustafson, E.J.; Romanski, M.C. 2017. Simulating ungulate herbivory across forest landscapes: a browsing extension for LANDIS-II. Ecological Modelling. 350: 11–29. https://doi.org/10.1016/j.ecolmodel.2017.01.014.

Dixon, G.E. 2022. Essential FVS: a user's guide to the Forest Vegetation Simulator. Internal report. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Forest Management Service Center. 226 p.

Du, B.; Jansen, K.; Kleiber, A.; Eiblmeier, M.; Kammerer, B.; Ensminger, I.; Gessler, A.; Rennenberg, H.; Kreuzwieser, J. 2015. A coastal and an interior Douglas fir provenance exhibit different metabolic strategies to deal with drought stress. Tree Physiology. 36(2): 148–163. https://doi.org/10.1093/treephys/tpv105.

Duarte, H.F.; Raczka, B.M.; Ricciuto, D.M.; Lin, J.C.; Koven, C.D.; Thornton, P.E.; Bowling, D.R.; Lai, C.-T.; Bible, K.J.; Ehleringer, J.R. 2017. Evaluating the Community Land Model (CLM4.5) at a coniferous forest site in northwestern United States using flux and carbon-isotope measurements. Biogeosciences. 14(18): 4315–4340. https://doi.org/10.5194/bg-14-4315-2017.

Dugan, A.J.; Birdsey, R.; Healey, S.P.; Pan, Y.; Zhang, F.; Mo, G.; Chen, J.; Woodall, C.W.; Hernandez, A.J.; McCullough, K.; McCarter, J.B.; Raymond, C.L.; Dante-Wood, K. 2017. Forest sector carbon analyses support land management planning and projects: assessing the influence of anthropogenic and natural factors. Climatic Change. 144(2): 207–220. https://doi.org/10.1007/s10584-017-2038-5.

Dury, M.; Hambuckers, A.; Warnant, P.; Henrot, A.; Favre, E.; Ouberdous, M.; François, L. 2011. Responses of European forest ecosystems to 21st century climate: assessing changes in interannual variability and fire intensity. iForest – Biogeosciences and Forestry. 4(2): 82–99. https://doi.org/10.3832/ifor0572-004.

Dymond, C.C.; Beukema, S.; Nitschke, C.R.; Coates, K.D.; Scheller, R.M. 2015. Carbon sequestration in managed temperate coniferous forests under climate change. Preprint. Biogeochemistry: Greenhouse Gases. Biogeosciences. 13: 1933–1947. https://doi.org/10.5194/bg-13-1933-2016.

Earles, J.M.; North, M.P.; Hurteau, M.D. 2014. Wildfire and drought dynamics destabilize carbon stores of fire-suppressed forests. Ecological Applications. 24(4): 732–740. https://doi.org/10.1890/13-1860.1.

Edenhofer, O; Pichs-Madruga, R.; Sokona, Y.; Farahani, E.; Kadner, S.; Seyboth, K.; Adler, A.; Baum, I.; Brunner, S.; Eickemeier, P.; Kriemann, B.; Savolainen, J.; Schlömer, S.; von Stechow, C.; Zwickel, T.; Minx, J.C., eds. 2014. Climate change 2014: mitigation of climate change: working Group III contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. New York, NY: Cambridge University Press. 1435 p.

Emmett, K.D.; Renwick, K.M.; Poulter, B. 2021. Adapting a dynamic vegetation model for regional biomass, plant biogeography, and fire modeling in the Greater Yellowstone Ecosystem: evaluating LPJ-GUESS-LMfireCF. Ecological Modelling. 440: 109417. https://doi.org/10.1016/j.ecolmodel.2020.109417.

Fang, Y.; Leung, L.R.; Knox, R.; Koven, C.; Bond-Lamberty, B. 2022. Impact of the numerical solution approach of a plant hydrodynamic model (v0.1) on vegetation dynamics. Geoscientific Model Development. 15(16): 6385–6398. https://doi.org/10.5194/gmd-15-6385-2022.

Fei, S.; Morin, R.S.; Oswalt, C.M.; Liebhold, A.M. 2019. Biomass losses resulting from insect and disease invasions in US forests. Proceedings of the National Academy of Sciences. 116(35): 17371–17376. https://doi.org/10.1073/pnas.1820601116.

Ferguson, B.A.; Dreisbach, T.A.; Parks, C.G.; Filip, G.M.; Schmitt, C.L. 2003. Coarse-scale population structure of pathogenic *Armillaria* species in a mixed-conifer forest in the Blue Mountains of northeast Oregon. Canadian Journal of Forest Research. 33(4): 612–623. https://doi.org/10.1139/x03-065.

Fisher, R.A.; Wieder, W.R.; Sanderson, B.M.; Koven, C.D.; Oleson, K.W.; Xu, C.; Fisher, J.B.; Shi, M.; Walker, A.P.; Lawrence, D.M. 2019. Parametric controls on vegetation responses to biogeochemical forcing in the CLM5. Journal of Advances in Modeling Earth Systems. 11(9): 2879–2895. https://doi.org/10.1029/2019MS001609.

Flint, C.G.; McFarlane, B.; Müller, M. 2009. Human dimensions of forest disturbance by insects: an international synthesis. Environmental Management. 43(6): 1174–1186. https://doi.org/10.1007/s00267-008-9193-4.

Flower, C.E.; Gonzalez-Meler, M.A. 2015. Responses of temperate forest productivity to insect and pathogen disturbances. Annual Review of Plant Biology. 66(1): 547–569. https://doi.org/10.1146/annurev-arplant-043014-115540.

Foster, J. 2011. Dissertation: forest insect defoliation and carbon dynamics: linking remote sensing with simulation modeling. 189 p. Ph.D. dissertation. http://rgdoi.net/10.13140/2.1.2673.3763. (May 3, 2023).

Fried, J.S.; Potts, L.D.; Loreno, S.M.; Christensen, G.A.; Barbour, R.J. 2017. Inventory-based landscape-scale simulation of management effectiveness and economic feasibility with BioSum. Journal of Forestry. 115(4): 249–257. https://doi.org/10.5849/jof.15-087.

Geng, A.; Yang, H.; Chen, J.; Hong, Y. 2017. Review of carbon storage function of harvested wood products and the potential of wood substitution in greenhouse gas mitigation. Forest Policy and Economics. 85: 192–200. https://doi.org/10.1016/j.forpol.2017.08.007.

Girardin, M.P.; Guo, X.J.; Gervais, D.; Metsaranta, J.; Campbell, E.M.; Arsenault, A.; Isaac-Renton, M.; Hogg, E.H. 2022. Cold-season freeze frequency is a pervasive driver of subcontinental forest growth. Proceedings of the National Academy of Sciences. 119(18): e2117464119. https://doi.org/10.1073/pnas.2117464119.

Golub, A.; Sohngen, B.; Cai, Y.; Kim, J.; Hertel, T. 2022. Costs of forest carbon sequestration in the presence of climate change impacts. Environmental Research Letters. 17(10): 104011. https://doi.org/10.1088/1748-9326/ac8ec5.

Goodale, C.L.; Apps, M.J.; Birdsey, R.A.; Field, C.B.; Heath, L.S.; Houghton, R.A.; Jenkins, J.C.; Kohlmaier, G.H.; Kurz, W.; Liu, S.; Nabuurs, G.-J.; Nilsson, S.; Shvidenko, A.Z. 2002. Forest carbon sinks in the northern hemisphere. Ecological Applications. 12(3): 891–899. https://doi.org/10.1890/1051-0761(2002)012[0891:FCSITN]2.0.CO;2.

Graup, L.J.; Tague, C.L.; Harpold, A.A.; Krogh, S.A. 2022. Subsurface lateral flows buffer riparian water stress against snow drought. Journal of Geophysical Research: Biogeosciences. 127(12): e2022JG006980. https://doi.org/10.1029/2022JG006980.

Grigal, D.F. 2000. Effects of extensive forest management on soil productivity. Forest Ecology and Management. 138(1–3): 167–185. https://doi.org/10.1016/S0378-1127(00)00395-9.

Groffman, P.M.; Hardy, J.P.; Driscoll, C.T.; Fahey, T.J. 2006. Snow depth, soil freezing, and fluxes of carbon dioxide, nitrous oxide and methane in a northern hardwood forest: soil freezing and trace gases. Global Change Biology. 12(9): 1748–1760. https://doi.org/10.1111/j.1365-2486.2006.01194.x.

Gustafson, E.J.; Miranda, B.R.; Sturtevant, B.R. 2018. Linear Wind Disturbance v2.0 LANDIS-II Extension User Guide. Madison, WI: U.S. Department of Agriculture, Forest Service, Northern Research Station.

Gustafson, E.J.; Shifley, S.R.; Mladenoff, D.J.; Nimerfro, K.K.; He, H.S. 2000. Spatial simulation of forest succession and timber harvesting using LANDIS. Canadian Journal of Forest Research. 30(1): 32–43. https://doi.org/10.1139/x99-188.

Halofsky, J.S.; Conklin, D.R.; Donato, D.C.; Halofsky, J.E.; Kim, J.B. 2018. Climate change, wildfire, and vegetation shifts in a high-inertia forest landscape: western Washington, U.S.A. PLOS ONE. 13(12): e0209490. https://doi.org/10.1371/journal.pone.0209490.

Hanan, E.J.; Ren, J.; Tague, C.L.; Kolden, C.A.; Abatzoglou, J.T.; Bart, R.R.; Kennedy, M.C.; Liu, M.; Adam, J.C. 2021. How climate change and fire exclusion drive wildfire regimes at actionable scales. Environmental Research Letters. 16(2): 024051. https://doi.org/10.1088/1748-9326/abd78e.

Hanan, E.J.; Tague, C.; Choate, J.; Liu, M.; Kolden, C.; Adam, J. 2018. Accounting for disturbance history in models: using remote sensing to constrain carbon and nitrogen pool spin-up. Ecological Applications. 28(5): 1197–1214. https://doi.org/10.1002/eap.1718.

Harmon, M.E.; Domingo, J.E. 2001. A user's guide to STANDCARB 2.0: a model to simulate carbon stores in forest stands. Corvallis, OR: Oregon State University, Department of Forest Science.

Harmon, M.E.; Ferrell, W.K.; Franklin, J.F. 1990. Effects on carbon storage of conversion of old-growth forests to young forests. Science. 247(4943): 699–702. https://doi.org/10.1126/science.247.4943.699.

Harmon, M.E.; Marks, B.; Hejeebu, N.R. 1996. A user's guide to STANDCARB version 1.0: a model to simulate the carbon stores in forest stands. Corvallis, OR: Oregon State University, Department of Forest Science.

Hawkins, B.J.; Guest, H.J.; Kolotelo, D. 2003. Freezing tolerance of conifer seeds and germinants. Tree Physiology. 23(18): 1237–1246. https://doi.org/10.1093/treephys/23.18.1237.

Healey, S.P.; Urbanski, S.P.; Patterson, P.L.; Garrard, C. 2014. A framework for simulating map error in ecosystem models. Remote Sensing of Environment. 150: 207–217. https://doi.org/10.1016/j.rse.2014.04.028.

Hemstrom, M.A.; Merzenich, J.; Reger, A.; Wales, B. 2007. Integrated analysis of landscape management scenarios using state and transition models in the upper Grande Ronde River subbasin, Oregon, USA. Landscape and Urban Planning. 80(3): 198–211. https://doi.org/10.1016/j.landurbplan.2006.10.004.

Hicke, J.A.; Allen, C.D.; Desai, A.R.; Dietze, M.C.; Hall, R.J.; Hogg, E.H.; Kashian, D.M.; Moore, D.; Raffa, K.F.; Sturrock, R.N.; Vogelmann, J. 2012. Effects of biotic disturbances on forest carbon cycling in the United States and Canada. Global Change Biology. 18(1): 7–34. https://doi.org/10.1111/j.1365-2486.2011.02543.x.

Hidy, D.; Barcza, Z.; Marjanović, H.; Ostrogović Sever, M.Z.; Dobor, L.; Gelybó, G.; Fodor, N.; Pintér, K.; Churkina, G.; Running, S.; Thornton, P.; Bellocchi, G.; Haszpra, L.; Horváth, F.; Suyker, A.; Nagy, Z. 2016. Terrestrial ecosystem process model Biome-BGCMuSo v4.0: summary of improvements and new modeling possibilities. Geoscientific Model Development. 9(12): 4405–4437. https://doi.org/10.5194/gmd-9-4405-2016.

Hlásny, T.; Barcza, Z.; Barka, I.; Merganičová, K.; Sedmák, R.; Kern, A.; Pajtík, J.; Balázs, B.; Fabrika, M.; Churkina, G. 2014. Future carbon cycle in mountain spruce forests of Central Europe: modelling framework and ecological inferences. Forest Ecology and Management. 328: 55–68. https://doi.org/10.1016/j.foreco.2014.04.038.

Huang, M.; Xu, Y.; Longo, M.; Keller, M.; Knox, R.G.; Koven, C.D.; Fisher, R.A. 2020. Assessing impacts of selective logging on water, energy, and carbon budgets and ecosystem dynamics in Amazon forests using the Functionally Assembled Terrestrial Ecosystem Simulator. Biogeosciences. 17(20): 4999–5023. https://doi.org/10.5194/bg-17-4999-2020.

Hudiburg, T.W.; Law, B.E.; Thornton, P.E. 2013. Evaluation and improvement of the Community Land Model (CLM4) in Oregon forests. Biogeosciences. 10(1): 453–470. https://doi.org/10.5194/bg-10-453-2013.

Hurteau, M.D.; Brooks, M.L. 2011. Short- and long-term effects of fire on carbon in US dry temperate forest systems. BioScience. 61(2): 139–146. https://doi.org/10.1525/bio.2011.61.2.9.

Hurteau, M.D.; North, M. 2010. Carbon recovery rates following different wildfire risk mitigation treatments. Forest Ecology and Management. 260(5): 930–937. https://doi.org/10.1016/j.foreco.2010.06.015.

Hwang, T.; Kang, S.; Kim, J.; Kim, Y.; Lee, D.; Band, L. 2008. Evaluating drought effect on MODIS Gross Primary Production (GPP) with an eco-hydrological model in the mountainous forest, East Asia. Global Change Biology. 14(5): 1037–1056. https://doi.org/10.1111/j.1365-2486.2008.01556.x.

Jain, T.B.; Fried, J.S.; Loreno, S.M. 2020. Simulating the effectiveness of improvement cuts and commercial thinning to enhance fire resistance in west coast dry mixed conifer forests. Forest Science. 66(2): 157–177. https://doi.org/10.1093/forsci/fxz071.

Janowiak, M.; Connelly, W.J.; Dante-Wood, K.; Domke, G.M.; Giardina, C.P.; Kayler, Z.; Marcinkowski, K.; Ontl, T.; Rodriguez-Franco, C.; Swanston, C.; Woodall, C.W.; Buford, M. 2017. Considering forest and grassland carbon in land management. Gen. Tech. Rep. WO-95. Washington, DC: U.S. Department of Agriculture, Forest Service. 76 p. https://doi.org/10.2737/WO-GTR-95.

Jiang, Y.; Kim, J.B.; Trugman, A.T.; Kim, Y.; Still, C.J. 2019. Linking tree physiological constraints with predictions of carbon and water fluxes at an old-growth coniferous forest. Ecosphere. 10(4): e02692. https://doi.org/10.1002/ecs2.2692. (August 9, 2022).

Kang, S.; Running, S.W.; Kimball, J.S.; Fagre, D.B.; Michaelis, A.; Peterson, D.L.; Halofsky, J.E.; Hong, S. 2014. Effects of spatial and temporal climatic variability on terrestrial carbon and water fluxes in the Pacific Northwest, USA. Environmental Modelling & Software. 51: 228–239. https://doi.org/10.1016/j.envsoft.2013.09.020.

Keane, R.E.; Loehman, R.A.; Holsinger, L.M. 2019. Selecting a landscape model for natural resource management applications. Current Landscape Ecology Reports. 4(2): 31–40. https://doi.org/10.1007/s40823-019-00036-6.

Kennedy, M.C.; Bart, R.R.; Tague, C.L.; Choate, J.S. 2021. Does hot and dry equal more wildfire? Contrasting short- and long-term climate effects on fire in the Sierra Nevada, CA. Ecosphere. 12(7): e03657. https://doi.org/10.1002/ecs2.3657.

Kennedy, M.C.; McKenzie, D.; Tague, C.; Dugger, A.L. 2017. Balancing uncertainty and complexity to incorporate fire spread in an eco-hydrological model. International Journal of Wildland Fire. 26(8): 706. https://doi.org/10.1071/WF16169.

Kim, J.B.; Kerns, B.K.; Drapek, R.J.; Pitts, G.S.; Halofsky, J.E. 2018a. Simulating vegetation response to climate change in the Blue Mountains with MC2 dynamic global vegetation model. Climate Services. 10: 20–32. https://doi.org/10.1016/j.cliser.2018.04.001.

Kim, J.B.; Monier, E.; Sohngen, B.; Pitts, G.S.; Drapek, R.; McFarland, J.; Ohrel, S.; Cole, J. 2017. Assessing climate change impacts, benefits of mitigation, and uncertainties on major global forest regions under multiple socioeconomic and emissions scenarios. Environmental Research Letters. 12(4): 045001. https://doi.org/10.1088/1748-9326/aa63fc.

Kim, J.H.; Hwang, T.; Yang, Y.; Schaaf, C.L.; Boose, E.; Munger, J.W. 2018b. Warming-induced earlier greenup leads to reduced stream discharge in a temperature mixed forest catchment. Journal of Geophysical Research: Biogeosciences. 123(6): 1960–1975. https://doi.org/10.1029/2018JG004438.

Klenner, W.; Kurz, W.; Beukema, S. 2000. Habitat patterns in forested landscapes: management practices and the uncertainty associated with natural disturbances. Computers and Electronics in Agriculture. 27(1–3): 243–262. https://doi.org/10.1016/S0168-1699(00)00110-1.

Koven, C.D.; Knox, R.G.; Fisher, R.A.; Chambers, J.Q.; Christoffersen, B.O.; Davies, S.J.; Detto, M.; Dietze, M.C.; Faybishenko, B.; Holm, J.; Huang, M.; Kovenock, M.; Kueppers, L.M.; Lemieux, G.; Massoud, E.; McDowell, N.G.; Muller-Landau, H.C.; Needham, J.F.; Norby, R.J.; Powell, T.; Rogers, A.; Serbin, S.P.; Shuman, J.K.; Swann, A.L.S.; Varadharajan, C.; Walker, A.P.; Wright, S.J.; Xu, C. 2020. Benchmarking and parameter sensitivity of physiological and vegetation dynamics using the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) at Barro Colorado Island, Panama. Biogeosciences. 17(11): 3017–3044. https://doi.org/10.5194/bg-17-3017-2020.

Kramer, M.G.; Hansen, A.J.; Taper, M.L.; Kissinger, E.J. 2001. Abiotic controls on long-term windthrow and temperate rain forest dynamics in southeast Alaska. Ecology. 82(10): 2749–2768. https://doi.org/10.1890/0012-9658(2001)082[2749:ACOLTW]2.0.CO;2.

Krankina, O.N.; Harmon, M.E.; Schnekenburger, F.; Sierra, C.A. 2012. Carbon balance on federal forest lands of western Oregon and Washington: the impact of the Northwest Forest Plan. Forest Ecology and Management. 286: 171–182. https://doi.org/10.1016/j.foreco.2012.08.028.

Kull, S.J.; Rampley, G.J.; Morken, S.; Metsaranta, J.; Neilson, E.T.; Kurz, W.A. 2019. Operational-scale Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) version 1.2: user's guide. Edmonton, Alberta: Canadian Forest Service, Northern Forestry Centre.

Kurz, W.; Beukema, S.; Merzenich, J.; Arbaugh, M.; Schilling, S. 1999. Long-range modeling of stochastic disturbances and management treatments using VDDT and TELSA. Portland, OR: Society of American Foresters National Convention: Landscape Analysis session.

Kurz, W.A.; Apps, M.J. 2006. Developing Canada's national forest carbon monitoring, accounting, and reporting system to meet the reporting requirements of the Kyoto Protocol. Mitigation and Adaptation Strategies for Global Change. 11(1): 33–43. https://doi.org/10.1007/s11027-006-1006-6.

Kurz, W.A.; Dymond, C.C.; White, T.M.; Stinson, G.; Shaw, C.H.; Rampley, G.J.; Smyth, C.; Simpson, B.N.; Neilson, E.T.; Trofymow, J.A.; Metsaranta, J.; Apps, M.J. 2009. CBM-CFS3: a model of carbon-dynamics in forestry and land-use change implementing IPCC standards. Ecological Modelling. 220(4): 480–504. https://doi.org/10.1016/j.ecolmodel.2008.10.018.

Kurz, W.A.; Shaw, C.H.; Boisvenue, C.; Stinson, G.; Metsaranta, J.; Leckie, D.; Dyk, A.; Smyth, C.; Neilson, E.T. 2013. Carbon in Canada's boreal forest—A synthesis. Environmental Reviews. 21(4): 260–292. https://doi.org/10.1139/er-2013-0041.

Lafon, C.W. 2016. Ice storms in central hardwood forests: the disturbance regime, spatial patterns, and vegetation influences. In: Greenberg, C.H.; Collins, B.S., eds. Natural disturbances and historic range of variation: managing forest ecosystems. Springer Cham: Springer International Publishing: 147–166. https://doi.org/10.1007/978-3-319-21527-3_7.

Landry, G.; Thiffault, E.; Cyr, D.; Moreau, L.; Boulanger, Y.; Dymond, C. 2021. Mitigation potential of ecosystem-based forest management under climate change: a case study in the Boreal-Temperate Forest Ecotone. Forests. 12(12): 1667. https://doi.org/10.3390/f12121667.

Latham, P.; Tappeiner, J. 2002. Response of old-growth conifers to reduction in stand density in western Oregon forests. Tree Physiology. 22(2–3): 137–146. https://doi.org/10.1093/treephys/22.2-3.137.

Latta, G.S.; Baker, J.S.; Ohrel, S. 2018. A Land Use and Resource Allocation (LURA) modeling system for projecting localized forest CO_2 effects of alternative macroeconomic futures. Forest Policy and Economics. 87: 35–48. https://doi.org/10.1016/j.forpol.2017.10.003.

Laurent, J.-M.; Francois, L.; Bar-Hen, A.; Bel, L.; Cheddadi, R. 2008. European bioclimatic affinity groups: data-model comparisons. Global and Planetary Change. 61(1–2): 28–40. https://doi.org/10.1016/j.gloplacha.2007.08.017.

Law, B.E.; Sun, O.J.; Campbell, J.; Van Tuyl, S.; Thornton, P.E. 2003. Changes in carbon storage and fluxes in a chronosequence of ponderosa pine. Global Change Biology. 9(4): 510–524. https://doi.org/10.1046/j.1365-2486.2003.00624.x.

Law, B.E.; Thornton, P.E.; Irvine, J.; Anthoni, P.M.; Van Tuyl, S. 2001. Carbon storage and fluxes in ponderosa pine forests at different developmental stages. Global Change Biology. 7(7): 755–777. https://doi.org/10.1046/j.1354-1013.2001.00439.x.

Law, B.E.; Waring, R.H. 2015. Carbon implications of current and future effects of drought, fire and management on Pacific Northwest forests. Forest Ecology and Management. 355: 4–14. https://doi.org/10.1016/j.foreco.2014.11.023.

Lawrence, D.M.; Fisher, R.A.; Koven, C.D.; Oleson, K.W.; Swenson, S.C.; Bonan, G.; Collier, N.; Ghimire, B.; van Kampenhout, L.; Kennedy, D.; Kluzek, E.; Lawrence, P.J.; Li, F.; Li, H.; Lombardozzi, D.; Riley, W.J.; Sacks, W.J.; Shi, M.; Vertenstein, M.; Wieder, W.R.; Xu, C.; Ali, A.A.; Badger, A.M.; Bisht, G.; van den Broeke, M.; Brunke, M.A.; Burns, S.P.; Buzan, J.; Clark, M.; Craig, A.; Dahlin, K.; Drewniak, B.; Fisher, J.B.; Flanner, M.; Fox, A.M.; Gentine, P.; Hoffman, F.; Keppel-Aleks, G.; Knox, R.; Kumar, S.; Lenaerts, J.; Leung, L.R.; Lipscomb, W.H.; Lu, Y.; Pandey, A.; Pelletier, J.D.; Perket, J.; Randerson, J.T.; Ricciuto, D.M.; Sanderson, B.M.; Slater, A.; Subin, Z.M.; Tang, J.; Thomas, R.Q.; Val Martin, M.; Zeng, X. 2019. The Community Land Model Version 5: description of new features, benchmarking, and impact of forcing uncertainty. Journal of Advances in Modeling Earth Systems. 11(12): 4245–4287. https://doi.org/10.1029/2018MS001583.

Lenihan, J.M.; Bachelet, D.; Neilson, R.P.; Drapek, R. 2008. Simulated response of conterminous United States ecosystems to climate change at different levels of fire suppression, CO_2 emission rate, and growth response to CO_2. Global and Planetary Change. 64(1–2): 16–25. https://doi.org/10.1016/j.gloplacha.2008.01.006.

Levine, N.M.; Zhang, K.; Longo, M.; Baccini, A.; Phillips, O.L.; Lewis, S.L.; Alvarez-Dávila, E.; Segalin de Andrade, A.C.; Brienen, R.J.W.; Erwin, T.L.; Feldpausch, T.R.; Monteagudo Mendoza, A.L.; Nuñez Vargas, P.; Prieto, A.; Silva-Espejo, J.E.; Malhi, Y.; Moorcroft, P.R. 2016. Ecosystem heterogeneity determines the ecological resilience of the Amazon to climate change. Proceedings of the National Academy of Sciences. 113(3): 793–797. https://doi.org/10.1073/pnas.1511344112.

Ling, P.; Prince, S.; Baiocchi, G.; Dymond, C.; Xi, W.; Hurtt, G. 2020. Impact of fire and harvest on forest ecosystem services in a species-rich area in the southern Appalachians. Ecosphere. 11(6): e03150. https://doi.org/10.1002/ecs2.3150. (May 8, 2023).

Liu, S.; Bond-Lamberty, B.; Hicke, J.A.; Vargas, R.; Zhao, S.; Chen, J.; Edburg, S.L.; Hu, Y.; Liu, J.; McGuire, A.D.; Xiao, J.; Keane, R.; Yuan, W.; Tang, J.; Luo, Y.; Potter, C.; Oeding, J. 2011. Simulating the impacts of disturbances on forest carbon cycling in North America: processes, data, models, and challenges. Journal of Geophysical Research. 116: G00K08. https://doi.org/10.1029/2010JG001585.

Longo, M. 2014. Amazon forest response to changes in rainfall regime: results from an individual-based dynamic vegetation model. Cambridge, MA: Harvard University. 71 p. Ph.D. dissertation.

Longo, M.; Knox, R.G.; Levine, N.M.; Alves, L.F.; Bonal, D.; Camargo, P.B.; Fitzjarrald, D.R.; Hayek, M.N.; Restrepo-Coupe, N.; Saleska, S.R.; da Silva, R.; Stark, S.C.; Tapajós, R.P.; Wiedemann, K.T.; Zhang, K.; Wofsy, S.C.; Moorcroft, P.R. 2018. Ecosystem heterogeneity and diversity mitigate Amazon forest resilience to frequent extreme droughts. New Phytologist. 219(3): 914–931. https://doi.org/10.1111/nph.15185.

Longo, M.; Knox, R.G.; Medvigy, D.M.; Levine, N.M.; Dietze, M.C.; Kim, Y.; Swann, A.L.S.; Zhang, K.; Rollinson, C.R.; Bras, R.L.; Wofsy, S.C.; Moorcroft, P.R. 2019. The biophysics, ecology, and biogeochemistry of functionally diverse, vertically and horizontally heterogeneous ecosystems: the Ecosystem Demography model, version 2.2—part 1: model description. Geoscientific Model Development. 12(10): 4309–4346. https://doi.org/10.5194/gmd-12-4309-2019.

Loreno, S.; Fried, J.S.; Yost, A. 2015. Applying management modeling to assess the feasibility of accelerating landscape restoration on federal forests in eastern Oregon. In: Pushing boundaries: new directions in inventory techniques and applications: Forest Inventory and Analysis (FIA) Symposium 2015. [Proceedings]. Gen. Tech. Rep. PNW-GTR-931. Portland, OR: U.S. Department of Agriculture, Forest Service. 384 p. https://doi.org/10.2737/PNW-GTR-931.

Lovell, H.C. 2010. Governing the carbon offset market. Wiley Interdisciplinary Reviews: Climate Change. 1(3): 353–362. https://doi.org/10.1002/wcc.43.

Lucash, M.S.; Marshall, A.M.; Weiss, S.A.; McNabb, J.W.; Nicolsky, D.J.; Flerchinger, G.N.; Link, T.E.; Vogel, J.G.; Scheller, R.M.; Abramoff, R.Z.; Romanovsky, V.E. 2023. Burning trees in frozen soil: Simulating fire, vegetation, soil, and hydrology in the boreal forests of Alaska. Ecological Modelling. 481: 110367. https://doi.org/10.1016/j.ecolmodel.2023.110367.

Lucash, M.S.; Scheller, R.M. 2021. LANDIS-II climate library v4.2 user guide. Eugene, OR: University of Oregon.

Luo, Y.; Ahlström, A.; Allison, S.D.; Batjes, N.H.; Brovkin, V.; Carvalhais, N.; Chappell, A.; Ciais, P.; Davidson, E.A.; Finzi, A.; Georgiou, K.; Guenet, B.; Hararuk, O.; Harden, J.W.; He, Y.; Hopkins, F.; Jiang, L.; Koven, C.; Jackson, R.B.; Jones, C.D.; Lara, M.J.; Liang, J.; McGuire, A.D.; Parton, W.; Peng, C.; Randerson, J.T.; Salazar, A.; Sierra, C.A.; Smith, M.J.; Tian, H.; Todd-Brown, K.E.O.; Torn, M.; Groenigen, K.J.; Wang, Y.P.; West, T.O.; Wei, Y.; Wieder, W.R.; Xia, J.; Xu, X.; Xu, X.; Zhou, T. 2016. Toward more realistic projections of soil carbon dynamics by earth system models. Global Biogeochemical Cycles. 30(1): 40–56. https://doi.org/10.1002/2015GB005239.

Maness, T.C. 2009. Forest management and climate change mitigation: good policy requires careful thought. Journal of Forestry. 107(3):119–124. https://doi.org/10.1093/jof/107.3.119.

Martínez-Sancho, E.; Treydte, K.; Lehmann, M.M.; Rigling, A.; Fonti, P. 2022. Drought impacts on tree carbon sequestration and water use—evidence from intra-annual tree-ring characteristics. New Phytologist. 236(1): 58–70. https://doi.org/10.1111/nph.18224.

Martinkus, N.; Latta, G.; Morgan, T.; Wolcott, M. 2017. A comparison of methodologies for estimating delivered forest residue volume and cost to a wood-based biorefinery. Biomass and Bioenergy. 106: 83–94. https://doi.org/10.1016/j.biombioe.2017.08.023.

Masek, J.G.; Goward, S.N.; Kennedy, R.E.; Cohen, W.B.; Moisen, G.G.; Schleeweis, K.; Huang, C. 2013. United States forest disturbance trends observed using Landsat time series. Ecosystems. 16(6): 1087–1104. https://doi.org/10.1007/s10021-013-9669-9.

Maxwell, C.; Scheller, R.M.; Long, J.W.; Manley, P. 2022. Frequency of disturbance mitigates high-severity fire in the Lake Tahoe Basin, California and Nevada. Ecology and Society. 27(1): art21. https://doi.org/10.5751/ES-12954-270121.

McDowell, N.G.; Fisher, R.A.; Xu, C.; Domec, J.C.; Hölttä, T.; Mackay, D.S.; Sperry, J.S.; Boutz, A.; Dickman, L.; Gehres, N.; Limousin, J.M.; Macalady, A.; Martínez-Vilalta, J.; Mencuccini, M.; Plaut, J.A.; Ogée, J.; Pangle, R.E.; Rasse, D.P.; Ryan, M.G.; Sevanto, S.; Waring, R.H.; Williams, A.P.; Yepez, E.A.; Pockman, W.T. 2013. Evaluating theories of drought-induced vegetation mortality using a multimodel–experiment framework. New Phytologist. 200(2): 304–321. https://doi.org/10.1111/nph.12465.

McKinley, D.C.; Ryan, M.G.; Birdsey, R.A.; Giardina, C.P.; Harmon, M.E.; Heath, L.S.; Houghton, R.A.; Jackson, R.B.; Morrison, J.F.; Murray, B.C.; Pataki, D.E.; Skog, K.E. 2011. A synthesis of current knowledge on forests and carbon storage in the United States. Ecological Applications. 21(6): 1902–1924. https://doi.org/10.1890/10-0697.1.

Medvigy, D.; Wang, G.; Zhu, Q.; Riley, W.J.; Trierweiler, A.M.; Waring, B.G.; Xu, X.; Powers, J.S. 2019. Observed variation in soil properties can drive large variation in modelled forest functioning and composition during tropical forest secondary succession. New Phytologist. 223(4): 1820–1833. https://doi.org/10.1111/nph.15848.

Medvigy, D.; Wofsy, S.C.; Munger, J.W.; Hollinger, D.Y.; Moorcroft, P.R. 2009. Mechanistic scaling of ecosystem function and dynamics in space and time: Ecosystem Demography model version 2. Journal of Geophysical Research. 114(G1): G01002. https://doi.org/10.1029/2008JG000812.

Meigs, G.W.; Kennedy, R.E.; Gray, A.N.; Gregory, M.J. 2015. Spatiotemporal dynamics of recent mountain pine beetle and western spruce budworm outbreaks across the Pacific Northwest region, USA. Forest Ecology and Management. 339: 71–86. https://doi.org/10.1016/j.foreco.2014.11.030.

Merganičová, K.; Merganič, J.; Lehtonen, A.; Vacchiano, G.; Sever, M.Z.O.; Augustynczik, A.L.D.; Grote, R.; Kyselová, I.; Mäkelä, A.; Yousefpour, R.; Krejza, J.; Collalti, A.; Reyer, C.P.O. 2019. Forest carbon allocation modelling under climate change. Tree Physiology. 39(12): 1937–1960. https://doi.org/10.1093/treephys/tpz105.

Metsaranta, J.M.; Hudson, B.; Smyth, C.; Fellows, M.; Kurz, W.A. 2023. Future fire risk and the greenhouse gas mitigation potential of forest rehabilitation in British Columbia, Canada. Forest Ecology and Management. 529: 120729. https://doi.org/10.1016/j.foreco.2022.120729.

Mildrexler, D.; Yang, Z.; Cohen, W.B.; Bell, D.M. 2016. A forest vulnerability index based on drought and high temperatures. Remote Sensing of Environment. 173: 314–325. https://doi.org/10.1016/j.rse.2015.11.024.

Minet, J.; Jacquemin, I.; François, L. 2013. CARAIB User's Guide. Liège, Belgium, University of Liège. https://hdl.handle.net/2268/155872. (July 9, 2024).

Mitchell, S.R.; Harmon, M.E.; O'Connell, K.E.B. 2012. Carbon debt and carbon sequestration parity in forest bioenergy production. GCB Bioenergy. 4(6): 818–827. https://doi.org/10.1111/j.1757-1707.2012.01173.x.

Mladenoff, D.J. 2004. LANDIS and forest landscape models. Ecological Modelling. 180(1): 7–19. https://doi.org/10.1016/j.ecolmodel.2004.03.016.

Mladenoff, D.J.; Baker, W.L., eds. 1999. Spatial modeling of forest landscape change: approaches and applications. Cambridge, New York: Cambridge University Press. 352 p.

Momodu, P.A. 2019. Terrain susceptibility to windthrow of trees in subalpine forests, Canadian Rockies. Calgary, Alberta: University of Calgary. 112 p. M.S. thesis.

Moura Costa, P.; Stuart, M.; Pinard, M.; Phillips, G. 2000. Elements of a certification system for forestry-based carbon offset projects. Mitigation and Adaptation Strategies for Global Change. 5(1): 39–50. https://doi.org/10.1023/A:1009656501414.

Nave, L.E.; DeLyser, K.; Domke, G.M.; Holub, S.M.; Janowiak, M.K.; Kittler, B.; Ontl, T.A.; Sprague, E.; Sucre, E.B.; Walters, B.F.; Swanston, C.W. 2022. Disturbance and management effects on forest soil organic carbon stocks in the Pacific Northwest. Ecological Applications. 32(6): e261. https://doi.org/10.1002/eap.2611.

Nemens, D.G.; Varner, J.M.; Kidd, K.R.; Wing, B. 2018. Do repeated wildfires promote restoration of oak woodlands in mixed-conifer landscapes? Forest Ecology and Management. 427: 143–151. https://doi.org/10.1016/j.foreco.2018.05.023

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

Oleson, K.W.; Lawrence, D.M.; Flanner, M.G.; Kluzek, E.; Levis, S.; Swenson, S.C.; Thornton, E.; Dai, A.; Decker, M.; Dickinson, R.; Feddema, J.; Heald, C.L.; Lamarque, J.-F.; Niu, G.-Y.; Qian, T.; Running, S.; Sakaguchi, K.; Slater, A.; Stöckli, R.; Wang, A.; Yang, L.; Zeng, X.; Zeng, X. 2010. Technical description of version 4.0 of the Community Land Model (CLM). Boulder, CO: National Center for Atmospheric Research, Climate and Global Dynamics Division. 266 p.

Otto, D.; Rasse, D.; Kaplan, J.; Warnant, P.; François, L. 2002. Biospheric carbon stocks reconstructed at the last glacial maximum: comparison between general circulation models using prescribed and computed sea surface temperatures. Global and Planetary Change. 33(1–2): 117–138. https://doi.org/10.1016/S0921-8181(02)00066-8.

Overpeck, J.T.; Rind, D.; Goldberg, R. 1990. Climate-induced changes in forest disturbance and vegetation. Nature. 343(6253): 51–53. https://doi.org/10.1038/343051a0.

Pan, Y.; Chen, J.M.; Birdsey, R.; McCullough, K.; He, L.; Deng, F. 2011. Age structure and disturbance legacy of North American forests. Biogeosciences. 8(3): 715–732. https://doi.org/10.5194/bg-8-715-2011.

Parks, S.A.; Abatzoglou, J.T. 2020. Warmer and drier fire seasons contribute to increases in area burned at high severity in Western US forests from 1985 to 2017. Geophysical Research Letters. 47(22): e2020GL089858. https://doi.org/10.1029/2020GL089858. (March 13, 2023).

Perry, G.L.W.; Enright, N.J. 2006. Spatial modelling of vegetation change in dynamic landscapes: a review of methods and applications. Progress in Physical Geography: Earth and Environment. 30(1): 47–72. https://doi.org/10.1191/0309133306pp469ra.

Peterman, W.; Bachelet, D.; Ferschweiler, K.; Sheehan, T. 2014. Soil depth affects simulated carbon and water in the MC2 dynamic global vegetation model. Ecological Modelling. 294: 84–93. https://doi.org/10.1016/j.ecolmodel.2014.09.025.

Pilli, R.; Grassi, G.; Kurz, W.A.; Moris, J.V.; Viñas, R.A. 2016. Modelling forest carbon stock changes as affected by harvest and natural disturbances. II. EU-level analysis. Carbon Balance and Management. 11(1): 20. https://doi.org/10.1186/s13021-016-0059-4.

Pokharel, R.; Latta, G.S. 2020. A network analysis to identify forest merchantability limitations across the United States. Forest Policy and Economics. 116: 102181. https://doi.org/10.1016/j.forpol.2020.102181.

Pokharel, R.; Latta, G.S.; Ohrel, S.B. 2023. Estimating climate-sensitive wildfire risk and tree mortality models for use in broad-scale U.S. forest carbon projections. Forests. 14(2): 302. https://doi.org/10.3390/f14020302.

Potts, L.; Bross, L.; Loreno, S.; Mozelewski, T.; Fried, J.; Busby, S. In press. FIA BioSum: a user's guide. Gen. Tech. Rep. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Prisley, S.P.; Mortimer, M.J. 2004. A synthesis of literature on evaluation of models for policy applications, with implications for forest carbon accounting. Forest Ecology and Management. 198(1–3): 89–103. https://doi.org/10.1016/j.foreco.2004.03.038.

Rabin, S.S.; Melton, J.R.; Lasslop, G.; Bachelet, D.; Forrest, M.; Hantson, S.; Li, F.; Mangeon, S.; Yue, C.; Arora, V.K.; Hickler, T.; Kloster, S.; Knorr, W.; Nieradzik, L.; Spessa, A.; Folberth, G.A.; Sheehan, T.; Voulgarakis, A.; Prentice, I.C.; Sitch, S.; Kaplan, J.O.; Harrison, S.; Arneth, A. 2016. The Fire Modeling Intercomparison Project (FireMIP), phase 1: experimental and analytical protocols. Preprint. Geoscientific System Modeling. 10: 1175–1197. https://doi.org/10.5194/gmd-10-1175-2017.

Raymond, C.L.; Healey, S.; Peduzzi, A.; Patterson, P. 2015. Representative regional models of post-disturbance forest carbon accumulation: integrating inventory data and a growth and yield model. Forest Ecology and Management. 336: 21–34. https://doi.org/10.1016/j.foreco.2014.09.038.

Rebain, S.A. 2010. The fire and fuels extension to the Forest Vegetation Simulator: updated model documentation. Rev. 2022. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Forest Management Service Center. 409 p.

Reinhardt, E.; Crookston, N.L. 2003. The Fire and Fuels Extension to the Forest Vegetation Simulator. RMRS-GTR-116. Ft. Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 209 p. https://doi.org/10.2737/RMRS-GTR-116.

Robert, L.-E.; Sturtevant, B.R.; Kneeshaw, D.; James, P.M.A.; Fortin, M.-J.; Wolter, P.T.; Townsend, P.A.; Cooke, B.J. 2020. Forest landscape structure influences the cyclic-eruptive spatial dynamics of forest tent caterpillar outbreaks. Ecosphere. 11(8): e03096. https://doi.org/10.1002/ecs2.3096. (December 16, 2022).

Rog, I.-E.; Tague, C.; Jakoby, G.; Megidish, S.; Yaakobi, A.; Wagner, Y.; Klein, T. 2021. Interspecific soil water partitioning as a driver of increased productivity in a diverse mixed Mediterranean forest. Journal of Geophysical Research: Biogeosciences. 126(9): e2021JG006382. https://doi.org/10.1029/2021JG006382. (June 29, 2023).

Rogers, B.M.; Neilson, R.P.; Drapek, R.; Lenihan, J.M.; Wells, J.R.; Bachelet, D.; Law, B.E. 2011. Impacts of climate change on fire regimes and carbon stocks of the U.S. Pacific Northwest. Journal of Geophysical Research: Biogeosciences. 116(G3): G03037. https://doi.org/10.1029/2011JG001695.

Ryyppö, A.; Repo, T.; Vapaavuori, E. 1998. Development of freezing tolerance in roots and shoots of Scots pine seedlings at nonfreezing temperatures. Canadian Journal of Forest Research. 28(4): 557–565. https://doi.org/10.1139/x98-022.

Sakaguchi, K.; Zeng, X.; Leung, L.; Shao, P. 2016. Influence of dynamic vegetation on carbon-nitrogen cycle feedback in the Community Land Model (CLM4). Environmental Research Letters. 11(12): 124029. https://doi.org/10.1088/1748-9326/aa51d9.

Saksa, P.C.; Conklin, M.H.; Battles, J.J.; Tague, C.L.; Bales, R.C. 2017. Forest thinning impacts on the water balance of Sierra Nevada mixed-conifer headwater basins. Water Resources Research. 53(7): 5364–5381. https://doi.org/10.1002/2016WR019240.

Sanchez-Ruiz, S.; Chiesi, M.; Fibbi, L.; Carrara, A.; Maselli, F.; Gilabert, M.A. 2018. Optimized application of Biome-BGC for modeling the daily GPP of natural vegetation over peninsular Spain. Journal of Geophysical Research: Biogeosciences. 123(2): 531–546. https://doi.org/10.1002/2017JG004360.

Sangüesa-Barreda, G.; Linares, J.C.; Camarero, J.J. 2015. Reduced growth sensitivity to climate in bark-beetle infested Aleppo pines: connecting climatic and biotic drivers of forest dieback. Forest Ecology and Management. 357: 126–137. https://doi.org/10.1016/j.foreco.2015.08.017.

Scheller, R.; Kretchun, A.; Hawbaker, T.J.; Henne, P.D. 2019. A landscape model of variable social-ecological fire regimes. Ecological Modelling. 401: 85–93. https://doi.org/10.1016/j.ecolmodel.2019.03.022.

Scheller, R.M.; Spencer, W.D.; Rustigian-Romsos, H.; Syphard, A.D.; Ward, B.C.; Strittholt, J.R. 2011. Using stochastic simulation to evaluate competing risks of wildfires and fuels management on an isolated forest carnivore. Landscape Ecology. 26(10): 1491–1504. https://doi.org/10.1007/s10980-011-9663-6.

Seidl, R.; Aggestam, F.; Rammer, W.; Blennow, K.; Wolfslehner, B. 2016. The sensitivity of current and future forest managers to climate-induced changes in ecological processes. Ambio. 45(4): 430–441. https://doi.org/10.1007/s13280-015-0737-6.

Sheehan, T.; Bachelet, D.; Ferschweiler, K. 2019. Fire, CO_2, and climate effects on modeled vegetation and carbon dynamics in western Oregon and Washington. PLOS ONE. 14(1): e0210989. https://doi.org/10.1371/journal.pone.0210989.

Shields, C.; Tague, C. 2015. Ecohydrology in semiarid urban ecosystems: modeling the relationship between connected impervious area and ecosystem productivity. Water Resources Research. 51(1): 302–319. https://doi.org/10.1002/2014WR016108.

Shifley, S.R.; He, H.S.; Lischke, H.; Wang, W.J.; Jin, W.; Gustafson, E.J.; Thompson, J.R.; Thompson, F.R.; Dijak, W.D.; Yang, J. 2017. The past and future of modeling forest dynamics: from growth and yield curves to forest landscape models. Landscape Ecology. 32(7): 1307–1325. https://doi.org/10.1007/s10980-017-0540-9.

Sinton, D.S.; Jones, J.A.; Ohmann, J.L.; Swanson, F.J. 2000. Windthrow disturbance, forest composition, and structure in the Bull Run basin, Oregon. Ecology. 81(9): 2539–2556. https://doi.org/10.1890/0012-9658(2000)081[2539:WDFCAS]2.0.CO;2.

Sitch, S.; Smith, B.; Prentice, I.C.; Arneth, A.; Bondeau, A.; Cramer, W.; Kaplan, J.O.; Levis, S.; Lucht, W.; Sykes, M.T.; Thonicke, K.; Venevsky, S. 2003. Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. Global Change Biology. 9(2): 161–185. https://doi.org/10.1046/j.1365-2486.2003.00569.x.

Smith, B.; Prentice, I.C.; Sykes, M.T. 2001. Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space. Global Ecology and Biogeography. 10(6): 621–637. https://doi.org/10.1046/j.1466-822X.2001.t01-1-00256.x.

Smyth, C.E.; Xu, Z.; Lemprière, T.C.; Kurz, W.A. 2020. Climate change mitigation in British Columbia's forest sector: GHG reductions, costs, and environmental impacts. Carbon Balance and Management. 15(1): 21. https://doi.org/10.1186/s13021-020-00155-2.

Spies, T.A.; White, E.; Ager, A.; Kline, J.D.; Bolte, J.P.; Platt, E.K.; Olsen, K.A.; Pabst, R.J.; Barros, A.M.G.; Bailey, J.D.; Charnley, S.; Morzillo, A.T.; Koch, J.; Steen-Adams, M.M.; Singleton, P.H.; Sulzman, J.; Schwartz, C.; Csuti, B. 2017. Using an agent-based model to examine forest management outcomes in a fire-prone landscape in Oregon, USA. Ecology and Society. 22(1): art25. https://doi.org/10.5751/ES-08841-220125.

Stinson, G.; Kurz, W.A.; Smyth, C.E.; Neilson, E.T.; Dymond, C.C.; Metsaranta, J.M.; Boisvenue, C.; Rampley, G.J.; Li, Q.; White, T.M.; Blain, D. 2011. An inventory-based analysis of Canada's managed forest carbon dynamics, 1990 to 2008. Global Change Biology. 17(6): 2227–2244. https://doi.org/10.1111/j.1365-2486.2010.02369.x.

Stringham, T.K.; Krueger, W.C.; Shaver, P.L. 2003. State and transition modeling: an ecological process. Journal of Range Management. 56(2): 106–113. https://doi.org/10.2307/4003893.

Sturtevant, B.R.; Gustafson, E.J.; Li, W.; He, H.S. 2004. Modeling biological disturbances in LANDIS: a module description and demonstration using spruce budworm. Ecological Modelling. 180(1): 153–174. https://doi.org/10.1016/j.ecolmodel.2004.01.021.

Sturtevant, B.R.; Scheller, R.M.; Miranda, B.R.; Shinneman, D.; Syphard, A. 2009. Simulating dynamic and mixed-severity fire regimes: a process-based fire extension for LANDIS-II. Ecological Modelling. 220(23): 3380–3393. https://doi.org/10.1016/j.ecolmodel.2009.07.030.

Suvanto, S.; Peltoniemi, M.; Tuominen, S.; Strandström, M.; Lehtonen, A. 2019. High-resolution mapping of forest vulnerability to wind for disturbance-aware forestry. Forest Ecology and Management. 453: 117619. https://doi.org/10.1016/j.foreco.2019.117619.

Tague, C.; Peng, H. 2013. The sensitivity of forest water use to the timing of precipitation and snowmelt recharge in the California Sierra: implications for a warming climate. Journal of Geophysical Research: Biogeosciences. 118(2): 875–887. https://doi.org/10.1002/jgrg.20073.

Tague, C.L.; Band, L.E. 2004. RHESSys: Regional Hydro-Ecologic Simulation System—an object-oriented approach to spatially distributed modeling of carbon, water, and nutrient cycling. Earth Interactions. 8(19): 1–42. https://doi.org/10.1175/1087-3562(2004)8<1:RRHSSO>2.0.CO;2.

Tague, C.L.; McDowell, N.G.; Allen, C.D. 2013. An Integrated model of environmental effects on growth, carbohydrate balance, and mortality of *Pinus ponderosa* forests in the Southern Rocky Mountains. PloS ONE. 8(11): e80286. https://doi.org/10.1371/journal.pone.0080286.

Temperli, C.; Veblen, T.T.; Hart, S.J.; Kulakowski, D.; Tepley, A.J. 2015. Interactions among spruce beetle disturbance, climate change and forest dynamics captured by a forest landscape model. Ecosphere. 6(11): art231. https://doi.org/10.1890/ES15-00394.1.

Thompson, J.R.; Simons-Legaard, E.; Legaard, K.; Domingo, J.B. 2016. A LANDIS-II extension for incorporating land use and other disturbances. Environmental Modelling & Software. 75: 202–205. https://doi.org/10.1016/j.envsoft.2015.10.021.

Thonicke, K.; Spessa, A.; Prentice, I.C.; Harrison, S.P.; Dong, L.; Carmona-Moreno, C. 2010. The influence of vegetation, fire spread and fire behaviour on biomass burning and trace gas emissions: results from a process-based model. Biogeosciences. 7(6): 1991–2011. https://doi.org/10.5194/bg-7-1991-2010.

Thornton, P.E. 1998. Regional ecosystem simulation: combining surface- and satellite-based observations to study linkages between terrestrial energy and mass budgets. Missoula, MT: University of Montana. 295 p. M.S. thesis.

Thornton, P.E.; Law, B.E.; Gholz, H.L.; Clark, K.L.; Falge, E.; Ellsworth, D.S.; Goldstein, A.H.; Monson, R.K.; Hollinger, D.; Falk, M.; Chen, J.; Sparks, J.P. 2002. Modeling and measuring the effects of disturbance history and climate on carbon and water budgets in evergreen needleleaf forests. Agricultural and Forest Meteorology. 113(1–4): 185–222. https://doi.org/10.1016/S0168-1923(02)00108-9.

Thornton, P.E.; Running, S.W.; Hunt, E.R. 2005. Biome-BGC: Terrestrial Ecosystem Process Model, version 4.1.1.p. 1.2711 MB. Oak Ridge, TN: National Aeronautics and Space Administration, Oak Ridge National Laboratory Distributed Active Archive Center. (November 15, 2022).

Tonini, F.; Jones, C.; Miranda, B.R.; Cobb, R.C.; Sturtevant, B.R.; Meentemeyer, R.K. 2018. Modeling epidemiological disturbances in LANDIS-II. Ecography. 41(12): 2038–2044. https://doi.org/10.1111/ecog.03539.

Tsamir, M.; Gottlieb, S.; Preisler, Y.; Rotenberg, E.; Tatarinov, F.; Yakir, D.; Tague, C.; Klein, T. 2019. Stand density effects on carbon and water fluxes in a semi-arid forest, from leaf to stand-scale. Forest Ecology and Management. 453: 117573. https://doi.org/10.1016/j.foreco.2019.117573.

Turner, D.P.; Ritts, W.D.; Kennedy, R.E.; Gray, A.N.; Yang, Z. 2015. Effects of harvest, fire, and pest/pathogen disturbances on the West Cascades ecoregion carbon balance. Carbon Balance and Management. 10(1): 12. https://doi.org/10.1186/s13021-015-0022-9.

Turner, D.P.; Ritts, W.D.; Kennedy, R.E.; Gray, A.N.; Yang, Z. 2016. Regional carbon cycle responses to 25 years of variation in climate and disturbance in the US Pacific Northwest. Regional Environmental Change. 16(8): 2345–2355. https://doi.org/10.1007/s10113-016-0956-9.

Van Kooten, G.C.; Johnston, C.M.T.; Mokhtarzadeh, F. 2019. Carbon uptake and forest management under uncertainty: why natural disturbance matters. Journal of Forest Economics. 34(1–2): 159–185. https://doi.org/10.1561/112.00000446.

Vetter, M.; Churkina, G.; Jung, M.; Reichstein, M.; Zaehle, S.; Bondeau, A.; Chen, Y.; Ciais, P.; Feser, F.; Freibauer, A.; Geyer, R.; Jones, C.; Papale, D.; Tenhunen, J.; Tomelleri, E.; Trusilova, K.; Viovy, N.; Heimann, M. 2008. Analyzing the causes and spatial pattern of the European 2003 carbon flux anomaly using seven models. Biogeosciences. 5(2): 561–583. https://doi.org/10.5194/bg-5-561-2008.

Visser, L.; Latta, G.; Pokharel, R.; Hoefnagels, R.; Junginger, M. 2022. Exploring the limits to sustainable pellet production for international markets: the impact of increasing pellet production in the US Southeast on feedstock use, production cost and carbon sequestration in forest areas. GCB Bioenergy. 14(8): 896–917. https://doi.org/10.1111/gcbb.12946.

Wade, C.M.; Baker, J.S.; Jones, J.P.H.; Austin, K.G.; Cai, Y.; de Hernandez, A.B.; Latta, G.S.; Ohrel, S.B.; Ragnauth, S.; Creason, J.; McCarl, B. 2022. Projecting the impact of socioeconomic and policy factors on greenhouse gas emissions and carbon sequestration in U.S. forestry and agriculture. Journal of Forest Economics. 37(1): 127–131. https://doi.org/10.1561/112.00000545.

Wade, C.M.; Baker, J.S.; Latta, G.; Ohrel, S.B. 2019. Evaluating potential sources of aggregation bias with a structural optimization model of the U.S. forest sector. Journal of Forest Economics. 34(3–4): 337–366. https://doi.org/10.1561/112.00000503.

Wardle, P. 1993. Causes of alpine timberline: a review of the hypotheses. In: Alden, J.N.; Mastrantonio, J.L.; Ødum, S., eds. Forest Development in Cold Climates. Boston, MA: Springer US: 89–103. https://doi.org/10.1007/978-1-4899-1600-6_7.

Warnant, P.; François, L.; Strivay, D.; Gérard, J.-C. 1994. CARAIB: A global model of terrestrial biological productivity. Global Biogeochemical Cycles. 8(3): 255–270. https://doi.org/10.1029/94GB00850.

Weed, A.S.; Ayres, M.P.; Hicke, J.A. 2013. Consequences of climate change for biotic disturbances in North American forests. Ecological Monographs. 83(4): 441–470. https://doi.org/10.1890/13-0160.1.

Whitlock, C.; McWethy, D.B.; Tepley, A.J.; Veblen, T.T.; Holz, A.; McGlone, M.S.; Perry, G.L.W.; Wilmshurst, J.M.; Wood, S.W. 2015. Past and present vulnerability of closed-canopy temperate forests to altered fire regimes: a comparison of the Pacific Northwest, New Zealand, and Patagonia. BioScience. 65(2): 151–163. https://doi.org/10.1093/biosci/biu194.

Whitlock, C.; Shafer, S.L.; Marlon, J. 2003. The role of climate and vegetation change in shaping past and future fire regimes in the northwestern US and the implications for ecosystem management. Forest Ecology and Management. 178(1–2): 5–21. https://doi.org/10.1016/S0378-1127(03)00051-3.

Williams, C.A.; Gu, H.; MacLean, R.; Masek, J.G.; Collatz, G.J. 2016. Disturbance and the carbon balance of US forests: a quantitative review of impacts from harvests, fires, insects, and droughts. Global and Planetary Change. 143: 66–80. https://doi.org/10.1016/j.gloplacha.2016.06.002.

Wimberly, M.C.; Liu, Z. 2014. Interactions of climate, fire, and management in future forests of the Pacific Northwest. Forest Ecology and Management. 327: 270–279. https://doi.org/10.1016/j.foreco.2013.09.043.

Witcosky, J.J. 1985. Root-colonizing insects recovered from Douglas-fir in various stages of decline due to black-stain root disease. Phytopathology. 75(4): 399. https://doi.org/10.1094/Phyto-75-399.

Xu, C.; Christoffersen, B.; Robbins, Z.; Knox, R.; Fisher, R.A.; Chitra-Tarak, R.; Slot, M.; Solander, K.; Kueppers, L.; Koven, C.; McDowell, N. 2023. Quantification of hydraulic trait control on plant hydrodynamics and risk of hydraulic failure within a demographic structured vegetation model in a tropical forest (FATES-HYDRO V1.0). Geoscientific Model Development. 16: 6267–6283. https://doi.org/10.5194/gmd-16-6267-2023.

Xu, H.; Latta, G.; Lee, U.; Lewandrowski, J.; Wang, M. 2021. Regionalized life cycle greenhouse gas emissions of forest biomass use for electricity generation in the United States. Environmental Science & Technology. 55(21): 14806–14816. https://doi.org/10.1021/acs.est.1c04301.

Xu, X.; Medvigy, D.; Powers, J.S.; Becknell, J.M.; Guan, K. 2016. Diversity in plant hydraulic traits explains seasonal and inter-annual variations of vegetation dynamics in seasonally dry tropical forests. New Phytologist. 212(1): 80–95. https://doi.org/10.1111/nph.14009.

Zhang, F.; Chen, J.M.; Pan, Y.; Birdsey, R.A.; Shen, S.; Ju, W.; He, L. 2012. Attributing carbon changes in conterminous U.S. forests to disturbance and non-disturbance factors from 1901 to 2010. Journal of Geophysical Research. 117: G02021. https://doi.org/10.1029/2011JG001930.

Zhang, J.; Bras, R.L.; Longo, M.; Heartsill Scalley, T. 2022. The impact of hurricane disturbances on a tropical forest: implementing a palm plant functional type and hurricane disturbance module in ED2-HuDi V1.0. Geoscientific Model Development. 15(13): 5107–5126. https://doi.org/10.5194/gmd-15-5107-2022.

Zhang, K.; de Almeida Castanho, A.D.; Galbraith, D.R.; Moghim, S.; Levine, N.M.; Bras, R.L.; Coe, M.T.; Costa, M.H.; Malhi, Y.; Longo, M.; Knox, R.G.; McKnight, S.; Wang, J.; Moorcroft, P.R. 2015. The fate of Amazonian ecosystems over the coming century arising from changes in climate, atmospheric CO_2, and land use. Global Change Biology. 21(7): 2569–2587. https://doi.org/10.1111/gcb.12903.

Zhao, F.; Healey, S.P.; Huang, C.; McCarter, J.B.; Garrard, C.; Goeking, S.A.; Zhu, Z. 2018. Assessing the effects of fire disturbances and timber management on carbon storage in the Greater Yellowstone Ecosystem. Environmental Management. 62(4): 766–776. https://doi.org/10.1007/s00267-018-1073-y.

Glossary

biophysical process model—A forest model that uses biological processes (e.g., photosynthesis, respiration, transpiration) and how it changes with physical properties (e.g., precipitation, light, temperature). Specifically, plants use CO_2 absorbed from the atmosphere and water taken up by the root system to make sugars to fuel respiration and growth.

cohort—A category of trees with similar life history attributes (e.g., species longevity, shade tolerance), or a common mixture of species.

empirical growth and yield model—A forest model that is based on growth and yield curves, and correlative relationships between environment and growth.

gap model—A forest model that is theoretically based on canopy gap dynamics and individual tree establishment, growth, and mortality.

plant functional types (PFTs)—Growth forms of plant types, such as needle-leaf evergreen, broadleaf evergreen, needle-leaf deciduous, broadleaf deciduous, C3 herbaceous, and C4 herbaceous lifeforms.

state and transition model—A forest model that focuses on transitions from one state to another (such as grassland to forest) when the landscape crosses biophysical or disturbance thresholds.

stochastic—A method by which a disturbance or process is randomly assigned.

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