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Forest Ecosystem Carbon Models: Structure and Suitability for Current Issues on the West Coast of North America

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Cover photos: Examples of western forest ecosystems and conditions, clockwise from the upper left: pinyon-juniper forest in Nevada, Douglas-fir/western hemlock forest in western Oregon, managed Douglas-fir forest in western Washington, burned mixed-conifer forest in the California Sierra Nevada. All photos by Andrew Gray.

Abstract

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Increasing carbon dioxide and other greenhouse gases (GHG) in the atmosphere are warming and changing climate globally. Policymakers and land managers want to know the effectiveness of different approaches to reduce the increase in GHG while mitigating effects of future climate change. Forests can store large amounts of carbon and can gain or lose carbon relatively rapidly, making them a focus of study. A variety of ecosystem models have been applied to estimate hard-to-measure forest stocks and processes and to project alternative management scenarios into the future.

We examined the structure and application of ecosystem models for carbon projections, focusing on the West Coast of the United States and Canada. Our goals were to help scientists and managers (1) select models that best address specific questions, and (2) evaluate model results given inherent uncertainties embedded in the data, calibration, and assumptions used. We describe the primary functional attributes of biophysical process, individual-tree, stand growth and yield, landscape process, state-and-transition, and imputation models, and their application to West Coast forests. We discuss the strengths and limitations of each model type for questions concerning climate change, tree harvest, wildfire and fuel reduction treatments, other disturbances, social and economic drivers, hydrology, and wildlife. No single model can simulate forest management, disturbance, and response to climate change well. Efforts using models with different strengths, focusing on consistent parameterization of vegetation, definition of initial conditions and scenarios, and metrics for results, can improve forest carbon projections.

KEYWORDS:
Forest carbon
Simulation
Management
Disturbance
Climate change

Contents

Introduction

Human combustion of fossil fuels and land-use practices are increasing levels of carbon dioxide and other greenhouse gases (GHG) in the atmosphere, which is warming and changing climatic conditions all over the planet (Masson-Delmotte 2021), including the West Coast of North America (Avery et al. 2023). Policymakers and land managers want to know the effectiveness and consequences of different approaches of reducing GHG emissions while mitigating effects of future climate change. The management and fate of forests are of particular interest because forests cover 31 percent of the planet's land area (FAO 2020), can store large amounts of carbon, and can gain or lose carbon relatively rapidly compared to other natural and seminatural ecosystems (e.g., rangelands). For example, productive forests aged 20–60 years old can accumulate more than 3 Mg C/ha/yr (Gray et al. 2016), while a large wildfire event can emit about 19 Mg C/ha (Campbell et al. 2007). Significant amounts of forest carbon are also stored in harvested wood products and solid waste, or are used for energy production or soil amendments, providing more potential for climate change mitigation. National and international carbon assessments typically estimate both in-forest and harvested carbon as one sector. Carbon **stocks** in the U.S. forest sector are currently increasing and absorb about 14 percent of domestic fossil fuel emissions annually (Domke et al. 2023b, USEPA 2023). However, some forests are already experiencing climate change effects and significant losses, particularly in dry forests in the Western United States (Domke et al. 2023a, Hogan et al. 2024).

Some U.S. states are working towards, or already have, policies to reduce GHG emissions. These GHG reduction goals often promote climate change mitigation and adaptation strategies through "natural climate solutions," of which, alternative forest management and conservation measures are potentially the most effective approaches (Fargione et al. 2018, Griscom et al. 2017). For example, the U.S. Climate Alliance, which is composed of 25 U.S. states, created the Natural and Working Lands challenge to promote more resilient and climate-adapted natural landscapes (U.S. Climate Alliance 2026).

Land managers and policymakers are interested in assessing the carbon effects of a variety of proposed approaches to managing and regulating forests, starting from current forest conditions. Modeling forest carbon stocks and **fluxes** is an important tool for evaluating the effects of planned management activities and accounting for the effects of unplanned disturbances and future changes in climate (Munro et al. 2025). Forest ecosystems on the West Coast of North America (in Alaska, British Columbia, California, Oregon, and Washington) are being modeled to investigate questions, such as the following:

- How will different harvest rotations, thinning and burning practices (e.g., to promote resilience), disturbance regimes, and approaches to providing or maintaining early- or late-seral habitat in riparian or upland forests affect carbon stores in forest ecosystems?
- How will simulated changes in forest ecosystems affect other forest values of interest, including air quality, wildlife habitat, water quantity and quality, amenity values, or employment and livelihoods?
- How will specific types of policy incentives or disincentives—including revenue from trading carbon credits, subsidies for bioenergy or mass timber products, fees or taxes, or forest practice rules—affect land management?

Calculating the net carbon balance of diverse carbon pools in forests while accounting for the many factors that affect storage and loss of carbon can be difficult. Measuring all the components of forest carbon flux is not possible across entire landscapes; even wall-to-wall remote sensing cannot detect all carbon pools, and errors in estimation of aboveground live carbon and disturbance attribution are substantial (Gray et al. 2019, Ståhl et al. 2024). Projecting forests into the future requires simulation models. Forest ecosystem simulation models are therefore employed to provide estimates for hard-to-measure pools and processes, and to evaluate future implications of alternative climate, disturbance, and management scenarios.

Modelers have applied many different forest ecosystem simulation models to assess alternative forest management, conservation, or future trajectories of forest carbon stocks and flux, often with contradictory conclusions (Cabiyo et al. 2022, Dass et al. 2018, Graves et al. 2020, Gundersen et al. 2021, Leturcq 2020, Moomaw et al. 2019). This can be challenging for forest managers who want to evaluate policy options that are potential solutions or to set legislatively required GHG reduction and carbon sequestration targets.

Although there are recent papers that review or synthesize carbon simulation models, many are written for technical audiences, address one type of model, or do not analyze assumptions and limitations behind selecting one modeling approach over another (e.g., Blanco et al. 2020, Bugmann and Seidl 2022, Dietze et al. 2018, Fisher et al. 2018, Huntzinger et al. 2017, Laubmeier et al. 2020, Zald et al. 2016). To our knowledge, there are also few or no published syntheses that describe a broad range of modeling alternatives for social, ecosystem, and economic components to assist land manager decision making, particularly for the productive forests of the West Coast of the United States and Canada. The U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station established a carbon research initiative to address information gaps in forest carbon cycle science (USDA Forest Service PNWRS 2024). The Pacific Northwest Research Station established this initiative to address the needs of coproducers—including resource managers, policymakers, and scientists—who are interested in assessments that describe a range of likely carbon futures for individual states, provinces, or regions within them. They hope to realistically capture the differences in vegetation and management for the mosaic of forest ownerships and ecoregions found within each state. Companion reports have compared models and approaches to estimate carbon stocks, fluxes, and GHG implications of harvested wood products (Lucey et al. 2024), and synthesized approaches to simulating disturbance (Wood et al. 2025).

Our goal for this report is to provide guidance and sufficient detail to land managers and others to (1) help them select forest ecosystem carbon models to address specific questions and (2) evaluate model results given the inherent uncertainties embedded in data, knowledge, and assumptions. We focus on models that have been applied to the West Coast of the United States and Canada but believe the comparison of model types is broadly applicable to many forested regions across the globe.

Useful elements of forest ecosystem models include predicting carbon stocks; rates of carbon accumulation and decay; and the effects of climate, disturbances, and management treatments on stocks and subsequent responses. The largest carbon pools in most forest ecosystems are soils (mineral and organic layers), followed by live trees, **dead wood** (standing and down), and nontree vegetation (e.g., Domke et al. 2023b). Carbon is transferred between pools and exchanged with the atmosphere via fairly well-known mechanisms.

These pools and flows are represented in different ways, which affects the utility of different models to answer particular questions of interest (Kimmins et al. 2008). Describing simulation models is challenging, in part, because model developers regularly update models; developers may alter their behavior, borrow algorithms from colleagues, adapt to increased computing power, or create different versions of open-source software to meet changing needs (Blanco et al. 2020).

We first discuss basic approaches to model design, followed by an overview of the known drivers of forest carbon stocks and change. Subsequent sections describe how specific models represent carbon dynamics of live trees and other vegetation, dead wood, and **forest floor** and **mineral soils**. Finally, we assess the suitability of those models to evaluate specific questions of interest to managers and policymakers.

The terminology used colloquially for carbon dynamics can be confusing; forests are often described as "storing" or "sequestering" carbon, but it is rarely clear if the terms refer to the amount of carbon in an area at a given point in time or the rate at which the area is accumulating carbon. To avoid confusion, we define stocks as the amount of carbon in one or more pools at a particular point in time, **stock change** as the rate at which the carbon in one or more pools is changing over time, and flux as the net exchange of carbon between an ecosystem and the atmosphere.

Model Scope and Scale

Models are abstractions and simplifications of the real world. Models are typically constructed for two basic reasons: test understanding or predict the future. Models designed to test understanding focus on interactions of different system components with the goal of identifying causes and effects of system behavior. Models designed for prediction may share many features with theoretical models. However, the goal is to make the most accurate estimate of a potential future state, and they may not represent key processes. The role of models in the context of natural resource management is not to predict the future exactly but to organize and explore known ideas and concepts in an explicit framework that allows users to narrow the possible range of outcomes to a plausible subset (Littell et al. 2011).

Models that simulate the terrestrial biome cannot be easily divided into groups because many have overlapping characteristics with different focuses (Fisher et al. 2014). Different models, or model components, operate at different geographic and temporal scales. For example, biophysical process models simulate the flow of energy, water, and carbon and other essential elements through an ecosystem, and may be based on a single forested stand, which is simulated under a range of conditions. This could be useful for estimating the relative magnitude of changes that different drivers (e.g., climates) cause and could be quite accurate for a focal vegetation type.

Alternatively, a biophysical process model may attempt to simulate all vegetation types in a geographic region as individual stands that represent a variety of conditions, likely with some reduction in detail in representing within-stand processes. Landscape process models focus on the spatial placement and movement of disturbances, species, commodities, or scheduling of harvest using mapped information. Across model types, some processes may be simulated with hourly time steps (e.g., photosynthesis), while others may use monthly, annual, or 10-year time steps (e.g., tree growth or mortality). Because it takes time for effects of ecosystem changes across large regions or ownership classes to become evident, many carbon model simulation studies are relatively long term (e.g., 50 years or more) (Kim et al. 2018, Law et al.

2018). Models of landowner behavior and economic drivers often aggregate socioeconomic factors into large spatial units and work at the state, regional, or national level.

Even relatively simple simulation models can contain more variables controlling system behavior than can be reliably measured at any one place and time. Most models, whether process-based or statistical, use empirical data to constrain the range of potential parameters and to calibrate model behavior to align model results with measurements (Taylor et al. 2009). Models, by design, fit average predictions from multiple observations; no model can or should be expected to replicate the behavior of individual trees, stands, or rare events (e.g., severe droughts).

Although not considered simulation models, allometric equations are statistical models that are either directly or indirectly fundamental to all live-tree carbon estimates (e.g., MacLean and Berger 1976, Means et al. 1994, Ritchie et al. 2013). Allometric equations use individual-tree diameter and (usually) height to estimate aboveground and belowground volume, biomass, and carbon in different tree components (e.g., wood, bark, foliage, and coarse roots). Equations can be developed for trees from a small area (e.g., an experimental forest) or from trees sampled across a large region (Standish et al. 1985). Applying independently derived equations to estimate volume and biomass on the same trees can lead to incompatible trends between the two with changes in tree size. Temesgen et al. (2015) and Weiskittel et al. (2015) summarized problems with existing equations in the United States. A recent national effort collected new data and compiled existing raw data to develop more robust equations, but there are still many gaps (Frank et al. 2019). The Forest Service's Forest Inventory and Analysis (FIA) program recently adopted a new system of harmonized volume and biomass equations for live and standing-dead trees (Westfall et al. 2024). Highly accurate biomass equations may not be critical for research efforts focused on the relative amounts of carbon in different treatments or forest types. Having accurate equations becomes more important if the objective requires high precision (e.g., estimated annual carbon flux at the state level to assess progress towards GHG reduction targets).

Key Forest Carbon Processes Represented in Simulation Models

Forest carbon models attempt to simulate many processes that control the forest carbon cycle (e.g., Waring and Running 1998). Here, we briefly review the processes underpinning the models.

Photosynthesis is the mechanism by which green plants use the energy in solar radiation to chemically combine carbon dioxide from the atmosphere with water pulled from the soil, resulting in carbohydrates and oxygen. The diffusion of carbon dioxide into leaves occurs via **stomates**, with oxygen and water released to the atmosphere in the process. The amount of carbon "fixed" in this process is referred to as **gross primary production** (GPP). A substantial portion of the fixed carbon provides chemical energy for living cells in plants and is subsequently respired as **autotrophic respiration**. The remaining carbon compounds are combined with mineral nutrients pulled from the soil to create new plant matter, including foliage, wood, roots, fruits, and seeds, referred to as **net primary production** (NPP). The new matter might remain part of the live plant for weeks in the case of **fine roots** (<2 mm in diameter) and root exudates; months to years for flowers, cones, leaves, or needles; and years to decades for the wood and bark in coarse roots (≥2 mm in diameter), boles, and branches (Clark et al. 2001). As the components senesce, they enter the **litter** and dead wood pools (fig. 1).

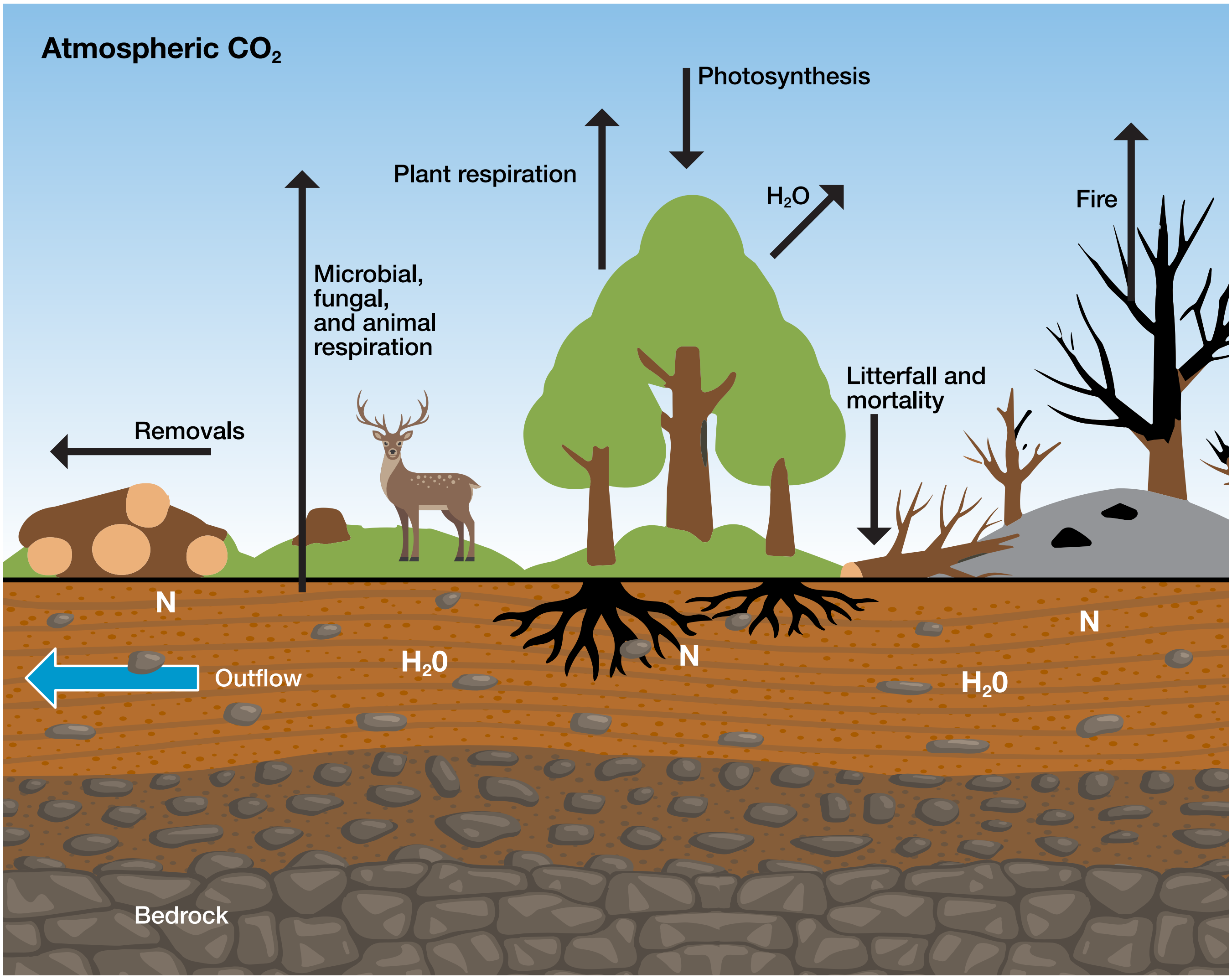

Figure 1—Key components of the carbon cycle in forested ecosystems. Live plants photosynthesize carbon dioxide (CO_2) from the atmosphere, using water (H_2O) and nitrogen (N) in the process, and emit much of the carbon back as live cells respire. Animals and microbes consume and decompose dead plant matter in the soil and on the forest floor. Fire combusts live and dead carbon, and logging removals transfer carbon from the ecosystem.

The rates of GPP and autotrophic respiration fluctuate hourly, daily, and seasonally with solar radiation, air and soil temperature, atmospheric **vapor pressure deficit**, and **soil moisture**. Low light, cold air or soil, high vapor pressure deficit, and low soil moisture can result in closed or restricted stomatal openings. Leaves at different positions in plant canopies experience different light levels, leaf and air temperatures, and internal plant water potential, which drops with height above the ground. Different species have different optimum and limiting conditions for each of the factors affecting photosynthesis. Increasing drought conditions and atmospheric carbon dioxide concentrations can enable plants to maintain GPP with greater stomatal closure and less water loss (Jiang et al. 2019b).

Carbon cycling also varies spatially with different site conditions. Climate varies geographically and with elevation, affecting air and soil temperature, precipitation, and snowpack. Soil depth, texture, and rock content vary with topography and geology, affecting the amount of moisture and nutrients available at a site through the year. The slope and aspect of a site affect levels of solar radiation and soil moisture drainage.

Once entire plants or portions of them are consumed by animals or fungi, or after they die or senesce, they are decomposed by vertebrate and invertebrate animals, fungi, and microbes that fragment and consume the carbohydrates and minerals, releasing carbon dioxide in a process referred to as **heterotrophic respiration**. Climate and moisture conditions, as well as the lignin, carbon-to-nitrogen ratios, and decay-suppressing compounds in the available biomass affect decomposition (Harmon et al. 1986). Moisture and temperature conditions for standing-dead trees are different from wood lying on the forest floor; decomposition is reduced if the wood is saturated and anaerobic, or if it is too dry to support biological activity.

The forest floor layer on the ground surface is composed primarily of dead wood fragments, leaves/needles, and roots, with the surface layer consisting of fresh litter, and increasingly decomposed **duff** and **humus** below. The mineral soil layer and decomposed bedrock underneath contain organic carbon compounds leached from the litter layer as well as those derived from decomposed roots.

Carbon leaves forest ecosystems through mechanisms beyond decomposition of organic matter. Groundwater transports dissolved organic matter, including carbon and other compounds, from soils to streams, where carbon dioxide is emitted from the surface or becomes part of aquatic food webs. Wood and litter that enter streams through senescence or disturbance (e.g., floods) can move downstream and become part of aquatic and ocean food webs. Live plants, and litter and soil microorganisms, release volatile organic compounds into the atmosphere (Šimpraga et al. 2019). Direct combustion of living and dead matter in fires emits carbon dioxide and can kill live vegetation, transferring matter to the dead carbon pools. Cutting of trees also transfers matter from live to dead material, a portion of which is transferred offsite for human uses (e.g., lumber, pulp, fuel, landscaping). In these cases, the fate of carbon will depend on the type of product and the length of time that it remains in service before eventually decomposing or being permanently stored in landfills.

Forests can emit GHGs in addition to carbon dioxide. Methane can be released (or absorbed) by soils, dead wood, and trees, particularly in wetland ecosystems (Covey and Megonigal 2019). Combustion in forest fires can release methane as well as nitrous oxide, and forest fertilization can also result in emissions of nitrous oxide (Hiraishi et al. 2014).

Species' population processes are important to carbon cycling too, because individual plants carry out photosynthesis and produce matter. Regeneration, sprouting, or planting control plant species composition and abundance; while growth, aging, competition, and susceptibility to insects, pathogens, disturbance, and cutting control senescence and mortality.

Model Simulation of Live Trees and Other Vegetation

Live forest carbon stocks at any point in time represent a balance between regeneration and growth on the plus side, and mortality and harvest on the minus side. In the absence of disturbance or harvest, live vegetation accumulates carbon to a maximum density that can be supported at a particular location within a range of average climatic conditions (Foster et al. 2014, Gray et al. 2016). Modelers have used different approaches to represent these processes (table 1). We assess the application of specific models below. Additional details on all the models mentioned in this report, including names and links to model webpages, are in the appendix and supplemental table 1. Download supplemental table 1 (an Excel workbook file) here: https://doi.org/10.2737/pnw-gtr-1046.

Table 1—Types of ecosystem models and key attributes

Model type	Example model(s)[a]	Primary process	Vegetation representation	Disturbance implementation	Silviculture implementation	Strengths
Biophysical process	MC2, 3-PG	Carbon, nitrogen, water cycling	Functional types	Process or stochastic	None, or pool fraction cut	Climate change, global and regional
Growth and yield	CBM-CFS3, LURA	Net growth with age	Species groups	Stochastic	Stand fraction, alternative curve	Simplicity
Individual tree	FVS, Organon	Tree survival and growth	Tree species	Deterministic	Any type	Stand management, short term
Landscape process	LANDIS_II	Tree establishment and growth	Tree species	Spatial process	Proportions of species cohorts	Spatial processes, integrative
State transition	STMs (VDDT)	Transition probabilities	Species groups	Deterministic	Defined outcomes	Management classes
Imputation	RPA-FDM	Transition probabilities	Sample plots	Deterministic	Defined outcomes	Simplicity

[a] 3-PG = Physiological Principles Predicting Growth model, CBM-CFS3 = Carbon Budget Model of the Canadian Forest Sector3, FVS = Forest Vegetation Simulator model, LANDIS-II = Landscape Disturbance and Succession model, LURA = Land Use Resource Allocation model, MC2 = Mapped Atmosphere-Plant-Soil System [MAPSS]-CENTURY2 model, RPA-FDM = Resources Planning Act imputation model, STM = state-and-transition model, VDDT = Vegetation Dynamics Development Tool.

Biophysical Process Models

Researchers and educators initially designed biophysical process models to represent the key energetic, chemical, and physical transfers within ecosystems. Using climate and soils data, these models use systems of equations to estimate rates of photosynthesis and the key components of production (i.e., GPP, autotrophic respiration, and NPP). Live vegetation is represented as pools of biomass, usually split into aboveground and belowground pools, and often divided into additional components (e.g., stems, branches, foliage, fine and coarse roots). Foliage is abstracted to either a single, flat layer or can include additional partially shaded layers. Plant species are usually abstracted to a few plant functional types (PFTs) (e.g., grass, shrub, broad-leaved tree, needle-leaved tree) to reflect major differences in species function (fig. 2). Dynamic global vegetation models are a type of biophysical model that simulates changes in vegetation and biomes in response to climate over large spatial and temporal scales. Some biophysical models merge ecosystem function and plant population dynamics to better represent the function of forests with multiple species and a range of plant sizes (Fisher et al. 2018).

Modelers use frequent measurements of plant physiology, weather, and soil processes at a range of sites to build models as working hypotheses of biophysical processes (e.g., Coops et al. 2001, Law et al. 2006). Eddy covariance micrometeorology measurements have enabled near-instantaneous and long-term measurement of forest carbon exchange at the top of the canopy (e.g., Schwalm et al. 2010). At these sites, ecosystem models are calibrated to replicate subdaily, seasonal, and interannual patterns of biomass accumulation, mortality, growth response, and other available measurements in their ecosystems of interest.

Most biophysical models are self-contained in that they employ a spinup phase of several centuries from bare ground using average historical climate to reach equilibrium in the slowest pool, soil carbon. The models can then be initialized with desired vegetation conditions before applying measurements or projections of key climatic variables and soil characteristics controlling carbon accumulation, using either daily, weekly, or seasonal values. Biophysical process models are often used to explore the response of NPP to changes in

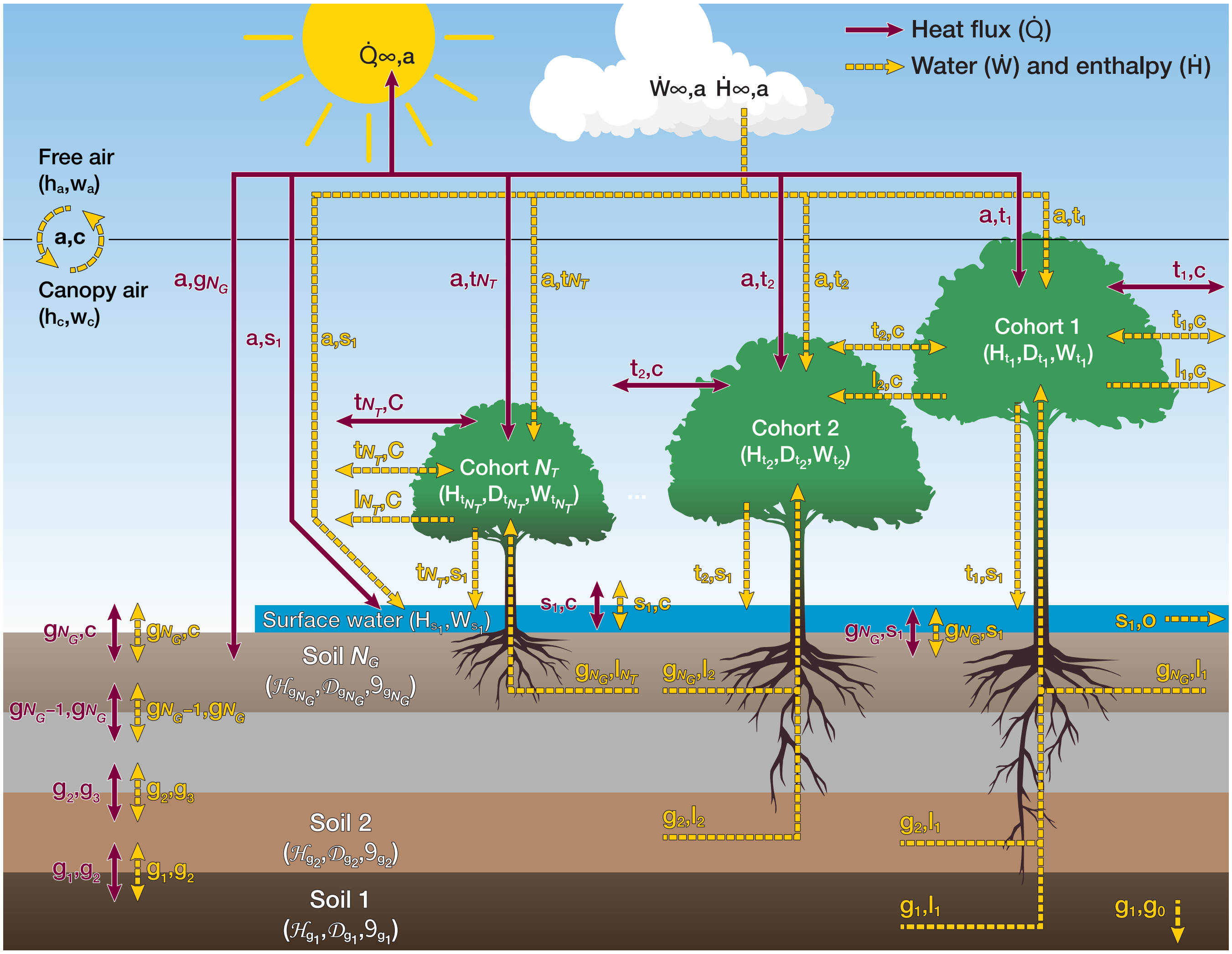

Figure 2—Example of carbon (C) pools and fluxes for an individual stand in a biophysical model, in this case Ecosystem Demography2 (ED2). Letters near the arrows identify the fluxes, and subscripts (1, 2 .. N_T) refer to cohort number. Solid red arrows represent heat flux with no exchange of mass, and dashed yellow arrows represent exchange of mass and associated enthalpy. Adapted from Longo et al. (2019). See Longo et al. (2019) for additional details.

temperature, precipitation, atmospheric carbon dioxide levels, and nitrogen deposition, including models for recent climate or projected future climates which may have no current analogues. Future climate projections are based on different future GHG emission scenarios and selected global climate models with differing estimates of the degree and seasonality of changes in temperature and precipitation. Global climate model outputs are often downscaled to the spatial and temporal resolutions desired to run the ecosystem model.

Model parameters and functions can either be **diagnostic**, in which the modeler or external data (e.g., leaf area determined by satellite imagery) provide values, or **prognostic**, in which the solution of internal equations determines values (Hayes et al. 2012). A comparison of 19 dynamic global vegetation models found that they differed in their use of diagnostic and prognostic functions; simplifying assumptions; base environmental data and initial conditions; and in how they determined growth, decomposition, and disturbance (Huntzinger et al. 2012). By prescribing common approaches to diagnostic datasets, agreement among models improved but still differed substantially in estimates of GPP, live carbon stocks, and soil carbon (Huntzinger et al. 2013).

MC2 (Mapped Atmosphere-Plant-Soil System [MAPSS]-CENTURY2) (Bachelet et al. 2001) is one of the dynamic global vegetation models that modelers have applied in West Coast forests (e.g., Bachelet et al. 2015, Halofsky et al. 2022, Kim et al. 2018). The primary purpose of the model is to project changes in the distribution of vegetation types in response to changes in climate and atmospheric carbon dioxide concentrations. The model integrates modules for biogeography (physiologically based determination of vegetation lifeforms using MAPSS), biogeochemistry (nutrient and element cycling), and fire disturbance. The biophysical functions of the model are simulated with a modified CENTURY model (Parton et al. 1993), which simulates competition for light, water, and nutrients between an idealized tree and grass at each grid cell and resulting NPP. Parameters are defined for different PFTs, including maximum NPP, growth sensitivity to temperature and soil moisture, and how production changes with leaf area index. Mortality and litter production rates are fixed parameters. Fire consumption and severity are based on simulated fuel loads, fuel moisture, an average tree size determined by the size of the live carbon pool, and the defined fire-return interval for each PFT. The PFT for each model pixel is determined by physiological tolerances, estimated growth rates, and fire frequency.

Kim et al. (2018) applied MC2 to simulate future forest change in the Blue Mountains of northeastern Oregon using future climate estimates downscaled to about 800-m grid cells, a soil map based on soil surveys, and maps of potential vegetation types under current climate. Boisramé et al. (2022) applied MC2 to examine if and where in the Western United States fuel loads have increased over the past century. Model development to date has focused more on the effects of climate change and natural disturbance on the distributions of plant communities than on comprehensive carbon modeling and has not simulated tree cutting and removal. Additional details on all models mentioned in this report, including names and links to model webpages, are in the appendix and supplemental table 1.

Modelers developed Biome-BGC (Biogeochemical Cycles) to examine global and regional interactions of climate, disturbance, and biogeochemical cycles by simulating cycling of carbon, nitrogen, and water in ecosystems on a daily time step (Thornton et al. 2002). The primary drivers are the physiological processes that control photosynthesis, respiration, growth, mortality, and decay, run on a daily time step. Mortality rates for different PFTs can be fixed or dynamic with succession (Turner et al. 2015). Turner et al. (2011) used the wood biomass by stand age relationship from FIA plots to adjust PFT- and ecoregion-specific parameters for fraction of leaf nitrogen as rubisco and annual mortality rates. Disturbances are diagnostic, not simulated; Turner et al. (2007) used satellite change detection of disturbance to estimate change and stand age in the Pacific Northwest, and Schmid et al. (2006) used historic records to simulate partial harvest. Biome-BGC has been applied to estimate the implications of recent changes in weather, drought, and disturbance, but has rarely been used for projections (Hlásny et al. 2014).

CLM (Community Land Model) is the terrestrial component of the Community Earth System Model, with the primary purpose of quantifying ecological climatology, or how natural and human changes in vegetation affect climate (Lawrence et al. 2019). Vegetated portions of climatologically defined grid cells can support multiple PFTs with their own leaf area and canopy height, for which energy and water flux are calculated. The model represents all land cover types including forest, range, agriculture, nonvegetated, and water. The use of the FATES (Functionally Assembled Terrestrial Ecosystem Simulator) extension incorporates simulation of individual-tree cohorts (age classes) by modeling an individual representative of each cohort. Mortality rates are set (with a default annual rate of 2 percent), and fire area is modeled from diagnostic frequency of lightning or human ignitions and level of suppression, and prognostic fuel loads, fuel moisture, and windspeed. Fire effect is based on diagnostic combustion and mortality proportions for different live and dead pools by PFT, with the defaults reduced by half in Hudiburg et al. (2013) to align with observations. CLM has been applied to Oregon forests (Hudiburg et al. 2013) and to all Western U.S. forests (Buotte et al. 2020).

ED2 (Ecosystem Demography2) couples biophysical models with plant community dynamics to capture the heterogenous nature of plant communities (Longo et al. 2019). The model defines sites based on climate, soils, and topography, and patches within sites based on time since disturbance and disturbance type. The model is simpler than many biophysical models in that energy and mass are the primary prognostic variables. Water and energy budgets for vegetation are calculated at the individual cohort level, allowing the model to represent vertical and horizontal heterogeneity, and interactions among cohorts (e.g., competition). Disturbance rates are assigned, but fire ignition depends on a soil moisture threshold, and mortality can be assigned by cohort but the default fire mortality is 100 percent and results in new patches of age zero. Jiang et al. (2019a) calibrated ED2 and applied the model to a site with an eddy covariance flux tower in the Washington Cascades to examine the mechanisms of reduction in GPP due to summer drought.

STANDCARB/LANDCARB simulates carbon accumulation with forest succession in a landscape with mixed tree species and ages, and spatially variable climate, soil, topography, and history (Harmon and Domingo 2001). Simpler than most mechanistic models, functional curves simulate the effects of transpiration, temperature, and soil moisture on potential photosynthesis and respiration by species on a monthly time step. Cells within stands interact by shading and propagation of disturbance. Simulations of even- and uneven-aged silvicultural prescriptions, prescribed fire, and partial or stand-replacing wildfire are possible. The model has been primarily used in the Pacific Northwest to examine the effects of harvest, disturbance, and aging (i.e., succession) on forest composition and carbon storage (e.g., Harmon and Marks 2002, Harmon et al. 1990, Mitchell et al. 2012).

Descriptions of key features of additional biophysical models that are less commonly used in the Western United States, including 3-PG (Physiological Principles Predicting Growth), RHESSys (Regional Hydro-Ecologic Simulation System), CARAIB (CARbon Assimilation In the Biosphere), and LPJ-GUESS (Lund-Potsdam-Jena General Ecosystem Simulator), are in the appendix and supplemental table 1.

Individual-Tree Growth and Yield Models

In individual-tree models, plant physiological interactions with the environment are commonly represented with estimates of site index or plant community type and the observed growth of particular species of interest over decades in those environments. Competitive effects of neighboring vegetation and trees on an individual tree are approximated based on the abundance, relative size, species identity, and proximity of its neighbors. Spatially explicit models represent the effects of neighbors based on proximity, while generalized models represent these effects using relative size and abundance at the stand level. Although stand structure studies on the West Coast have used spatially explicit, individual-tree models with physiological or demographic functions, such as SORTIE, ZELIG, and iLand (e.g., Coates et al. 2003, Hansen et al. 1995, Seidl et al. 2012), few studies have used these models for carbon projections of landscapes and regions.

FVS (Forest Vegetation Simulator) is the primary individual-tree model in broad use across a range of forest types in the Western United States (e.g., Cabiyo et al. 2022, Diaz et al. 2018, Raymond et al. 2015). It is considered a type of growth and yield model, focused on silviculture and based on equations built from tree growth and mortality measurements (Weiskittel et al. 2011). Other specialized growth and yield models used in the region focus primarily on industrial forestry (Joo et al. 2025). The primary purpose of FVS is to assess the response of individual stands to alternative silvicultural prescriptions on National Forest System lands (Dixon 2026) (fig. 3).

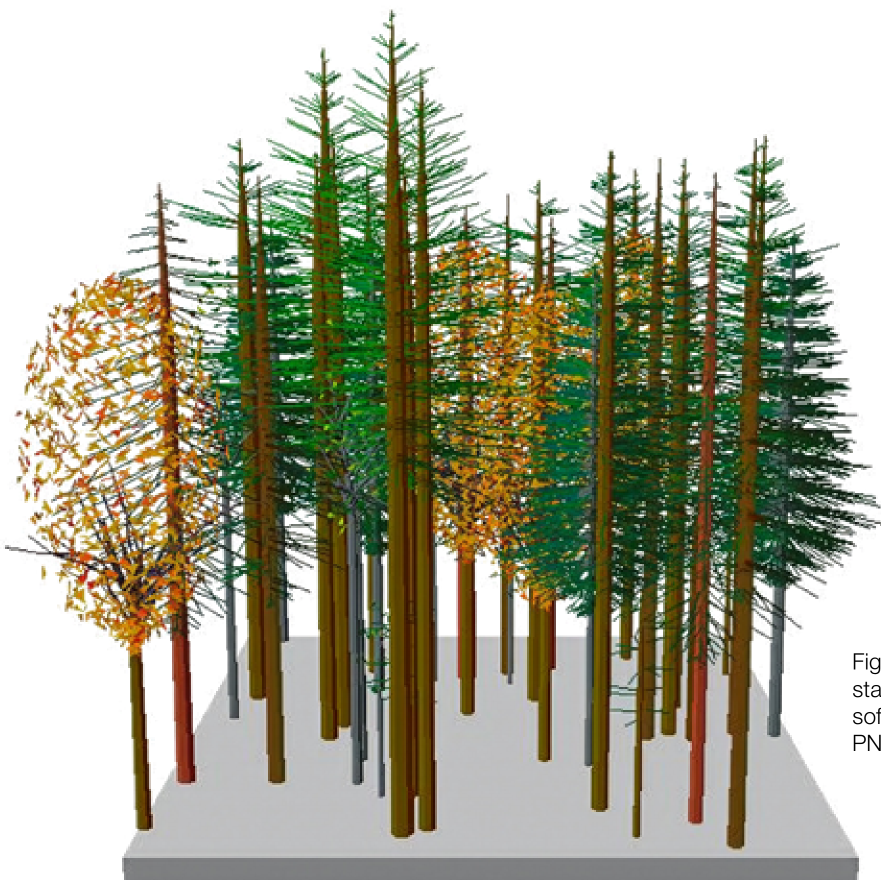

Figure 3—Example Forest Vegetation Simulator stand depicted in the Stand Visualization System software. Graphic source: USDA Forest Service PNWRS (2018).

For site-specific and regional applications, expert tweaking of parameters and variables is usually applied to improve model behavior (Swann et al. 2025, Vandendriesche 2010). However, the model can be applied "out of the box" (without modification), as in Hurteau and North (2009), a study that projected the effect of different thinning and burning treatments on carbon storage in mixed conifer stands in the Sierra Nevada. Regional variants of the model are parameterized from inventories and other research data. A variety of allometric equations are used to calculate merchantable and total volume and biomass of all stems, branches, and coarse roots from estimates of tree diameter and height. Individual-tree growth and mortality from competition are controlled by species-specific equations using site index, elevation, and tree size relative to the rest of the live trees in the stand. A key parameter determining potential carbon accumulation is maximum stand density index, which is determined by plant association code or by species unless set by the user or modeled from climate and soil data (e.g., Kimsey et al. 2019). Modelers have great flexibility in assigning the timing, type, and intensity of silvicultural prescriptions by species, size, and density. Fire behavior—expressed as flame length, likelihood of crown fire, and tree mortality—is determined by user-specified windspeed, fuel moisture, air temperature, and general fuel characteristics determined by forest type and structure (Rebain 2025). An extension estimating nontree vegetation cover and biomass by lifeform has been developed for some variants (Moeur 1985). FVS has a climate module based on comparing the future climate to the range of climates where current species are found, which primarily affects tree mortality in addition to growth and regeneration (Crookston 2014).

BioSum (Bioregional Inventory Originated Simulation Under Management) is an application that uses FVS outputs (generated from FIA inventory plot locations and data) to identify optimum management prescriptions based on goals that the user selects, which may include carbon storage, revenue, or resilience to fire (Fried et al. 2017). The model runs all chosen alternative prescriptions for all plots in a region through FVS and quantifies results against user-identified criteria to rank treatment effectiveness. In addition to implementing growth, treatments, and disturbances to measured inventory plots with FVS, BioSum applies tree allometric equations and inventory stratum weights used by the FIA program to enable direct comparison with current conditions. The model estimates logging and transportation costs as well as revenues for different types of harvested products as inputs to the optimization algorithm. For example, Jain et al. (2019) projected the potential area treated, effectiveness, and net revenues of treatments to improve resilience to wildfire in mixed conifer forests in northern California, eastern Oregon, and eastern Washington, given different constraints on ability to pay.

Stand-Level Growth and Yield Models

The net change in live-tree volume and carbon follow characteristic patterns of accumulation since stand initiation, represented as "stand age" (fig. 4). Stand-level models depict the aggregate effect of tree regeneration, growth, and mortality for groups of individuals (i.e., stands, usually 10–400 ha). The environmental suitability of a site is represented through estimates of site index or plant community type, which modify the shape of the volume, biomass, or carbon accumulation curves based on dominant species in the stand and time since stand origin (e.g., clearcut or high-severity disturbance). Foresters often use "normal" growth and yield curves of merchantable volume, which are developed from measurements of single species on fully stocked stands with little or no disturbance since stand origin. The most robust curves are based on repeated measurements or dissections of

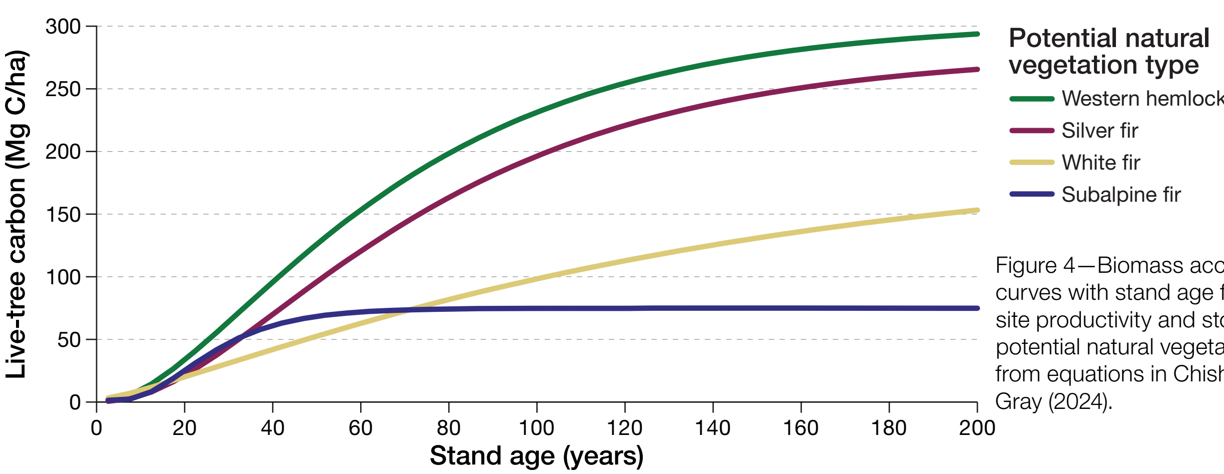

Figure 4—Biomass accumulation curves with stand age for median site productivity and stockability by potential natural vegetation type from equations in Chisholm and Gray (2024).

tree growth over time (e.g., Cochran 1979). In contrast, "empirical" curves are developed from measurements of a broader variety of stand conditions of different ages and rely on the chronosequence assumption that stands of different ages on similar sites developed under the same conditions (e.g., Chisholm and Gray 2024, Gray et al. 2016). DFSIM (Douglas-Fir Simulator) was an early stand-level model for Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) in western Oregon and Washington that incorporated site index, thinning, and fertilization in its calculations (Curtis et al. 1981). Most stand-level models estimate merchantable volume, so conversion factors are needed to estimate whole-tree biomass and carbon. Stand-level volume tables were developed for the ATLAS (Advanced Topographic Laser Altimeter System) model (Mills and Kincaid 1992), which became the foundation for the national carbon calculator tool FORCARB (Smith et al. 2006). Hoover et al. (2021) updated these tables with newer empirical data. Individual-tree or cohort models, like FVS or LANDIS-II, can also generate stand-level curves (e.g., Dymond et al. 2020, Raymond et al. 2015).

CBM-CFS3 (Carbon Budget Model of the Canadian Forest Sector3) is a model that uses live-tree merchantable volume growth and yield curves to project regional carbon stores in response to harvest and disturbance (Kull et al. 2024, Kurz et al. 2009). The model can accommodate different growth and yield curves for natural and managed stands of any forest type, as well as transitions between curves to reflect changes after disturbance or partial cutting. Modelers can define multiple yield curves for a specific stand type, each representing the volume associated with a particular leading species. The model calculates live stem, branch, and root biomass pools from each vegetation-specific volume curve. NPP, heterotrophic respiration, and senescence of foliage and fine roots are also estimated based on age and pool size. Disturbances and treatments are applied stochastically to stands within appropriate spatial units. Disturbance and harvest effects are defined by the proportion of each carbon pool that is transferred to another carbon pool, the atmosphere, or the harvested wood product sector. A new growth and yield curve applied to the stand defines postdisturbance dynamics, and the model allows one or more new growth and yield curves to be assigned to different proportions of the disturbed area. Climate does not affect live-tree dynamics in CBM-CFS3. In addition to projecting alternative management and disturbance regimes to current mapped or inventoried data, Canada uses the model in its national GHG reporting for the forest sector, using remotely sensed change detection and harvest data to update inventories (Kurz et al. 2009, Stinson et al. 2011). Researchers have applied the model in British Columbia (e.g., Giles-Hansen et al. 2021, Kurz et al. 2008), some Eastern U.S. states (Dugan et al. 2018, 2021), and California and Oregon (DeLyser et al. 2025).

Other models that use stand-level growth and yield curves include ForCaMF/InTEC (Forest Carbon Management Framework/Integrated Terrestrial Ecosystem Carbon), which combines curves generated by FVS with satellite change detection and a biophysical model to estimate changes in carbon on national forests since 1990 (Birdsey et al. 2019) to assist in planning efforts (USDA Forest Service, n.d.). A model called LURA (Land Use Resource Allocation) is based on 676 unique empirical yield curves built from FIA data to simulate the effect of forest product demand on in-forest ecosystem carbon (Latta et al. 2018).

Other modeling approaches rely on empirical inventory plot data, using recently-measured carbon stocks and flux, calculating responses to disturbance and management with satellite imagery, and filling in missing ecosystem components and processes with measurements taken from detailed studies (e.g., Hudiburg et al. 2011, Law et al. 2013). Simpler approaches can combine empirical data with satellite change detection to "update" inventory plots to a common, recent year (e.g., Gray et al. 2019).

Landscape Process Models

LANDIS-II (Landscape Disturbance and Succession) is a landscape process model that simulates vegetation succession and disturbance by including the spatial processes of plant dispersal and the propagation of disturbances (e.g., fire, wind, insects) across large (about 1 million ha) landscapes (Scheller et al. 2007). Vegetation is represented as within-stand age cohorts of tree and shrub species. Species life history characteristics, in terms of shade tolerance, longevity, and susceptibility to disturbance, drive forest succession simulations. Species cohorts compete for water, nitrogen, and solar radiation, and reproduce by sprouting or seed dispersal within and among surrounding grid cells. Species have defined optimum growth rates and maximum biomass values for species cohorts and shrubs, and mortality rates increase as species reach their specified longevity.

A variety of modules have been developed for LANDIS-II, including those for biophysical processes and carbon cycling based on climate, soils, and topography; biomass and fuels tracking; harvest scheduling; and fire spread. Wildfire is modeled within constraints of size and ignition probabilities. Creutzburg et al. (2017) assigned a disturbance regime to each cell, and wildfire was simulated as a function of ignitions, fuels, topography, and daily fire weather. Several studies have applied LANDIS-II to different regions in West Coast forests to investigate effects of climate change and alternative management on species distributions, disturbance regimes, and carbon stocks (e.g., Laflower et al. 2016, Liang et al. 2018, Maxwell and Scheller 2020).

State-and-Transition Models

State-and-transition models (STMs) simulate changes between different structural and compositional forest stages that result from succession, disturbance, or cutting (Kerns et al. 2012b). The system being modeled is divided into discrete states that are linked by deterministic or probabilistic transition pathways (fig. 5). For example, the process of succession from shrubland (a state) to forest (another state) can be modeled as a deterministic transition that occurs once a patch reaches a certain age, while the stochastic process of fire converting forest to shrubland can be modeled as a probabilistic transition. A large number of states can be defined. Hemstrom et al. (2007) defined states by overstory species, disturbance history, potential vegetation, tree diameter, number of layers, and open or closed canopy (in addition to grass and shrub stages), resulting in 308 states. STMs can include discrete counters to track patch age and time since transition, and can represent transitions as target areas (e.g., treat 100 ha/yr) or probabilities that only apply to certain conditions (e.g., thinning in stands 70–90 years old) (Daniel et al. 2016). Spatial processes (e.g., spread of fire or insects) can be incorporated by allowing transition probabilities to change depending on the status of neighboring patches, and detailed modeling of fire weather and flame lengths can also be incorporated to determine transitions given the current state of each patch or pixel in the model (Prichard et al. 2023).

Modeling carbon stocks and changes with STMs can be as simple as calculating mean values for the vegetation type in each state and estimating how those stocks change over time (Zhou and Hemstrom 2012). Alternatively, regressions of carbon stocks over stand age can be applied to the age and state type for every patch and to track changes over time (Spies et al. 2017). It is also possible to include processes, such as carbon flows and fluxes, within STMs to provide more refined estimates of carbon change over time (Sleeter et al. 2022). STMs have been used in the Pacific Northwest to analyze departure from reference conditions and potential effects of climate change, and to inform land management decisions (Halofsky et al. 2014a, Haugo et al. 2015, Kerns et al. 2012a).

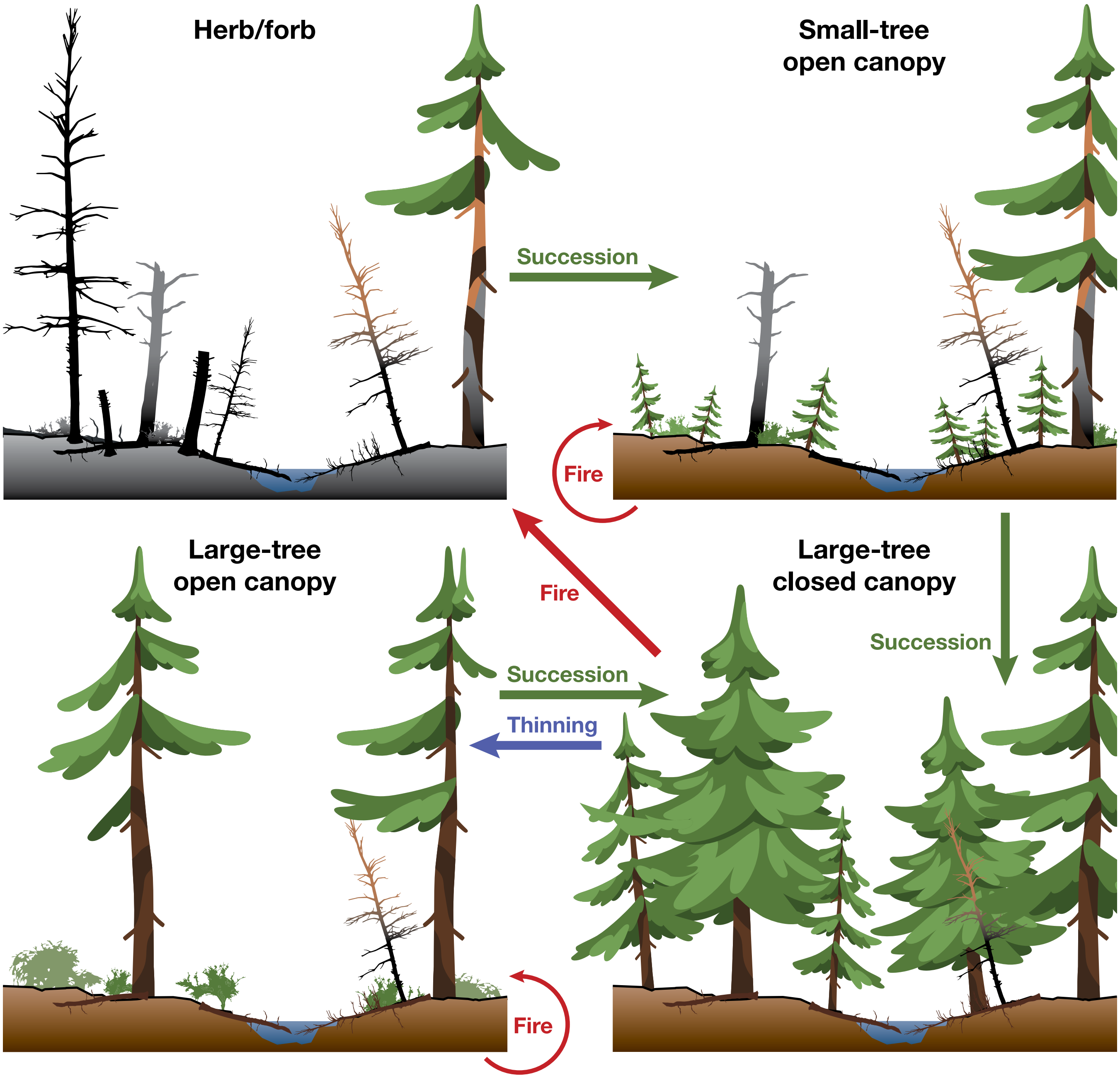

Figure 5—States and transitions (arrows) in an example of a four-stage forest model illustrating the effects of succession, fire, and thinning. Adapted from Kerns et al. (2012b).

Imputation Models

Resources Planning Act (RPA) modules include those projecting population, economy, climate change, and forest change to meet requirements of the Resources Planning Act (1974) and simulate future land use, harvest, status, and trends of forests in the United States. The current RPA Forest Dynamics Model (RPA-FDM) for the 2020 RPA sets probabilities for inventory plots transitioning to different states to project forest response to changes in management, disturbance, and climate (Coulston et al. 2023). The model relies on FIA plots, which have been consistently remeasured on most forest lands of the United States since the year 2000 (Wear and Coulston 2019). Coulston et al. (2015) used the measured changes in land use and the forest response to harvest, disturbance, and growth to create transition matrices of the probability of a plot in a predefined type moving to a different age class. Although catastrophic disturbances and clearcutting move plots to age zero, partial harvest and disturbance move plots to a younger age class. Projected changes in land use, timber prices, or disturbance based on other RPA modules are used to change the transition matrix probabilities. The new age class and site variables for a location, including future climate conditions, define the pool of plots from which a plot is imputed to represent the new condition at time 2. Imputing a new plot at time 2 can be used to estimate net change; alternatively, a plot that meets transition matrix criteria could be imputed to a target plot, and the time 1-time 2 remeasured values for growth, mortality, and harvest used to estimate components of change (Coulston 2020).[1] Where uneven-aged management or partial disturbances are common, defining stand age and its progression becomes problematic and may contribute to overestimating growth (Wear and Coulston 2019). The same approach, using empirical transition matrices from remeasured FIA plots, is used to project plots from their last measurement date to the current assessment year for the U.S. national GHG inventory (Domke et al. 2023b, USEPA 2023).

Model Simulation of Dead Wood and Forest Floor

Dead wood in a forest ecosystem consists of boles and branches of trees and shrubs that have died—for example, from senescence, competition, disturbance, or cutting. Dead wood can be standing (i.e., snags) or down (in contact with the forest floor); models that track standing-dead wood separately include functions for snag fall and transfer to down wood over time. Coarse roots are usually included in the standing-dead or stump pool. Dead fine roots are usually considered part of the forest floor or mineral soil pool, depending on location. Down woody material is often separated into **coarse woody material** (≥7.5-cm diameter) or **fine woody material** (<7.5-cm diameter). In addition to being important for modeling carbon pools, dead wood sizes and amounts, and forest floor depth and composition, can be used to model fire behavior. Fine wood is an important fuel class, but for carbon assessments it is sometimes lumped in with the forest floor pool (e.g., USEPA 2023). Depending on the model, forest floor is part of the soil carbon pools (i.e., as the soil organic horizon), in the dead wood pools, or treated separately. Most biophysical process models group all fresh dead material into a “litter” pool regardless of size or type.

Sizes and fluxes of the dead wood and forest floor pools in undisturbed forests depend on rates of input from live vegetation and rates of decay. Decay releases carbon dioxide and methane emissions to the atmosphere and humified compounds to the duff layer and mineral soil. Disturbance and harvest events can result in a pulse of dead matter input, changes in temperature and moisture affecting decomposition, and combustion or charring of dead matter in the case of fire. The amounts and sizes of dead matter are important determinants of fire spread and intensity, but fuel mass is not the most important attribute affecting fire. Fuels require oxygen to combust, and the packing density of fine fuels greatly affects how rapidly they will burn. For example, a litter layer of loosely packed pine needles will burn much more readily than a snow-compressed litter layer of fir needles of the same mass. This is why the dominant approach to fire behavior modeling in the United States is based on a limited set of archetypal “fuel models” that describe the typical fuel characteristics of different vegetation types (Sandberg et al. 2001, Scott and Burgan 2005).

[1] Coulston, J.W. 2020. Personal communication. Research forester, U.S. Department of Agriculture, Forest Service, Southern Research Station, 1650 Research Center Drive, Blacksburg, VA 24060, john.coulston@usda.gov.

Biophysical Process Models

In the MC2 model (Bachelet et al. 2015), dead wood and forest floor dynamics are simulated by the CENTURY model (Parton et al. 1993), which simulates flows of matter from live shoots to standing dead to surface litter, and live roots to root litter. Dead matter is not split into separate pools for coarse wood, fine wood, litter, and duff, but is partitioned into lignin and cellulose structural components resistant to decomposition, and metabolic components that are readily decomposable (fig. 6). Decomposition of these pools is controlled by an inherent maximum decomposition rate for each pool, modified by average monthly temperature at the soil surface and monthly soil moisture. CENTURY models the combustion and mineralization of nutrients by three different intensities of fire. However, MC2 applies a separate fire module that controls combustion of live and dead fuels, as well as elevated postfire mortality.

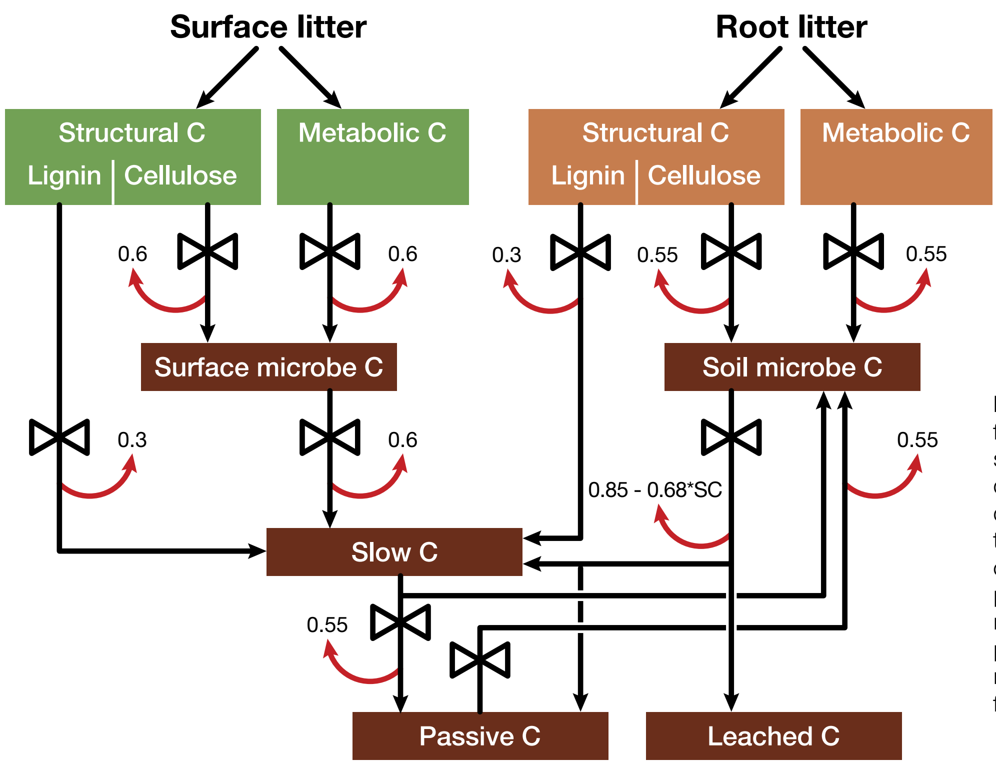

Figure 6—Soil organic matter module for the CENTURY model. The valve symbols represent factors controlling decomposition (e.g., maximum decomposition rate modified by temperature, moisture, and lignin content), and the values are the proportions of carbon emitted due to microbial decomposition for each flow path. C = carbon, SC = the fraction of mineral soil that is silt + clay. Adapted from Parton et al. (1994).

In Biome-BGC (Thornton et al. 2002), dead woody litter enters a coarse wood pool that degrades physically before entering the active litter pools where it is subject to decomposition. Three cascading litter pools are defined based on concentrations of lignin and cellulose, which degrade chemically at different rates, with undecomposed matter moving from the least to most recalcitrant pools. Soil temperature, soil moisture, and the availability of nitrogen in the system control decomposition rates (Golinkoff 2010). Proportional consumption of live and litter pools in fires is controlled by a disturbance severity parameter with proportional consumption of coarse wood set to half the rate for the other pools.

The CLM model (Lawrence et al. 2019) allows users to choose between the CENTURY decomposition algorithms or a submodel derived from Biome-BGC, which is characterized by faster decomposition rates. Fire combustion is modeled separately, and the default model assumes that fire consumes 50 percent of the litter and 28 percent of the coarse wood. In the

ED2 model (Longo et al. 2019), decomposition and fire combustion are based on an implementation of the CENTURY model.

The STANDCARB/LANDCARB model (Harmon and Domingo 2001) simulates a dead pool for each contributing live pool as well as three stable pools for highly decomposed foliage, wood, and soil. Dead sapwood and heartwood are further subdivided into snag and log components. Cohorts of dead matter are tracked separately until the remaining mass transfers to a stable pool. Substrate quality of different plants contributing to dead pools (e.g., herb versus tree) as well as temperature and moisture affect decomposition rates. Combustion of each pool by fire is specified for three levels of fire intensity.

Other Models

The FVS individual-tree model simulates dead wood in snags, coarse roots, and size classes of down wood, as well as litter and duff with the Fire and Fuels Extension (FFE) (Rebain 2025). It can initialize dead wood pools with inventory data or can assign default values based on dominant tree species, the potential natural vegetation type, or the general fuel structure type. Live-tree inputs from litterfall and branch mortality, and dead tree inputs from breakage, falldown, and harvest activity are simulated. Dead matter decay is modeled as a proportional rate that varies by size class, although users can adjust decay rates by species. Some model variants integrate variations in snag breakage and decay rates by implied moisture and temperature regimes of different climax plant associations. Two percent of the original mass of each dead matter pool ends up in the duff pool, while the remaining biomass is lost as carbon dioxide. Combustion of dead wood and forest floor carbon pools by fire events depends on fuel type, size class, and moisture content. Inventory data on fuel mass can be used to interpolate between fuel model values that control fire behavior (Scott and Burgan 2005).

The CBM-CFS3 stand-level model tracks aboveground and belowground dead wood and forest floor pools in three decay rate classes, with transitions of remaining material to slow decay pools. The initial dead wood, litter, and soil pool sizes are derived by simulating multiple rotations of growth and disturbance until humified soil pools stabilize (Kurz et al. 2009). Stands are then simulated for three rotations with wildfire and modeled to the starting age to set up initial conditions. Decay rates vary as a function of mean annual temperature and stand age. Combustion rates for different materials vary by ecological zone.

The LANDIS-II landscape model includes the Net Ecosystem Carbon and Nitrogen extension (e.g., Maxwell et al. 2022b), which simulates stocks and changes of down wood, litter, and coarse and fine roots, as well as three soil pools (fast, slow, and passive) following the CENTURY model. The modeler specifies the proportion of dead biomass that is combusted by fire or removed by harvest. Fuel type is assigned by species groups and age ranges (e.g., Maxwell and Scheller 2020) independent of the dead biomass pools.

STMs can include dead wood and forest floor carbon pools defined for each state in the model or can include changes in values within states built from regressions of carbon stocks as a function of stand age (Spies et al. 2017). Sleeter et al. (2022) integrated the CBM-CFS3 model into an STM to simulate carbon across the conterminous United States, including the input and decay of dead wood and forest floor carbon pools. Combustion of dead wood and forest floor has apparently not been simulated directly, but wildfire effects are parameterized as changes in pools in response to fires of different severities.

Imputation models can include measured or modeled estimates of dead wood, forest floor, and soils for the plots being imputed to future time steps, with carbon flux estimated as the net change in carbon stocks for each pool (e.g., USEPA 2023). Fuel effects on fire behavior are not simulated. Models that estimate carbon stocks of coarse woody material based on forest type and state (USEPA 2023), and litter and fine woody material based on location, climate, forest type, and live-tree carbon (Domke et al. 2016), are applied to the nationwide forest inventory to report carbon stocks and flux on forest land.

Model Simulation of Soils

Forests cover one-third of the land area of the United States and store 50 to 70 percent of the total soil carbon (Pan et al. 2011). Soil carbon is the largest pool in forested ecosystems (Domke et al. 2017) but is usually the least represented in measurements and models. Soil carbon modeling can account for either the total soil carbon stocks or the net stock change of soil carbon into and out of the ecosystem over time. Both model approaches rely on predictors related to spatially explicit soil carbon accumulation to provide comprehensive estimates across the landscape because continuous direct measurements of soils are difficult and sparse. Forest Service land management plans now include soil carbon stock and change estimates, compelling application of model approaches across large forested areas (Janowiak et al. 2017). These comprehensive forest soil carbon estimates require the application of models for prediction of both soil stock and stock change to provide estimates of net ecosystem carbon balance. Forest soil carbon models face many challenges because of much greater variability and fewer field measurements compared to soils in agricultural settings. A current challenge in soils research is to improve soil carbon estimates using advanced analytical techniques and to quantify the mechanisms and rates that govern soil carbon turnover and stock change.

Soil Carbon Stock

Modeled estimates of soil carbon have evolved in complexity and accuracy for over 40 years (Batjes 2016, Post et al. 1982, Turner et al. 1995). Estimates of current global soil carbon stocks have a median across all studies of about 1500 Pg C (1 Pg = 10^{15} g) to 1-m depth (Batjes 1996) and up to 2300 Pg C to 3-m depth (Jobbágy and Jackson 2000). Studies have produced modeled estimates of soil carbon stocks from field measurements and environmental covariates at varying spatial extents. Worldwide estimates of soil carbon stocks can be used as approximations for management areas, although the accuracy of these models is not always available. The SoilGrids system (Hengl et al. 2017) and Harmonized World Soil Database (Batjes 2016) use field data combined with gap-filling algorithms and landscape predictors to create continuous carbon stock estimates at 5- and 1-km resolutions, respectively. Soil carbon stock estimates on the West Coast of the United States are hindered by the sparse amount of soil sampling and pedon description in the National Cooperative Soil Survey inventory. Therefore, the State Soil Geographic Database (STATSGO) can only provide broadly extrapolated estimates of soil properties, including carbon (USDA NRCS 2016).

Concerted efforts are underway to improve predictive soil map coverage and resolution. The “Soils2026” initiative is applying digital soil mapping approaches to create soil class maps and soil property prediction maps at a resolution of 30 m (Thompson et al. 2020). One of the key properties is estimating soil carbon to a depth of 1 m. Improved resolution of the carbon stocks is available at regional and subregional scales, which are more appropriate to land management planning or carbon cycle projects. For example, McNicol et al. (2019) used a combination of field data and machine learning to estimate a continuous 30-m resolution soil carbon stock for southeast Alaska's perhumid coastal temperate rainforest, which includes the large and carbon-dense Tongass National Forest. The LandCarbon project provided soil carbon stock estimates for the Marine West Coast Forest and Western Cordillera ecoregions of the Pacific Northwest (Zhu and Reed 2012). Domke et al. (2017) modeled estimates of forest soil carbon stocks to 1-m depth from available soil samples using climate, forest type group, and soil order to provide FIA plot-based estimates. Recently, Jones and D'Amore (2024) produced an ensemble model that provided carbon estimates for Alaska, British Columbia, Washington, Oregon, California, and Hawai'i for soil depths of 30 and 100 cm.

Soil Carbon Persistence

Soil carbon was treated as a mostly inert, stable pool in early ecosystem carbon models, with a minor, rapidly cycled component assigned to the "active" phase in most models (Smith et al. 1997). However, investigations into the physical and chemical structure of soil organic matter (SOM) revealed discrepancies between the model formulation and the actual structure and turnover of SOM, prompting reconsideration of process models and measurement techniques (Jackson et al. 2017, Kleber and Johnson 2010, Lehmann et al. 2008). Original conceptual ideas regarding soil carbon proposed that alteration of SOM and the formation of humic substances governed the decomposition process (Schlesinger 1977, Stevenson 1994). Measurements of SOM used extracts that converted the organic matter to either insoluble or soluble forms, which were interpreted to act as stable or labile (unstable) pools (Stevenson 1994). However, recent research has challenged the idea that SOM molecular conversion progresses in a manner consistent with the humic substances model and proposes that the assumption of carbon stability resulted from the byproducts of the extraction procedure (Piccolo 2002). A range of research has led to a new conceptual model that highlights soil conditions as controlling SOM turnover, rather than the structure of organic matter and the concept of soil carbon "persistence" (Lehmann et al. 2008, Schmidt et al. 2011). Therefore, the susceptibility of organic matter to accumulation or decomposition is related more to the emergent properties within the soil that are governed by the soil-forming factors (parent material, climate, topography, organisms, and time) (Jackson et al. 2017). Organic molecules are composed of reduced organic carbon and are susceptible to decomposition, but the arrangement of organic matter within the soil matrix, occlusion or protection of organic matter by physical structures, and physical and chemical conditions influence the fate of the SOM and overall carbon balance (e.g., Kleber et al. 2015).

Representing Soil Carbon Stock and Turnover in Models

Soil carbon modeling developed along with early estimates of worldwide soil carbon pools. Attempts to quantify changes to SOM date to the 19th century but generally point to the attempts to estimate soil carbon stocks by Waksman (1938). Subsequent models that used algorithms to generate SOM outcomes—"process models"—were developed to predict changes in the soil organic pool driven by primary physical and biological functions that influenced the chemistry of the organic matter. A suite of models that are often used today relied on the concepts of organic matter humification as an indicator of relative stability (e.g., RothC, CENTURY). Note the use of the CENTURY submodel in the forest carbon models in the "Model Simulation of Dead Wood and Forest Floor" section.

Although there are more than 200 possible SOM models to consider (Campbell and Paustian 2015), we provide an overview of what the models are designed to achieve through the differing process steps, with a focus on forest carbon models used on the West Coast. The CENTURY model, which is used in the MC2, ED2, and LANDIS-II models, uses conceptual decomposition classes of material in active, passive, and slow decomposition pools (fig. 6). Turnover rates in the active pool and transfer to the passive pool are functions of soil texture, clay content, soil moisture, and soil temperature. This type of organic matter characterization dominated many model approaches for two decades and is still used in many landscape modeling configurations. The SOM is partitioned into "slow" and "fast" turnover pools to represent the loss and persistence of organic material in soils across large geographic areas in the CENTURY model. Soil carbon is modeled similarly by Biome-BGC, whereas the CLM model allows users to choose between the Biome-BGC approach and the CENTURY approach. The CBM-CFS3 model uses a simplified CENTURY approach driven by temperature and a forest type parameter. FVS does not simulate soil stocks or stock change.

A comparison of nine models, including CENTURY, evaluated their performance across different ecosystems in a study that focused on the European soil organic matter decomposition consortium (Smith et al. 1997). This comparison included the three pool CENTURY model (Parton et al. 1993, 1994) and the widely used RothC multicompartment model (Jenkinson et al. 1991). The CENTURY approach agreed with five of the other eight models in the comparison, while the three remaining models were similar to each other but had larger model error (Smith et al. 1997). The variation in model performance depended on how far outside the model calibration structure the model was applied. For example, SOM cycling in a grassland is somewhat different than in a forest, leading to subtle changes in many of the parameter values that are used to drive model outcomes. A more recent review of 71 microbial models focused on the revised SOM paradigm of organo-mineral interaction as the persistence mechanism in soils (Chandel et al. 2023). This review emphasized the importance of using well-constrained rate limitations in microbial turnover and change based on relevant field and lab trials (Chandel et al. 2023).

Microbial community patterns of decomposition have been critical for understanding SOM transformation, such as the potential for physical occlusion and preservation of soil carbon in aggregates or other compounds within the soil (Sollins et al. 1996). Models have attempted to represent the microbial community influence on carbon pools across space and time (Schimel and Weintraub 2003). Recent forested watershed modeling approaches have demonstrated the ability of process-based microbial models, trained with field data, to adequately predict carbon stock changes and uncertainty around those estimates (Pierson et al. 2022, Wieder et al. 2015).

Model performance for a distinct project area is an important consideration in model selection, particularly when land managers need to understand the effect of alternative management approaches on soil carbon. Nave et al. (2022) conducted a review of research on the effects of disturbance and management on forest SOM in the Pacific Northwest. Management and disturbance can affect SOM, but conditions at individual locations matter, leading to numerous exceptions to any rule. Direct mechanisms of SOM loss include combustion by fire; fire-altered soil structure that exposes SOM to decomposition; and mechanical mixing, compaction, and movement of soil. Indirect mechanisms of SOM loss include wind and water erosion; reduced inputs from fewer live plants; reduced shading and litter, which increases soil moisture and temperature, resulting in increased decomposition; and changes in pH that increase microbial activity. Most of the variation in SOM stocks across the region was due to topography, climate, and vegetation type, with weaker effects from land use, management, and disturbance. Results indicated that wildfires diminished SOM stocks throughout the soil profile, while prescribed fire only influenced surface organic materials, and harvesting had no significant overall effect on SOM (Nave et al. 2022). However, few of the controlled studies that provided the strongest inference extended for more than 5 years after the disturbance or treatment. Not all carbon loss from undisturbed soils is via respiration to the atmosphere; substantial amounts of organic and inorganic carbon leave forest soils via groundwater and streams, where they can become part of the aquatic food web and be respired to the atmosphere (Argerich et al. 2016, Butman et al. 2016, Edwards et al. 2021).

Key Soil Research Needs

Estimates of soil carbon stocks rely on extreme amounts of interpolation and have large error estimates. Evaluating the stocks with greater certainty is needed as a gross terrestrial estimate but also to provide a baseline for modeling and quantifying change in this carbon pool (e.g., Jones and D'Amore 2024). Forest soils are some of the most difficult to estimate because of the rugged terrain, disturbance regimes, and remote locations. Improved remote sensing provides a means to improve covariate model inputs (e.g., landform mapping with lidar), but additional ground measurements of soil carbon are needed to validate existing models and calibrate new model runs. Along with improved estimates of carbon stocks, soil carbon stock change is perhaps the greatest challenge in carbon cycle science. Detecting small changes in this large and variable carbon pool is difficult because of error estimates of stocks exceeding mean stock change estimates.

Process-based models that use input variables related to processes connected with plant physiology, rooting, interaction with microbial communities, and soil physical and chemical properties need to be tested and compared across varying ecosystems. Expanded field pedon description and sampling need to accompany the model development to address the spatial uncertainty in models from the lack of field calibration sites. Fundamental research is needed on specific soil processes, such as components that drive SOC changes in diverse microbial communities and interactions with plant roots. The next generation of process models will need to improve estimates of spatial and temporal patterns in biological communities coupled with physical and chemical variables in soil environments.

Suitability of Model Types to Questions of Interest

Climate Change

Climate change affects forest carbon stocks and flux through changes in precipitation (snow and rain), temperature, vapor pressure deficit, and their seasonality. Global climate models simulate future climate conditions under plausible climate change pathways by accounting for chemical and physical interactions among the atmosphere, oceans, land surfaces, and ice. These future climate projections differ with respect to changes in temperature, precipitation, and aridity for given levels of GHGs. Coarse resolution global projections are routinely downscaled to local scales (e.g., to a 6-km grid resolution and daily time steps) to translate global patterns to local patterns using observed data as a reference. In mountainous terrain, topography can buffer sites from expected broad-scale warming (Daly et al. 2010). Vegetation modelers may apply additional downscaling or adjustments to account for differences in elevation and topography within global climate model grid cells.

Most biophysical process models are designed to use observed or global climate model-generated future climate data to drive ecosystem processes. Many also include potential effects of atmospheric carbon dioxide enrichment and nitrogen deposition from human pollution (table 2). Models that are directly driven with climate data are more likely to reliably simulate the effects of novel climates and physiological drivers that are expected with continuing climate change. Comparisons of different physiologically based models indicate that differing sensitivities to climate and carbon dioxide enrichment drivers result in

Table 2—Summary of suitability of ecosystem model types to different questions

Questions	Model type (examples)[a]					
	Biophysical process (MC2, ED2, CLM)	**Growth and yield (CBM-CFS3)**	**Individual tree (FVS)**	**Landscape process (LANDIS-II)**	**State and transition (STMs)**	**Imputation (RPA-FDM)**
Climate change	Direct climate, soil, CO_2- and N-enrichment effects on growth and decomposition[b]	Modified volume curves	Potentially: modified density, growth, or mortality scalars	Biophysical process submodels incorporated, disturbance spread modeled	Biophysical process submodels incorporated in some efforts	Impute current plots to locations with similar future climate
Tree harvest	Proportional biomass removal, stand-level response	Proportional biomass removal, response with modified curves or age reset	Can specify sizes and species removed, individual tree response	Proportional biomass removal, cohort response, regeneration from seed sources	Treatments define transitions and removals, response is new state	Economic drivers of harvest, response specified by empirical change
Wildfire and fuel reduction treatments	Fire regime assigned, severity determined by fuel loads and fire weather, limited treatments	Fire regime assigned, effects defined by type	Fire regime assigned; severity determined by fuel model, height to crown base, fire weather	Fire ignition spread and severity determined by fuel loads and fire weather, fuel treatments possible	Fire and treatments are defined transitions	Fire regime assigned
Other disturbances	Drought included in some models	Insect and disease modules available	Not available in current variants	Browsing, insect, and disease submodels available	Can be defined as transitions among states	Not modeled explicitly
Social and economic drivers	Rarely included in simulations	Economic criteria can determine what is harvested	Economic criteria can be assessed with BioSum	Economic criteria can determine what is harvested	Rarely included in simulations	Economic criteria can determine what is harvested or converted
Hydrology	Only RHESSys models it	Not modeled explicitly	Not modeled explicitly	Not modeled explicitly	Not modeled explicitly	Not modeled explicitly
Wildlife	Forest composition and structure can inform habitat models					

Models ranked as a good fit are shaded green, moderate fit shaded yellow, and poor fit unshaded.

[a] BioSum = Bioregional Inventory Originated Simulation Under Management model, CBM-CFS3 = Carbon Budget Model of the Canadian Forest Sector3, CLM = Community Land Model, ED2 = Ecosystem Demography2 model, FVS = Forest Vegetation Simulator model, LANDIS-II = Landscape Disturbance and Succession model, MC2 = Mapped Atmosphere-Plant-Soil System [MAPSS]-CENTURY2 model, RHESSys = Regional Hydro-Ecologic Simulation System model, RPA-FDM = Resources Planning Act-Forest Dynamic Model, STM = state-and-transition models.

[b] CO_2 = carbon dioxide, N = nitrogen.

differences in carbon sequestration, even when estimating similar amounts of GPP (De Kauwe et al. 2014, Huntzinger et al. 2017). Many of the applications of biophysical models, and the landscape and STM models that incorporate them, to climate change on the West Coast focus on shifts in tree species and plant communities (e.g., Kim et al. 2018, Maxwell and Scheller 2020), with some studies also emphasizing effects on carbon stores and flux (e.g., Buotte et al. 2020, Halofsky et al. 2022).

Climate change effects can be estimated with empirical models based on the current relationship between climate and species distributions, process models which represent the biophysical mechanics of different species, or hybrids of the two (Iverson and McKenzie 2013). The RPA-FDM imputation model that we assessed is an example of an empirical model that imputes plot-measured species composition and carbon stocks to new locations based on their similarity to projected future climate. Most process models are hybrids to some extent because they constrain species climatic tolerances using observations of current species distribution and physiology. One study applied the CBM-CFS3 model in California and adjusted the growth and yield curves to reflect future climate, based on process model results (DeLyser et al. 2025). Few studies have used individual-tree models to estimate climate change effects on the West Coast, although Fekety et al. (2020) found that FVS results were highly sensitive to mortality parameters. A model comparison study found wide divergence in estimated climate effects caused by the mortality functions, despite relatively good agreement with historical, empirical data (Bugmann et al. 2019). Case et al. (2021) summarized research and knowledge gaps on climate change effects on carbon stores in the Pacific Northwest.

The Forest Service, Pacific Southwest Region has produced climate change assessments that describe past and projected future trends in climate for each national forest in California (USDA Forest Service PSW Region, n.d.). These assessments summarize past changes in hydrology, fire, vegetation composition, and wildlife, and likely future changes by summarizing existing research. Similarly, the Western Wildland Environmental Threat Assessment Center has produced climate vulnerability assessments for the Pacific Northwest Region's national forests in Oregon and Washington and other areas in the West including the Sierra Nevada, using modeling from MC2 and LANDIS-II and also synthesizing existing research (USDA Forest Service PNWRS 2026).

A potential deficiency for many models applied to the Western United States may be in the representation of regeneration after severe disturbance (Woodall et al. 2025). Of the models we investigated, LANDIS-II is the only model that requires proximate seed sources; the other models typically assume postdisturbance regeneration from a species list, provided that the climate remains within the range of conditions required for a species to grow. Assumptions about tree regeneration can have a strong effect on long-term model performance and predictions of carbon stores. For example, tree seedlings may be more vulnerable to changes in climate (e.g., more droughty conditions) than suggested by species distributions based on mature trees, resulting in models that underrepresent the potential for regeneration failure (e.g., Davis et al. 2023). In the California CBM-CFS3 study, DeLyser et al. (2025) adjusted postfire regeneration based on Davis et al. (2023) data to reflect an 82 percent potential failure to regenerate after high-severity fire by the year 2071.

Tree Harvest

Tree harvest is an important change agent in many forests. Harvest determines the amounts and types of wood, bark, and foliage that are removed to be utilized as forest products or severed and left in the stand as dead material. Harvest also affects the growth and mortality of residual and regenerating trees. Harvests are frequently augmented with additional treatment activities aimed at moderating future fire severity and reducing vegetation that competes with trees as described in the next section. Modelers specify the kinds of silvicultural treatments to apply, such as precommercial thinning, commercial thinning (from below or to maintain or achieve a desired diameter distribution), or rotation ending events that initiate regeneration, such as clearcut, shelterwood, and seed tree cuts. Modelers can include assumptions regarding utilization of harvested trees, for example, for manufactured wood products, bioenergy production, and biochar (used in situ or applied elsewhere). Modelers also specify treatment timing, often triggered by stand age or density, dependent on whether or not there is sufficient harvestable volume for treatment to be economically feasible. Through such simulations, the effects of rotation length, tree marking rules, and harvest method on forest carbon dynamics, forest resilience, and the potential to produce specific kinds of wood products can be explored.

Models vary in their ability to simulate different types of harvest. Some of the biophysical models delete a fraction of forest carbon at each time step to simulate harvest (e.g., MC2, 3-PG), but most simulate the removal of all or a portion of the live-tree aboveground biomass pool. Most of the biophysical models that we evaluated track stem wood, or even merchantable-size stem wood, as separate components of the live-tree pool for all trees (e.g., CBM-CFS3, Biome-BGC, RHESSys) or for age cohorts of trees (e.g., LANDIS-II, ED2, CLM). Models that track age cohorts by species or functional type can also apply crosswalks to estimate tree density and mean diameter for each cohort, allowing for more refined application of harvest to specific tree sizes and species, and estimating amounts of merchantable-size material removed (e.g., Maxwell et al. 2022a). In contrast, individual-tree models allow a more nuanced application of treatments based on tree species and size as well as an estimation of merchantable and nonmerchantable volume based on individual-tree allometry (e.g., Cabiyo et al. 2022). Most harvested wood product models are based on merchantable cubic-foot volume and use empirical data to determine the distribution of wood volume to different types of products (Lucey et al. 2024). Direct estimation of merchantable volume, or conversion factors from tree biomass to merchantable volume, can be used to estimate inputs to harvested wood products. In state-and-transition models, different types of harvest are specified in the transitions among states (e.g., Halofsky et al. 2014b). The ability of the RPA-FDM imputation model to simulate new or uncommon types of harvest is likely constrained by having to select from available empirical data.

Modeling silvicultural trajectories is inextricably linked to the modeling of stand growth and stand development because the timing of silvicultural treatments and the scale of harvest removals in projections depends on crossing a threshold of timber removal that meets economic feasibility criteria. Harvest activity is also closely tied to landowner objectives and economic conditions, which we discuss below. Carbon model choices require consideration of the complexity needed to accurately represent management scenarios; for example, uneven-age management and species- or size-specific criteria on removals may favor individual-tree models.

Wildfire and Fuel Reduction Treatments

Models use different approaches for simulating fire initiation, fire behavior, and effects on forest carbon stocks (Wood et al. 2025). For MC2, fire ignition occurs whenever extended drought and dry conditions occur, and fire-return interval is prescribed for each vegetation type (Conklin et al. 2016). CLM uses empirical data on frequency of lightning and human ignition (Lawrence et al. 2019). Most other models use empirical observations of fire frequency and size as a basis for simulating fire.

Fire behavior is characterized by spread and surface flame length, which depend on fuel availability, fuel moisture, and windspeed. The effect of fuel availability on fire behavior is primarily influenced by particle density and surface area (e.g., the mixture of air and fuel), and secondarily by the mass of fuel (Rothermel 1972). The dominant approach to represent fuels in the United States has been to use "fuelbed models" that apply Rothermel's (1972) mathematical model to predict fire intensity and rate of spread in homogenous fuels. Each of the 53 fuelbed models, which represent dry or humid fuel systems and a range of stand structures, consists of a 12-element vector of fuelbed parameters, most of which relate to loadings and surface area-to-volume ratios of fine, dead, and down wood by size class and live, woody and herbaceous fuel loads (Ricciardi et al. 2007, Scott and Burgan 2005).

Selecting the fuelbed model that best represents the most likely fire behavior under a given set of weather conditions is more involved than matching modeled quantities of live and dead fuels in the forest. In FVS-FFE, typically two (but up to four) fuelbed models are selected, along with associated weights that will be applied to their resulting fire behavior and effects predictions. For biophysical process models that do not distinguish dead biomass by standing, down, or size class, fuel modeling will be coarse. Fuel moisture and windspeed are based on simulated soil moisture and daily climate in biophysical process models, or are assigned, as in FVS, typically from at least a couple of points within the range of weather that such forests historically experienced during the active fire season. However, the largest West Coast wildfires tend to occur during extreme wind and low relative humidity events, which are difficult to replicate in simulation models, particularly for future climates. Busby and Fried (2025) modeled silvicultural trajectories with probabilities for different timing and weather severity for simulated wildfires based on recent fires. A weighted combination of these modeled trajectories can yield expected value carbon outcomes for any assumption set. Predictions of crown fire spread are based on fire behavior, heights to the base of the forest canopy, and canopy bulk density (Scott and Reinhardt 2001, Van Wagner 1977). LANDIS-II and RHESSys are two models that propagate fire spatially across landscapes; the other models that we evaluated apply fire stochastically or deterministically to grid cells or plots. FSim is another landscape fire propagation model that has been linked with FVS to estimate wildfire interactions with treatments based on empirical relationships of weather and ignitions (Ager et al. 2020).

Modeling of fire effects on forest carbon depends on submodels that predict tree mortality, fuel consumption, and emissions driven by fire behavior for most models (e.g., MC2, LANDIS-II, and FVS), but the driving variables differ substantially. In other models, the modeler assigns fire effects (e.g., ED2, CBM-CFS3, STMs). In most cases, model parameterization constrains or defines the area burned.

Treatments to reduce potential fire severity include reducing amounts of surface fuels (forest floor and down dead wood), elevating the height to canopy base, reducing crown density, and emphasizing the retention of large trees of fire-resistant species (Agee and

Skinner 2005). Tree harvest can reduce forest density; the resulting bole wood of merchantable size and species can be utilized for timber products, with branches, tops, and small noncommercial trees finding lower-valued uses as mulch, biochar, and bioenergy feedstock (Evans and Finkral 2009, Jones et al. 2010). Lopping, chipping and scattering, piling and burning, or broadcast burning can reduce the fuel profile of dead biomass left in the stand. Broadcast burning or low- to moderate-severity wildfire can reduce fuels without mechanical treatment (Davis et al. 2024). Because the modeler plans fuel treatments, their intended effects on forest structure, fuel profiles, carbon stores, and emissions can be readily specified in most model frameworks. Simplifying assumptions can make the task more tractable. For example, one does not need to know the exact weather under which a prescribed fire will be implemented if it is reasonable to assume that a manager will select a burn window that facilitates consumption of surface fuels without killing trees in the residual stand.

Fire modeling is an active field of research with a lot of competing approaches. It is difficult to identify one or more as being superior to the others. Kim et al. (2018) used MC2 to simulate climate change and fire on vegetation in the Blue Mountains, Oregon. Hudiburg et al. (2013) applied CLM to the Northwest, but they reduced default combustion and mortality functions to provide reasonable results. Maxwell et al. (2022b) applied LANDIS-II to evaluate effects of wildfire and alternative fuel treatments in northern Sierra Nevada forests. Several studies have applied FVS to simulate effects of alternative fuel treatments on subsequent wildfire and carbon stocks (Cabiyo et al. 2022, Finney et al. 2007, Hurteau and North 2009). Although more mechanistic methods might seem to be a better approach for predicting potential future conditions, assigning different disturbance rates based on stand conditions and expected general climates may be adequate for studies focused on other carbon dynamics.

Other Disturbances

Most of the models that we evaluated simulate the effects of fire and harvest, the primary disturbances in Western forests. However, other disturbances, like drought, wind, insects, and diseases, can affect carbon stocks and stock change to varying degrees depending on vegetation type and region. In many cases, mortality from these agents can be chronic and low level, and difficult to distinguish from background mortality rates already accounted for in the models. The occurrence of severe events, like extended drought, large windstorms, or insect outbreaks, can be hard to predict and incorporate in model projections. Disturbances are often linked; for example, large-scale windthrow events or extended drought can trigger bark beetle outbreaks. Many climate change assessments discuss implications for these disturbances qualitatively even if they do not attempt to model them quantitatively.

Wood et al. (2025) described model capabilities for nonfire disturbances. The LANDIS-II model has extensions that modelers can incorporate to simulate wildlife browsing, insects, and disease. CBM-CFS3 also has options for including insect and other disturbance effects on carbon pools and cycling. Current regional variants of FVS do not have insect and pathogen models but Fekety et al. (2020) used the distribution of disturbance severity from FIA data to stochastically simulate the probabilities of occurrence and severity in FVS. STMs can include a wide array of disturbance agents in their transition matrices (e.g., Spies et al. 2017). The RHESSys model includes drought as a disturbance type. The MC2 model simulates drought in terms of growth declines but not expected tree mortality (Halofsky et al. 2022).

Social and Economic Factors

Public land managers' and private forest landowners' management practices in forest ecosystems are influenced by social, economic, and political factors, which are typically not dynamically incorporated into the ecosystem carbon models that we examined. However, a combination of management approaches, potentially including land use, vegetation management, silvicultural treatments, fire suppression or promotion, wildlife management, and recreation management, can potentially be addressed as "scenarios" to be simulated in forest ecosystem models. For example, such scenarios can be used to account for differences among forest landowner types and public land management administrative designations to reflect varied economic, social, and political circumstances that may factor into forest and land management decisions on both public and private forest lands.

Addressing social and economic factors solely through scenarios in biophysical-focused forest ecosystem carbon models may not fully account for potential endogeneity (or feedbacks) between biophysical and socioeconomic variables, which over time, could influence forest management choices (Fuller et al. 2025). This potential shortcoming could be most notable when policymakers and managers need to accurately evaluate potential long-term forest carbon outcomes resulting from public policies or programs intended to affect increases in stored carbon, such as through regulation, tax incentives, or carbon cap and trade programs. For example, harvest type and rotation on private forests can vary as economic conditions change, and the objectives of individual forest landowners can also vary with parcel size and other factors (Kline et al. 2000).

Although many kinds of management approaches can potentially be simulated in ecosystem models, the relevant management is what landowners will actually do. Landowners and land managers can be surveyed to understand what management they will pursue under both business-as-usual and alternate scenarios that reflect changes in economic or ecological parameters, such as elevated wildfire risk or penalties for carbon emissions, or under new constraints or incentives (e.g., Rushakoff et al. 2024). Modelers can address these landowner goals and likely behaviors via scenarios or build them directly into landowner specific choice sets (Busby and Fried 2025). Studies have indicated that higher prices for wood products can result in increased investment in forest land, resulting in increases in forest area and carbon stores in stands managed for production (Adams et al. 1996, Sohngen et al. 1999). Long-term models can also estimate the loss of forest land from urbanization and population growth, or the effects of policies that incentivize afforestation, under different economic scenarios (Coulston et al. 2023, Haight et al. 2019, Latta et al. 2016, Sleeter et al. 2022). Additionally, long-term models can examine the full ranges of production possibilities for, and tradeoffs among, other forest outputs, such as timber and habitat, relative to carbon outcomes (Kline et al. 2016).

The economic and logistical feasibility of management scenarios is important to consider when modeling policy options. Harvest scheduling approaches, which are often spatially explicit, can be helpful in this regard and can include factors such as sustainability of production, road construction, wood haul costs, and logging costs, in addition to the amount of potential wood products available over time. For example, the BioSum model combined FVS projections of fire resistance and tree volume on individual FIA plots with logging and haul cost estimation workflows, mill networks, and wood values to estimate the economic feasibility of elevating fire resistance in mixed conifer forests given different levels of revenue or subsidy (Cabiyo et al. 2022, Jain et al. 2019). The LURA model applies macroeconomic projections of wood demand to availability of wood products using generalized forest growth and yield projections. It then assesses transport costs to potential mill locations to estimate optimum allocations of merchantable and other biomass to wood products and energy generation (Baker et al. 2023, Latta et al. 2018). The Woodstock model similarly optimizes the scheduling and type of treatments across simulation landscapes (e.g., Dymond et al. 2020). Most models, however, can use basic criteria for determining which stands are harvested by specifying a minimum age, merchantable volume, or biomass at which stands become eligible for selection for harvest treatments, and treatments are executed regardless of logistic or economic feasibility.

Coupled social-ecological models have been developed that simulate decisions made by individuals or groups to balance a set of objectives reflecting their particular values, mandates, and policies for the specific parcels that they manage (Bolte et al. 2007). Spies et al. (2017) applied this approach with an STM to simulate alternative future landscapes and forest conditions, including carbon stocks, in central Oregon (fig. 7).

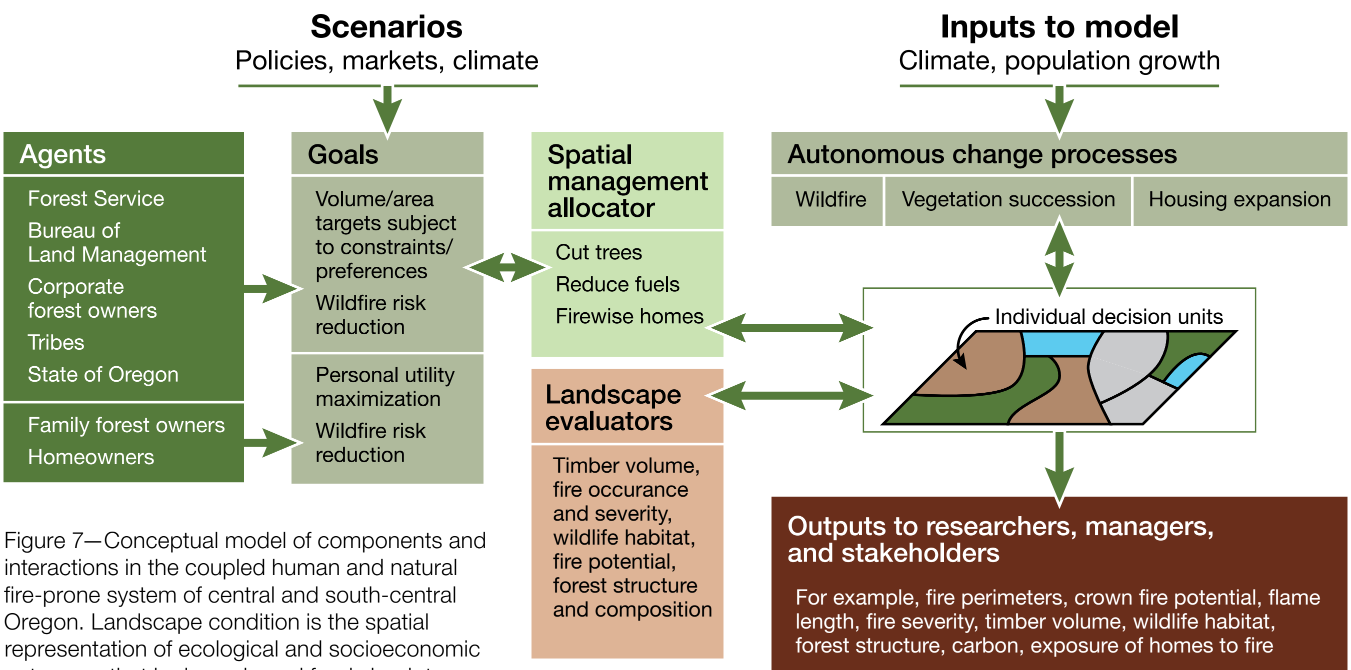

Figure 7—Conceptual model of components and interactions in the coupled human and natural fire-prone system of central and south-central Oregon. Landscape condition is the spatial representation of ecological and socioeconomic outcomes that is dynamic and feeds back to human perceptions, decision making, and actions in the forest and at home sites. Adapted from Spies et al. (2017).

Hydrology

Water flow, quality, and seasonality are important attributes that can be affected by changes in land use, vegetation composition and structure, and climate. Although most of the biophysical process models covered in this assessment incorporate information on soil depth and texture; precipitation, evaporation, and evapotranspiration; and vegetation cover, few simulate the flow of water from forests downslope, into groundwater, and into streams. The RHESSys model (Tague and Band 2004) is the only one in our list that simulates watershed hydrology and interactions with vegetation, with vegetation dynamics based on

Biome-BGC. The model estimates daily streamflow of small to medium (1st to 5th order) watersheds, as well as nitrate concentrations (but not dissolved organic carbon).

At least some hydrologic models use relatively simple representations of land cover and geology, combined with precipitation (snow and rain) and temperature, to estimate streamflow. This suggests that as long as an ecosystem model provides wall-to-wall estimates of forest and nonforest cover, it should be possible to couple a hydrologic model with it. For example, Edwards et al. (2021) estimated seasonal water flow into the Gulf of Alaska using basic land cover data and predicted dissolved organic carbon from empirical data based on the proportion of each watershed in low slope angles or covered by glaciers.

Wildlife

Maintaining wildlife habitat and healthy populations of wildlife species is often a key concern for forest managers and policymakers. Forest carbon models estimate forest structure and changes that may also inform habitat elements important to wildlife, allowing managers to more fully understand the costs and benefits of policy choices. Wildlife habitat is defined as the suite of conditions that allow individuals of a species to survive and reproduce (Johnson and O'Neill 2001, Thomas 1979). Although some species are generalists and can survive in a wide range of vegetation conditions (e.g., deer), others require specific features to complete part of their life cycle (e.g., ponds for frog reproduction or large snags for pileated woodpecker [*Dryocopus pileatus*] nests). Snags and logs are often key habitat elements determined by tree mortality, so modeling of carbon trajectories with stand development, wildfire, and reburn potential can be fruitful for estimating habitat trajectories (Chafe and Fried 2025). Some rare or endangered species are themselves dependent on rare plant species—e.g., Fender's blue butterfly (*Icaricia icarioides fenderi*) and Kincaid's lupine (*Lupinus oreganus* A. Heller var. *kincaidii* C.P. Sm.)—while other species vary in the amount of habitat they require, such as thousands of acres of older forest for spotted owl (*Strix occidentalis*) foraging. Fragmentation can be important as well, as predators may be more abundant near forest edges and able to prey on animals needing to cross clearings or open stands between preferred habitat patches. Connectivity is important for some species, such as salmon migrating to headwaters to reproduce or salamanders traveling from one headwater to the next drainage. The ability of forest ecosystem models to estimate fundamental attributes of wildlife models to approximate habitat suitability varies greatly depending on the scale and scope of the models.

The simplest wildlife models estimate wildlife habitat based on species ranges and forest composition. Hashida et al. (2020) combined an economic model of forest management with climate change projections to simulate habitat availability for 38 species of concern on the West Coast. Other wildlife models (e.g., wildlife habitat relationships) combine forest composition with forest structure classes based on dominant tree size and canopy cover to infer suitability for feeding, breeding, or cover for a wide range of species (CDFW 2026, Johnson and O'Neill 2001). These models may include features that particular species need within or close to these habitat types (e.g., open water nearby for bats, down logs for salamanders). Biophysical process models that simulate live and dead biomass as aggregate pools are less capable of estimating structural characteristics important to wildlife. Wildlife models are, to a large extent, binary (e.g., presence/absence) and not quantitative (e.g., estimated numbers of breeding pairs). Data on habitat requirements are sparse for most wildlife species, so many of these classifications are based on expert judgement and generalization.

For a few well-studied species, quantitative wildlife models have been developed to predict population sizes and trends. For example, using a synthesis of northern spotted owl (*Strix occidentalis caurina*) demography data, Dugger et al. (2015) modeled the effect of competitors, climate, and habitat patterns and abundance on long-term population trends. On a more local scale, Zielinski et al. (2010, 2012) built models to predict fisher (*Pekania* [formerly *Martes*] *pennanti*) resting habitat based on forest composition and structure at individual inventory plots, which have been incorporated as a module in FVS. Because patch size and fragmentation are important habitat attributes for many species, most wildlife models are based on mapped projections of forest conditions. In some studies, species with disparate habitat requirements were selected and their habitat capabilities were estimated across landscapes under different scenarios instead of attempting to model hundreds of species in an area. These landscape models used vegetation simulations from gap and growth and yield models in the Oregon Coast Range (Spies et al. 2007), and an STM in central Oregon (Spies et al. 2017).

A recent study used projections of tree cohorts and shrub biomass from LANDIS-II to estimate forest composition and diameter classes, and applied the California Wildlife Habitat Relationships (CDFW 2026) classifications to simulate breeding habitat for 159 vertebrate species in the Lake Tahoe Basin (White et al. 2022). Zeller et al. (2023) applied the same approach to a larger region in the central Sierra Nevada.

Practical Considerations and Conclusions

The analysis in the previous section demonstrates that models vary substantially in their ability to simulate different processes, such that no single model is able to simulate forest management, disturbance, and response to climate change well (table 2). Models also vary substantially in their ease of use, both in the compiling of input data and the parameterization and calibration required to run them (table 3). We conclude with some suggestions on operational considerations and applications of the models that we reviewed.

Stand-level growth and yield models, like CBM-CFS3, are probably the easiest types of ecosystem carbon models to use. Input data consist of spatial polygons or inventory plots of forest types and their stand ages, and parameterization consists of applying existing growth and yield curves or building empirical curves from inventory data. CBM-CFS3 is often used to simulate different scenarios or update inventories at state, province, or national levels, and provides estimates of carbon stocks, net emissions, and changes in stores of harvested wood products through a coupled harvested wood product model. Climate change effects on growth can be incorporated by specifying assumed changes to growth curves and changes in disturbances. Limitations include the need to specify assumed changes to growth curves with changing climate, the difficulty of representing uneven-aged forests with a single stand age, the danger of yield curves built from chronosequences of stands that developed with different histories and characteristics, and the vagaries of curve fitting where the shape of statistical models can be strongly affected by the scatter of data into unrealistic patterns. Nevertheless, it may be most suitable for evaluating gross differences in policy outcomes across large areas and multiple forest types.

STMs can be very efficient; they do not simulate detailed ecosystem processes at every point on a landscape and focus on specific vegetation types and structures that are of management and conservation interest. The input data can be plots or polygons across a landscape or region, classified into the states used by the model. Transition probabilities can

Table 3—Summary of ease of use for different ecosystem model types

Questions	Model type (examples)					
	Biophysical process (MC2, ED2, CLM)	Growth and yield (CBM-CFS3)	Individual tree (FVS)	Landscape process (LANDIS-II)	State and transition (STMs)	Imputation (RPA-FDM)
Data requirements	High: daily or monthly climate, soils, vegetation types and ages	Low: vegetation types and ages	Moderate: individual tree measurements	High: daily or monthly climate, soils, spatial depiction of vegetation types and ages	Low: vegetation types and ages	Moderate: large datasets of inventory plots
Parameterization	High: multiple physiological parameters required for each lifeform	Low: growth and yield curves built from empirical data	Low-moderate: default values available, but accuracy can be greatly improved by adjustment	High: multiple physiological parameters required for each lifeform	Moderate: vegetation stages and transition events need to be defined	Moderate: transition matrices need to be defined, based on inventory data
Scope	Most simulate all terrestrial ecosystems	Forests	Forests	Forests	Any ecosystem type	Forests
Scale	Global to stand, depending on model	National to regional	Regional to stand	Landscapes (<1 million ha)	Regional to landscape	National to regional
Polygons or plots	Both	Both	Both	Polygons, LANDIS-II is the only model with spatial processes	Both	Plots

CBM-CFS3 = Carbon Budget Model of the Canadian Forest Sector3, CLM = Community Land Model, ED2 = Ecosystem Demography2 model, FVS = Forest Vegetation Simulator model, LANDIS-II = Landscape Disturbance and Succession model, MC2 = Mapped Atmosphere-Plant-Soil System [MAPSS]-CENTURY2 model, RPA-FDM = Resources Planning Act-Forest Dynamic Model, STM = state-and-transition models.

be based on expert opinion, analyses of research or inventory data, or both. Although the conceptual models can be simple, it is also possible to build substantial complexity, based on empirical data or other models, into STM forest and landscape dynamics.

FVS has similar capabilities as CBM-CFS3, including tracking the fate of wood products over time but at a much more detailed resolution. FVS is capable of specifying management based on tree size, species, volume, and harvest residues. Minimum input data consist of stand- or plot-level tree lists, and the program has a large suite of default settings that make initial use easy. However, accurate predictions sometimes require extensive model calibration, which adds considerable analytic burden for each of the forest types and regional variants that the model uses to ensure realistic estimates of tree growth and mortality (Swann et al. 2025, Vandendriesche 2010). Running FVS out-of-the-box (i.e., uncalibrated) can generate egregious errors in growth prediction, even over a single decade; these errors are compounded over extended simulation time periods (Herbert et al. 2023).

Biophysical process models and other model types that use them (e.g., LANDIS-II) are best able to simulate ecosystem responses to past and expected future climates. These types of models take substantial effort to run, in terms of acquiring all the climate, soils, topography, and vegetation data necessary, and creating or evaluating the many physiological parameters that control their dynamics. Unlike most of the other models (besides some

STMs), these models attempt to identify shifts in ecosystem types (e.g., forest to nonforest, alpine to dry forest). Models like ED2 incorporate demographic changes into biophysical modeling with species cohorts. Landscape models like LANDIS-II simulate biophysical processes as well as species age cohorts but differ from most of the others by including spatial interactions among nearby stands. They may be best able to assess the propagation of fires across landscapes under future climate and the potential for changes in regenerating species. The data and parameterization required to run LANDIS-II are comparable to biophysical models.

Regardless of the model structure, the somewhat hidden art of ecosystem modeling lies in parameterization for the forest types, landscapes, or regions being modeled, and in the decisions made for the level and type of abstraction for different processes. The publicly available FIA data on carbon stocks, stock changes, disturbance, and management (Gray et al. 2012) are frequently used to calibrate ecosystem and economic models in the United States. Spatial models of FIA data (Bell et al. 2023, Riley et al. 2021) are frequently used to initialize ecosystem models. Ecosystem process and soil carbon data across regions and a range of vegetation types are much less available. Long-term experiments that compare responses to specific treatments can also be useful in setting parameters for models of similar ecosystems.

Given the range of capabilities of different ecosystem simulation models, it is unlikely that there is a "one-size-fits-all" solution that will address all land management questions satisfactorily. Models cannot maximize reality, generality, and precision at the same time, nor can they maximize resolution (spatial and temporal), complexity, and generality at the same time (Prisley and Mortimer 2004). Running simulations with ranges of values for key parameters can be useful for assessing the sensitivity of the model or the modeled ecosystems (Campbell and Ager 2013). If possible, running models in parallel with the same inputs and scenarios and comparing their responses can improve insights into potential outcomes. Different models can also be run sequentially—examples include using FVS results to calibrate LANDIS-II, using empirical growth and yield curves to calibrate FVS, and using LANDIS-II to parameterize future fire extent and severity in CBM-CFS3 and FVS. There is a great deal of new ecosystem modeling work taking advantage of greater data availability and integrating disparate modeling structures with new analytical approaches (Blanco and Lo 2023, Laubmeier et al. 2020). Because ecology has relatively few firm theories and laws to guide model development, there is a lot of freedom in model design, but with it comes a substantial need for rigorous model evaluation by developers, ideally by comparing behavior of similar model types (Bugmann and Seidl 2022).

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U.S. Standard Equivalents

When you know:	Multiply by:	To find:
Millimeters (mm)	0.0394	Inches
Centimeters (cm)	0.394	Inches
Meters (m)	3.28	Feet
Kilometers (km)	0.621	Miles
Hectares (ha)	2.47	Acres
Grams (g)	0.0022	Pounds
Petagram (Pg)	1.102×10^9	Tons
Megagrams per hectare (Mg/ha)	0.446	Tons per acre

Metric Equivalents

When you know:	Multiply by:	To find:
Acres	0.405	Hectares
Cubic feet	0.0283	Cubic meters
Pounds	454	Grams

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Appendix: Individual Model Descriptions

Biophysical Process Models

MC2 (Mapped Atmosphere-Plant-Soil System [MAPSS]-CENTURY)

Type and key citation—Global vegetation model (Bachelet et al. 2001).

Model statement of purpose—MC2 is a global vegetation model designed to simulate effects of future climate on vegetation dynamics. The model integrates modules for biogeography (physiologically based determination of vegetation life forms), biogeochemistry (nutrient and element cycling), and fire disturbance. The model simulates dominant vegetation life forms (trees, grass, shrubs) and ecosystem carbon (C) pools.

Key model processes—The model functions in a grid format with spatially referenced cells and is composed of three submodels: CENTURY model, MC-Fire wildfire simulation model, and MAPSS vegetation biogeography model. CENTURY simulates competition for light, water, and nutrients between individual tree and grass plant functional types (PFTs) (Parton et al. 1993). CENTURY also simulates net primary production (NPP), decomposition, soil respiration, and net ecosystem carbon balance (NECB). Each grid cell is classified into 1 of 30 different biomes; an algorithm within the MAPPS module (based on thresholds in climate, productivity, and fire) determines each biome and accompanying PFTs. The ecosystem state is passed to MC-Fire once each month, which simulates fire effects on vegetative communities (not the spread of individual fires); fire events can only happen once per year in each individual cell.

Spatial and temporal resolution and extent—The basic unit is a user-defined pixel size, covering scales from individual national parks to continental and global. The CENTURY and MAPPS submodels run on a monthly time step, while MC-Fire runs on a daily time step. There is no temporal limit for running the model.

Mechanisms for ecosystem carbon pools and changes—Carbon sequestration and flux are primarily controlled by the CENTURY model. The CENTURY manual is no longer available, but descriptions of DAYCENT, the daily time-step version of the model, are available on the CSU NREL (n.d.) website. DAYCENT simulates fluxes of carbon and nitrogen among the atmosphere, vegetation, and soil (Del Grosso et al. 2001, Parton et al. 1998). Key submodels include soil water content and temperature by layer, plant production and allocation of net primary production, decomposition of litter and soil organic matter (SOM), mineralization of nutrients, nitrogen gas emissions from nitrification and denitrification, and methane oxidation in nonsaturated soils. The size of the pools, carbon-to-nitrogen ratio and lignin content of material, and abiotic water/temperature factors control flows of carbon and nitrogen between the different SOM pools. Plant production is a function of genetic potential, phenology, nutrient availability, water/temperature stress, and solar radiation. NPP is allocated to plant components (e.g., roots versus shoots) based on vegetation type, phenology, and water/nutrient stress. A maximum leaf area index setting can constrain live vegetation carbon pools (Bachelet et al. 2001, King et al. 2013). Woody plant pools are leaves, branches, large wood, large roots, and fine roots; grass pools are leaves and fine roots. Nutrient concentrations of plant components vary within specified limits, depending on vegetation type and nutrient availability relative to plant demand.

The SOM submodel simulates the dynamics of carbon, nitrogen, phosphorus, and sulfur in the organic and inorganic parts of the soil system. Surface and root litter are subdivided into metabolic and structural pools, with the latter divided into cellulose and lignin. Decomposition and nutrient mineralization of litter and subsequent SOM are functions of substrate availability, substrate quality (percentage of lignin, carbon-to-nitrogen ratio), and water/temperature stress. The inherent maximum decomposition rate of the different pools and the water- and temperature-controlled decomposition factor control the flows of carbon. Average monthly soil temperature at the soil surface controls the temperature function, and the ratio of stored water (0- to 30-cm depth) plus current monthly precipitation to potential evapotranspiration is the input for the moisture function. Microbial respiration occurs for each of the decomposition flows. The partitioning of decomposition between stabilized SOM and carbon dioxide is a function of soil texture for the stabilization of active carbon into slow carbon (increasing carbon dioxide for sandy soils and less soil carbon storage).

The MC2 model works in three phases: (1) "equilibrium" phase—30-year period of historical climate data, 1895–1924, (2) "spinup" phase—detrended climate data from 1895–2008, and (3) "transient" phase—future scenarios, using 2008 state (Daly et al. 2008) as inputs for future projections from 2009–2100. Fire suppression can be turned on or off within the model.

Climate change modeling approach—Climate data (past or projected) are used to determine vegetation type, ecosystem function, and fire effects.

Disturbance modeling approach—The MCFire wildfire submodel incorporates moisture content of live and dead fuels (from soil moisture calculated in the ecosystem model), and live and dead fuel bed types (from the biogeography model). MCFire simulates the fraction of the grid cell burned as a reciprocal of the prescribed fire-return interval for the PFT. Fire severity for the grid cell, including the occurrence of a canopy fire, is calculated for a single representative tree; fuel loads in different size classes are estimated based on size-class coefficients by PFT multiplied by live and dead carbon pool sizes (Conklin et al. 2016). At the end of each simulated year, a biogeography submodel classifies the ecosystem state of the grid cell into a PFT, which is used, in turn, to look up fire regime parameters, including fire occurrence thresholds and return intervals. Fire occurrence is based on climate data compared to threshold values (e.g., Kim et al. [2018] used LANDFIRE as comparison for benchmarks).

Harvest and wood products modeling approach—Harvest and wood products are not explicitly included.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—The model requires monthly maximum and minimum air temperature and precipitation, elevation, and soil data—at least three layers of soil textures as well as soil depth and bulk density, but the modeler sets the number of soil layers using depth to bedrock and the vegetation type (for rooting depth).

Options for parameterizing or modifying the model—Modelers can change the biome and PFT classifications and parameters (e.g., Kim et al. [2018] defined potential vegetation groups), fire-return interval definitions, and ecosystem production parameters.

Model website—https://databasin.org/articles/8e01bd5f101c4863a0d6a69d58c9298b (Bachelet 2015).

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Biome-BGC (Biogeochemical Cycles)

Type and key citation—Biophysical process model (Hidy et al. 2016).

Model statement of purpose—Biome-BGC examines global and regional interactions of climate, disturbance, and biogeochemical cycles. Hidy et al. (2016) created Biome-BGCMuSo to address existing uncertainties with the previous Biome-BGC (Thornton et al. 2002). They added more management options (including thinning) and a more detailed, seven-layer soil module. They also added capability to parameterize soil water saturation, which was not an option in the prior model.

Key model processes—The primary drivers for Biome-BGC are the physiological processes that control photosynthesis, respiration, growth, mortality, and decay. Forests are defined as plant functional types (PFTs—evergreen and deciduous needleleaf forest, and evergreen and deciduous broadleaf forest). All ecosystem carbon pools and changes are simulated. Satellite change detection has been used to estimate past disturbance and stand age for stands that were disturbed pre-1980 (Turner et al. 2007). The model has been rarely used for projecting future conditions (but see Hlásny et al. 2014).

Spatial and temporal resolution and extent—The basic unit is a stand, which is often modeled as a selected size of square pixels (1-km cells in Turner et al. [2015]). Spatial extent is unlimited, except by computing power. The model runs on a daily time step.

Mechanisms for ecosystem carbon pools and changes—Biome-BGC uses daily ecosystem processes to estimate carbon stock and flux, nitrogen, and water cycling for vegetation and soil carbon pools. Daily meteorological data drives these ecosystem processes. The model tracks ecosystem gross primary production (GPP), NPP, net ecosystem production (NEP), maintenance and growth respiration, heterotrophic soil respiration, and net ecosystem carbon dioxide exchange (Wang et al. 2005). An algorithm is used to populate values if humidity and radiation data are missing. If insufficient meteorological data are available for a specific site, then it is taken from a nearby weather station or average of several nearby weather stations. All plant litter is divided into three pools on the basis of the weight fractions of lignin, cellulose plus hemicellulose, and remaining mass in the litter. These litter pools undergo chemical degradation at different rates, producing a connected series of soil organic matter pools (Thornton et al. 2002).

Schmid et al. (2006) modeled mixed forest stands as separate PFTs and then combined them. The model can use historic atmospheric and harvest trends to simulate prior conditions (e.g., to represent preindustrial levels of carbon dioxide and nitrogen-deposition). Schmid et al. (2006) found that the model generally is a better predictor of photosynthetic properties related to sinks than emissions associated with sources. Mortality rates are fixed by default, but modelers can use measured mortality rates to re-create past development or set rates as dynamic with succession (Turner et al. 2007).

Turner et al. (2011) optimized the model for the conifer cover class by ecoregion to "minimize bias in the age-specific patterns in wood mass" based on Forest Inventory and Analysis plot data (Gray et al. 2012) by tweaking the fraction of leaf nitrogen as rubisco (FLNR) and annual mortality (percentage). The model was parameterized to run partial disturbance (Schmid et al. 2006, Turner et al. 2015).

Climate change modeling approach—Climate directly affects plant physiology and carbon accumulation, but there is no direct connection to disturbance regimes. Hidy et al. (2016) created a module for drought-related mortality.

Disturbance modeling approach—Satellite change detection has been used to estimate past disturbance and stand age for stands disturbed pre-1980 (Turner et al. 2007). The model rarely has been used for projections, maybe because of the need to supply a daily time step (but see Hlásny et al. 2014).

Harvest and wood products modeling approach—Stands are modeled as even-aged forests. The model has been used to simulate rotation as well as partial harvest, the latter as a proportion of the live-tree pool killed or removed and routed to dead wood accordingly (Schmid et al. 2006, Turner et al. 2015). Harvested wood products are not tracked.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Daily meteorological data (daily maximum and minimum temperatures, daylight average temperature, daily total precipitation, daylight average partial pressure of water vapor, daylight average shortwave radiant flux density) are used as the drivers for the ecosystem processes, along with soil texture and depth. Regional applications use maps of vegetation conditions to initialize the model.

Options for parameterizing or modifying the model—Modelers can adjust the parameters used to run the model by modifying code.

Model website—https://www.umt.edu/numerical-terradynamic-simulation-group/project/biome-bgc.php (UM NTSG 2026).

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CLM (Community Land Model)

Type and key citation—Biophysical process model (Lawrence et al. 2020).

Model statement of purpose—CLM was designed to quantify ecological climatology, the interdisciplinary field that studies how natural and human interactions with vegetation affect climate. Through the study of physical, chemical, and biological interactions, the model's purpose is to understand how terrestrial ecosystems affect, and are affected by, climate across various temporal and spatial scales. The assumption is that the cycling of physical and chemical elements, water, and energy are important for determining climate. The CLM is the land component of the larger Community Earth System Model (CESM), which includes models of atmosphere, ocean, sea ice, and a coupler.

Key model processes—CLM combines biophysical, biochemical, and physical processes to simulate landscape change and understand how natural and human actions affect these interactions. The processes include heat fluxes, solar radiation, heterogenous land types and ecosystems, soil hydrology, soil and litter decomposition, plant mortality, land cover, and land-use change. The model represents all land cover types, including nonvegetated areas and water bodies. Vegetation is modeled as PFTs with identified physiological tolerances and rates. Dead wood, litter, and soil carbon decomposition are modeled as separate components. The use of the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) extension incorporates modeling of individual tree cohorts by modeling one individual representative of each cohort.

Spatial and temporal resolution and extent—The model uses a grid system where grid cells are defined by climate, within which are land units corresponding to surface features (e.g., soils, lakes). These surface features can contain separate columns of belowground resources (e.g., crops versus natural vegetation), which are further divided into PFTs or, with the use of FATES, patches with different disturbance histories. Temporal scale varies by process.

Mechanisms for ecosystem carbon pools and changes—The model uses 40 physiological variables for each PFT and is sensitive to carbon and nitrogen enrichment. Mortality is a fixed rate. CLM allows the user to define, at compile time, between two contrasting hypotheses of decomposition as embodied by two separate decomposition submodels: the CLM-CN pool structure used in CLM4.0 (based on Biome-BGC), or a second pool structure, characterized by slower decomposition rates, based on the CENTURY model (Parton et al. 1988). Bonan et al. (2011) found that CLM4.0 tended to overestimate GPP, and there was bias around latent heat flux. Duarte et al. (2017) found that CLM4.5 poorly estimated ecosystem respiration and soil moisture stress; evapotranspiration was also overestimated, while forest biomass and GPP were underestimated. Duarte et al. (2017) also found that CLM4.5 tended to underestimate fine and coarse roots compared to observed data. Both Bonan et al. (2011) and Duarte et al. (2017) attempted to fix these errors through model parameterization. Duarte et al. (2017) concluded that more parameterization was needed, including base rate of maintenance respiration and base decomposition rates for each SOM and litter pool to better simulate observed ecosystem respiration. Duarte et al. (2017) also recommended that CLM 4.5 should move away from deficit-based accounting and use carbohydrate storage pools. Furthermore, they recommended that site-specification and calibration would help the model's accuracy relative to observed data.

Climate change modeling approach—Simulating vegetation response to current and future climates is a key focus of the model.

Disturbance modeling approach—Fire area is modeled for each time step as ignitions (lightning or human frequency, dependent on sufficient fuel and fuel moisture; and level of suppression, based on population density and gross domestic product) and fire spread (based on windspeed, maximum spread by PFT, fuel moisture, and suppression effort). Fire effect is based on combustion and mortality proportion for different live and dead pools by PFT (reduced by half in Hudiburg et al. [2013]). Forest harvest is modeled as a proportion of area and biomass by PFT, with 30 percent slash assumed. Harvest and land-use change is based on a harmonized global historic dataset and future scenarios.

Harvest and wood products modeling approach—Harvest and wood products are not explicitly integrated.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Model inputs consist of detailed estimates of radiation, wind, temperature, and precipitation; soil depth and texture; and parameters defining physiology of different PFTs used in the model.

Options for parameterizing or modifying the model—Hudiburg et al. (2013) improved model performance by downscaling from the basic 2nd-degree to ⅛th-degree resolution, and modifying physiology, wood allocation, and mortality parameters by ecoregion for Oregon. Buotte et al. (2020) used CLM4.5 with custom parameterization for species and forest types, enhanced drought sensitivity, and regional ignition probabilities across the West to identify carbon sequestration potential and vulnerability to fire.

Model website—https://www.cesm.ucar.edu/models/clm (NCAR UCAR 2026).

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ED2 (Ecosystem Demography2)

Type and key citation—Biophysical process model (Longo et al. 2019).

Model statement of purpose—ED2 was designed to represent the role of terrestrial ecosystems on the energy, water, and carbon cycles, while including the effects of within-ecosystem heterogeneity and diversity in plant function and size. The model solves the energy, water, and carbon cycles separately for a series of vegetation cohorts (groups of individual plants of similar size and PFT) distributed across a series of spatially implicit patches (representing collections of microenvironments that have a similar disturbance history).

Key model processes—ED2 models radiation, energy, water, carbon, and nutrient cycling with leaf physiology and climate controls for PFT cohorts in multiple canopy layers. The model is simpler than many biophysical models in that energy and mass are the primary prognostic variables. The water and energy budget equations for vegetation are solved at the individual cohort level and microenvironment shared by plant cohorts, allowing the model to represent vertical and horizontal heterogeneity, and interactions among cohorts (e.g., competition). Carbon from litter and mortality is routed to dead pools and decays over time based on temperature and moisture.

Spatial and temporal resolution and extent—The model uses a grid system which is further divided into polygons, sites, and patches. Polygons are defined in a grid, and each polygon represents one eddy flux tower within a horizontal atmospheric grid cell where above-canopy climate is spatially the same. Sites within polygons are defined by abiotic conditions like soil texture and depth, elevation, slope, aspect, and topographic moisture index. Patches within sites are characterized by time since last disturbance and the type of disturbance that generated them. The highest temporal resolution is seconds to minutes for the thermodynamics and biophysics functions, with lower resolutions for phenology, growth and mortality, and disturbances.

Mechanisms for ecosystem carbon pools and changes—PFT and plant density, which are related to plant size, describe patches defined by times since last disturbance. Plant size consists of biomass of leaves, fine roots, sapwood, heartwood, and nonstructural carbon stores. The energy, water, and carbon dioxide cycles are solved separately for each patch; within each patch, fluxes and storage associated with individual plants are solved for each cohort. Patches do not interact. Radiation, energy, water, carbon, and nutrient cycling are modeled with leaf photosynthesis, respiration, gas exchange, and climate controls for multiple canopy layers and cohorts. PFT specifies physiological thresholds and allometries. Heterotrophic respiration is based on a simplified implementation of the CENTURY model (Parton et al. 1993) that estimates decomposition for three soil carbon pools: fast (metabolic litter and microbial), intermediate (structural debris), and slow (humified and passive soil carbon). Snags and down wood are not simulated as separate components within the intermediate soil carbon pool.

Climate change modeling approach—Simulating vegetation response to current and future climates is a key focus of the model.

Disturbance modeling approach—Disturbances include fire, logging, tree-fall, cropland/pasture, abandonment, and forest plantation. The modeler prescribes disturbance rates. The original fire model was being improved to account for size- and bark-thickness-dependent survivorship, and to account for natural and anthropogenic drivers of ignition, fire intensity, fire spread, and fire duration, building on existing process-based fire models (Longo et al. 2019).

Harvest and wood products modeling approach—Harvest and wood products are not explicitly integrated.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Model inputs consist of detailed estimates of radiation, wind, temperature, and precipitation; soil depth and texture; and parameters defining physiology of different PFTs used in the model.

Options for parameterizing or modifying the model—Jiang et al. (2019) evaluated the model at the Wind River Experimental Forest flux tower site in an old-growth forest in southern Washington. They used field data to adjust six key PFT-specific parameters and to modify the diameter at breast height-to-height allometric functions for the northern pine and the late-successional conifer PFTs to represent the two dominant tree species, Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) and western hemlock (*Tsuga heterophylla* (Raf.) Sarg.).

Model website—https://github.com/EDmodel/ED2 (see Longo et al. 2019).

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3-PG (Physiological Principles Predicting Growth)

Type and key citation—Biophysical process model (Landsberg and Waring 1997).

Model statement of purpose—3-PG was developed to bridge the gap between conventional, mensuration-based growth and yield, and process-based carbon balance models. The output variables that it produces are of interest and relevance to forest managers. It has been shown to be a valuable teaching tool (The University of British Columbia, n.d.).

Key model processes—3-PG calculates the radiant energy absorbed by forest canopies and converts it into biomass production. The effects of nutrition, soil drought (the model includes continuous calculation of water balance), atmospheric vapor pressure deficits, and stand age modify the efficiency of radiation conversion. Only change in live trees is modeled (no dead wood or soils).

Spatial and temporal resolution and extent—The basic unit is a stand, which can be defined as a polygon of any size. The model runs on a monthly time step.

Mechanisms for ecosystem carbon pools and changes—3-PG is a relatively simple model based on climate inputs and starting values for stand-level foliage, stem, and root biomass. Numbers of stems are calculated with the −3/2 power law of density and average stem size, parameterized for individual species. The modeler can set additional parameters, including allocation of biomass production among components, age-related changes in stomatal conductance, proportion of GPP resulting in NPP, and proportion of mass in litterfall. Initial tree populations are specified and changes in stem populations calculated using a well-established mortality function. Output includes stem biomass and volume, average stem diameters, stand basal area at any time step, and the time course of leaf area index. Root turnover, litter production, and mortality outputs can be used as inputs to a separate decomposition model.

Climate change modeling approach—3-PG simulates growth responses to climate but not effects on decomposition or disturbance.

Disturbance modeling approach—The model framework does not simulate disturbance incidence or effects.

Harvest and wood products modeling approach—Harvest and wood products are not explicitly integrated.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Model inputs consist of values for total short-wave radiation, mean monthly daytime vapor pressure deficit, total monthly precipitation, number of days per month with frost, and starting values for stand-level foliage, stem, and root biomass.

Options for parameterizing or modifying the model—Modelers can change the default values controlling production, mortality, and age-related changes for species of interest. There is a simple Microsoft Excel version as well as a spatial version that can also use satellite-based estimates of leaf area.

Model website—https://3pg.forestry.ubc.ca/ (The University of British Columbia, n.d.).

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RHESSys (Regional Hydro-Ecologic Simulation System)

Type and key citation—Biophysical process model (Tague and Band 2004).

Model statement of purpose—RHESSys was designed to model watershed hydrology and interactions with vegetation.

Key model processes—RHESSys is a geographic information system (GIS)-based model that simulates snowpack, soil water, and streamflow based on climate and geology. It also simulates vegetation evapotranspiration, NPP, and carbon and nitrogen cycling. Model structure is based on hydrologic basins within which uniform hillslopes are defined (e.g., from digital elevation models and stream layers).

Spatial and temporal resolution and extent—The basic unit is a user-defined hillslope-vegetation patch, which can be a polygon of any size, within a watershed basin (km^2, 1st to 4th or 5th order). Temporal resolution is a daily time step for climate and a daily or annual time step for vegetation, with no limit on temporal extent.

Mechanisms for ecosystem carbon pools and changes—The program evolved from coupling Biome-BGC and CENTURY with landscape-level climate and hydrology. Carbon and nitrogen stores are partitioned into leaves, roots, stems, and coarse roots. Stem and coarse-root stores also include both live and dead wood components to account for differences in respiration and carbon-to-nitrogen ratios. Mortality is set as a fixed percentage of current biomass and transferred to the litter and coarse wood pools. The model simulates vertical and horizontal soil water movement with unsaturated and saturated soil layers, and simulates water storage in litter, canopy interception, and snowpack. Model structure is based on hydrologic basins within which uniform hillslopes are defined (e.g., from digital elevation models and stream layers). Zones delineate areas of similar climate, parameterized from nearby climate stations and modified based on zone elevation, aspect, and slope. Patches delineate areas of similar soil moisture and land cover within hillslopes and zones where infiltration and soil nutrient cycling happens. Within patches, canopy strata are defined where photosynthesis and transpiration occur, constrained by shading, and where a litter layer is fed by canopy layers.

Climate change modeling approach—Biophysical simulation can use projections of future climate.

Disturbance modeling approach—Burke and Tague (2019) described a “multiscale routing” addition to RHESSys that incorporates disturbance by adding multiple aspatial units for each of the smallest patch model units. These aspatial units differ in vegetation properties (e.g., height, biomass, root depth) and surface properties (e.g., litter) that influence energy, water, and carbon fluxes. This approach allows for the transfer of water and nutrients between these aspatial units and additionally accounts for edge effects—notably the shading that occurs between neighboring trees of different heights.

Harvest and wood products modeling approach—Harvest treatments can be implemented as a percent of biomass removal, and tree stems are modeled as a separate pool. The model does not explicitly track wood products.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Most model parameters are derived from topographic, land cover, and soil map layers. Daily climate data are needed to run the hydrology and biophysical components.

Options for parameterizing or modifying the model—Modelers can choose criteria to define hillslope and vegetation patches.

Model website—https://rhessys.github.io/index.html (RHESSys, n.d.).

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STANDCARB/LANDCARB

Type and key citation—Biophysical process/forest gap hybrid model (Harmon and Domingo 2001).

Model statement of purpose—The models were designed to simulate the accumulation of carbon over succession in a landscape with mixed species-mixed aged forest stands and spatially variable climate, soil, topography, and history. STANDCARB was designed to incorporate the features of a gap simulation model with an ecosystem process model. LANDCARB uses a spatial meta-model approach to capture the overall response of the more detailed simulation models in STANDCARB without all the computational burdens of the full model.

Key model processes—STANDCARB is a stand-level model that simulates the effects of colonization, succession, and disturbance severity on rates of carbon accumulation and decomposition over time. Stands are comprised of tree cohorts initiated by different episodes of disturbance and colonization. Mortality changes the light environment and provides opportunities for regeneration or sprouting and transition to, and decomposition of, dead matter. Succession may also occur from shade-tolerant species establishing under earlier cohorts.

Spatial and temporal resolution and extent—STANDCARB simulates dynamics of multiple cells within a stand, with each cell representing the canopy area of a single mature tree (0.04 ha). Cells interact spatially by shading. LANDCARB uses gridded cells, 0.25 to 100 ha, with each cell representing a stand with multiple tree cohorts that may contain multiple species and tree ages. Each cell is broken down into stands with landscape attributes. The models were developed for western Oregon and western Washington forests but could be used elsewhere if parameterized. They run on an annual time step, except for variables affected by climate, which run on a monthly time step.

Mechanisms for ecosystem carbon pools and changes—Cohorts within stands can contain up to four vegetation layers (upper, lower, shrubs, and herbs) and different age classes, all of which can have varied levels of live, dead, and stable biomass. Tree layers in STANDCARB can have multiple species. Each of the layers within cohorts can potentially have seven live pools: foliage, fine roots, branches, sapwood, heartwood, coarse roots, and heart rot. Each of the live pools contributes material to a corresponding dead pool. The dead pools contribute material to one of three stable pools for very decomposed matter. Surface and subsurface charcoal pools are specified as well. Functional curves simulate the effects of transpiration, temperature, and soil moisture on potential photosynthesis and on respiration.

Climate change modeling approach—Simulating vegetation response to current and future climates is a key focus of the models.

Disturbance modeling approach—Disturbance is shaped based on the characteristics of the cell and disturbances in neighboring cells. Heterogeneity is created within cells because of variation in disturbance and interactions between cohorts (regenerating or existing) within cells. The model supports simulations of even- and uneven-aged silvicultural prescriptions, prescribed fire, and partial or stand-replacing wildfire.

Harvest and wood products modeling approach—The models estimate mass and volume of boles removed during harvest and use an aggregated submodel to calculate material end use (Harmon et al. 1996).

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Model inputs consist of monthly temperature and precipitation, soil texture, depth, and rock content. Species-level parameters define temperature, soil moisture, light limits for growth and respiration, wood density, and tree dimensions. Most parameters are proportions of total biomass or maximum resource availability.

Options for parameterizing or modifying the model—Krankina et al. (2012) calibrated the model for western Oregon and western Washington using inventory data to replicate live biomass accumulation with stand age.

Model website—https://landcarb.forestry.oregonstate.edu/tutorial-works.aspx (Harmon et al. 2016) (model no longer available on web).

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CARAIB (CARbon Assimilation In the Biosphere)

Type and key citation—Biophysical process model (Warnant et al. 1994).

Model statement of purpose—The model purpose is to study the role of vegetation in the global carbon cycle in the present and the past, using mechanistic models to predict NPP at the global scale.

Key model processes—CARAIB calculates carbon and water fluxes between the terrestrial biosphere and atmosphere. The model is divided into five modules: hydrologic budget, canopy photosynthesis and stomatal respiration, carbon allocation and plant growth, heterotrophic respiration and litter/soil carbon dynamics, and plant competition and biogeography (François et al. 2011).

Spatial and temporal resolution and extent—The global scale model operates on 0.5° × 0.5° grid cells, with multiple PFTs possible in each grid cell. The model runs on an annual time step for shrubs and trees, monthly for herbs, daily for carbon and water reservoirs, and a 2-hour time step for photosynthesis and plant respiration. There is no limit to temporal projections.

Mechanisms for ecosystem carbon pools and changes—CARAIB estimates NPP of continental vegetation using three submodels: leaf assimilation (includes respiration and stomatal conductance), canopy, and wood respiration. The model has 26 woody ecosystem PFTs (15 arboreal, 3 herbaceous, and 8 shrub), 16 crop PFTs, and 2 grass PFTs. The model calculates change of two carbon reservoirs for plants and three for soil. The model assumes PFTs need at least one dry month for germination.

The model estimates four ecosystem pools and associated fluxes: leaves, the rest of the plant (branches, stems, roots), litter, and humus. Types of mortality modeled include senescence, fire, cold temperatures, shading, and drought. The model divides autotrophic respiration between maintenance and growth respiration. Maintenance respiration is parameterized as the exponential function of temperature and the linear function of carbon in live plants. Growth respiration is assumed to be proportional to increasing biomass. Carbon allocation between leaves and the rest of the plant depends on the weather; when temperature is between a minimum and a maximum and soil water content is above a critical value, carbon is allocated equally between components; otherwise, all the carbon goes to the rest of the plant. New leaf layers only form if productivity is higher than mortality. Litter decomposition is a function of temperature, soil water content, and litter carbon content. Mortality occurs during seasonal leaf fall, canopy regeneration, and climatic conditions.

Biomes are assigned to each grid cell, based on cover fraction, NPP, and leaf area index, in addition to two climatic constraints: growing degree days (measure of heat accumulation used to predict growth rates) and minimum temperature. Vegetation distribution in the model is driven by precipitation and evapotranspiration.

Henrot et al. (2016) found that agreement between the model and data is lower than 60 percent for cold and cool PFTs. Henrot et al. (2016) also recommended 40 PFTs for greater model-data agreement. Otto et al. (2001) determined that CARAIB is very sensitive to windspeed (because it determines evapotranspiration and soil water content), but it can simulate large-scale vegetation distribution in the current climate. It also effectively simulates preindustrial carbon stock levels. The model is also generally in agreement with other models' biome predictions.

Climate change modeling approach—CARAIB models past and projected climate effects on ecosystem function.

Disturbance modeling approach—On a given grid cell, the emergence of a fire is conditioned by the three factors of the fire triangle: the availability of fuel (biomass, litter), the combustibility of the fuel (soil moisture), and the presence of a source of ignition (natural or anthropogenic). These determine a probability of fire occurrence (Dury et al. 2011). Fire spreads within a grid cell until extinguished by weather. No insect or disease effects are modeled.

Harvest and wood products modeling approach—Harvest and wood products are not explicitly integrated.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Model inputs include climate, global land cover, and PFT parameterization.

Options for parameterizing or modifying the model—The model has been adapted for a variety of uses and integrated in other modeling systems.

Model website—https://www.isimip.org/impactmodels/details/11/ (ISIMIP, n.d.).

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Individual-Tree Models

FVS (Forest Vegetation Simulator)

Type and key citation—Individual tree (Dixon 2026).

Model statement of purpose—The model simulates forest vegetation response to disturbance, succession, and management actions. Initially developed with data from national forests to assist silviculturists in planning alternative management treatments for individual stands, the model has grown to include carbon pools, fire effects, and fates of wood products.

Key model processes—The primary driver for FVS is the growth and mortality of individual trees in a stand, based on site productivity, habitat type (i.e., plant association), topography, stand density, and tree size in relation to other trees in the stand. Allometric equations estimate volume, biomass, and carbon of individual trees from tree diameter and height, and production of litter and dead wood simulated from change in live and dead trees. A wide range of tree harvest prescriptions can be defined. Wildfire can be simulated under specified weather conditions. Default values can be used for most variables based on regional estimates if not provided by the modeler.

Spatial and temporal resolution and extent—The basic unit is a stand of trees, which can be based on existing data or simulated from bare ground. There is no limit to the number of stands that can be simulated. The model runs on 10-year time steps, with no temporal limit, though few applications have exceeded 40 years in length.

Mechanisms for ecosystem carbon pools and changes—The core FVS program simulates live-tree growth and survival, and the Fire and Fuels Extension (FFE) simulates other carbon pools (Rebain 2025). Live-tree simulation is primarily driven by empirically based equations of diameter growth as a function of multiple variables, including tree diameter, crown ratio, stand site index, density of larger trees, or elevation, depending on species. Tree mortality is assigned a background rate when the stand density index is less than 0.55 times maximum stand density index and higher rates for stand density indices above that level. FVS uses regional volume equations from the National Volume Estimator Library (USDA Forest Service, n.d.a) as a default (and then converts volume to biomass according to species-specific densities). Belowground biomass for live trees and snags is estimated using Jenkins et al. (2003) equations; there is a default root-decay rate associated with these values, which the user can adjust. Separate biomass equations by geographic variant are used to calculate biomass in the crown. Biomass is assumed to be 50 percent carbon for all forest carbon pools except forest floor, which is estimated to be 37 percent carbon (Smith and Heath 2002).

FVS-FFE tracks surface fuels by modeling transitions to these pools (litter, duff, and woody fuels by size class) from aboveground sources, including snags, live trees, and harvest activity. Snags modeled in FVS go through decay, breakage, and falldown based on tree diameter and species. Annual litterfall is modeled based on species data for foliage lifespan and weight. Crown lifting uses the ratio of the change in height of the base of the crown to the previous total length of the crown to simulate the dieback of lower branches as a tree grows. Background crown breakage from snow, wind, disease, or falldown of adjacent stems is simulated by adding a small, constant proportion of each crown component to the debris pools each year.

Surface fuel decay (litter, duff, and down wood) is modeled using a constant proportional loss model based on fuel size class. However, users can adjust decay rates to be based on a species decay-rate class (very slow, slow, fast, or very fast) or the decay status of the input material (hard versus soft). Two percent of decayed matter from each fuel pool is added to the duff compartment, while the remaining biomass is lost as carbon dioxide. For some of the variants covering Oregon, Washington, and Alaska (Pacific Northwest Coast, Westside Cascades, East Cascades, South Central Oregon and Northeast California, Blue Mountains, and Alaska), the snag dynamics and down-wood decay rates are adjusted based on temperature and moisture classifications of the stand habitat type code supplied in the input FVS database.

FVS does not dynamically simulate herbs and shrubs, but it does represent them with biomass values determined from the stand's percentage of canopy cover and dominant overstory species. Herb and shrub biomass will only change if the percentage of canopy cover or species composition of the overstory changes (e.g., from fire, harvesting, planting, growth, or mortality). Soil carbon, NPP, and respiration are not included in FVS-FFE carbon accounting.

Climate change modeling approach—Climate-FVS (Crookston 2014) is available for the Western United States and changes growth, mortality, and regeneration in response to future climate. The primary function is a comparison between the future climate and the climate range of the species in a stand. The probability of a tree's survival declines with the departure from the current climatic range of a species. Climate also modifies site productivity and maximum density. Growth is also affected by the change in climate, using the width of species' seed zones to approximate genetic suitability to specific climates. Thus, growth of an individual tree can be reduced to zero (resulting in mortality) even if the future climate is still within the range of the species as a whole.

Disturbance modeling approach—The modeler applies disturbances. For fire, the modeler determines the year of, and the fire weather during, the event; the model estimates the fuel consumption and tree mortality based on the fuels, stand structure, and weather parameters. Fire effects in FVS-FFE are based on fuel models, modified by measurements if available, and apply Rothermel's (1972) and Van Wagner's (1977) algorithms to estimate flame length and crown fire, respectively. The model uses methods from the First Order Fire Effects Model (Reinhardt et al. 1997) for predicting tree mortality, fuel consumption, and smoke production. There are modules for simulating effects of dwarf mistletoe and root disease. The bark beetle modules are out of date as of 2024 (Dixon 2026).

Harvest and wood products modeling approach—The modeler can pick from a wide range of silvicultural prescriptions (e.g., clearcut, thin from below, thin proportional to diameter) or specify the prescription themselves. The modeler can also select the method for dealing with residues. The fate of wood products removed and their storage over time are simulated using general relationships.

Social and economic modeling approach—An economic model extension enables the assessment of economic costs and revenues of stand treatments and enables the scheduling of treatments based on economic criteria.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated, although a resting habitat module for fisher (*Pekania* [formerly *Martes*] *pennanti*) has been created based on stand structure (Zielinski et al. 2010).

Data needed to run the model—The model can run in default mode and from bare ground with minimal input of location and habitat type data. In practice, most modelers provide measured live-tree data for stands or plots of interest, and some provide a more complete suite of live and dead carbon pools, site index, and habitat type information.

Options for parameterizing or modifying the model—The behavior of FVS can be modified in a variety of ways by changing the maximum density parameters; providing growth data for remeasured trees; and modifying growth, mortality, or regeneration functions (e.g., Vandendriesche 2010).

Model website—https://www.fs.usda.gov/managing-land/forest-management/fvs (USDA Forest Service, n.d.b).

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BioSum (Bioregional Inventory Originated Simulation Under Management)

Type and key citation—Analytical tool (Fried et al. 2017).

Model statement of purpose—BioSum is designed to assess the costs and effectiveness of alternative forest management policies that can include forest health restoration, fuel treatments, sustainable yields of timber and biomass for energy generation, locations for siting biomass energy facilities, and implications for forest carbon.

Key model processes—BioSum model is based on Forest Inventory and Analysis (FIA) data (Gray et al. 2012). FIA plot data are used to initialize the simulation of forest growth and disturbance and management effects using the FVS model. FIA plot locations, ownership, and reserve status help determine the feasibility, likelihood, and cost of different types of management simulated in FVS. The OpCost model (Bell et al. 2017) is used to estimate harvesting costs. The FIA poststratification design is used to estimate population totals, means, and variances (Bechtold and Patterson 2005). A variety of management options are run on each inventory plot, and the results are compared in terms of effectiveness, costs, or other desired criteria.

Spatial and temporal resolution and extent—The basic unit is an FIA plot. Any number of FIA plots can be simulated within a desired region. Simulations run on the 10-year FVS time step for updating stands and can be run for many decades, although 40 years is a common limit.

Mechanisms for ecosystem carbon pools and changes—The FVS model handles all ecosystem carbon pools. The national FIA volume and biomass equations (Westfall et al. 2024) are used on the FVS output to maintain consistency with the national data.

Climate change modeling approach—Climate change is not addressed to date in BioSum projects, given lack of confidence in the FVS approach.

Disturbance modeling approach—The FVS model handles the disturbance modeling. Many BioSum projects have assessed the effectiveness of density management and fuel treatments on reducing wildfire severity (e.g., Jain et al. 2019).

Harvest and wood products modeling approach—The modeler simulates harvest treatments with the FVS model, which also tracks wood product storage over time. BioSum also assesses harvest and transportation costs for each treatment at each FIA plot.

Social and economic modeling approach—Social and economic factors are not explicitly integrated as model drivers, although economic costs of management are included.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Publicly available FIA plot data (USDA Forest Service, n.d.) and a road network map are needed to run BioSum.

Options for parameterizing or modifying the model—Modelers need to devise the management scenarios they want to evaluate and the criteria they want to compare.

Model website—http://biosum.info/ (USDA Forest Service PNWRS, n.d.).

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Stand-Level Models

CBM-CFS3 (Carbon Budget Model of the Canadian Forest Sector3)

Type and key citation—Stock and change model (Kurz et al. 2009).

Model statement of purpose—In 2002, the Canadian Forest Service originally designed CBM-CFS3 because the forest industry wanted an "operational-scale carbon accounting tool" to comply with sustainable forest management requirements and for land managers to keep track of the carbon balance for their land. It is used for Canada's national forest accounting and reporting. It produces annual estimates of forest ecosystem carbon stocks, emissions, effects of disturbance and harvest, and harvested wood product stocks.

Key model processes—The primary driver for CBM-CFS3 is merchantable volume growth and yield curves commonly used in forestry (e.g., models of live-tree volume with stand age). Conversions to biomass in different pools and simulation of ecosystem processes (foliage and fine root production, decomposition of dead organic matter) are primarily based on the stand age and volume curves. Dead wood and forest floor pools are also dependent on prior disturbance and management. Disturbances are applied stochastically, and harvest can be applied deterministically or stochastically.

Spatial and temporal resolution and extent—The basic unit is a stand, which can be defined as a polygon of any size, or as an inventory plot with a defined area weight. Users can specify up to 10 classifiers for each stand including area, age, land class, ownership, and site class. CBM-CFS3 can run project to national scales. The model runs on an annual time step with no temporal limit.

Mechanisms for ecosystem carbon pools and changes—Stinson et al. (2011) described the creation of merchantable volume yield curves. Yield curves are defined by jurisdiction (province/territory), ecozone, forest type, predominant genus, site class, and stocking class. Separate curves were generated for hardwood and softwood components of each forest type. Yield curves were fit to inventory data with an exponential model constrained by a maximum volume, but local yield curves were used in 377 of 589 types used for Canada. The yield curves are used to derive stand-level biomass carbon increments by stand age in each of the aboveground and belowground tree biomass carbon pools tracked by the model. A curve-smoothing algorithm is used to estimate biomass in young stands with little or no merchantable volume.

Some modelers developed growth and yield curves from other models; Hennigar et al. (2008) and Neilson et al. (2006) used STAMAN (Stand Management) and Woodstock to develop curves. Dugan et al. (2018) pulled growth and yield curves from the now-defunct Carbon Online Estimator (COLE), while studies in progress for California and Oregon have developed curves from Forest Inventory and Analysis data. Modelers can transition to different curves after partial disturbance or harvest events.

There are 21 carbon pools estimated by the model: 10 live biomass pools (including hardwood and softwood merchantable stem wood; foliage; coarse roots; fine roots; and "other," which includes branches, seedlings, and saplings) and 11 dead pools (including woody litter, the soil organic horizon, and mineral soil). NPP is estimated by adding the carbon gains associated with the net biomass increment to the carbon uptake that is required to replace losses from foliage and fine root biomass turnover, applied as proportions of stocks (Stinson et al. 2011). Size and composition of dead organic matter is dependent on prior disturbance and management decisions. The dead pools are separated by rate of decay and composition. Decay rates for dead matter and soil carbon are calculated as a function of mean annual temperature and stand-level age, and from Trofymow et al. (2002). The model tracks the various carbon stocks, transfers between pools, and all emissions associated with disturbance, including carbon dioxide, methane, and carbon monoxide.

The initial dead wood, litter, and SOM carbon pool sizes are obtained from an initialization procedure that simulates multiple rotations of growth and disturbance until humified SOM pools at the end of consecutive rotations stabilize (Kurz et al. 2009). Soil carbon is set at values appropriate to the vegetation zone, and stands are simulated for three rotations with wildfire to set up initial conditions and model to the starting age. The model can represent planting through reductions in the regeneration delay in growth and yield curves or through switching to a different growth and yield curve.

Climate change modeling approach—CBM-CFS3 does not include direct climate mechanisms, although temperature does affect decomposition.

Disturbance modeling approach—Disturbances are applied stochastically to stands. The effect of disturbances, including prescribed fire, is defined in "disturbance matrices" that define the proportion of each biomass and carbon pool that is transferred to another carbon pool, the atmosphere, or the forest product sector. Fires are assigned during model runtime to randomly selected forest stands within the appropriate spatial analysis units. The postdisturbance dynamics of the stand are defined primarily by the new growth and yield curve applied to the stand. The model allows the user to define one or more new growth and yield curves to which proportions of the disturbed area will be allocated. With this framework, the user can simulate a wide range of natural disturbances (Kull et al. 2024).

Harvest and wood products modeling approach—The modeler can specify criteria for harvest to occur (e.g., stand age by forest type and ownership). For even-aged management, a stand resets to age zero; other silvicultural systems can be approximated by switching to modified growth curves after harvest.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Growth and yield curves for all forest types and zones of interest, and rates and criteria for when to invoke land-use change, disturbances, and harvest are needed to run the model.

Options for parameterizing or modifying the model—Modelers can change the default volume-to-biomass conversions, litterfall and decomposition rates, types of disturbances and their effects, and use of harvest scheduling from other models.

Model website—https://natural-resources.canada.ca/climate-change/climate-change-impacts-forests/carbon-budget-model (NRC 2026).

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Landscape Process Models

LANDIS-II (Landscape Disturbance and Succession)

Type and key citation—Landscape process (Scheller et al. 2007).

Model statement of purpose—LANDIS-II is designed to model disturbance and forest succession and their spatial interactions for large landscapes. The model tracks cohorts of individual tree species and their physiological responses to climate in defined pixels while simulating seed dispersal and disturbance propagation from adjoining pixels.

Key model processes—Vegetation is simulated as age cohorts of different species, emphasizing how species life history attributes (including longevity, shade tolerance, fire tolerance) affect succession and disturbance effects. The basic model architecture is designed to accommodate different modules and extensions shared in an open, peer-reviewed environment. For example, the Net Ecosystem Carbon and Nitrogen (NECN) succession extension simulates species change in addition to carbon cycling through primary production, mortality, decomposition, and nutrient cycling; the Social-Climate Related Pyrogenic Processes and their Landscape Effects (SCRPPLE) wild and prescribed fire extension simulates spread and intensity of fire across a landscape; and the Biological Disturbance Agent (BDA) extension simulates bark beetle outbreaks (e.g., Maxwell et al. 2022).

Spatial and temporal resolution and extent—The basic unit is a pixel, which can be defined as a square of any size. Extent is unlimited, but for a current high-powered desktop computer, 1-million-ha landscapes at 150-m pixel resolution (2.25 ha) is the practical limit (about 450 thousand pixels), with pixels in similar climatic, topographic, and edaphic conditions grouped into types. The core architecture can accommodate different user-specified time steps for different ecological processes (e.g., 1 day for fire weather, 10 years for succession).

Mechanisms for ecosystem carbon pools and changes—While the details vary among extensions, most of the succession modules track the major live and dead carbon pools. The NECN succession extension tracks carbon and nitrogen and how species respond to changing climate via establishment, growth, reproduction, and mortality. Dead biomass is tracked as down wood, litter, and coarse and fine dead roots. Soil organic carbon is tracked in fast, slow, and passive pools based on the CENTURY model (Parton et al. 1994). Individual live-tree cohorts compete for resources (soil moisture, nitrogen, and light) within each cell (Creutzburg et al. 2017). Light availability is determined by the accumulated leaf area index in a pixel; new cohorts can only establish if sufficient resources are available. Species-specific parameters define optimum growth rates, which are limited by availability of resources.

Climate change modeling approach—Climate effects on species growth and mortality are determined by tolerances and responses defined for each tree species. Extended drought can result in direct tree mortality as well as bark beetle outbreaks. Simulated temperature and moisture affect decay rates. Daily weather also affects the spread and intensity of wildfire.

Disturbance modeling approach—A variety of disturbance extensions are available depending on the type of disturbance and the data available to parameterize them. Wildfire events can be constrained to historical distributions of size and rate of spread, and pixels can be assigned to different disturbance regimes. The SCRPPLE extension has different ignition, suppression, and intensity patterns for lightning, accidental, and prescribed fire. Wildfire spread is a function of ignition, fuels, topography, and fire weather. Daily weather is used to identify maximum fire spread based on the Canadian Fire Weather Index (NRC, n.d.) and windspeed. Empirical data on maximum spread area is regressed to create a starting point for the parameters, which are then iteratively adjusted. A relativized amount of fine fuels with Fire Weather Index and wind define spread potential. A site-level severity is simulated based on percentage of clay content of the soil, the previous year's potential evapotranspiration, effective windspeed, climatic water deficit, relativized fine fuel loading, and amount of ladder fuels. The simulated mortality of a species-age cohort, given the site-level severity, is based on age (and diameter) and bark thickness. Parameters are iteratively adjusted based on fits to empirical data on large fires.

Harvest and wood products modeling approach—Harvest can be specified in relation to cohorts, including total or proportional removal (i.e., clearcut or thinning). Because the model tracks species biomass by age class, conversions developed from other data are necessary to estimate tree sizes and volumes removed. The model does not track harvested wood products.

Social and economic modeling approach—Social and economic factors are not explicitly integrated.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Spatial representations of soils (depth, texture, water-holding capacity), topography, weather/climate, and initial vegetation are needed to run the model. Species physiological and life history parameters, which may be available from prior projects, also need to be supplied.

Options for parameterizing or modifying the model—Modelers can parameterize shrubs and grasses in addition to trees, and species can be grouped into similar functional types if desired. Many extensions are available to run simulations of interest, and modification to the open-source code is possible.

Model website—http://www.landis-ii.org (LANDIS-II Foundation, n.d.).

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State-and-Transition Models

STM (State-and-Transition Model)

Type and key citation—Stage transition model (ESSA Technologies 2007).

Model statement of purpose—Most STMs in the Pacific Northwest region have been based on the Vegetation Dynamics Development Tool (VDDT) (ESSA Technologies 2007). The tool provides a landscape modeling framework for examining the role of disturbance agents and management actions in vegetation change. It allows users to create and test descriptions of vegetation dynamics, simulating them at the landscape level.

Key model processes—State-and-transition simulation models applied to forest ecosystems define different conditions, or states, of one or more vegetation types, and the probabilities of transitions to another state at each model time step. For example, an early-seral forest transitioning to a closed pole-size stand, or a mature forest being burned and transitioning to an early-seral forest. The model can be integrated with other models (e.g., process models) that simulate processes or conditions (Daniel et al. 2018). STMs explicitly simulate landscape change and ecological processes such as succession and fire. They are well suited to simulations of disturbance effects on vegetation, which can be a limitation for some empirical and process models (Littell et al. 2011).

Spatial and temporal resolution and extent—Landscape polygons of any shape and size can be defined and assigned to vegetation states of any desired extent. Hemstrom et al. (2007) defined states by overstory species, disturbance history, potential vegetation, tree diameter, number of layers, open or closed canopy, and grass and shrub stages, resulting in 308 states. Temporal resolution is flexible (often annual), and extent is unlimited.

Mechanisms for ecosystem carbon pools and changes—In most applications, stocks are associated with the states, so emissions and flows happen with the transitions. However, units can be individually tracked in terms of age to enable succession after an appropriate time (Spies et al. 2017). Succession transitions can be developed/checked by running growth and yield models (e.g., FVS). Halofsky et al. (2017) was based entirely on area in different states, no fluxes. Halofsky et al. (2014) reported changes in timber volume over time, presumably using averages by state. Traditional discrete state variables tracked for each landscape unit are state type, age, and time since transition. Daniel et al. (2018) presented an approach for extending STMs to account for continuous state variables, which allows for any number of continuous stocks to be defined for every spatial cell, along with a suite of continuous flows specifying the rates at which stock levels change over time (e.g., carbon flows between biomass, dead wood, and soil). The change in stocks is simulated for each spatial cell as a discrete-time stochastic process. The method was demonstrated for land-use/land-cover change in the state of Hawaiʻi, where continuous stocks are pools of terrestrial carbon, and the flows are the possible fluxes of carbon between these pools. Several of these carbon fluxes are triggered by corresponding land-use/land-cover transitions in the STM.

STMs were incorporated in coupled social-ecological modeling in central Oregon (Spies et al. 2017). For 41 combinations of potential natural vegetation groups and dominant tree species, Spies et al. (2017) built models using inventory data to estimate basal area, tree density (trees per hectare), volume, and biomass from characteristics described by the state-and-transition models: stand age, quadratic mean diameter, canopy cover, and number of canopy layers. The predicted values assigned to each potential natural vegetation group by structure stage were calculated by multiplying the regression coefficients by the midpoints of quadratic mean diameter and canopy cover and the means of age values for inventory plots. Independent landscape units were tracked for stand age to control deterministic transitions to other structure classes, but apparently the other values (e.g., biomass) were not changed. Spies et al. (2017) used an actor-based spatial modeling framework, Envision (Bolte et al. 2007; OSU, n.d.), to represent preferences of different landowners, and incorporate biological attributes and feedbacks.

Climate change modeling approach—The model does not include direct climate mechanisms, although transition matrices can be adjusted for different climates.

Disturbance modeling approach—Disturbances are applied stochastically or deterministically as transition probabilities between different states. Significant differences in disturbance severities result in transitions to different states (e.g., understory burn resulting in lower density stand dominated by large trees versus crown fire resulting in early-seral stand).

Harvest and wood products modeling approach—Harvest transitions can estimate the amount of biomass and volume removed with different treatments. Simulation of harvested wood products has not been incorporated into models used in the Pacific Northwest region.

Social and economic modeling approach—Social and economic factors are not explicitly integrated but can be compatible (see Spies et al. 2017).

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated.

Data needed to run the model—Definitions of states and transitions, and classification of initial landscape are needed to run the model.

Options for parameterizing or modifying the model—State types, transition types, and transition probabilities can all be modified as desired. Existing models can be used as starting points for modification to new landscapes or scenarios.

Model website—https://essa.com/explore-essa/tools/vddt/ (ESSA Technologies Ltd., n.d.).

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Imputation Models

RPA-FDM (Resources Planning Act-Forest Dynamics Model)

Type and key citation—Stochastic imputation model (Wear and Coulston 2019).

Model statement of purpose—RPA-FDM creates projections of timber supply and forest conditions (including carbon stocks) in different regions of the United States with FIA plot data. The model addresses disturbance, aging, harvest, management, climate change, and land-use changes based on scenarios used in the RPA assessments (Coulston et al. 2023).

Key model processes—Transition matrices that specify probabilities of an FIA plot changing to a new state drive the RPA-FDM imputation. The new state is populated from FIA plots that meet the criteria for the new state, reflecting aging, harvest, disturbance, land-use change, or climate change. The transition matrices are built from remeasured FIA plots and from the probabilities of plots moving to a different age class or forest type, and then modified by scenarios developed in other RPA modules.

Spatial and temporal resolution and extent—The basic unit is an FIA plot (about ⅙ acre). The FIA program samples all lands of the United States, with plot weights defined by the sample design and local densification of the base grid (1 plot per 6,000 acres) and the standard FIA poststratification. The model is run on 5-year time steps, with no limit to future projections (although RPA uses a 50-year projection window).

Mechanisms for ecosystem carbon pools and changes—Carbon stocks are calculated from FIA plot measurements of live and standing dead trees or modeled for down wood and forest floor. Projected changes in land use, timber prices, or disturbance based on other RPA modules are used to change the transition matrix probabilities. The new age class and site variables, including future climate conditions, from the transition matrix define the pool of plots from which a plot is imputed to represent the new condition at the next time step. Carbon change is simply the difference between the original plot and the one imputed at the next time step.

RPA-FDM is linked to trade, economics, and land-use change models to inform transition probabilities and harvest rates to use in projections (Wear et al. 2019). Model outputs are described as forest projections for forest conditions on all forested plots. The transition matrices determine the change in age class based on disturbance, harvest, growth for the class (e.g., planted private stands), forest type, and projected future climate to select a closest-matching plot to impute as the new value for the target location. All the transitions captured are empirically derived because they come straight from FIA observations. The model also takes into consideration climate change and changes in productivity.

The model uses Intergovernmental Panel on Climate Change land-use classifications—Forestland remains forestland if either naturally regenerated or replanted postharvest. Forest areas that burned were also still considered forestland. Coulston et al. (2015) applied the model to forests in the Southeastern United States, and the current transition matrices suggest that carbon sequestration will decline in the near future because of forest aging.

Climate change modeling approach—Future climate at a given plot location is used to select plots currently growing in that climate. Carbon dioxide enrichment is incorporated with transition probabilities to different productivities, and climate informs the probability of fire disturbance. The model assumes future climates have existing analogs somewhere in the dataset.

Disturbance modeling approach—Disturbances are embedded in the transition matrix, initially defined by current remeasurements of FIA plots and modified by future scenarios.

Harvest and wood products modeling approach—Harvest transitions and changes in calculated volume and carbon from FIA plot measurements determine the frequency of harvest and volumes removed. RPA-FDM does not model fates of wood products, but the outputs from the model are used in other RPA modules that do.

Social and economic modeling approach—Social and economic factors are not explicitly integrated; scenarios are determined by other RPA modules.

Wildlife, watershed, and ecosystem services modeling approach—Wildlife, watershed, and ecosystem services are not explicitly integrated, although outputs do inform some analyses in other RPA modules.

Data needed to run the model—FIA data, scenarios to modify empirical transition matrices, and estimates of future climate are needed to run the model.

Options for parameterizing or modifying the model—These options are unclear.

Model website—https://research.fs.usda.gov/inventory/rpaa (USDA Forest Service 2025).

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Glossary

autotrophic respiration—Metabolism of carbohydrates by living plants, resulting in consumption of sugars and oxygen and emissions of carbon dioxide.

coarse roots—Tree roots ≥2 mm in diameter.

coarse woody material—Dead wood ≥7.5 cm in diameter.

dead wood—Boles, branches, and roots of trees and shrubs that have died because of senescence, competition, or disturbance, or left as biomass after cutting. Usually includes wood and bark unless specified otherwise. Can be standing (snags) or down (debris).

diagnostic—A type of model function in which the modeler or external data (e.g., leaf area determined by satellite imagery) provide values.

duff—Partially decomposed forest floor layer usually found between the litter and humic layers.

fine roots—Tree and other vegetation roots <2 mm in diameter.

fine woody material—Dead wood <7.5 cm in diameter.

flux—The net exchange of carbon between an ecosystem and the atmosphere.

forest floor—Layer of dead organic matter on top of rock or mineral soil, consisting of litter, duff, or humus. Fine wood is sometimes included with forest floor; forest floor is sometimes included with soils.

gross primary production (GPP)—The amount of carbon converted chemically from atmospheric carbon dioxide to sugars through the process of photosynthesis. This is usually expressed in terms of mass per unit time, or mass per unit time per unit area (e.g., Mg/ha/yr).

heterotrophic respiration—Metabolism of living or dead carbon compounds by bacteria, fungi, or animals, resulting in consumption of sugars and oxygen and emissions of carbon dioxide.

humus—Well-decayed organic material usually found under the duff layer and on top of mineral soil, the lower layer of the forest floor.

litter—Freshly dead organic material with little decay, usually on the ground surface and the top layer of the forest floor.

mineral soil—A layer usually occurring above bedrock and below humus that is a mix of inorganic material (sand, clay, silt, rock), organic compounds, and microbes.

net primary production (NPP)—The net amount of carbon produced by living plants after accounting for the maintenance needs of their living tissue, or gross primary production minus autotrophic respiration.

prognostic—A type of model function in which the solution of internal equations (e.g., those concerning leaf area determined by climate, soils, and stand age) determines values.

sink—A carbon pool that is accumulating carbon.

soil—Often synonymous with mineral soil but can include forest floor depending on the model.

soil moisture—Water content of soil, which can be expressed volumetrically (volume of water per unit volume of soil) or in terms of water potential (the potential energy of water per unit volume relative to pure water in reference conditions).

source—A carbon pool that is emitting carbon.

stock—The amount of carbon in one or more pools at a particular point in time.

stock change—The rate at which the carbon in one or more pools is changing over time.

stomates—The openings in leaves or stems where gas exchange occurs in living plants, including absorption of carbon dioxide and loss of water vapor. The degree of stomatal opening is the primary mechanism that controls plant water loss and carbon dioxide absorption.

vapor pressure deficit—A measure of the dryness of the air, calculated as the difference between the amount of moisture in the air and how much moisture the air can hold when it is saturated. It affects the degree of stomatal openness in many plants.

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