Fuller *et al.*
Carbon Balance and Management (2025) 20:2
https://doi.org/10.1186/s13021-024-00290-0

Carbon Balance and Management

REVIEW

Open Access

Advancing forest carbon projections requires improved convergence between ecological and economic models

Madisen R. Fuller[1*], Manaswini Ganjam[1], Justin S. Baker[1] and Robert C. Abt[1]

Abstract

Forests have the potential to contribute significantly to global climate policy efforts through enhanced carbon sequestration and storage in terrestrial systems and wood products. Projections models simulate changes future in forest carbon fluxes under different environmental, economic, and policy conditions and can inform landowners and policymakers on how to best utilize global forests for mitigating climate change. However, forest carbon modeling frameworks are often developed and applied in a highly disciplinary manner, e.g., with ecological and economic modeling communities typically operating in silos or through soft model linkages through input–output parametric relationships. Recent disciplinary divides between economic and ecological research communities confound policy guidance on levers to increase forest carbon sinks and enhance ecosystem resilience to global change. This paper reviews and summarizes the expansive literature on forest carbon modeling within economic and ecological disciplines, discusses the benefits and limitations of commonly used models, and proposes a convergence approach to better integrating ecological and economic systems frameworks. More specifically, we highlight the critical feedback loops that exist when economic and ecological carbon models operate independently and discuss the benefits of a more integrated approach. We then describe an iterative approach that involves the sharing of methodology, perspectives, and data between the regimented model types. An integrated approach can reduce the limitations or disciplinary bias of forest carbon models by exploiting and merging their relative strengths.

Introduction

Background

Forests play a critical role in the global carbon cycle. They can act both as a carbon sink and source of emissions through changes in land use, management and disturbance [1–4]. Globally, forests cover approximately 31% of the terrestrial land mass, store approximately 45% of the total terrestrial carbon (861 ± 66 Pg C) in aboveground (AG) and belowground (BG) live biomass, soils, deadwood and litter [5, 6]. Forests account for approximately 32% of the total annual land carbon (C) sink globally. Analysis of potential forest C mitigation strategies often relies on the use of forest C models to simulate C storage, sequestration, and emissions fluxes under changing environmental, policy, and socioeconomic conditions, including emerging disturbance regimes (e.g. wildfire, hurricanes, pest and pathogens, land use). Recent modeling research suggests that forests could play an increasingly important role in stabilizing climate change long-term through enhanced C sequestration (in terrestrial and wood product pools) and the supply of biomass feedstocks to the energy system [7–11].

However, despite the importance of forests to the global C budget and policy ambitions to mitigate climate change through forest preservation, management, and expansion [9], critical research gaps remain regarding future forest C stock development and how it might be

*Correspondence:
Madisen R. Fuller
mrfulle2@ncsu.edu
[1] North Carolina State University, Raleigh, NC, USA

impacted by global change drivers. We have categorized the drivers influencing the forest ecosystems into three broad divisions: socioeconomic, resource management, and ecosystem change drivers- discussed in detail in Supplementary Table S1, Additional File 1. These drivers apply both direct and indirect influences on C storage and sequestration within forest ecosystems. Direct and indirect impacts of these drivers on forest C stock development are complex, involving multiple levels of influence and associated interactions that are challenging to study empirically or through field observation [12]. Ecosystem drivers, including deforestation, wildfires, and changing temperatures, have a direct influence on the C dynamics, but management and land use change dynamics are affected by the policy and markets for land-based commodities. For instance, land use changes like deforestation, afforestation, and fragmentation are largely driven by policy decisions and global market forces, but interact with C, water, and nutrient cycling at local scale. Higher population growth can lead to increased meat consumption and agricultural demand and the need for more developed land, driving deforestation [13], but proportionally higher levels in income growth can result in forest expansion [10]. In contrast, policies to mitigate GHG emissions and increase land carbon stocks can result in additional forest expansion and more sustainable management practices, which will influence local ecological systems [14]. Furthermore, an increased market demand for wood-based bioenergy (supported by recent IPCC reports), expansion of C markets that offer incentives for improved forest management, and afforestation can have meaningful impacts on C balances at ecosystem scale, but ecological models are not designed to simulate land management responses to policy and market drivers [15]. Given the complex interactions between ecological and economic systems, one cannot fully decouple ecological perspectives on C dynamics from economic drivers that affect land use and management decisions.

Economic and ecological models play an important role in the scientific literature for assessing the potential impacts of natural and anthropogenic disturbances, changes in land use, and forest management practices on natural resource conditions and C fluxes [16, 17]. Models vary in complexity, temporal and spatial domains, the input parameters required for model execution, and types of model outputs, including ones that can be validated from field and/or remote measurements. Further, models vary in their accounting of the driving factors of climate change. Forest C projections are often developed using a single model or disciplinary focus and may not capture critical feedback loops between ecological and socioeconomic systems. Forest C modeling must continue advancements to support mitigation and adaptation strategies that are resilient to future market and environmental changes. This scientific advancement will require tighter coupling of ecological and economic modeling.

To address the integration of socio-economic and ecological models in forest carbon research, it is essential to build on existing literature that has made significant strides in this area. For instance, Seidl et al. discuss the spatial variability in forest carbon density and the multiscale drivers affecting it through high-resolution simulation models and Lidar data [18]. Rammer examine the vulnerability of sustainable forest management to climate change, emphasizing the need for integrated ecological and socioeconomic models [19]. Additionally, Rammer and Seidl explore the integration of human and natural systems through adaptive management strategies in forest landscapes, highlighting the importance of socioeconomic factors in ecological modeling [20]. Similarly, Van Kooten and Sohngen provides an overview of the economics of forest carbon sinks, discussing the role of economic models in forest carbon sequestration and their integration with ecological models [21]. Van Kooten further delves into the intersection of climate science, economics, and policy, focusing on renewable energy and forest carbon management [22]. These studies underscore the necessity of coupling ecological and economic models to enhance the accuracy and relevance of forest carbon projections.

Ecological modeling of forest C stocks and fluxes is often limited in its analysis on potential impacts of market or socioeconomic factors that drive land use and management change, which could affect long-term simulations of ecosystem productivity. Ecological models often hold land use or management interventions fixed and exogenous over time, allowing ecosystem processes to operate in the absence of market- or policy-induced management regime changes. Although ecological models have frequently incorporated these market, policy, and land use factors into sensitivity analyses, they are infrequently endogenous within the structure of the model. Conversely, economic models can fall short in representing the complexity of the C cycle estimates, including relationships between nutrient and water cycles and forest productivity. Additionally, economic models can oversimplify mechanics of biogeochemical cycles in managed forest systems, including the magnitude of autotrophic and heterotrophic respiration following forest harvest or disturbance. While research is extensive regarding the role of non-biomass carbon pools (i.e., dead organic matter, soils) in optimizing harvest rotations [23–26], this type of analysis is typically restricted to a stand or forest-level due to limited data availability. However, the compounded effect of extensive spatial scale disturbances and their enduring repercussions for prolonged time periods emerges as consequential in large-scale forest management decisions. The data is particularly lacking for assessing soil and below-ground effects of restoration efforts like afforestation [27], which is increasingly of interest to economic models aiming to estimate C effects of such initiatives. Given the immense complexity of forest ecosystems and forest markets, perfectly accounting for both aspects in a single model has proven to be difficult. Nonetheless, advancing forest C science and modeling will require continued efforts towards converging single-disciplinary models. While there is precedent for data-sharing and soft linkages between ecological and economic systems, we argue that the limitations of each approach and common methods for linking projections of ecosystem productivity change with economic models of forest and land management could bias forest C projections.

Objectives

This paper aims to review the substantial scientific literature on forest C modeling. Rather than a comprehensive technical review, we tailor our synthesis around broad model types, advantages, limitations, and previous efforts to couple ecological and economic systems. Within each of these two modeling categories, a diverse array of model types exists, differing in temporal resolution, spatial scope, economic or ecological assumptions, and application. We review widely adopted models in each discipline, provide examples of their application, and address prominent limitations. A broader goal of this research is to provide policymakers, forest carbon scientists, the land use modeling community, and organizations that develop forest carbon projections with an improved understanding of the potential tradeoffs of different modeling approaches and the need for improved systems thinking around forest carbon modeling. We use this review to guide our discussion on key points of integration and feedback loops that should be captured in integrated systems to improve long-term simulations of forest C dynamics. The specific objectives of this manuscript are as follows:

1. Provide an overview of common ecological and economic models of forest C, highlighting relative strengths and deficiencies of individual models
2. Highlight current research gaps and provide contextual examples to highlight how modeling ecological or economic systems in isolation misses critical feedback loops
3. Suggest a roadmap for improved convergence of forest C modeling between ecological and economic disciplines.

Ecological forest carbon models

Empirical models

Empirical, also called growth and yield, models like the USFS Forest Vegetation Simulator and LobDSS are designed to simulate forest survival, growth, and yield by considering factors such as edaphic conditions, competition, and silvicultural treatments. Empirical models often rely on extensive datasets of field measurements collected in a systematic approach to calibrate and validate the simulations. Field measurements involve sample plots, or subsets of plots, from the study region and are used to extrapolate simulation results. Inventory data typically includes site characteristics, management history, and disturbance history. Observations also monitor stand growth, forest establishment, and mortality, supporting the development of allometric equations to simulate C accumulation, stocking, and productivity as a function of time, ecological inputs, and climate inputs [28]. These models are primarily focused on predicting AG biomass volume, as these attributes can be readily converted into estimates of biomass C. Repeated simulations conducted with these models yield estimates of wood C accumulation rates.

A prominent empirical ecological model is the European Forest Information SCENario Model (EFISCEN), which projects European forest development using national inventory data. The required data consists of area, stock volume, and annual growth defined by productivity, ownership, species, stand age, and region. Based on this data, EFISCEN estimates forest compositional attributes, thinning and harvests, forest carbon volume, and climate attributes [29]. This model has been applied widely in Europe on both a national and regional scale. Verkerk et al. uses estimates from EFISCEN to assess potential availability of biomass in 39 European countries, providing insights on target locations for policies aiming to increase woody biomass supply [30]. EFISCEN has also been used in tandem with other models, such as in Lotze-Campen et al. where it is coupled with two other models (CAPRI and Dyna-CLUE) to create a large array of land-use data at a sub-national scale in the EU [31].

The Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) relies on growth and yield curves from inventory data to derive AG biomass volume [27, 32]. However, it also incorporates process-based components such as C distribution to BG pools, temperature-dependent decay rates, and disturbance to account for management and simulate impacts on carbon stocks [33, 34]. National Forest Inventory (NFI) models in Europe are notable for their enhanced spatial analysis and mapping accuracy through the inclusion of remote sensing technologies and GIS. These models utilize satellite imagery, LiDAR, and GIS to provide detailed and accurate forest metrics. For example, a study on European NFIs highlights the use of remote sensing for pre-classifying sample plots and improving growing stock monitoring [35]. Additionally, the integration of NFI data with airborne laser scanning in Spain has been shown to significantly improve forest yield predictions [36].

Succession models

Succession models simulate the forests over a defined time horizon period using simplified parameters for environmental variables and processes in a study area. They monitor long-term changes in the structure of forest ecosystems using species-specific characteristics under varying climatic conditions and disturbances. Bioclimatic variations (i.e. availability of water, nutrients, and light) reflect the competition and growth limitations impacting forest growth dynamics. Gap models are the first generation of succession models and simulate individual trees on a grid and how they interact and compete for resources, reflecting the gap dynamics resulting from natural disturbances. The second generation of these models represent landscape-level dynamics, simplifying stand-level processes. Landscape models assess the impact of extrinsic disturbances at a larger spatial scale. Recent developments in the field of geomatics have improved the efficiency of models in handling large temporal and spatial data to simulate long-term multiple disturbance mechanisms.

Gap models

The JABOWA model, first developed in 1970, laid the foundation for gap models in forest ecology. It simulates individual tree growth, regeneration, and mortality functions for individual trees on a small homogeneous patch at an annual time step [37, 38]. The latest version, JABOWA-3, incorporates detailed carbon dynamics, allowing for growth and yield predictions under diverse forest conditions [39]. Although the first-generation gap models were not explicitly designed to simulate carbon dynamics, they are crucial as the conceptual basis for many current ecological carbon models.

Building on JABOWA's principles are FORET, ZELIG and LINKAGES models. FORET evaluates the long-term effects of species loss on forest composition and structure [40] by incorporating growth reductions as biomass approaches its maximum recorded value [41]. ZELIG captures interactions and competition between grid cells, reflecting landscape structures and succession dynamics [42, 43]. LINKAGES represents soil processes, BG nutrient cycles, water dynamics, and species composition to determine tree growth, mortality, and establishment [44].

The FORECE model, derived from FORET, simulates the alpine region of south central Europe, classifying growth-limiting factors into intrinsic (species-specific) and extrinsic (climate and environmental) variables [45]. Further building on FORECE, FORCLIM specializes in examining the forest impacts of climate change [46]. FORSKA models are unique in their explicit representation of vertical canopy distribution. They assume uniform leaf area distribution along the stem height, simplifying the modeling of shading within the crown [47]. FORSKA models, however, share similar representations of climate and resource dynamics with the FORET model and are largely deterministic [48]. FORSKA models simulate forest succession and associated atmospheric C exchanges based on the distribution of species by age class, AG biomass, and productivity [49].

SORTIE, a second-generation Individual Based Model (IBM), improves on gap modeling by introducing light competition and spatial assignments for individual tree [41], which supports the determination of the distribution of species, age class structure, and landscape C dynamics [50]. Additionally, the PICUS model, a hybrid forest gap model, combines a 3D gap model approach with the physiologically-based production approach of 3PG (Process model) [51], and is widely applied in Europe to assess the impact of climate change and develop adaptive management strategies such as thinning and alternative harvest regimes [52].

Landscape models

Landscape models such as LANDIS II are spatially explicit forest landscape models that simulate ecological succession, incorporating factors such as seed dispersal, land management, disturbances, C dynamics, and climate change on various spatial scales [53–55], providing improved flexibility in spatial and temporal resolution compared to its predecessor [56, 57]. The structure of the model enables users to select from various extensions covering different ecological processes [58]. Notable extensions include the Forest Carbon Succession Extension [59] and the Net Ecosystem Carbon & Nitrogen (NECN) Succession extension [60–62].

Recent applications of LANDIS II demonstrate its versatility in addressing complex ecological questions. For example, the model has been used to simulate fire, vegetation, soil, and hydrology interactions in boreal forests under climate change scenarios [61, 63, 64]. More recently, LANDIS-II has been integrated with an economic optimization model to explore trade-offs among timber production, carbon sequestration, and biodiversity conservation goals [65]. The PnET-Succession extension has been used to build carbon projections by integrating key climate and environmental variables [66].

LANDCLIM is another landscape model that simulates the impact of climate change on vegetation structure and landscape-level forest dynamics [67]. This model operates at multiple spatial and temporal scales, simulating stand-level processes similar to conventional gap models and aggregating results to the landscape level over a 10-year time-frame [68]. It also simulates disturbances similar to LANDIS II, accounting for their selective influence on individual portions of the broader cohort.

Biogeochemical process models

Ecosystem process models depict the spatial interconnections between C, water, and nutrient cycles, operating in a range of spatial and temporal scales. They incorporate consistent ecophysiological subroutines based on fundamental biophysical processes to simulate net C storage, annual fluxes and nutrient cycles [16]. Instead of empirical equations derived from the statistical stand measurements, process-based models rely on processes such as radiation interception, photosynthesis, decomposition, and C allocation to project forest growth and mortality over time. The key aspect of these models lies in their quantitative representation of ecological processes through mathematical algorithms and structural equations. These models thus depict dynamics of energy, matter, nutrient flow and exchange, and transformation across ecosystems. These models often incorporate disturbances and management practices as external forcings on internal processes that affect ecosystem structure and function. Disturbances are typically represented as events that alter biomass, nutrient cycling, and energy flows [69]. Management practices are often simulated as modifications to vegetation structure, resource availability, or disturbance regimes. Many ecosystem process models include modules for fire, insect outbreaks, and various land management activities, allowing for the assessment of their impacts on carbon, water, and nutrient cycles [18].

The 3PG model, short for "Physiological Principles Predicting Growth," bridges the gap between conventional empirical models and more complex C balance models. 3PG relies on a relatively small set of parameters and climate data inputs including solar radiation, atmospheric vapor pressure deficit, precipitation, frost days per month, and average temperature [17]. Ecosystem productivity is estimated through light use efficiency and photosynthetic active radiation coefficients [70]. 3PG is well suited for even-aged, homogeneous forest ecosystems and has been used for a wide range of forest ecosystems and is widely adopted by foresters [71]. Recent extensions of 3PG have been used to simulate future pine productivity in the US south under stochastic climate scenarios [72]. In contrast, PnET (Photosynthesis EvapoTranspiration) operates on a monthly time-step and is primarily designed for temperate deciduous forests [73]. PnET captures interrelations between photosynthetic capacity and leaf nitrogen content and the dependence of stomatal conductance on photosynthetic rate. Notably, PnET ecosystem processes differ from models like FOREST-BGC that used soil and atmospheric physics (e.g Penman-Monteith), simulating average monthly leaf area index, C, and water balances using these structural ecological relationships [73].

The Terrestrial Ecosystem Model (TEM) model estimates distribution and magnitude of C, nitrogen, and water fluxes in terrestrial ecosystems [74]. Different TEM versions were incorporated into local and global scale modeling frameworks to examine the influences of climate, energy, and economic policies on land use and ecological processes [75]. CENTURY assesses C and nutrient dynamics across different ecosystems including forests, grasslands, agricultural, and savannas [76, 77]. CENTURY considers the effects of management practices such as fertilizer, irrigation, cultivation, grazing, and fire [78]. FOREST-BGC captures water, C, and nitrogen cycles comprehensively. The model requires daily climate data and 62 species-specific characteristics to simulate forest ecosystems [79]. The Running and Gower version uses coupled water and nitrogen cycles to dynamically allocate C across vegetation components. In contrast, Biome BGC is versatile, adaptable to various terrestrial biomes, and captures interactions between direct C, nitrogen, and water cycles [79, 80]. The model depicts photosynthesis as a function of climate and specific leaf area variables [81] and reflects respiration to account for C losses to the atmosphere from both the vegetation and below ground processes [81].

Dynamic global vegetation models

Dynamic Global Vegetation Models (DGVMs) are developed upon the same ecological principles as processes-based models, simulating large-scale ecosystem dynamics at broader spatial and temporal scales accounting for interactions between vegetation and global environmental factors. In ecological models, the term "dynamic" specifically refers to their consideration of spatial and temporal aspects, or the influence of time on vegetation growth (primary production). DGVMS capture complex interactions within Earth System Models (ESM) [82]. While process based models are concentrated in modeling local scale ecosystem processes using site specific soil and species characteristics as inputs, DGVMs typically represent aggregated vegetation categories to allow for the incorporation of global scale datasets of land use, climate variables, and other environmental factors. DGVMs offer a holistic framework to evaluate ecosystem responses to shifting environmental inputs or land use change, and they can incorporate feedback mechanisms between vegetation and climate to assess how changes in vegetation influence climate patterns. DGVMs represent disturbances and management as processes that influence vegetation dynamics, biogeochemical cycles, and land-atmosphere interactions, including natural disturbances such as fire, drought, and windthrow, as well as anthropogenic disturbances like land-use change and forest management [82]. DGVMs typically simulate the effects of these processes on vegetation composition, structure, and distribution, as well as on carbon storage and fluxes [83]. Some advanced DGVMs also incorporate feedback mechanisms between disturbances, vegetation, and climate, allowing for the assessment of how changes in vegetation can influence climate patterns and vice versa [84]. While ecosystem process models focus on internal ecosystem processes and their immediate responses to disturbances and management practices, DGVMs provide a robust framework to evaluate ecosystem responses to shifting environmental inputs or land use change, integrating feedback mechanisms that reflect the dynamic interactions between vegetation and climate.

MC2 and LPJmL are both spatially explicit models that simulate large-scale ecological processes. MC2 uses a combination of statistical and mechanistic approaches to model ecosystem responses to global change [85] and employs a biogeochemistry module similar to Century for C allocation across vegetation components using allometric relationships. MC2 also considers climate-influenced variations in vegetation composition and simulates disturbances and post-fire succession [86]. LPJmL, the Lund-Potsdam-Jena Managed Land Model, also offers a comprehensive representation of ecological processes, including photosynthesis, respiration, and decomposition [84]. LPJmL incorporates land use changes like deforestation and afforestation, influencing vegetation growth and C allocation. ORCHIDEE (Organizing Carbon and Hydrology in Dynamic Ecosystems) is another prominent DGVM that simulates the interactions between land surface and atmosphere [87]. ORCHIDEE's multi-layer canopy representation enables better representation of light penetration, photosynthesis, and energy balance at different canopy levels, and ORCHIDEE can simulate various forestry practices such as thinning, clear-cutting, and selective logging [88]. JSBACH (Jena Scheme for Biosphere-Atmosphere Coupling in Hamburg) incorporates a fully coupled carbon-nitrogen cycle to facilitate plant growth limitations and ecosystem responses to changes in nitrogen availability [89]. Furthermore, JSBACH includes a process-based fire model (SPITFIRE) that simulates fire occurrence and simulations of disturbance regimes and their effects on vegetation dynamics [90]. Furthermore, JSBACH includes a process-based fire model (SPITFIRE) that simulates fire occurrence, spread, and impacts based on climate conditions, vegetation characteristics, and human activities, enabling accurate simulations of disturbance regimes and their effects on vegetation dynamics [90]. Furthermore, JSBACH includes a process-based fire model (SPITFIRE) that simulates fire occurrence, spread, and impacts based on climate conditions, vegetation characteristics, and human activities, enabling accurate simulations of disturbance regimes and their effects on vegetation dynamics [90]. LPJmL is integrated into various Earth System Models to simulate broad ecosystem responses to global change drivers. For example, Bond-Lamberty et al. extended Biome-BGC by incorporating multiple vegetation types and spatial heterogeneity, expanding the scope of the model and enabling its application to global scale projects [91]. Furthermore, Hidy et al. have improved the structural component of the Biome-BGC model by including a multi-layer soil module and management modules for forests and crop land, making it applicable to contrasting biomes [92].

Limitations

In general, most ecological models discussed here do not incorporate economic or policy drivers that influence land use changes and management practices. Instead, they often treat land use changes or disturbances as external inputs rather than dynamic variables that evolve over time and across space in response to changing market demands, relative land values, and policy incentives. While ecological models provide a superior representation of ecological processes compared to economic models, they still have limitations in capturing the full complexity of ecosystem C dynamics. Furthermore, some ecological models may not capture ecosystem C dynamics. Empirical model predictions heavily rely on field data and remote sensed data, and thus the precision and accuracy of these models depend on the availability of quantitative data. Additionally, empirical models are typically developed for specific species and site conditions, making it challenging to adapt them to diverse ecosystems.

Successional and biogeochemical models, while advanced in representing ecological processes and anthropogenic impact through management, still have areas for improvement. Successional models simplify certain aspects of forest carbon dynamics, such as interannual changes in C fluxes, respiration [93], ecosystem response to climate change, and management interventions [94]. Biogeochemical models are complex mathematical representations of ecosystem processes that require numerous parameters specific to plant functional types and site conditions, which can be difficult to tailor to a specific context. These model types can be challenging to accurately parameterize and validate due to their complexity [95]. Furthermore, spatial representations in these models may not align perfectly with reality or fully capture the influence of human management interventions [96]. Some models assume a uniform grid with consistent plant functional types, age class structure, and site conditions, although ecological processes are diverse and heterogeneous across space [82, 97].

Economic forest carbon modeling

Empirical simulation models

Empirical models use a bottom-up approach, using collected observational data to make predictions. Methods have been presented to simulate factors such as harvests, growth, and changes in forest type based on related historical data. One prominent example of this method is from Wear and Coulston, which projects future C fluxes in US regions [98]. This approach links inventory data and empirically derived transition probabilities for different forest types, land use, and disturbance on future C stock development, similar to gap or succession models, but with more emphasis on exogenous drivers of land use change (e.g., market demand for timber). This method was also used in a 2004 study that compared model estimates of soil C dynamics with Finnish inventory data, with a particular focus on age-class dynamics [99], which are crucial in understanding changes in C stocks. This framework also features prominently in the 2020 Resources Planning Act Assessment [100]. Nave et al. also uses a simulation approach to estimate potential changes in soil C from reforestation using data from the International Soil Carbon Network for the US Forest Service (USFS) [101].

The Global Forest Model (G4M), which is often used as the forestry sub-module of the multi-sector Global Biosphere Management Model (GLOBIOM) and can be applied globally on a regional or country-level scale, is another example of an empirical simulation model [102]. G4M can be used to determine optimal spatiotemporal harvest decisions and depicts competition for land between forestry and agriculture [103]. Specifically, it has been used to simulate levels of reforestation, deforestation, and afforestation (as well as associated changes in carbon) given variations in economic and ecological parameters such as NPP, population growth, and planting costs [104]. This model has also been used to assess changes in forest productivity under a range of climate change scenarios [105].

A limitation of simulation models is data uncertainty, as discussed in Nave et al. [101]. Thürig et al. further highlights this point by evaluating the accuracy of an existing empirical tree model, asserting that these models can only be as good as the data it uses, suggesting improved data or improvements to the framework as a whole [106]. A final limitation of this approach is the exclusion of market feedback mechanisms, where price changes affect management and harvest patterns, potentially shifting spatiotemporal distribution of harvests and management intensity and, in return, forest C fluxes [107]. Given the interactions between forest management and markets described in [107], it is important to account for these key market feedbacks when projecting future C fluxes,but simulation approaches hold these interactions fixed or exogenously defined.

Empirical structural models

Empirical structural models can project forest C changes as an outcome of market, harvest, and land use changes. This type of model also (typically) bases growth and C estimates on forest inventory data, but with the addition of market parameters (i.e., prices, costs, supply/demand elasticities). This approach explicitly recognizes the relationships between markets for pulpwood and sawtimber, demands for non-forest land, and implications of market or policy changes on land use/management decisions.

One example is the Sub-Regional Timber Supply Model (SRTS), presented first in Abt et al. [108]. SRTS is an empirically validated, regionally applicable, partial equilibrium model that has been used to assess market and resource changes in the southern U.S. forest sector. SRTS represents the intersection between markets and forests, including factors such as prices, forest productivity, and economically driven decisions around spatial harvest patterns and wood supply in the southern U.S. Recent versions of SRTS such as Abt et al. which uses land rents and population data to assess how the bioenergy market could impact the type of forests to be managed [109]. Henderson et al. models the response to C fertilization on pine forests for biological and market systems under different Representative Concentration Pathways (RCPs), linking to forest productivity projections from the 3PG process model [110]. Henderson et al. simulates potential near- and long-term market and C implications of Hurricane Michael [111]. SRTS has also been used to model the effects of forest C policy, with Galik et al. estimating the potential regional impact of bioenergy policy on the environment and the economy [112]. SRTS has been applied to simulate the implications of hypothetical C offset programs on Mississippi pine pulpwood markets, addressing additionality concerns of harvest deferral markets [113]. Dhungel et al. use an extension of the SRTS framework to the Central Hardwoods Region to project market tipping points for white oak sustainability concerns [114]. FORMIT-M (created to project FORest management strategies to enhance the MITigation potential of European forests) is another example of a structural forest sector model which includes 10 European countries. This model uses observational data and structural equations representing ecological systems to estimate future harvest volume under different management and silvicultural regimes [115].

Though these models allow for some market considerations, others often remain exogenous, including land use change (in some contexts), C policy, climate change, and global trade. For example, Hashida and Lewis models how landowners adapt their management decisions related to exogenous changes in land use, carbon pricing, and observable climate factors [116]. Further, these models tend to be region-specific, which although useful in smaller scale assessments, provides limited insight into the national- or global-scale C impacts of market, policy, or climate changes.

Recursive partial equilibrium models

Partial equilibrium (PE) frameworks internalize market forces in the forest sector, and can be designed to simulate management responses to market changes endogenously. Recursive PE models generate market and resource consumption output for a single (static) period, which could represent a single year or multiple years simulated consecutively. The Global Biosphere Management Model (GLOBIOM) is a global model designed to address land use-related topics like climate change, deforestation, bioenergy policy, and agricultural policy [117]. This recursive partial equilibrium model allows for inclusion of climate mitigation impacts and socioeconomic development [118], allowing researchers to infer about potential futures to address prominent policy questions. For example, Lauri et al.(2019) uses GLOBIOM to assess the outcomes of different SSP-RCP scenarios on global biomass harvest and forest area [119]. Böttcher et al. relies heavily on GLOBIOM to project the future of the C sink in European Union Forests given changes in bioenergy policies [120, 121]. Similarly, Forsell et al. uses GLOBIOM to simulate market and C impacts of different scenarios of material substitution possibilities. GLOBIOM forest C projections are also summarized in a recently published global forest model inter-comparison [7]. Though this model and its associated studies have progressed the field immensely, there is still minimal ability to capture basic climate dynamics, with few advances in this aspect since an early example of this model type by Joyce et al. [122].

Another widely used global model is the Global Forest Product Model (GFPM), which simulates forest product supply and markets in different countries and how those countries interact through international trade. Including substantial detail on bilateral trade flows and trade-oriented policies is a distinctive feature of GFPM and the more recently developed FOROM models [123], since many of the commonly used models of forest C ignore the details global trade networks for forest products. Buongiorno (2003) describes potential applications of GFPM, including projections of timber production, consumption, trade, and prices [124]. The model can also support policy analysis as it relates to global forests and restrictions to global trade. The United States Forest Product Model (USFPM) is a derivation of the GFPM, which focuses on markets within the US. Nepal et al. uses these frameworks to project C sequestration and wood energy consumption in the US and global timber markets [125]. GFPM/ USFPM can also be used to assess economic and C impacts of different policy scenarios. For example, a 2013 paper assessed C, costs, and leakage outcomes of different C pricing schemes in the US [126]. Ince et al. similarly assesses future outcomes given different policies aimed at expanding wood energy consumption [127]. A more recent variant of these models is the FOrest Resource Outlook Model (FOROM), which was used in the 2020 Forest Service RPA assessment. This model optimizes consumer and producer surplus, accounting for factors such as transportation costs, resource availability, and market equilibrium constraints regarding prices, consumption, and production. This version also incorporates NPP responses to climate change and divides the US into 6 sub-regions, rather than a single region as in the GFPM [123]. A 2023 application of this model focuses on interactions between international forest product trade flows and market outcomes in the Southern US forest sector [128].

More recent PE frameworks account for spatial dependencies and data heterogeneity to improve future carbon projections and to linking local resource management decisions and national market systems. The Land Use and Resource Allocation Model (LURA) merges spatially explicit data on U.S. forest inventory, land use, and timber markets. Latta et al. highlights the relationship between forest plots (supply) and mills (demand), and discusses the importance of accounting for spatial dependencies when projecting forest C changes at different spatial scales [129]. Xu et al. links LURA with LCA to estimate the lifecycle C emissions from woody biomass in biomass electricity systems [130]. Wade et al. tested whether models that aggregate forest inventory data spatially or by activity sets introduce potential bias in forest C projections, with results supporting the use of spatially explicit empirical and partial equilibrium models [131]. The French Forest Sector Model (FFSM) is another localized, static PE model which focuses on the growing forest sector in France [132]. The two components of this model combine a representation of economic factors such as consumer preferences, supply-side changes, and wood product usage with a component of forest stock. Caurla et al. compares the impacts of one policy that provides payment for C sequestration and another that focuses on simulating fuelwood demand [133]. Similarly, Lecocq et al. compares payments for C sequestration with fossil fuel substitution [134]. Riviere and Caurla adds a spatial component to the FFSM and found high variation in the impacts of timber investment trends on forest management [135]. Such results can help support the design and implementation of effective forest C policy instruments.

Although static PE models offer key advantages in modeling forest C futures, there are limitations to this type of model. First, the output of these models typically exists at an annual or multi-year time step, limiting analysis of longer-term phenomena like climate change in which capturing time preferences and intertemporal resource management can be critical. Second, there is an assumption of myopic decision making, meaning that stakeholders lack insight into future market factors. This assumption is inconsistent with the reality of forest management, where expectations of future markets can heavily influence near-term decision making.

Dynamic intertemporal partial equilibrium models

In an economic context, a dynamic model refers specifically to the inclusion of a behavioral assumption that individuals are forward-thinking in decision making. In other words, a forestland owner in a dynamic representation considers likely changes in markets, policy, and climate. Static PE models do not account for dynamic decision-making, including management choices made in anticipation of future costs and benefits. Dynamic (intertemporal) optimization PE models differ from static PE models in the assumption of perfect foresight which allows a model to reflect how future expectations interact with changes in behavior (e.g., forest management changes made in anticipation of longer-term policy, market, or environmental change factors). Like recursive PE frameworks, intertemporal market models are price endogenous, though equilibrium conditions are determined for all time periods simultaneously as intertemporal economic welfare is maximized.

The Global Timber Model (GTM) has been used extensively to project global and regional C stock changes under different socioeconomic and policy conditions [7, 107, 136–138]. GTM is unique in that it also serves as an example of how economic and ecological models can be paired for analysis of climate impacts on productivity, markets, land use, and markets. One component of GTM is the advancement of empirical structural Timber Supply Model (TSM), which addresses the relationships between market parameters and was one of the earliest models incorporating a distinction between pulpwood and sawlogs, recognizing the connection between the supply of each product [139]. TSM (and now GTM) uses inventory data by age class, land type, and species to identify the optimal time of harvest given trends or shocks in market prices. Recent examples include GTM studies that incorporate productivity projections under different climate scenarios using both the MC2 model [140] and the LPJmL model [141, 142]. GTM studies incorporate projected changes in ecosystem productivity and mortality under different climate scenarios, reflecting a net change in productivity over time. CO_2 fertilization often results in higher net growth and productivity over time, a finding that is supported by global-scale ecological modeling and recent empirical work in the U.S. [143].

Another frequently used example is the US-focused Forestry and Agricultural Sector Optimization Model with Greenhouse Gasses (FASOMGHG), which presents a multi-sector approach for simulating long-term market, management, and environmental outcomes under different scenarios [144]. FASOMGHG has been used to analyze how climate policy incentives, showing that GHG abatement incentives would benefit agricultural producers [145, 146]. FASOMGHG's ability to capture cross-sector interactions and resource competition can benefit C modeling. Jones et al. uses a recently updated version of the model to project forest and agricultural outcomes using the SSP/RCP scenarios to decompose the effect of their components on long-term GHG emissions and C sequestration changes in forestry and agricultural systems, exploiting the model's representation of cross-sector market relationships [147]. Wade et al (2022) builds on Jones (2019) to represent all SSP scenarios and GHG mitigation price incentives [10]. Wade et al. illustrates how baseline components (i.e.,market demand, urbanization, and productivity) in forestry and agriculture can shift the opportunity costs of mitigation investments. FASOMGHG has also been calibrated to biophysical projections of crop and forest productivity changes from the DGVM MC2 and various crop models (e.g., Fei et al. [148]; Baker et al. [149]).

Some examples of dynamic PE models are limited to a single nation or region. NorFor is a forest sector model for Norway and was developed as an integrated model of forestry and industry, creating projections for the forest sector, assessing impacts of political/ economic factors, and tracking C flows [150]. The perfect foresight assumption is used to estimate the equilibrium value of consumer and producer surplus, but also optimizes for climate benefits like GHG reduction. NorFor was used to assess the impact of perfect foresight, finding a faster recovery to system shocks in a world with perfect foresight [151]. This study highlights how the treatment of time dynamics can impact projected outcome of future scenarios or policy incentives. Sjølie et al. uses NorFor to determine forest sector costs and benefits from climate mitigation strategies [152]. In one study, NorFor is compared to a dynamic recursive model in the same region, where they were applied using the same data and comparable assumptions [153]. Through this analysis, they find large differences in market shifts and elasticities between models. However, they argue that neither optimization assumption (myopic vs. perfect foresight) is "better" than the other- they are shown to have strengths and weaknesses that depend on the application and desired analysis.

Limitations

The effectiveness of economic models at projecting forest C stocks and fluxes is limited, with some model attributes being ideal in some research applications while providing little insight in other contexts. These models vary in temporal and spatial scales, but typically represent larger spatial scales. GTM is useful in global assessment of timber markets, but may not capture the nuance of regional forest systems [154]. Another difference between these modeling frameworks is the way in which different C pools are accounted for. LURA includes C pools involved in land use change, such as emissions from deforestation or storage from forest growth [129]. However, Nepal et al. applies the GFPM to estimate C storage under different wood fuel scenarios, focusing on stand C and wood product C [129]. Economic models are also limited in how they represent (or overlook) C and nutrient cycling at smaller spatial scales. While most economic models include estimates of AG C pool changes, very few account for heterotrophic respiration or C dynamics in forest soils [101], which can be a critical component of forest carbon dynamic in peatlands and other ecosystems. A major barrier to improving the representation of these vital ecological processes is based in the complexity of the interaction between the many geophysical processes, which complicates large-scale GHG inventory efforts [155]. Another barrier involves differences in temporal scope, with economic models representing costs and benefits of management interventions at annual or multi-year scale, while some process models are defined at sub-annual, sometimes daily increments. Yet another challenge is the motivation of discipline-specific studies, as ecologists and economists are often motivated to better understand different drivers of the same system. Accounting for soil emissions post harvest or disturbance could affect optimal rotation timing and management decisions, but rarely are these emissions accounted for in regional or global economic framework (in part due to the uncertainties associated with emissions from soil respiration). This shortcoming elucidates one disconnect between ecological and economic projections, despite them being heavily reliant on similar data inputs. Similarly, some studies include wood product carbon pools [7, 126, 156], while others ignore this component, focusing instead on land carbon fluxes [129]. Studies that do include wood product pools often assume little-to-no market interactions, which is particularly important when considering substitution of emission-intensive building materials (i.e., steel, concrete) [157]. This is, in part, due to the general absence of data on substitution elasticities or other assumptions needed to capture cross-market interactions, which require econometric analysis to estimate that is often not possible for new and emerging products like mass timber that can be used to substitute for emissions intensive steel and concrete [158, 159].

More recent modeling efforts include improved representation future scenario narratives, including alignment across SSPs and RCPs. While these narratives and scenario assumptions are useful for academic modeling exercises, there is work to be done to improve these frameworks for practitioners implementing management strategies or policies. The last, major limitation of these frameworks is how forest C projections from ecological process models are sometimes used to calibrate growth and yield assumptions for different forest types. This approach can create a misalignment between ecological projections, which are driven by their own assumptions of land use change and disturbance patterns (which ultimately affect NPP/NEP projections), and economic models, where land use and management changes are often endogenous.

Convergence approach to forest carbon modeling

Capturing critical feedback loops governing forest carbon fluxes

Despite the utility of existing forest C models, there is a clear disconnect between models that are designed to account for the details of economic and ecological processes in the existing literature, even in studies that link these frameworks through input–output relationships. In practice, there are interactions between economic and ecological systems that are vital for better capturing the full suite of forest C dynamics to allow for more reliant modeling and application. Economic models take a landscape-level perspective, but often represent ecological factors as exogenous forces and over-simplify environmental conditions that impact the elements they incorporate endogenously, e.g., management decisions as a function of land quality or site class determination. Land quality is often fixed and exogenous in economic models, but forest productivity can be affected by nutrient cycling, soil microbial processes, and disturbance represented in ecological frameworks. Figure 1 presents hypothetical NPP curves for a representative forest stand over time to demonstrate how variations in ecological and disturbance factors impact the C sink in a more nuanced way at the ecosystem scale. To further illustrate this disconnect at aggregated market scales, Fig. 2 represents changes in C storage from important economic factors in hypothetical scenarios that may not reflect ecological complexities at smaller sub-scales. In the sections below we outline key ecological and economic factors that have key influence over forest C projections at both local and aggregated scales, as well as important feedback loops that currently do not exist between ecological and economic approaches.We note that different policies or programs may have goals that go beyond AG (live-tree) carbon, thus limiting model selection to tools with an enhanced representation of carbon dynamics in all carbon pools. As policy or programmatic efforts evolve, forest carbon modeling tools will need to advance as well to match the level of insight or detail required of the end consumer of the model projections. For example, national accounting and projections to support government programs will require more comprehensive accounting, while some project-scale methods applied to voluntary C offset projects may require less detail (e.g., carbon fluxes in AG and harvested wood product pools).

Ecological models vary in their treatment of these dynamics, with each model displaying distinct

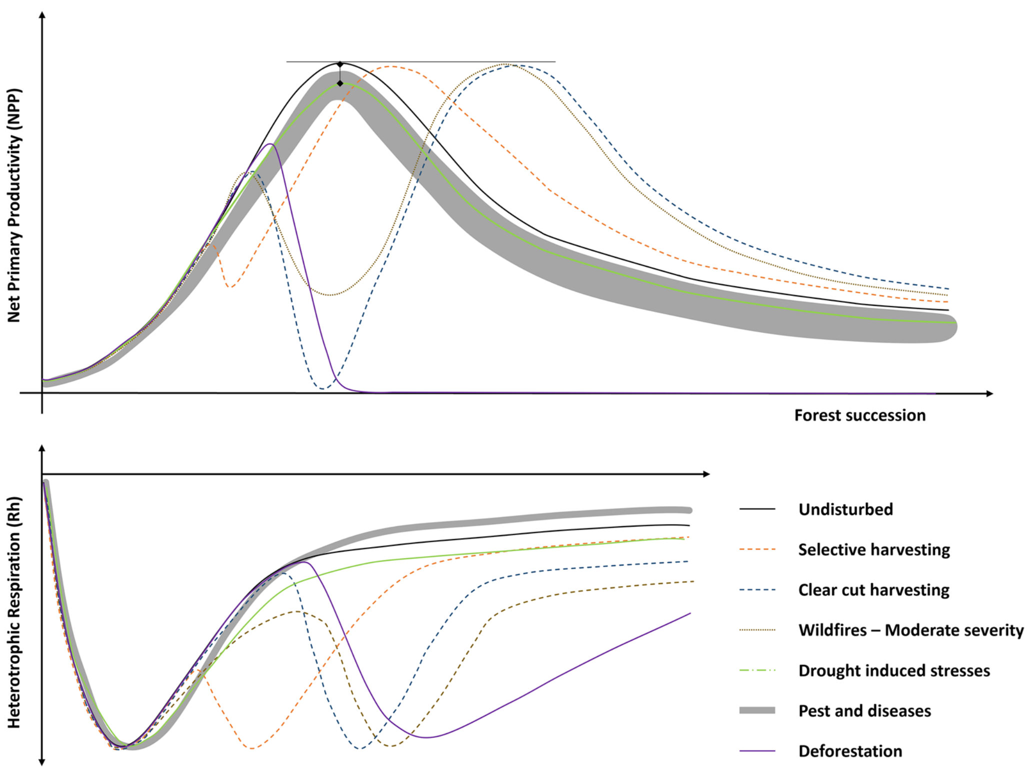

Fig. 1 Illustrates the dynamics of NPP and Rh in forest ecosystems influenced by various disturbances compared to undisturbed conditions, projected over stand age development. Forest age class structure plays a vital role in carbon fluxes and storage over time [160–162], and this figure showcases the diverging trajectories of NPP and Rh under different disturbance regimes. Harvesting, wildfires, drought, pests, and deforestation all have significant effects on forest mortality, structure, and functionality. Harvesting, whether selective or clear-cut, results in a loss of biomass and a subsequent decrease in NPP [163]. Additionally, the soil disturbances and logging residues significantly increase Rh. It is essential to note that our analysis assumes post-harvest replantation [164]. Wildfires have a similar impact on NPP and Rh [165], but wildfires often result in longer recovery times due to their more extensive damage and impact on soil, while harvesting can have a quicker recovery when managed with replantation efforts. Drought affects forest ecosystems in two distinct ways- first, it leads to drought-induced mortality and stresses, resulting in a notably lower peak value of NPP compared to undisturbed forests [166]. Additionally, drought influences soil moisture and soil temperature [167, 168], especially in combination with high atmospheric temperatures. While drought-induced mortality has a significant impact, it can also have a counter-intuitive minor effect on C fluxes through reduced competition for resources like water and nutrients in the ecosystem. Pest and pathogen disturbances are complex, as their effects vary depending on forest species, pest type, and ecosystem response [169]. These disturbances can range from altering forest species composition to organically reducing productivity in defense against diseases [170]. Deforestation can lead to a complete loss of NPP over time and in some contexts an increase in soil respiration [171]

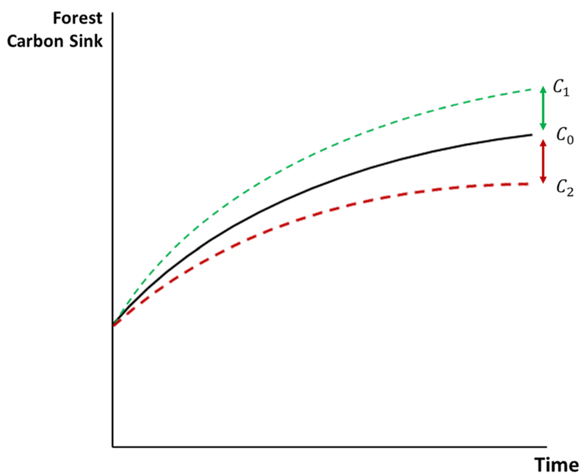

Fig. 2 Changes in forest C accumulation the forest carbon sink at a landscape level for changes in economic and management variables, representing the cumulative change in the C sink across a range of individual forest parcels in a landscape, which can be driven by markets, natural disturbance, or external economic forces including market conditions in the agricultural sector [144, 145, 147]. Trends of land degradation, increased opportunity costs of forest losses, and increased agricultural productivity have led to establishment of forests managed for timber production in some areas, increasing potential for C storage (a shift to C_1). Similar levels of investment could occur through C oriented policies that allocate financial resources to tree planting programs and improved forest management [9]. Alternatively, growing populations and higher demand for food products or urban development could increase incentives to clear forests for alternative land uses, diminishing the carbon sink (Shift to C_2). Large regional disturbances (hurricanes, sustained wildfires) could also decrease C stock accumulation over time in the absence of policy incentives to make up for diminished regional NPP

characteristics. Empirical models primarily rely on historical observational data to predict growth and yield, estimating NPP as a variable influenced by tree growth. Their treatment of Rh tends to remain relatively constant and disturbances are primarily characterized by factors like mortality rates. Succession models simulate forest succession with an emphasis on internal disturbances, and ecological processes being driven by environmental variables. These models integrate NPP and Rh factors by considering them as integral components of ecosystem dynamics. NPP is often linked to tree growth and competition, while Rh reflects the decomposition of organic matter in response to environmental conditions. Biogeochemical process-based models study extensively the physiological processes influencing C, water, and nutrient cycles in ecosystems. Many of these complex processes are not adequately captured in economic models that are aggregated over space and time. Proper decomposition of ecological processes on long-term C dynamics at local or global ecosystem scales facilitates analysis of long-term environmental change and can support identification of hot-spots for ecosystem protection or management interventions to improve system-wide forest C outcomes. On the other hand, economic models are ideal for assessing longer-term forest C outcomes from changes in forest management and land use driven by shifting policy and socioeconomic conditions. Although there are trade-offs in accuracy and accounting for ecological processes, there are aspects of forest C that are better captured in economic models. Specifically, forest management and land use respond to market signals in economic models, making forest C storage endogenous to drivers such as forest product demand, land use preferences, and policy incentives like C payments [7, 146, 172]. Additionally, these models endogenize disturbance-related management decisions, such as shorter rotations to reduce fire risk or avoid emissions associated with harvests and soil carbon losses. Figure 2 shows hypothetical pathways of the C sink for different potential shocks to the broader economic system. In some models, these stock changes also represent off-site sequestration in wood product pools that also accumulate over time, showing a positive increase in total C storage, despite forest C disturbances, growth, and land use change.

Forest carbon modeling limitations

This study identifies several broad limitations in studies that have integrated economic and ecological models through data sharing (input–output) routines:

- First, there is a clear disconnect between the spatial and temporal perspective used by each discipline and the contexts in which they are applicable. Recent evolution of process models allows for spatially explicit simulations of ecosystem productivity and responsiveness to alternative climate and environmental change assumptions. Computational advances, coupled with the proliferation of publicly available spatial datasets have pushed ecological modeling to produce spatially explicit projections of ecosystem changes. Conversely, most economic models operate at aggregated regional scales, in part due to limitations in the availability of economic data (e.g., price responses) at finer spatial resolution and the fact that these models rely on optimization approaches, not simulation (where the former typically requires more computational time as the dimensionality of a system grows). Further, there is often a mismatch in temporal scope, with economic models typically representing larger discrete time steps (annual or multi-year) and time frames (50–100+ years).
- Second, there are structural inconsistencies between the modeling frameworks driven by discipline-

specific goals, as well as the assumptions created to achieve these goals. Ecological process models seek to understand interactions between physical factors (climate inputs, nutrient cycling, soil biota, disturbances) and how these influence forest productivity, assuming management regimes and land use patterns are fixed. Economic models project forest resource utilization, markets, and land use/management under different drivers of global change, assuming static values for ecological factors such as temperature, species, soil dynamics and disturbances. Although making these assumptions has been useful in studying the dynamics within each discipline, it hinders the accuracy of the models by failing to incorporate the multiple complexities between forest C systems.

- Third, there is a lack of convergence between economic and ecological systems. Model integration through output/input sharing will not achieve convergence between economic and ecological systems models if there is not an iterative approach for capturing key feedback loops. Previous climate impact assessments at global and regional scales have used process model simulations of NPP changes to parameterize forest growth and yield assumptions in economic models (e.g., Favero et al. 2017 [172]). In these studies, outputs from ecological model simulations serve as inputs to economic models. While this may be ideal for establishing initial conditions and growth/yield parameters for economic models, it fails to capture inter-dependencies between local resource management decisions and nutrient/water cycling dynamics that alter productivity and species competition over time. A potential shortcoming of this unidirectional flow of information is that it misses key interactions between ecological productivity and management of forest resources. That is, productivity and land use in ecological model simulations likely miss key market drivers and the influence of management decisions on productivity. If the process flow were to work in the opposite direction, calibrating ecological simulations to economic model outputs and management responses to market changes, then process models would be constrained to management choices that may not reflect ecological complexity.

A roadmap for ecological and economic modeling convergence for improved forest carbon projections

There is a need to address the limitations and disciplinary bias of ecological and economic models that run in isolation or are coupled via soft-linkages (data sharing). We propose a convergence approach to forest C modeling where, in this example, convergence refers to both computational convergence across systems frameworks, as well disciplinary convergence around forest C modeling, integrating disciplinary perspectives from economics, ecology, and other disciplines to improve forest C projections. Convergence research methods can help break down disciplinary barriers and support new methodological advancement and research paradigms. There are several recent and emerging applications of convergence research approaches in other contexts, including integrated modeling coupling human, natural, technical, and biological systems (see [173] for more a detailed explanation of convergence research).

Convergence can occur by first recognizing disparate disciplinary perspectives on what drives an outcome of interest (forest C stock changes) and then exploiting these perspectives to improve our understanding of these fundamental drivers of forest C changes. Ecologists should strive to enhance ecological model frameworks by incorporating markets, management, and land use change components. Ecological models can be improved by linking with economic models that account for the influence of external factors that drive land use and management change, such as market signals and policy incentives. Ecologists should also recognize the important role of market dynamics in driving forest investment and the allocation of C to harvested wood product pools, economic logic to better guide baseline and counterfactual scenario development in ecological tools. Economists, meanwhile, should better incorporate water and nutrient cycling processes, their interactions with atmospheric CO_2 fertilization, and residual soil emissions from forest disturbance and harvests into their models. Economic frameworks would also benefit from improved spatial specificity, either by moving to a smaller spatial unit of analysis or, in the case of computational constraints, through improved spatial down-scaling of model outputs. Alternatively, economic models could solve for supply-side dynamics with more spatially detailed supply data (e.g., prices, elasticities).

How scenarios are developed and applied in ecological and economic contexts could also benefit from improved alignment. Economic modeling either develops policy scenarios relative to a single model baseline [9], or through scenarios with different assumptions on future socioeconomic, environmental, and policy conditions [7]. Ecological modeling literature captures long-term projected changes in climate, disturbance factors, and environmental conditions, but typically includes a coarse (and fully exogenous) representation of socioeconomic developments. While recent literature acknowledges the importance of counterfactual scenarios in quantifying mitigation benefits of forests [174], ecological literature still does not fully reflect the role that markets, incentives, and forest management play in driving forest C fluxes. Further, recent studies misapply the logic of counterfactual scenarios common in economics in a way that inflates the projected emissions of management and wood harvests [175].

Convergence can also occur through tighter integration of systems models. Oerther et al. links research on food and water systems to better understand the combined impact on child health for improved environmental health practice and policy [176]. Yang et al. focuses on water networks with multiple regeneration units, creating a framework that adjusts the concentration and flow rates of regenerated streams until their different iterations converge [4]. In the context of molecular biology, Gadkar et al. designed an iterative approach to model the identification of biological networks, discussing the need for the integration of experimental techniques and computational research [177].

Forest C modeling could also benefit from multi-model convergence approaches, as illustrated in the conceptual diagram below (Figure 3). Daigneault et al. provides a recent example of how ecological process and economic models can be integrated with widely used ecological model outputs [65]. An alternative to unidirectional data sharing (NPP projections to forest growth/yield inputs) could be an iterative process as described below:

- Start with ecological projections of NPP by forest type and then incorporate this information into economic models to reflect scenario-specific forest growth and yield assumptions, disaggregating spatially and forest type to the extent possible (following the standing approach).
- Develop economic projections and save key variable outputs such as total C stocks, land area by land use (including by forest type, time, and forest harvest levels by forest type and region).
- Pass projections of land use, forest type changes and harvests back to the ecological framework to serve as exogenous inputs for additional simulations.
- Repeat this process until convergence in forest C stock evolution has been achieved across the multiple frameworks.

This iterative process captures inter-dependencies between ecological and economic systems, while allowing each framework to play to its strengths without full reconciliation of spatial and temporal scale differences. This process of iteration can be repeated in a relatively efficient manner, particularly given the increasing computational abilities of the technology and programs used to execute these models. Once the results of these models reach a desired level of convergence, we are left with projections that simultaneously consider economic and ecological factors that impact the forest C dynamics. These estimates can, in turn, be used to develop effective forest C policies and programs in areas with the greatest ecological and economic C sequestration potential (at the lowest opportunity costs). An alternative would be to create iterative loops for individual time steps, using heuristics that spatially interpolate economic management and land use decisions to parameterize short term ecological projections in DGVMs or other process models.

It is important to note that, while the focus of this manuscript is on improved convergence between ecological and economic systems, *true convergence* on forest carbon modeling will require contributions from other disciplines, including climate and atmospheric sciences, forest science and engineering, and Earth systems science (as a few examples). Paradigm shifts in forest carbon research and modeling require a wide range of perspectives and analytical methods that ultimately go beyond economics and ecology.

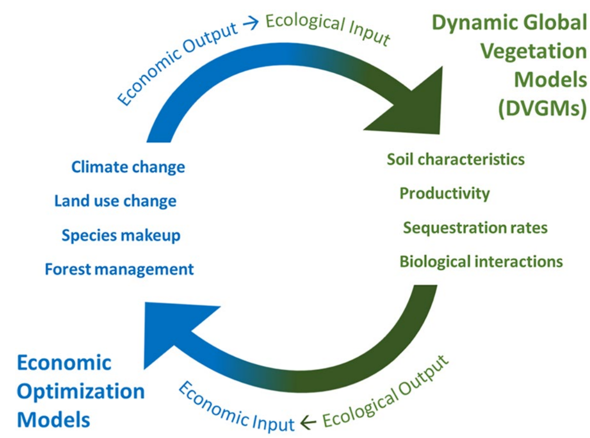

Fig. 3 This figure represents key feedback loops and data elements that could be better calibrated between economic and ecological systems models of forest carbon, although the approach can be applied to the multitude of potential feedback loops between these systems. Economic models can project changes in land use over time, which certainly impact ecosystem-level systems, such as nutrient cycling, but economic models run in isolation ignore this feedback loop between soil processes that affect forest productivity and emissions, which could bias the choice of location, forest type, and extent of management changes projected by economic simulations. Iterative feedback loops between ecological and economic systems could be developed by establishing convergence criteria for a key variable of interest (e.g., total C stocks over time)

Conclusions

This paper performs a detailed review of literature to provide a concise portrayal of the state of modeling forest C aiming to highlight their benefits and provide evidence of a deficiency of interdisciplinary approaches in the existing literature. We first classify forest C models into two broad categories- economic models, which typically take a more landscape approach that links markets and management outcomes to use in policy application, and ecological models, which use a more technical approach to provide a more detailed and comprehensive account of ecosystem-level processes. Ecological models are partitioned into four subcategories- empirical, succession, landscape, and biogeochemical process models. We similarly name four subcategories of economic models- empirical simulation, empirical structural, recursive dynamic, and partial equilibrium dynamic. We discuss each subcategory, provide examples of different model types and their applications, and assert their limitations. Our findings elucidate how differences in scale, assumptions, and applications of models, both within and across disciplines, impact the ability of models to accurately portray the dynamics of forest C.

A salient limitation of economic models is their assumptions related to environmental processes, resulting in a lacking ability to account for ecosystem-level changes that are highly relevant to C projections. As the climate continues to change in ways that are largely unpredictable, the relevance of ecosystem systems to predicting the future forest C sink will continue to grow. Most of these models rely on static assumptions about temperature, water availability, land nutrients, and species adaptation to changing climates. Our discussion of ecological modeling of forest C shows that these factors are highly dynamic and have important interactions not captured by economic approaches. Meanwhile, ecological models do not account for management and socioeconomic drivers of forest C changes. Each type of model serves an important purpose in the research on forest C and has improved our understanding of complex terrestrial C system dynamics. However, the disconnect between economic and ecological models leaves much to be desired, particularly when using C projections to inform decision making and resource allocation.

This study proposes an alternative approach to forest C modeling that draws on convergence research and computing, allowing ecological and economic tools to communicate with each other. The core idea is to use outputs from one model type as inputs for the other, then reincorporate the new set of outputs into the inputs of the original model. This iterative process would continue until the models reach a desired level of convergence, allowing them to fully incorporate both economic and ecological processes. This approach will significantly reduce the level of separation between the economic and ecological disciples in their approach to modeling environmental and socioeconomic systems. Further, this convergence of models will significantly improve the accuracy and reliability of the projections generated by forest C models. These models are used to inform climate policy creation, execution, and analysis, even when run in isolation. There is a need for improved coupled modeling to inform policymakers, requiring nuanced assessments of forest C storage and sequestration over space, time, C pool, and forest type. Conclusions can be drawn and decisions can be made based on future environmental stresses and changes within forest systems based on ecological forest C modeling. Landowners also, directly or indirectly, use information from these models to make management and silvicultural decisions. But a lack of information on potential impacts of factors like temperature, pests, and disturbance risk can result in non-optimal, and potentially detrimental, outcomes for individual forest managers or jurisdictional program managers.

There is growing awareness among global policymakers, NGOs, and individuals of the high C mitigation potential that forests hold. However, there is much uncertainty about the extent to which or how this potential can be harnessed. Although we cannot fully eliminate this uncertainty, there are ways to improve the accuracy of forest C projections for more effective policy design. Existing forest C models have played a crucial role in highlighting the role of forests in efforts to curb C emissions, but as public interest and investment in these methods grows, so must the complexity of models going forward. Using approaches aimed at convergence and integration of the economic and ecological systems that impact forest C, future modeling efforts can provide a more reliable and comprehensive range of forest C projections and ultimately to maximize the C storage potential of global forests with growing demands for food and fiber and under a rapidly changing climate.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13021-024-00290-0.

Supplementary Material 1.

Acknowledgements

The authors are grateful for the support and mentorship of Dr. Stith Tom Gower.

Author contributions

MF compiled and summarized the literature on economic forest carbon models, contributed to the manuscript drafts, and assisted in paper edits. MG compiled and summarized the literature on ecological forest carbon models, supported the formation of manuscript drafts, and provided edits to the review paper. JB contributed to the foundation and editing of the manuscript, provided guidance on economic modeling and the iterative approach to forest carbon modeling, and gave insights and edits throughout the writing process. RA provided guidance on the vision and scope of the review and proposed final edits to the manuscript.

Funding
This work was supported by the Jordan Family Graduate Fellowship for Natural Resource Innovation.

Availability of data and materials
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 31 March 2024 Accepted: 23 December 2024
Published online: 10 January 2025

References

1. Friedlingstein P, et al. Global carbon budget. Earth Syst Sci Data. 2022;14:1917–2005.
2. Turner DP, Ritts WD, Kennedy RE, Gray AN, Yang Z. Regional carbon cycle responses to 25 years of variation in climate and disturbance in the US Pacific Northwest. Reg Environ Change. 2016;16:2345–55. https://doi.org/10.1007/s10113-016-0956-9.
3. Friedlingstein, P. et al. Global carbon budget 2020. Earth Syst Sci Data Discuss. 2020. https://doi.org/10.5194/essd-12-3269-2020
4. Yang F, Fan X-Y, Jia X, Klemeš JJ, Liu Z-Y. An iterative design approach for water networks with multiple regeneration units. J Clean Prod. 2020;271: 122483.
5. Bonan GB. Forests and climate change: forcings, feedbacks, and the climate benefits of forests. Science. 2008;320:1444–9.
6. Pan Y, et al. A large and persistent carbon sink in the world's forests. Science. 2011;333:988–93. https://doi.org/10.1126/science.1201609.
7. Daigneault A, et al. How the future of the global forest sink depends on timber demand, forest management, and carbon policies. Glob Environ Change. 2022;76: 102582.
8. IPCC. Global warming of 1.5° C: IPCC special report on impacts of global warming of 1.5° C above pre-industrial levels in context of strengthening response to climate change, sustainable development, and efforts to eradicate poverty. 1st ed. Cambridge: Cambridge University Press; 2022.
9. Austin K, et al. The economic costs of planting, preserving, and managing the world's forests to mitigate climate change. Nat Commun. 2020;11:5946.
10. Wade CM, et al. Projecting the impact of socioeconomic and policy factors on greenhouse gas emissions and carbon sequestration in U.S. forestry and agriculture. J For Econ. 2022;37:127–31.
11. Law BE, et al. Creating strategic reserves to protect forest carbon and reduce biodiversity losses in the United States. Land. 2022;11:721.
12. Seidl R, et al. Forest disturbances under climate change. Nat Clim Change. 2017;7:395–402.
13. Sirén AH. Population growth and land use intensification in a subsistence-based Indigenous community in the Amazon. Hum Ecol. 2007;35:669–80. https://doi.org/10.1007/s10745-006-9089-y.
14. Smith J, Lenhart S. Climate change adaptation policy options. Clim Res. 1996;6:193–201.
15. Weng Y, Cai W, Wang C. Evaluating the use of BECCS and afforestation under China's carbon-neutral target for 2060. Appl Energy. 2021;299: 117263.
16. Landsberg J, Gower S. Applications of physiological ecology to forest management. 1st ed. Amsterdam: Elsevier; 1996.
17. Landsberg JJ, Waring RH. A generalised model of forest productivity using simplified concepts of radiation-use efficiency, carbon balance and partitioning. For Ecol Manag. 1997;95:209–28.
18. Seidl R, Rammer W, Scheller RM, Spies TA. An individual-based process model to simulate landscape-scale forest ecosystem dynamics. Ecol Model. 2012;231:87–100.
19. Rammer W. Climate change vulnerability of sustainable forest management in the Eastern Alps. Climatic Change. 2024. https://www.academia.edu/13072497/Climate_change_vulnerability_of_sustainable_forest_management_in_the_Eastern_Alps.
20. Rammer W, Seidl R. Coupling human and natural systems: Simulating adaptive management agents in dynamically changing forest landscapes. Glob Environ Change. 2015;35:475–85.
21. Van Kooten G, Sohngen B. Economics of forest ecosystem carbon sinks: a review. In: International review of environmental and resource economics. vol. 1. Now publishers;2007. pp. 237–69.
22. Van Kooten GC. Climate change, climate science and economics: prospects for an alternative energy future. Dordrecht: Springer; 2013. https://doi.org/10.1007/978-94-007-4988-7.
23. Asante P, Armstrong GW, Adamowicz WL. Carbon sequestration and the optimal forest harvest decision: a dynamic programming approach considering biomass and dead organic matter. J For Econ. 2011;17:3–17.
24. Dymond CC, Titus BD, Stinson G, Kurz WA. Future quantities and spatial distribution of harvesting residue and dead wood from natural disturbances in Canada. For Ecol Manag. 2010;260:181–92.
25. Asante P, Armstrong G. Carbon sequestration and the optimal forest harvest decision under alternative baseline policies. Can J For Res. 2016;46:656–65.
26. Asante P, Armstrong GW. Optimal forest harvest age considering carbon sequestration in multiple carbon pools: a comparative statics analysis. J For Econ. 2012;18:145–56.
27. Kurz W, et al. CBM-CFS3: a model of carbon-dynamics in forestry and land-use change implementing IPCC standards. Ecol Model. 2009;220:480–504.
28. Jenkins JC, et al. National scale biomass estimators for United States tree species. For Sci. 2003;49:12.
29. Schelhaas M, Nabuurs G, Verkerk P. Description of the modelling approach of the European Forest Information Scenario model (EFISCEN 4.1). European Forest Institute; 2018.
30. Verkerk PJ, et al. Spatial distribution of the potential forest biomass availability in Europe. For Ecosyst. 2019;6:1–11.
31. Lotze-Campen H, et al. A cross-scale impact assessment of European nature protection policies under contrasting future socio-economic pathways. Reg Environ Change. 2018;18:751–62.
32. Heffner J, Steenberg J, Leblon B. Comparison between empirical models and the CBM-CFS3 carbon budget model to predict carbon stocks and yields in nova scotia forests. Forests. 2021;12(9):1235.
33. Papa CC, et al. Modeling climate-smart forest management and wood use for climate mitigation potential in Maryland and Pennsylvania. Front For Glob Change. 2023. https://doi.org/10.3389/ffgc.2023.1259010/full.
34. Tang Y, Shao Q, Shi T, Lu Z, Wu G. Spatiotemporal dynamics of forest ecosystem carbon budget in Guizhou: customisation and application of the CBM-CFS3 model for China. Carbon Balance Manag. 2022;17(1):10. https://doi.org/10.1186/s13021-022-00210-0.
35. Gschwantner T, et al. Growing stock monitoring by European National Forest Inventories: historical origins, current methods and harmonisation. For Ecol Manag. 2022;505: 119868.
36. Novo-Fernández A, Barrio-Anta M, Recondo C, Cámara-Obregón A, López-Sánchez CA. Integration of national forest inventory and nationwide airborne laser scanning data to improve forest yield predictions in north-western Spain. Remote Sens. 2019;11:1693.
37. Botkin DB, Janak JF, Wallis JR. Some ecological consequences of a computer model of forest growth. J Ecol. 1972;60:849–72.

38. Botkin DB. Forest dynamics: an ecological model. New York: Oxford University Press; 1993.
39. Ashraf MI, Bourque CP-A, MacLean DA, Erdle T, Meng F-R. Using JABOWA-3 for forest growth and yield predictions under diverse forest conditions of Nova Scotia, Canada. For Chron. 2012;88:708–21. https://doi.org/10.5558/tfc2012-137.
40. Shugart HHJ, West DC. Development of an Appalachian deciduous forest succession model and its application to assessment of the impact of the chestnut blight. J Environ Manag. 1977;5:161.
41. Dyer M, Shugart H. Multi-level interactions arising from herbivory: a simulation analysis of deciduous forests utilizing Foret. Ecol Appl. 1992;2:376–86.
42. Smith TM, Urban DL. Scale and resolution of forest structural pattern. Vegetatio. 1988;74:143–50.
43. Urban D, Bonan G, Smith T, Shugart H. Spatial applications of gap models. For Ecol Manag. 1991;42:95–110.
44. Post WM, Pastor J. LINKAGES: an individual-based forest ecosystem biogeochemistry model. ORNL DAAC. 2013. https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1166. Accessed 2022.
45. Kienast F, Kuhn N. Simulating forest succession along ecological gradients in southern central Europe. Vegetatio. 1988;79:7–20.
46. Bugmann HKM. A simplified forest model to study species composition along climate gradients. Ecology. 1996;77:2055–74.
47. Leemans R, Prentice IC. Description and simulation of tree-layer composition and size distributions in a primaeval Picea-Pinus forest. Vegetatio. 1987;69:147–56. https://doi.org/10.1007/BF00038696.
48. Leemans R. Simulation and future projection of succession in a Swedish broad-leaved forest. For Ecol Manag. 1992;48:305–19.
49. Leemans R, Prentice I. FORSKA—a general forest succession model. Uppsala: Meddelanden fraan Vaextbiologiska Institutionen; 1989.
50. Pacala SW, et al. Forest models defined by field measurements: estimation, error analysis and dynamics. Ecol Monogr. 1996;66:1–43.
51. Lexer MJ, Hönninger K. A modified 3D-patch model for spatially explicit simulation of vegetation composition in heterogeneous landscapes. For Ecol Manag. 2001;144:43–65.
52. Seidl R, Lexer MJ, Jäger D, Hönninger K. Evaluating the accuracy and generality of a hybrid patch model. Tree Physiol. 2005;25:939–51.
53. Roberts DW. Modeling forest dynamics with vital attributes and fuzzy systems theory. Ecol Model. 1996;90:161–73.
54. Roberts DW. Landscape vegetation modeling with vital attributes and fuzzy systems theory. Ecol Model. 1996;90:175–84.
55. Mladenoff D, Host G, Boeder J, Crow T. LANDIS: a spatial model of forest landscape disturbance, succession and management. GIS World Books; 1996. p. 175–9.
56. Scheller RM, et al. Design, development, and application of LANDIS-II, a spatial landscape simulation model with flexible temporal and spatial resolution. Ecol Model. 2007;201:409–19.
57. Larocque Guy R. Ecological forest management handbook. Boca Raton: CRC Press; 2016.
58. Thompson JR, Simons-Legaard E, Legaard K, Domingo JB. A LANDIS-II extension for incorporating land use and other disturbances. Environ Model Softw. 2016;75:202–5.
59. Scheller RM, et al. Divergent carbon dynamics under climate change in forests with diverse soils, tree species, and land use histories. Ecosphere. 2012;3:1–16. https://doi.org/10.1890/ES12-00241.1.
60. Dymond CC, Beukema S, Nitschke CR, Coates KD, Scheller RM. Carbon sequestration in managed temperate coniferous forests under climate change. Biogeosciences. 2016;30(13):1933–47.
61. Lucash MS, et al. Burning trees in frozen soil: simulating fire, vegetation, soil, and hydrology in the boreal forests of Alaska. Ecol Model. 2023;481: 110367.
62. Furniss TJ, et al. Informing climate adaptation strategies using ecological simulation models and spatial decision support tools. Front For Glob Change. 2023. https://doi.org/10.3389/ffgc.2023.1269081.
63. Boulanger Y, et al. Multi-model projections of tree species performance in Quebec, Canada under future climate change. Glob Change Biol. 2022;28:1884–902. https://doi.org/10.1111/gcb.16014.
64. Robbins ZJ, Loudermilk EL, Mozelewski TG, Jones K, Scheller RM. Fire regimes of the Southern Appalachians may radically shift under climate change. Fire Ecol. 2024;20:2. https://doi.org/10.1186/s42408-023-00231-1.
65. Daigneault A, Simons-Legaard E, Weiskittel A. Tradeoffs and synergies of optimized management for maximizing carbon sequestration across complex landscapes and diverse ecosystem services. For Policy Econ. 2024;161:103178.
66. Gustafson EJ. PnET-Succession v 5.1: comprehensive description of an ecophysiological succession extension within the LANDIS-II forest landscape model 2023.
67. Schumacher S, Bugmann H, Mladenoff DJ. Improving the formulation of tree growth and succession in a spatially explicit landscape model. Ecol Model. 2004;180:175–94.
68. Schumacher S, Bugmann H. The relative importance of climatic effects, wildfires and management for future forest landscape dynamics in the Swiss Alps. Glob Change Biol. 2006;12:1435–50. https://doi.org/10.1111/j.1365-2486.2006.01188.x.
69. Smith B, Prentice IC, Sykes MT. Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space. Glob Ecol Biogeogr. 2001;10:621–37. https://doi.org/10.1046/j.1466-822X.2001.t01-1-00256.x.
70. Gower ST, Kucharik CJ, Norman JM. Direct and indirect estimation of leaf area index, fapar, and net primary production of terrestrial ecosystems. Remote Sens Environ. 1999;1(70):29–51.
71. Landsberg JJ, Waring RH, Coops NC. Performance of the forest productivity model 3-PG applied to a wide range of forest types. For Ecol Manag. 2003;172:199–214.
72. Restrepo HI, Montes CR, Bullock BP, Mei B. The effect of climate variability factors on potential net primary productivity uncertainty: an analysis with a stochastic spatial 3-PG model. Agric For Meteorol. 2022;315: 108812.
73. Aber JD, Federer CA. A generalized, lumped-parameter model of photosynthesis, evapotranspiration and net primary production in temperate and boreal forest ecosystems. Oecologia. 1992;92:463–74.
74. Raich JW, et al. Potential net primary productivity in south America: application of a global model. Ecol Appl. 1991;1:399–429.
75. Lu X, Kicklighter DW, Melillo JM, Reilly JM, Xu L. Land carbon sequestration within the conterminous United States: regional- and state-level analyses. J Geophys Res Biogeosci. 2015;120:379–98. https://doi.org/10.1002/2014JG002818.
76. Parton WJ. Evaluation of soil organic matter models. Berlin, Heidelberg: Springer; 1996. p. 283–91.
77. Parton WJ, Stewart JWB, Cole CV. Dynamics of C, N, P and S in grassland soils: A Model. Biogeochemistry. 1988;5:109–31.
78. Metherell AK, Harding LA, Cole CV, Parton JP. CENTURY soil organic matter model environment. Technical Documentation Great Plains System Research Unit Technical Report No. 4. 1993. https://www2.nrel.colostate.edu/projects/century/MANUAL/html_manual/man96.html.
79. Running SW, Coughlan JC. A general model of forest ecosystem processes for regional applications I Hydrologic balance, canopy gas exchange and primary production processes. Ecol Model. 1988;42:125–54.
80. Running SW, Hunt RE, editors. Scaling physiological processes: leaf to globe. San Diego: Academic Press; 1993.
81. White MA, Thornton PE, Running SW, Nemani RR. Parameterization and sensitivity analysis of the BIOME-BGC Terrestrial Ecosystem Model: net primary production controls. Earth Interact. 2000;4:1–85.
82. Fisher RA, et al. Vegetation demographics in earth system models: a review of progress and priorities. Glob Change Biol. 2018;24:35–54. https://doi.org/10.1111/gcb.13910.
83. Argles APK, Moore JR, Cox PM. Dynamic global vegetation models: searching for the balance between demographic process representation and computational tractability. PLoS Clim. 2022;1: e0000068. https://doi.org/10.1371/journal.pclm.0000068.
84. Sitch S, et al. Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. Glob Change Biol. 2003;9:161–85. https://doi.org/10.1046/j.1365-2486.2003.00569.x.
85. Bachelet D, Turner D, editors. Global vegetation dynamics: concepts and applications in the MC1 model. In: Geophysical monograph series. vol. 213. Washington D.C., Hoboken, New Jersey: AGU American Geophysical Union, John Wiley & Sons, Inc; 2015. p. 190.

86. Bachelet D, Ferschweiler K, Sheehan TJ, Sleeter BM, Zhu Z. Projected carbon stocks in the conterminous USA with land use and variable fire regimes. Glob Change Biol. 2015;21:4548–60. https://doi.org/10.1111/gcb.13048.
87. Krinner G, et al. A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system. Glob Biogeochem Cycles. 2005. https://doi.org/10.1029/2003GB002199.
88. Naudts K, et al. A vertically discretised canopy description for ORCHIDEE (SVN r2290) and the modifications to the energy, water and carbon fluxes. Geosci Model Dev. 2015;8:2035–65.
89. Reick CH, Raddatz T, Brovkin V, Gayler V. Representation of natural and anthropogenic land cover change in MPI-ESM. J Adv Model Earth Syst. 2013;5:459–82. https://doi.org/10.1002/jame.20022.
90. Reick C, Gayler V. JSBACH 3: the Land Component of the MPI Earth System Model: documentation of version 3.2. Max-Planck-Institut für Meteorologie. 2021. https://books.google.com/books?id=anOCzgEACAAJ.
91. Bond-Lamberty B, Gower ST, Ahl DE, Thornton PE. Reimplementation of the Biome-BGC model to simulate successional change. Tree Physiol. 2005;25:413–24. https://doi.org/10.1093/treephys/25.4.413.
92. Hidy D, et al. Terrestrial ecosystem process model Biome-BGCMuSo v4.0: summary of improvements and new modeling possibilities. Geosci Model Dev. 2016;9:4405–37.
93. Fischer R, et al. Lessons learned from applying a forest gap model to understand ecosystem and carbon dynamics of complex tropical forests. Ecol Model. 2016;326:124–33.
94. Shugart HH, et al. Gap models across micro- to mega-scales of time and space: examples of Tansley's ecosystem concept. For Ecosyst. 2020;7:14. https://doi.org/10.1186/s40663-020-00225-4.
95. Zaehle S, et al. Evaluation of 11 terrestrial carbon-nitrogen cycle models against observations from two temperate Free-Air CO2 Enrichment studies. New Phytol. 2014;202:803–22. https://doi.org/10.1111/nph.12697.
96. Blanco JA, Ameztegui A, Rodríguez F. Modelling Forest Ecosystems: a crossroad between scales, techniques and applications. Ecol Model. 2020;425: 109030.
97. Berardi D, et al. 21st-century biogeochemical modeling: challenges for century-based models and where do we go from here? GCB Bioenergy. 2020;12:774–88. https://doi.org/10.1111/gcbb.12730.
98. Wear DN, Coulston JW. From sink to source: regional variation in U.S. forest carbon futures. Sci Rep. 2015;5:16518.
99. Peltoniemi M, Mäkipää R, Liski J, Tamminen P. Changes in soil carbon with stand age—an evaluation of a modeling method with empirical data. Glob Change Biol. 2004;10:2078–91. https://doi.org/10.1111/j.1365-2486.2004.00881.x.
100. U.S. Forest Service. Future of America's forest and rangelands: Forest Service 2020 Resources Planning Act Assessment. U.S. Department of Agriculture, Forest Service. 2020. https://www.fs.usda.gov/research/treesearch/66413.
101. Nave LE, et al. Reforestation can sequester two petagrams of carbon in US topsoils in a century. Proc Natl Acad Sci. 2018;115:2776–81. https://doi.org/10.1073/pnas.1719685115.
102. Gusti M, Kindermann G. An approach to modeling landuse change and forest management on a global scale. 2011.
103. Gusti M. G4M model documentation tech. rep. ().
104. Gusti M. Uncertainty of BAU emissions in LULUCF sector: sensitivity analysis of the global forest model. In: Proceedings of the 3rd International Workshop on Uncertainty in Greenhouse Gas Inventories Lviv Polytechnic National University, Lviv, Ukraine. 2010. pp. 73–80.
105. Sung S, Forsell N, Kindermann G, Lee DK. Estimating net primary productivity under climate change by application of global forest model (G4M). J Korean Soc People Plants Environ. 2016;19:549–58.
106. Thürig E, Kaufmann E, Frisullo R, Bugmannc H. Evaluation of the growth function of an empirical forest scenario model. For Ecol Manag. 2005;204:53–68.
107. Tian X, Sohngen B, Baker J, Ohrel S, Fawcett A. Will US forests continue to be a carbon sink? Land Econ. 2018;94:97–113.
108. Abt RC, Cubbage FRW, Pacheco G. Southern forest resource assessment using the Subregional Timber Supply Model (SRTS). For Prod J. 2000;50:25.
109. Abt KL, Abt RC, Galik C. Effect of bioenergy demands and supply response on markets, carbon, and land use. For Sci. 2012;58:523–39.
110. Henderson JD, Parajuli R, Abt RC. Biological and market responses of pine forests in the US Southeast to carbon fertilization. Ecol Econ. 2020;169: 106491.
111. Henderson JD, Abt RC, Abt KL, Baker J, Sheffield R. Impacts of hurricanes on forest markets and economic welfare: the case of hurricane Michael. For Policy Econ. 2022;140:102735.
112. Galik CS, Abt RC, Latta G, Vegh T. The environmental and economic effects of regional bioenergy policy in the southeastern U.S. Energy Policy. 2015;85:335–46.
113. Rossi DJ, Baker JS, Abt RC. Quantifying additionality thresholds for forest carbon offsets in Mississippi pine pulpwood markets. For Policy Econ. 2023;156:103059.
114. Dhungel G, et al. Critical market tipping points for high-grade White Oak inventory decline in the Central Hardwood region of the United States. J For. 2023;121:224–34.
115. Härkönen S, et al. A climate-sensitive forest model for assessing impacts of forest management in Europe. Environ Model Softw. 2019;115:128–43.
116. Hashida Y, Lewis DJ. The intersection between climate adaptation, mitigation, and natural resources: An empirical analysis of forest management. J Assoc Environ Resour Econ. 2019;6:893–926.
117. Rautiainen A. Accounting for forest degradation in the Global Biospere Management Model (GLOBIOM). 2012.
118. Valin H. et al. Description of the GLOBIOM (IIASA) model and comparison with the MIRAGE-BioF (IFPRI) model. 2013.
119. Lauri P, et al. Global woody biomass harvest volumes and forest area use under different SSP-RCP scenarios. J For Econ. 2019;34:285–309.
120. Böttcher H, Kurz WA, Freibauer A. Accounting of forest carbon sinks and sources under a future climate protocol–factoring out past disturbance and management effects on age-class structure. Environ Sci Policy. 2008;11:669–86.
121. Lauri P, Forsell N, Di Fulvio F, Snäll T, Havlik P. Material substitution between coniferous, non-coniferous and recycled biomass-Impacts on forest industry raw material use and regional competitiveness. For Policy Econ. 2021;132:102588.
122. Joyce LA, et al. Forest sector impacts from changes in forest productivity under climate change. J Biogeogr. 1995;22:703–13.
123. Johnston CM, Guo J, Prestemon JP. The FOrest Resource Outlook Model (FOROM). 2021.
124. Buongiorno J, Zhu S, Zhang D, Turner J, Tomberlin, D. The Global Forest Products Model (GFPM): structure, estimation, applications; 2003.
125. Nepal P, Ince PJ, Skog KE, Chang SJ. Projection of U.S. forest sector carbon sequestration under U.S. and global timber market and wood energy consumption scenarios, 2010–2060. Biomass Bioenergy. 2012;45:251–64.
126. Nepal P, Ince PJ, Skog KE, Chang SJ. Forest carbon benefits, costs and leakage effects of carbon reserve scenarios in the United States. J For Econ. 2013;19:286–306.
127. Ince PJ, Kramp AD, Skog KE, Yoo D-I, Sample VA. Modeling future U.S. forest sector market and trade impacts of expansion in wood energy consumption. J For Econ. 2011;17:142–56.
128. Guo J, Prestemon J, Johnston C. Forest market outlook in the Southern United States. For Policy Econ. 2023;157:103091.
129. Latta GS, Baker JS, Ohrel S. A Land Use and Resource Allocation (LURA) modeling system for projecting localized forest CO2 effects of alternative macroeconomic futures. For Policy Econ. 2018;87:35–48.
130. Xu H, Latta G, Lee U, Lewandrowski J, Wang M. Regionalized life cycle greenhouse gas emissions of forest biomass use for electricity generation in the United States. Environ Sci Technol. 2021;55:14806–16. https://doi.org/10.1021/acs.est.1c04301.
131. Wade CM, Baker JS, Latta G, Ohrel SB. Evaluating potential sources of aggregation bias with a structural optimization model of the U.S. forestsector. J For Econ. 2019;34:337–66.
132. Caurla S, Lecocq F, Delacote P, Barkaoui A. The French Forest Sector Model: version 1.0. Presentation and theorical foundations. 2010.
133. Caurla S, Delacote P, Lecocq F, Barkaoui A. Stimulating fuelwood consumption through public policies: an assessment of economic and resource impacts based on the French Forest Sector Model. Energy Policy. 2013;63:338–47.

134. Lecocq F, Caurla S, Delacote P, Barkaoui A, Sauquet A. Paying for forest carbon or stimulating fuelwood demand? Insights from the French Forest Sector Model. J For Econ. 2011;17:157–68.
135. Riviere M, Caurla S. Landscape implications of managing forests for carbon sequestration. For Int J For Res. 2021;94:70–85.
136. Favero A, Yoo J, Daigneault A, Baker J. Temperature and energy security: will forest biomass help in the future? Clim Change Econ. 2023;14:2350018.
137. Favero A, Daigneault A, Sohngen B. Forests: carbon sequestration, biomass energy, or both? Sci Adv. 2020;6: eaay6792.
138. Kim SJ, Baker JS, Sohngen BL, Shell M. Cumulative global forest carbon implications of regional bioenergy expansion policies. Resour Energy Econ. 2018;53:198–219.
139. Sedjo RA, Lyon KS. Timber supply model 96: a global timber supply model with a pulpwood component. 1996.
140. Tian X, Sohngen B, Kim JB, Ohrel S, Cole J. Global climate change impacts on forests and markets. Environ Res Lett. 2016;11:035011.
141. Favero A, Mendelsohn R, Sohngen B. Can the global forest sector survive 11° C warming? Agric Resour Econ Rev. 2018;47:388–413.
142. Favero A, Mendelsohn R, Sohngen B, Stocker B. Assessing the long-term interactions of climate change and timber markets on forest land and carbon storage. Environ Res Lett. 2021;16:014051.
143. Davis EC, Sohngen B, Lewis DJ. The effect of carbon fertilization on naturally regenerated and planted US forests. Nat Commun. 2022;13:5490.
144. Beach RH, Zhang YW, Mccarl BA. Modeling bioenergy, land use, and GHG emissions with FASOMGHG: Model overview and analysis of storage cost implications. Clim Change Econ. 2012;03:1250012. https://doi.org/10.1142/S2010007812500121.
145. Baker JS, et al. Net farm income and land use under a U.S. greenhouse gas cap and trade. Agricultural and Applied Economics Association. Policy Issues. 2010.
146. Jackson RB, Baker JS. Opportunities and constraints for forest climate mitigation. BioScience. 2010;60:698–707.
147. Jones JPH, et al. Importance of cross-sector interactions when projecting forest carbon across alternative socioeconomic futures. J For Econ. 2019;34:205–31.
148. Fei C, et al. Future climate change impacts on US agricultural yields, production, and market. Anthropocene. 2023;42:100386.
149. Baker JS, et al. Projecting US forest management, market, and carbon sequestration responses to a high-impact climate scenario. For Policy Econ. 2023;147:102898.
150. Sjølie HK, Latta G, Gobakken T, Solberg B. NorFor—a forest sector model of Norway: Model overview and structure. 2011.
151. Sjølie HK, Latta GS, Adams DM, Solberg B. Impacts of agent information assumptions in forest sector modeling. J For Econ. 2011;17:169–84.
152. Sjølie HK, Latta GS, Solberg B. Potentials and costs of climate change mitigation in the Norwegian forest sector—does choice of policy matter? Can J For Res. 2013;43:589–98.
153. Sjølie HK, Latta GS, Trømborg E, Bolkesjø TF, Solberg B. An assessment of forest sector modeling approaches: conceptual differences and quantitative comparison. Scand J For Res. 2015;2(30):60–72. https://doi.org/10.1080/02827581.2014.999822.
154. Sohngen B, Mendelsohn R, Sedjo R. A global model of climate change impacts on timber markets. J Agric Resour Econ. 2001;26:326–43.
155. Lempriére T, et al. Canadian boreal forests and climate change mitigation. Environ Rev. 2013;21:293–321.
156. Johnston C, Buongiorno J, Nepal P, Prestemon J. From source to sink: past changes and model projections of carbon sequestration in the global forest sector. J For Econ. 2019;34:47–72.
157. Howard C, Dymond CC, Griess VC, Tolkien-Spurr D, van Kooten GC. Wood product carbon substitution benefits: a critical review of assumptions. Carbon Balance Manag. 2021;16:1–11.
158. Jochem D, Janzen N, Weimar H. Estimation of own and cross price elasticities of demand for wood-based products and associated substitutes in the German construction sector. J Clean Prod. 2016;137:1216–27.
159. Petersen AK, Solberg B. Environmental and economic impacts of substitution between wood products and alternative materials: a review of micro-level analyses from Norway and Sweden. For Policy Econ. 2005;7:249–59.
160. Odum EP. The strategy of ecosystem development. Science. 1969;164:262–70.
161. Alexandrov GA. Carbon stock growth in a forest stand: the power of age. Carbon Balance Manag. 2007;2:4. https://doi.org/10.1186/1750-0680-2-4.
162. Hoover CM, Smith JE. Aboveground live tree carbon stock and change in forests of conterminous United States: influence of stand age. Carbon Balance Manag. 2023;18:7. https://doi.org/10.1186/s13021-023-00227-z.
163. Peters EB, Wythers KR, Bradford JB, Reich PB. Influence of disturbance on temperate forest productivity. Ecosystems. 2013;16:95–110. https://doi.org/10.1007/s10021-012-9599-y.
164. Paul-Limoges E, Black T, Christen A, Nesic Z, Jassal R. Effect of clearcut harvesting on the carbon balance of a Douglas-fir forest. Agric For Meteorol. 2015;203:30–42.
165. Sparks AM, et al. Fire intensity impacts on post-fire temperate coniferous forest net primary productivity. Biogeosciences. 2018;15:1173–83.
166. Arain MA, et al. Heat and drought impact on carbon exchange in an age-sequence of temperate pine forests. Ecol Process. 2022;11:7. https://doi.org/10.1186/s13717-021-00349-7.
167. Kljun N, et al. Response of net ecosystem productivity of three boreal forest stands to drought. Ecosystems. 2006;9:1128–44. https://doi.org/10.1007/s10021-005-0082-x.
168. Zheng P, et al. Effects of drought and rainfall events on soil autotrophic respiration and heterotrophic respiration. Agric Ecosyst Environ. 2021;308: 107267.
169. Crowley KF, Lovett GM, Arthur MA, Weathers KC. Long-term effects of pest-induced tree species change on carbon and nitrogen cycling in northeastern U.S. forests: a modeling analysis. For Ecol Manag. 2016;372:269–90.
170. Lovett GM, Canham CD, Arthur MA, Weathers KC, Fitzhugh RD. Forest ecosystem responses to exotic pests and pathogens in eastern North America. BioScience. 2006;56:395.
171. Vasenev VI, et al. Megacities 2050: environmental consequences of urbanization. Cham: Springer International Publishing; 2018. p. 18–35.
172. Favero A, Mendelsohn R. The land-use consequences of woody biomass with more stringent climate mitigation scenarios. J Environ Prot. 2017;08:61–73. https://doi.org/10.4236/jep.2017.81006.
173. Roco, Mihail C. Principles and methods that facilitate convergence. In: Handbook of science and technology convergence. Springer; 2016. p. 17–41.
174. Grassi G, Pilli R, House J, Federici S, Kurz WA. Science-based approach for credible accounting of mitigation in managed forests. Carbon Balance Manag. 2018;13:1–16.
175. Peng L, Searchinger TD, Zionts J, Waite R. The carbon costs of global wood harvests. Nature. 2023;620:110–5.
176. Oerther DB, Voth-Gaeddert LE, Divelbiss DW. Improving environmental health practice and policy through convergence research: a case study of linked food-water systems enhancing child health. Environ Eng Sci. 2019;36:820–32. https://doi.org/10.1089/ees.2019.0058.
177. Gadkar KG, Gunawan R, Doyle FJ. Iterative approach to model identification of biological networks. BMC Bioinform. 2005;6:155. https://doi.org/10.1186/1471-2105-6-155.

Publisher's Note